



## The Differences in Mean and Volatility Shock Transmission among Bitcoin, Currencies from Developed Countries, and Currencies from Emerging Countries

Boubaker TOUIJRAT<sup>1\*</sup>

Brahim BENAID<sup>2</sup>

Hassane BOUZAHIR<sup>3</sup>

<sup>1,2,3</sup>ISTI Lab, ENSA, Ibnou zohr

University-Agadir, Morocco.

<sup>1</sup>Email: [boubakertoujrat@gmail.com](mailto:boubakertoujrat@gmail.com)

<sup>2</sup>Email: [brahim.benaïd@gmail.com](mailto:brahim.benaïd@gmail.com)

<sup>3</sup>Email: [hbouzahir@yahoo.fr](mailto:hbouzahir@yahoo.fr)

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(\* Corresponding Author)

### Abstract

This paper studied the mean and volatility transmission among Bitcoin as the most prominent cryptocurrency, exchange rates from developed countries/regions, and exchange rates from emerging countries/regions. Using daily returns between January 1, 2015, and December 31, 2018, and Bivariate VAR - Diagonal VECM models. The empirical results suggest there was no mean transmission between USD/EUR and USD/BTC. However, there was a unidirectional mean shock transmission link from USD/CNH, USD/MAD, and USD/IDR to USD/BTC. The results also suggested the existence of a bidirectional cross-volatility persistence link between bitcoin and all the exchange rates, except for USD/IDR and a bidirectional cross-volatility spillover link between USD/BTC and USD/CNH. A critical implication of these results is that they will be of use to investors, speculators, risk managers, and policymakers in understanding the degree of integration in terms of volatility and return among Bitcoin, currencies from developed, and currencies from emerging countries.

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## 1. Introduction

With Bitcoin's emergence as the first and, to date, most popular cryptocurrency, focus turned to this new asset, particularly in 2016 and 2017. It gained much traction in the investing world and the financial press. Bitcoin's price grew by more than 1,358 percent in 2017, valuing it at more than 215 billion dollars. The Chicago Mercantile Exchange (CME) Group was the first to recognize Bitcoin as a genuine asset. As a result, in December 2017, the Chicago Board Options Exchange (CBOE) issued futures contracts to maintain the value of Bitcoin. Many market players see this as a sign that Bitcoin has gained ground as a legitimate investment instrument. As a result, study on the return and volatility relationship between Bitcoin and other asset classes is vital. Bitcoin is characterized by exceptionally high returns and volatility (Baek & Elbeck, 2015), which might have an impact on many asset classes and, as a result, the economic system's stability (European Central Bank, 2012). Any indication of substantial return and volatility Shocktransfers between Bitcoin and other asset classes has an impact on asset selection and allocation, risk management choices, and regulatory measures aimed at ensuring the global financial system's stability. It's also essential for governments contemplating Bitcoin as part of their foreign reserves or experimenting with their own Bitcoin equivalents. From a theoretical economic standpoint, Ali, Barrdear, Clews, and Southgate (2014) suggest that a digital currency like Bitcoin might be classified as money based on how well it serves the three cardinal functions of cash, namely store of value, medium of exchange, and unit of account. These economic activities, however, are acknowledged to be time variable and are insufficient for digital currencies to be deemed money for legal and regulatory purposes. While digital currencies are now used by a small number of individuals and are mostly used as a store of value, Reyes (2016) draws on endogenous economic regulation, endogenous development, and functional financial regulation theories. Decentralized automation, such as blockchain technology and its underlying payment systems such as Bitcoin, Reyes claims, firmly support the concept of endogenous, technology-assisted regulation. Li and Wang (2017) provide a theory-driven approach to understanding technological adoption and monetary economics theories. Bitcoin is regarded as a value-

transfer economic tool that, like other monetary instruments, is progressively maturing into a competent position. In the long run, it is consistent with economic fundamentals. Finally, [Luis, de la Fuente, and Perote \(2019\)](#) suggest that, in addition to its other functions, Bitcoin fits well with the evolutionary theory of money because it optimizes transactions among economic agents.

To date, the few studies that have looked at the relationship between Bitcoin and financial factors have only looked at a few assets at a time, such as UK stocks, EUR/USD, and GBP/USD ([Dyhrberg, 2016a](#)). Notably, the current literature does not contain any empirical studies on the return and volatility spillovers between Bitcoin and other currency rates. Therefore, this study attempts to address these gaps:

1. No statistical analyses of mean and volatility spillovers have been conducted between Bitcoin, Chinese, European, Moroccan, and Indonesian currencies.
2. No empirical research looks at the differences in spillovers between countries that have prohibited cryptocurrencies and those that have not.
3. No empirical research investigates the differences in the mean and volatility spillovers between Bitcoin, developed-country currencies, and emerging-market currencies.

First, we considered a rich set of four exchange rates, namely USD/EUR, USD/CNH, USD/MAD, and USD/IDR. We selected emerging markets (Morocco and Indonesia) because of the growing popularity of Bitcoin in these nations. We also concentrated on China since Bitcoin is utilized there to circumvent capital controls, and China was one of the first states to accept cryptocurrencies with enthusiasm. Second, from January 1, 2015, to December 31, 2018, we employed a newly developed multivariate econometric approach called VaR-GARCH in the mean framework with the Diagonal VECH representation. This research might lead to a better understanding of Bitcoin's ability to function as a diversifier or hedge against these types of exchange rates.

## 2. Literature Review

Investors and speculators with various levels of risk appetite can benefit from well-functioning transaction platforms supported by blockchain technology. [Liu and Serletis \(2019\)](#) challenge the notion that Bitcoin investments are risky. Bitcoin's typical daily price movements are up to ten times greater than those of the regular currency market, and it is mostly driven by speculation. Similarly, [Kyriazis and Prassa \(2019\)](#) point out that, while Bitcoin investments can be extremely risky, they can also be quite rewarding, particularly during bullish market episodes. Given Bitcoin's extreme volatility, our research suggests that bearish markets have investment and profit-making possibilities. As a result, including Bitcoin in a well-diversified portfolio has been observed to be highly appealing, see ([Briere, Oosterlinck, & Szafarz, 2015](#); [Halaburda & Gandal, 2014](#)), given that Bitcoin average returns have stayed significantly high since its inception ([Bouri, Gupta, Tiwari, & Roubaud, 2017a](#)). [Ji, Bouri, Kristoufek, and Lucey \(2019\)](#) have recently demonstrated that steady asset removal relates more to Bitcoin exchange volatility connectivity than trade volume. The breadth of research on cryptocurrencies has grown exponentially in recent years, with [Corbet, Lucey, Urquhart, and Yarovaya \(2019\)](#) providing a thorough review of such developments, highlighting price efficiency, price volatility, and the presence of criminality as pressing issues within the products and exchanges on which they trade. Many research that have looked at the link between Bitcoin and other assets, such as [Bouri et al. \(2017a\)](#), [Bouri, Das, Gupta, and Roubaud \(2018\)](#), [Guesmi, Saadi, Abid, and Ftiti \(2019\)](#), and [Aslanidis, Fernandez Bariviera, and Martínez-Ibañez \(2019\)](#) have shown substantial evidence of a weak correlation. Bitcoin has many similar characteristics to gold and, as a result, the dollar, whether it's in terms of hedging capacities or as a means of trade ([Trabelsi, 2018](#)). However, [Bouri, Jalkh, Molnár, and Roubaud \(2017b\)](#) show that Bitcoin may be a safe haven and a solid hedge against commodities indexes. [Bouri, Shahzad, and Roubaud \(2019\)](#) use the cross-quantilegram technique to explore the connection and directional predictability from US stock sectors to eight cryptocurrencies ([Han, Linton, Oka, & Whang, 2016](#)). Some cryptocurrencies, they claim, may be useful digital asset classes. Bitcoin is advantageous as a diversifier, according to [Baek and Elbeck \(2015\)](#), due to its low correlation with bonds and stocks. [Briere et al. \(2015\)](#) investigated the relationship between Bitcoin and a variety of conventional (worldwide equity indices, bonds, fiat currencies) and unconventional (commodities, hedge funds, real estate) assets and found that, despite Bitcoin's high volatility, allocating 3% of a well-diversified portfolio to Bitcoin can often improve the risk-return trade-off of well-diversified portfolios. [Ji, Bouri, Gupta, and Roubaud \(2017\)](#) utilized a directed acyclic graph method to show that Bitcoin can help diversify portfolios owing to its separation from traditional assets. These earlier research, on the other hand, used an unconditional correlation analysis and did not take into consideration return and volatility Shocktransmissions, especially in different market situations. Using univariate GARCH, [Dyhrberg \(2016b\)](#) demonstrated Bitcoin's capacity to hedge against currency and stock market fluctuations in the UK. Multivariate GARCH models, on the other hand, are frequently found to disclose more about market linkages. Using regression models with dummy variables as supplements, ([Demir, Gozgor, Lau, & Vigne, 2018](#)) utilize quantile-on-quantile regressions to investigate the relationship between Bitcoin and the economic policy uncertainty index, and discover that Bitcoin is frequently used for hedging against uncertainty. [Gajardo, Kristjanpoller, and Minutolo \(2018\)](#) use MF-ADCCA to investigate the existence and asymmetry of cross-

correlation between currency rates, Bitcoin, the DJIA, gold prices, and crude oil prices. Their findings show that Bitcoin's association with commodities differs from its relationship with stock market indexes.

Zhang, Wang, Li, and Shen (2018) discovered persistent cross-correlation between the calculated index and the Dow Jones Industrial Average when designing a cryptocurrency composite index. As demonstrated by Chaim and Laurini (2018), such cross-correlations are also vulnerable to the occurrence of persistent levels of high unconditional volatility with rapid, abrupt price swings. Similarly, Bouri et al. (2018) discovered that Bitcoin price swings are quite comparable to those of different assets, especially commodities, indicating that Bitcoin is not totally isolated. There is, however, no empirical evidence of differences in return and volatility spillovers between Bitcoin, developed-country currencies, and emerging-country currencies.

### 3. Econometric Methodology

To examine the linkage differences among Bitcoin, currencies from developed countries, and currencies from emerging countries, we conducted the ARCH LM test to justify the GARCH model choice, then we constructed four bivariate VaR-DVECH models to capture return and volatility spillover effects, and finally, we conducted both residual diagnostics and a Wald test to confirm the adequacy and stability of our models.

#### 3.1. Conditional Mean, Covariance, and Variance Models

To examine the mean and volatility spillovers among the USD/BTC, USD/EUR, USD/CNH, USD/MAD, and USD/IDR exchange rates, we used a multivariate VaR-GARCH model. VaR-DVEC was developed by Bollerslev, Engle, and Wooldridge (1988) because the unrestricted VECH model in the simplest case of two assets contains 21 parameters. Estimating the unrestricted VECH model can quickly become unfeasible as the number of assets employed in the model increases.

Let  $r_t = (r_{1t}, \dots, r_{Nt})'$  be a vector of returns of N number of assets at time index  $t = (1, 2, \dots, T)$ . At time  $t$ , the set of information accessible is indicated by  $\mathfrak{F}_t$ . We assume that the dynamic multivariate assets return  $r_t$ , a vector autoregression of order  $p$  conditional on the information set can properly describe  $\mathfrak{F}_{t-1}$  as:

$$r_t | \mathfrak{F}_{t-1} = \Phi_0 + \sum_{l=1}^p \Phi(l)r_{t-l} + \varepsilon_t \quad (1)$$

Where in equation 1,  $E(r_t | \mathfrak{F}_{t-1}) = \Phi_0 + \sum_{l=1}^p \Phi(l)r_{t-l} = \mu_t$  and  $\Phi(l) = (\Phi_{ij}(l))$ , is the  $N \times N$  coefficient matrix of the lagged dependent variable of the mean model. The  $N \times 1$  intercept vector is denoted by  $\Phi_0$  and  $\varepsilon_t | \mathfrak{F}_{t-1} = H_t^{0.5} \zeta_t$ , where  $\zeta_t = (\zeta_{1t}, \dots, \zeta_{Nt})'$  is the independent and identically distributed (iid) random vectors of order  $N \times 1$  with  $E(\zeta_t) = 0$  and  $E(\zeta_t \zeta_t') = I_N$  where  $I_N$  is an Identity matrix of order  $N \times N$ . The symmetric conditional variance-covariance matrix  $H_t$  of order  $N \times N$  is defined as follows:

$$H_t = E(\varepsilon_t \varepsilon_t' | \mathfrak{F}_{t-1}) = E\left[(r_t - E(r_t))(r_t - E(r_t))' | \mathfrak{F}_{t-1}\right] \quad (2)$$

Model (1) with (2) is more compactly stated as  $r_t | \mathfrak{F}_{t-1} \sim D(\mu_t, H_t)$ , where  $D(\dots)$  is some specified probability distribution. Or, equivalently as  $\varepsilon_t | \mathfrak{F}_{t-1} \sim D(0, H_t)$ . Various parameterizations for  $H_t$  have been proposed in the literature, for example (Bollerslev et al., 1988; Engle, 2002), among others. Therefore, our model of return and volatility of returns takes the below form.

#### 3.2. Return Equations

$$r_t | \mathfrak{F}_{t-1} = \Phi_0 + \sum_{l=1}^p \Phi(l)r_{t-l} + \varepsilon_t, \quad \varepsilon_t | \mathfrak{F}_{t-1} \sim D(0, H_t) \quad (3)$$

Where  $\Phi_0$  is the intercept vector and  $\Phi(l)$  is the coefficient matrix of the autoregression of lag order  $l$  for the mean equation.

In our case study, the return Equation 3 becomes:

$$\begin{pmatrix} r_{i,t} \\ r_{j,t} \end{pmatrix}_{|\mathfrak{F}_{t-1}} = \begin{pmatrix} \Phi_{0,i} \\ \Phi_{0,j} \end{pmatrix} + \sum_{l=1}^p \begin{pmatrix} \Phi_{i,i}(l) & \Phi_{i,j}(l) \\ \Phi_{j,i}(l) & \Phi_{j,j}(l) \end{pmatrix} \begin{pmatrix} r_{i,t-l} \\ r_{j,t-l} \end{pmatrix} + \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{pmatrix} \quad (4)$$

Let:

$$\begin{aligned} \Phi_{i,i}(l) &= \phi_i(l) \\ \Phi_{j,j}(l) &= \phi_j(l) \\ \Phi_{j,i}(l) &= \phi_i(l) \\ \Phi_{i,j}(l) &= \phi_j(l) \end{aligned}$$

Equation 4 Becomes:

$$\begin{pmatrix} r_{i,t} \\ r_{j,t} \end{pmatrix}_{|\mathfrak{T}_{t-1}} = \begin{pmatrix} \Phi_{0,i} \\ \Phi_{0,j} \end{pmatrix} + \sum_{l=1}^p \begin{pmatrix} \phi_i(l) & \phi_j(l) \\ \phi_i(l) & \phi_j(l) \end{pmatrix} \begin{pmatrix} r_{i,t-l} \\ r_{j,t-l} \end{pmatrix} + \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{pmatrix} \quad (5)$$

Note: in our case of study  $i = \text{USD/BTC}$  and  $j = \text{USD/EUR}; \text{USD/CNH}; \text{USD/IDR}$

### 3.3. Variance-Covariance Model

Suppose  $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})$  such that  $E(\varepsilon_t) = 0$  and  $E(\varepsilon_t \varepsilon_t' | \mathfrak{T}_{t-1}) = H_t$  where  $H_t$  is positive definite and  $\varepsilon_t = H_t^{0.5} \zeta_t$  with  $\zeta_t \sim i.i.d.(0, I_N)$ .  $\mathfrak{T}_{t-1}$  Contains historical market data up to the period  $t-1$ . According to Bollerslev et al. (1988), the conditional variance equation (VECH model) is:

$$vech(H_t) = C + \sum_{k=1}^q A_k vech(\varepsilon_{t-k} \varepsilon_{t-k}') + \sum_{k=1}^p B_k vech(H_{t-k}) \quad (6)$$

Where in equation 6, each denotes the half vectorization operator. The  $A_k = (A_{ij,k})$  and  $B_k = (B_{ij,k})$  are coefficient matrices with  $N(N + 1)/2$  are coefficient matrices with C as a positive-element  $(N(N + 1)/2) \times 1$  intercept vector. Every conditional variance and covariance in the VECH specification is a linear function of all preceding conditional variance and covariance (Terasvirta, Tjostheim, & Granger, 2010). The DVECH(1,1) model is defined as follows:

$$H_t = C + A \circ (\varepsilon_{t-1} \varepsilon_{t-1}') + B \circ H_{t-1} \quad (7)$$

with  $\circ$  as the Hadamard product. The C, A, and B are  $N \times N$  symmetric matrices in equation 7, and it assumes that A and B in Equation 8 are diagonal. The equation can be written as:

$$h_{ij,t} = c_{ij} + A_{ij} \varepsilon_{i,t-1} \varepsilon_{j,t-1} + B_{ij} h_{ij,t-1} \quad (8)$$

### 3.4. Estimation Method

The conditional mean-variance system can be estimated jointly under the assumption of conditional normality. Maximizing the log-likelihood function may be used to estimate the parameters of multivariate VAR-GARCH models for any of the above specifications.

$$l(\theta) = -\frac{TN}{2} \log(2\Pi) - \frac{1}{2} \sum_{t=1}^T (\log |H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad (9)$$

Where  $\theta$  stand for all the unknown parameters to be estimated, N stands for the number of assets, T stands for the number of observations, and the rest of the notation is the same as before. Because the maximum-likelihood estimate  $\theta$  is asymptotically normal, standard statistical inference techniques may be used.

### 3.5. Residual Diagnostic

In multivariate conditional heteroscedasticity models, portmanteau statistics (Box & Pierce, 1970) have been employed as a benchmark for diagnosing model inadequacies. This test, which is based on cross products of standardized residuals, is frequently used as a diagnostic tool. Denoting  $\hat{\varepsilon}_t = (\hat{\varepsilon}_{t1}, \dots, \hat{\varepsilon}_{tk})'$  and the elements of  $\hat{\Sigma}_t$  by  $\hat{\sigma}_{ij,t}$ , we define i-th standardized residuals at time t as

$$\tau_{it} = \frac{\hat{\varepsilon}_{it}}{\sqrt{\hat{\sigma}_{iit}}}$$

Let  $\hat{\rho}_{ij,t}$  be the estimated conditional correlation coefficient defined by  $\hat{\rho}_{ij,t} = \frac{\hat{\sigma}_{ijt}}{\sqrt{\hat{\sigma}_{iit} \hat{\sigma}_{jjt}}}$ ; we consider  $C_{ij,t}$  defined by

$$C_{ij,t} = \begin{cases} \tau_{it}^2 - 1 & i = j \\ \tau_{it}\tau_{jt} & i \neq j \end{cases}$$

For  $i, j = 1, 2, \dots, k$  When the constant-correlation or the no-correlation models are estimated  $\hat{\rho}_{ij,t}$ , is a constant with respect to  $t$ . Under correct model specification,  $C_{ij,t}$  is asymptotically serially uncorrelated and  $E(C_{ij,t} | \Phi_{t-1}) \rightarrow 0$  as  $n \rightarrow \infty$ . As a result, a diagnosis based on the Box-Pierce statistic of the squared lag autocorrelation coefficient  $C_{ij,t}$  may be developed. Specifically, we denote  $r_{hij}$  as the lag- $h$  autocorrelation coefficient of  $C_{ij,t}$  and define

$$Q(i, j; m) = n \sum_{h=1}^m r_{hij}^2$$

If the multivariate conditional heteroscedasticity model fits the historical data,  $C_{ij,t}$  should be serially uncorrelated for  $i$  and  $j$ . Model insufficiency would be indicated by a high value of  $Q$ . In the empirical literature, the Test has been frequently used to diagnose both univariate and multivariate conditional heteroscedasticity models. [Tse and Tsui \(1999\)](#).

### 3.6. Wald Test

Unrestricted regression is used in this test. The Wald statistic analyzes how near the unconstrained estimates are to meeting the null hypothesis's constraints. If the constraints are reasonable, the unrestrained estimates should come close to meeting them.

Refer to Return [Equation 5](#) to test Return Spillovers among Bitcoin, currencies from developed countries, and currencies from emerging countries. The following hypotheses can be tested by using Wald Test:

- **Return Spillovers from market  $i$  to market  $j$**

$$H_1^0 : \phi_i(l) = 0$$

- **Return Spillovers from market  $j$  to market  $i$**

$$H_2^0 : \phi_j(l) = 0$$

Refer to the multivariate volatility model [Equation 8](#) for ( $N = 2$ ). The following hypotheses are of interest to test the volatility spillover effects among Bitcoin, currencies from developed countries, and currencies from emerging countries by Wald test. The following hypotheses can be tested.

- **Volatility Spillovers between market  $i$  and market  $j$**

$$H_3^0 : A_{12} = B_{12} = 0$$

- **Spillovers between market  $i$  and market  $j$**

$$H_4^0 : H_1^0, H_2^0, H_3^0 \text{ Are true}$$

Note:  $i = \text{USD/BTC}$  and  $j = \text{USD/EUR; USD/CNH; USD/IDR}$

## 4. Results and Discussions

### 4.1. Data

We used Bitcoin, two exchange rates from developed countries/regions (USD/EUR & USD/CNH), and two exchange rates from emerging countries (USD/MAD & USD/IDR).

We chose bitcoin as a proxy of cryptocurrency as it proves its dominance among other cryptocurrencies ([Yi, Xu, & Wang, 2018](#)). The data is collected over the sample period from 01 January 2015 until 31 December 2018, giving a total of 1461-time series observations to investigate the differences in linkage among Bitcoin, developed country's currency and emerging country's currency. Continuously compounded daily returns are calculated based on the following logarithmic filter:

$$r_{i,t} = \text{Ln}\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

Where  $r_{i,t}$  and  $P_{i,t}$  represent percentage daily returns and opening index/exchange rate  $i$  prices at day  $t$ , respectively. To compensate for the missing data values, we smoothed out by filling the missing data by the close price of the day before ( $P_{i,t-1}(\text{close})$ ).

4.2. Descriptive Statistics

The characteristics of our data set presented in Table 1, USD/BTC offered on average the highest return (17,0546%) compared to the other currencies that only offered (0,3639% for USD/EUR, 0,6848% for USD/CNH, 0,3651% for USD/MAD and 0,1023% for USD/IDR) in one hand, on the other hand, Bitcoin showed comparatively higher risk (Std.Dev 4.132702) compared to other stock indexes rates (Std.Dev 0.472538 for USD/EUR, Std.Dev 0.242615 for USD/CNH, Std.Dev 0.316907 for USD/MAD and Std.Dev 0.314198 for USD/IDR ). Non-normality and fat tails are also suggested by the data in Table 1. The Jarque-Bera Lagrange Multiplier Test failed to reject the null hypothesis that the data were normally distributed, with p-values of 0 for all the time series above. The Ljung-Box statistics detected significant autocorrelation in all cases. USD/EUR returns did not show a significant autocorrelation for Q(10), but its other lags are significant. The ADF and PP unit root tests are used to determine if the return series is stationary. The unit root Null Hypothesis is rejected, implying that the return series under investigation are stationary processes. Furthermore, the LM test for ARCH effects is calculated to support the GARCH model structure. The relevant F-statistics and Engle’s LM tests were significant in all return series with the exception of lag 10 in USD/BTC and USD/EUR LM test. However, it was not the case for the bitcoin test’s sixth lag and seventh lag and USD/EUR test’s fourth and fifth lags, thus GARCH was chosen as an acceptable model for this investigation since it supports the occurrence of ARCH effects.

Table-1. Descriptive Statistics.

Data					
Descriptive stat	USD-BTC	USD-EUR	USD-CNH	USD-MAD	USD-IDR
Mean	0.170546	0.003639	0.006848	0.003651	0.010230
Median	0.175965	0.000000	0.000000	0.000000	0.000000
Maximum	23.72200	2.430363	2.761291	1.692403	1.587482
Minimum	-34.54095	-2.995268	-1.498392	-2.095637	-3.280184
Std. Dev.	4.132702	0.472538	0.242615	0.316907	0.314198
Skewness	-0.581551	-0.114031	0.359718	-0.050945	-1.539452
Kurtosis	10.57846	7.179935	19.47888	7.978226	21.10656
Jarque-Bera	3576.136	1066.035	16550.99	1508.248	20520.74
(Prob.)	0.000000	0.000000	0.000000	0.000000	0.000000
Q(10)	19.628	12.694	16.716	16.805	23.791
(Prob.)	0.033	0.241	0.081	0.079	0.008
ADF Test	-39.64077	-37.87227	-37.67601	-38.18082	-34.94068
(Prob.)	0.000000	0.000000	0.000000	0.000000	0.000000
PP Test	-41.09201	-37.87232	-37.68775	-38.18082	-35.20356
(Prob.)	0.000000	0.000000	0.000000	0.000000	0.000000
ARCH LM (9) F-Stat	1.525468	1.248758	1.784922	1.713224	2.476143
(Prob.)	0.1335	0.2608	0.0666	0.0811	0.0084
ARCH LM (9) Obs*R <sup>2</sup>	13.69423	11.22929	15.99785	15.36200	22.09933
(Prob.)	0.1336	0.2603	0.0669	0.0815	0.0086

Note:

<sup>a</sup> Q(10) is the Ljung-Box for serial correlation in the residuals, we did the test for 36 lags.

<sup>b</sup> The critical values for the ADF and PP test are -3.432 and -2.863, for 1% and 5% respectively.

<sup>c</sup> to test the null hypothesis of no ARCH effect up to order 9 in the residuals, we specified a regression of the squared residuals on a constant and lagged squared residuals up to 9.

5. Results and Discussion

As the study focused on the differences in mean and volatility Shock transmissions among Bitcoin, exchange rates from developed countries/regions, and exchange rates from emerging countries, four VaR-DVECH bivariate models were estimated using Eviews program version 10. Each model was calibrated with daily Bitcoin returns and exchange rate returns.

- The difference in the mean and the volatility linkages among Bitcoin, exchange rates from developed countries, and those from emerging markets:

The results shown in Table 2 demonstrate no cross mean spillovers between Bitcoin and USD/EUR. However, Bitcoin’s returns were influenced by USD/CNH return’s ninth lag, USD/MAD return’s third lag, and USD/IDR return’s first lag, since ( $\phi_{USD/CNH}(9)$ ),  $\phi_{USD/MAD}(3)$  and  $\phi_{USD/IDR}(1)$ ) were statistically significant.

As for cross volatility spillovers (refer to Equation 8 and Table 3, the results showed that there were no cross volatility spillovers in all the equations except for Bitcoin-USD/CNH equation since A(1,2) in this equation was statistically significant, which means that Bitcoin’s and USD/CNH past innovations were influenced by one another.

Table-2. Estimated Mean Models.

Mean Systems				
Coefficients	BIT-USD/EUR	BIT-USD/CNH	BIT-USD/MAD	BIT-USD/IDR
$\Phi_0, Bitcoin$	0.233173***	0.248062***	0.227475***	0.227788***
$\Phi_0, USD/EUR$	-0.001324	-	-	-
$\Phi_0, USD/CNH$	-	0.004790	-	-
$\Phi_0, USD/MAD$	-	-	-0.005526	-
$\Phi_0, USD/IDR$	-	-	-	0.006054
$\varphi Bitcoin(6)$	0.001870	-0.001443	-	0.001987
$\varphi USD/EUR(4)$	0.034926	-	-	-
$\varphi USD/EUR(12)$	-0.039361	-	-	-
$\varphi USD/CNH(1)$	-	0.013006	-	-
$\varphi USD/CNH(5)$	-	-0.041141	-	-
$\varphi USD/CNH(9)$	-	0.061662**	-	-
$\varphi USD/MAD(3)$	-	-	-0.053098**	-
$\varphi USD/MAD(4)$	-	-	0.011386	-
$\varphi USD/IDR(1)$	-	-	-	0.106109***

Note:

<sup>a</sup> \*significant at the level of 10%, \*\*significant at the level of 5%, \*\*\*significant at the level of 1%.

<sup>b</sup> BIT stands for Bitcoin.

In terms of cross-volatility persistence, the results shown in Table 3 also indicated that B(1,2) was significant in all the equations except for BIT-USD/IDR, which means that (Bitcoin & USD/EUR), (Bitcoin & USD/CNH), and (Bitcoin & USD/MAD) shared bidirectional relationships in terms of cross volatility persistence.

**Note:** the results above were confirmed by the Wald Test see Table 4.

Table-3. Estimated Volatility Models.

Variance Systems				
DVECH Coefficients	BIT-USD/EUR	BIT-USD/CNH	BIT-USD/MAD	BIT-USD/IDR
M(1,1)	0.612739***	0.555495***	0.537583***	0.546250***
M(1,2)	-0.004587	0.001431	-0.000352	0.006881
M(2,2)	0.000344**	0.004281***	0.000128***	0.000802***
A(1,1)	0.123475***	0.114466***	0.120950***	0.118984***
A(1,2)	0.001482	-0.056486***	-0.006239	0.003900
A(2,2)	0.009554***	0.034656***	0.002863**	0.093448***
B(1,1)	0.849189***	0.860519***	0.858984***	0.858984***
B(1,2)	0.881232***	0.806417***	0.977542***	0.627997
B(2,2)	0.988284***	0.892074***	0.994615***	0.909112***

Note:

<sup>a</sup> \*significant at the level of 10%, \*\*significant at the level of 5%, \*\*\*significant at the level of 1%

<sup>b</sup> BIT stands for Bitcoin

Table-4. Wald Test.

Wald Test Hypothesis				
Samples	$H_1^0$	$H_2^0$	$H_3^0$	$H_4^0$
BIT-USD/EUR	0.678054	4.440534	59.36305***	71.34097***
BIT-USD/CNH	0.864181	6.732085*	86.45647***	101.9535***
BIT-USD/MAD	-	5.473250*	6300.759***	6323.911***
BIT-USD/IDR	2.403496	13.04667***	0.111983	15.73580***

Note:

<sup>a</sup> \*significant at the level of 10%, \*\*significant at the level of 5%, \*\*\*significant at the level of 1%

<sup>b</sup> BIT stands for Bitcoin.

Overall, the findings revealed that neither country growth nor policymakers could have an impact on the nature of the relationship between their respective currency rates and cryptocurrencies. Even though Morocco is a third world country that prohibits the usage or purchase of cryptocurrencies, USD/MAD returns impact USD/BTC returns. In addition, the Moroccan exchange rate and Bitcoin have a bidirectional volatility persistence link. The European region, on the other hand, does not prohibit the usage of cryptocurrencies; nonetheless, there was no cross mean spillover link between USD/EUR and USD/BTC, nor was there a cross-volatility persistence relationship. The hypothesis that bitcoin and

exchange rates from developed nations where the usage of cryptocurrencies is permitted might explain these outcomes. Speculators, risk managers, and portfolio hedgers coupled Bitcoin and emerging-market exchange rates in attempt to diversify their portfolios.

**5.1. Residual Diagnostic**

Finally, the portmanteau test see [Table 5](#) using standard residuals only showed weak evidence of autocorrelation in the standardized residuals in (Bitcoin – USD/CNH) from lag 6 to 7 and from lag 9 to 11 based on these results, we can safely assume that our mean equations were correctly specified.

**Table-5. Portmanteau test.**

<b>Q-Stat for each sample</b>				
<b>Lags</b>	<b>BIT-USD/EUR</b>	<b>BIT-USD/CNH</b>	<b>BIT-USD/MAD</b>	<b>BIT-USD/IDR</b>
1	4.931825	9.408731*	6.526397	4.051917
2	8.599118	13.74501*	10.30315	6.713698
3	17.35626	16.08077	16.80415	11.51277
4	21.89043	21.83604	24.40428*	15.55513
5	24.54709	26.45821	27.14492	19.23421
6	30.26992	31.79043	33.05771	27.17896
7	33.28569	34.38143	36.99813	32.86189
8	33.83274	36.13763	38.23852	35.60941
9	37.99877	38.02257	43.19052	38.49292
10	42.74523	44.02685	47.85109	43.99237
11	44.46186	48.0302	50.56836	46.75357
12	54.36554	51.37984	57.51094	47.60944

Note:

- <sup>a</sup> \*significant at the level of 10%, \*\*significant at the level of 5%, \*\*\*significant at the level of 1%
- <sup>b</sup> The test is valid only for lags larger than the System lag order.
- <sup>c</sup> BIT stands for Bitcoin.

**6. Conclusion**

Our investigation is motivated by the scarce literature on the return and volatility Shocktransmissions between Bitcoin and a selection of exchange rates, namely, USD/EUR, USD/CNH, USD/MAD, and USD/IDR. This study examines the differences in linkages between Bitcoin and currencies from both emerging countries and developed ones. This investigation has led to subsequent pieces of evidence. Firstly, the empirical results provide convincing findings for the return spillover effect in a unidirectional way, from all the exchange rates except for USD/EUR to Bitcoin. One possible conclusion that could be drawn is that profits from the more regular forex markets are transferred to the unregulated cryptocurrency market, resulting in establishing relationships in terms of cross-returns spillovers between exchange rates from emerging countries and Bitcoin despite the cryptocurrency ban in those nations.

Second, the results show the existence of bidirectional cross-volatility persistence effects between Bitcoin and all other exchange rates, except for USD/IDR. In contrast, only USD/CNH and Bitcoin have a bidirectional relationship in terms of cross volatility spillover. Because cryptocurrencies are interconnected and exhibit comparable connectedness patterns to other exchange rates, our findings support the idea that they may be considered as a new financial asset class. The findings also show that we cannot determine the degree of Bitcoin integration solely on a country's technical advancements and market openness.

Because Bitcoin has shown signs of moderate integration with most of the asset classes studied, investors and fund managers should exercise caution when combining Bitcoin with most of the asset classes, as several previous studies have shown (Baek & Elbeck, 2015, Baur, Hong, & Lee, 2018, Bouri et al., 2017a, Bouri et al., 2017b, Briere et al., 2015, and Ji et al., 2017). Market players should consider market circumstances while doing so. When making Bitcoin investing selections, they should distinguish between global, emerging, and Chinese markets.

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