Analysis of Cryptocurrency Dynamics in the Emerging Market Economies: Does Reinforcement or Substitution Effect Prevail?

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Abstract

We analyzed cryptocurrency dynamics in the global U.S. dollar–denominated market and the emerging market economies (EMEs) with a view to ascertaining whether activities in these markets are predominantly shaped by reinforcement or substitution effect. Cryptocurrencies analyzed include the Bitcoins, Ethereum, Litecoin, Stellar, Bitcoin Cash, and USD Tether. The results suggest that, on average, correlation between digital assets in the cryptocurrencies’ ecosystem is positive. However, there is evidence of an outlier with respect to the USD Tether (USDT) in the global market, revealing that the USDT is negatively associated with all other cryptocurrencies. This is supported by the dynamic regression results that provided evidence of reinforcement effect in favor of the USDT in the global crypto market, thus confirming the status of the USDT as “Stablecoin” as it is pegged 1:1 to USD. In the global market context, the results also revealed that USDT/USD returns had identical outliers that could portend lesser chances of extreme gains or losses compared with suggestions of extreme gains or losses in the EMEs. Furthermore, USDT did not seem to have similar evolution in the EMEs where it had relatively marginal influence in the markets. The vector error correction (VEC) estimate showed mixed results between Altcoins in all the markets; moreover, our finding showed that reinforcement effects hold in favor of Stellar (XLM) both in the Russian ruble and Indian rupee crypto markets, whereas the Chinese yuan crypto market was predominantly characterized by substitution effect in favor of Bitcoin.

Keywords

cryptocurrency, Bitcoin, Altcoins, reinforcement effect, substitution effect, emerging market economies

Introduction

Besides the global cryptocurrency market, where digital assets are traded in the USD, the burgeoning cryptocurrency markets in the emerging markets economies (EMEs) continue to hold sway. The EMEs selected in this article include Russia, India, and China. The choice of these countries is based on the fact that they are core of the BRICS (Brazil, Russia, India, China, and South Africa) countries that represent the face of EMEs. However, we settled for Russia, India, and China because these are the only countries in the block with available data for the cryptocurrency pairs of interest. In the respective economies, trade and exchanges in digital assets are on a rapid increase in both volume and value. Innovations have also led to an increase in the number of digital currencies in these markets, making them strong and attractive to traders and portfolio investors. Given that empirical studies on the transmissions between cryptocurrencies in these economies are still embryonic, this article is contributing to extant literature by assessing the developments in these nascent cryptocurrency markets and comparing them with the evolutions in the advanced USD crypto market, with a view to understand their peculiar dynamics.

In recent years, the global financial system witnessed a new way of making payments with virtual currencies otherwise known as cryptocurrencies. Weaver (2018) opines that “the primary notion behind Bitcoin’s (BTC) design is to

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enable a censorship-resistant and irreversible payment system and it is intended that there should be no central authority that can say ‘thou shalt not’ or ‘thou shouldn’t have.’” An important development in the advances in encryption and network has been the emergence of digital currencies, which are driving transformational change in the world economy (He et al., 2016). Digital currencies allow for instant domestic and international transactions and serves as an effective medium for a direct peer-to-peer electronic payment that prevents transaction time and fees of going through a financial intermediary (Aloosh, 2017). Gantori et al. (2017) explains that by allowing direct and un-intermediated transactions between two parties, the process could make transacting faster and cheaper. A most popular example and largest cryptocurrency is the BTC. Being an unconventional unit of exchange, it has become imperative that investors in this new asset must understand the behaviors and the modeling of these currencies (Pärlstrand & Rydén, 2015).

A defining feature of a cryptocurrency is in its organic nature; being a decentralized currency that is outside the control of economic systems and central banks (Baumann & Lesoisnier, 2018; European Central Bank, 2015) it is, as a result, insulated from political influences usually applied or instigated by governments and corporations. Aloosh (2017) argues that innovations surrounding decentralized currencies will promote customers’ welfare, significantly reduce banks’ revenues from currency trading fees, and shrink governments’ revenues from currency trading taxes.

Nonetheless, digital currency is designed to serve as a medium of exchange, using cryptography, to keep transactions secure and to control further creation of additional units of the currency (Chu et al., 2017). With increasing interest in this digital asset, the need to quantify its variation becomes necessary. It is widely acknowledged that cryptocurrencies are highly volatile compared with conventional currencies. Vejačka (2014) asserts that cryptocurrencies have extremely high volatility compared with basic investment instruments. Definitely, their exchange rates cannot be presumed to be independently and identically distributed (Chan et al., 2017).

Dyhrberg (2015) asserts that the market for computer-generated currencies has grown vastly since 2008 in terms of the number of new digital currencies, consumer base, and transaction frequency. Digital asset has culminated into a unique market where many players enter and compete. For instance, after the invention and trading of BTC in 2009, several other currencies have continued to emerge and ostensibly make a difference by improving on the shortcomings of the existing currencies (Dyhrberg, 2015). Bullard (2018) posits that currency competition is nothing new, and neither is the electronic delivery of value, and privately issued currency like the BTCs can fit into this context of many competing virtual currencies. At equilibrium, however, one type of currency need not crowd out the other—rather, both are required to allow all intended trade to occur (Bullard, 2018).

Among the most traded cryptocurrencies, beside BTC, include Litecoin (LTC), Ripple (XRP), Ethereum (ETH), Peercoin (PPC), Namecoin (NMC), Bitcoin Cash (BCH), Feathercoin (FTC), Terracoin (TRC), Dash, EOS, Novacoin (NVC), and so on. Sophistication of digital currencies and their free entry into the market has possibly induced network effects where a winner-takes-all dynamics is imminent and hugely expected (Gandal & Halaburda, 2016). When network effects set in, convergence to one single digital asset is possible. Thus, when a particular currency becomes more popular, it is perceived to be more useful and also easily attracts new users. This creates what is called reinforcement effect as opposed to substitution effect.

The reinforcement effect describes a situation where it is expected that the most popular cryptocurrency would, by and large, get even more recognized and could possibly dominate the entire market (Gandal & Halaburda, 2016). On the contrary, a user’s preference for one currency over another may be due to competition. Later currencies may have possibly fixed the deficiencies in the existing currency and, as a result, could relatively have a better appeal compared with other currencies in the market. This is called substitution effect. Gandal and Halaburda (2016) contend that the availability of better or differentiated cryptocurrencies allows for a substitution effect where it is beneficial for users to substitute one cryptocurrency for another. So far, empirical studies on the network and competition effects are sketchy and still evolving.

Most existing literature has often assumed that cryptocurrencies are only traded directly for the U.S. dollar, thereby potentially foreclosing the understanding of peculiar dynamics in other economies or markets where they are traded directly for other conventional currencies. Against this backdrop, it becomes necessary not only to analyze the reinforcement effect (due to network effect) and substitution effect dynamics (due to competition) for BTCs and Alts traded directly for the USD, but to also examine the narratives for trades completed directly, and particularly, for currencies of the emerging market countries. This will not only allow us to have a broader perspective in both developed and emerging markets, but will also enable us make comparisons that could have both policy and practical relevance.

**Related Literature**

A vast majority of studies seem to agree that the concept of an open-source currency where payments can be made directly between parties without the involvement of a financial service provider is new (Alfonso et al., 2016; Badev & Chen, 2014; Brosens & Cocuzzo, 2017; Guo & Antulov-Fantulin, 2018; Hileman & Rauchs, 2017; Lánský, 2016; Zhao, 2015). Unlike conventional money assets issued and controlled by a central authority, a cryptocurrency is a privately issued digital currency created and managed through the use of advanced encryption techniques referred to as
The VAR model results showed that variations in BTC price that cryptocurrencies form hierarchical clusters, suggesting BTC. The results obtained using the MST approach revealed log-returns of cryptocurrencies, with a special emphasis on Altcoins without evidence of lagged effects. Functions confirmed a strong contemporaneous correlation temporaneously, whereas the generalized impulse-response functions indicated that most of the information transmission is basically contemporaneous (VAR) modeling approach. The finding indicated the strongest contemporaneous correlation between major cryptocurrencies, using a vector autoregression model. The results showed a positive association between different cryptocurrency market structures.

Given that private e-currencies are not issued by any central authority, they are rendered theoretically immune to government interference or manipulation (Baumann & Lesosmier, 2018). The emergence of other digital currencies has also sparked competitions and considerable volatilities in the currency market in which competition is proven to play a major role (Gandal & Halaburda, 2014).

Gandal and Halaburda (2016) analyzed the influence of network effects on competition in the cryptocurrency market using the correlation matrix and the traditional regression analysis. The data did not provide any evidence of a winner-takes-all effect early in the crypto market, whereas for a relatively long period, a few other virtual currencies competing with BTC appreciated much more rapidly than BTC. However, BTC appreciated against the USD, whereas other digital currencies depreciated against the USD.

Francés et al. (2018) evaluated the characteristics of the daily price series of selected cryptocurrencies using the Minimum Spanning Tree (MST) and the Pearson correlations between daily returns. The results identified a high correlation between price movements for all the analyzed cryptocurrencies. In addition, the ETH, rather than BTC, was identified to have significant influence in the currency market and was attributed to its increasing popularity and rising trading volume. In contrast, Aste (2019) examined the cryptocurrency market structure as well as the collective evolution of both prices and social sentiment associated with traded cryptocurrencies. The results revealed that most major capitalized cryptocurrencies, such as BTC, play a central role in the price correlation network but that the Altcoins, with small capitalization, play a critical role in shaping the currency market structure.

Burnie (2018) employed correlation networks to detect characteristics that have influence on the evolution of currency prices over time. Excluding USD Tether (USDT), the results showed a positive association between different cryptocurrencies, which was statistically significant.

Baçao et al. (2018) investigated the information transmission between major cryptocurrencies, using a vector autoregression (VAR) modeling approach. The finding indicated that most of the information transmission is basically contemporaneous, whereas the generalized impulse-response functions confirmed a strong contemporaneous correlation without evidence of lagged effects.

Zięba et al. (2019) examined interdependencies between log-returns of cryptocurrencies, with a special emphasis on BTC. The results obtained using the MST approach revealed that cryptocurrencies form hierarchical clusters, suggesting potential topological features of the cryptocurrency market. The VAR model results showed that variations in BTC price had no effect and were not affected by changes in prices of other currencies.

Hyun et al. (2019) examined dependence relationships among five selected cryptocurrencies, namely, BTC, ETH, LTC, XRP, and Steller (XLM), using a Gaussian copula marginal beta regression model. The results show that the copula directional dependence from BTC to LTC is stronger among all ordered directional dependencies, whereas the copula directional dependence from ETH to the other four cryptocurrencies is relatively higher than the magnitude established from those cryptocurrencies to ETH. This finding suggests that the return shocks of BTC could have the most influence on LTC and that the return shocks of ETH relatively affect the shocks on the other four cryptocurrencies.

Ferreira and Pereira (2019) employed the detrended cross-correlation analysis to assess the contagion effect between BTC and other major cryptocurrencies. The results provided evidence of a contagion effect, with the analyzed market being more integrated currently than in the past. Chan et al. (2017) examined the statistical properties of BTC and other selected cryptocurrencies relative to the U.S. dollar by fitting parametric distributions to them. The finding showed that returns are clearly non-normal, and no single distribution fits well jointly to all the digital currencies analyzed.

Data and Method

In our analysis, we employed daily cryptocurrency prices that were obtained from finance.yahoo.com. Historical data on this site are publicly available. The data set spanned the period from August 1, 2017 to November 30, 2018. This period marks a phase of moderate volatilities in the crypto market. Our choice of the beginning day is due to the fact that it is a common day for which BTC and selected Altcoins prices were available, hence allowing us to include more Altcoins in our sample. Altcoins refers to traded cryptocurrencies other than the BTC. The “adjusted closing price” was used as our price as it reflects the daily closing rate at midnight GMT.

Our primary cryptocurrency of interest is the BTC, which commands the largest share as well as more popularity in the market. Moreover, six Altcoins competing with the BTC and traded on daily basis for the period under review were selected. The Altcoins include ETH, LTC, XRP, BCH, USDT, and XLM. These are among the most important traded digital currencies globally. Our justification for choosing these Altcoins is because they are the top seven most capitalized cryptocurrencies and attract a larger proportion of the market. Within the coverage period of the study, they were the only cryptocurrencies with market capitalization of at least one billion U.S. dollars and with substantial trade volumes relative to the BTC. Thus, we consider these set of Altcoins capable of competing effectively with BTC, with the possibility of provoking either reinforcement or substitution effects in the burgeoning crypto market.
We included the currency pairs that were traded throughout the sample period. Specifically, BTC and Altcoins traded directly for USD and for currencies of the selected emerging market economies (EMEs) whose trading pairs and data are publicly available. These include the Russian ruble (RUB), Indian rupee (INR), and the Chinese yuan (CNY). Trading pairs are mostly dominated in the USD and few existing studies have really looked beyond the USD-cryptocurrency narratives. With the expansion as well as sophistication of the digital currency market, trading in EMEs continues to gain prominence as investors leverage on movements of conventional currency exchange rates in the emerging markets vis-à-vis digital currencies.

In summary, our daily price data comprise the following: BTC and Altcoins traded directly for USD:

\[
p_t \left( \frac{\text{BTC}}{\text{USD}} \right), p_t \left( \frac{\text{ETH}}{\text{USD}} \right), p_t \left( \frac{\text{LTC}}{\text{USD}} \right), p_t \left( \frac{\text{XRP}}{\text{USD}} \right), p_t \left( \frac{\text{BCH}}{\text{USD}} \right), p_t \left( \frac{\text{USDT}}{\text{USD}} \right), p_t \left( \frac{\text{XLM}}{\text{USD}} \right)
\]

BTC and Altcoins traded directly for the RUB:

\[
p_t \left( \frac{\text{BTC}}{\text{RUB}} \right), p_t \left( \frac{\text{ETH}}{\text{RUB}} \right), p_t \left( \frac{\text{LTC}}{\text{RUB}} \right), p_t \left( \frac{\text{XRP}}{\text{RUB}} \right), p_t \left( \frac{\text{BCH}}{\text{RUB}} \right), p_t \left( \frac{\text{USDT}}{\text{RUB}} \right), p_t \left( \frac{\text{XLM}}{\text{RUB}} \right)
\]

BTC and Altcoins traded directly for the INR:

\[
p_t \left( \frac{\text{BTC}}{\text{INR}} \right), p_t \left( \frac{\text{ETH}}{\text{INR}} \right), p_t \left( \frac{\text{LTC}}{\text{INR}} \right), p_t \left( \frac{\text{XRP}}{\text{INR}} \right), p_t \left( \frac{\text{BCH}}{\text{INR}} \right), p_t \left( \frac{\text{USDT}}{\text{INR}} \right), p_t \left( \frac{\text{XLM}}{\text{INR}} \right)
\]

BTC and Altcoins traded directly for the CNY:

\[
p_t \left( \frac{\text{BTC}}{\text{CNY}} \right), p_t \left( \frac{\text{ETH}}{\text{CNY}} \right), p_t \left( \frac{\text{LTC}}{\text{CNY}} \right), p_t \left( \frac{\text{XRP}}{\text{CNY}} \right), p_t \left( \frac{\text{BCH}}{\text{CNY}} \right), p_t \left( \frac{\text{USDT}}{\text{CNY}} \right), p_t \left( \frac{\text{XLM}}{\text{CNY}} \right)
\]

where \( t \) denotes time, being daily between August 1, 2017, and November 30, 2018. BTC = Bitcoin, ETH = Ethereum, LTC = Litecoin, XRP = Ripple, BCH = Bitcoin cash, USDT = USD Tether, and XLM = Stellar.

However, the prices were transformed in return rates, using the traditional difference of price between two consecutive moments as follows:

\[
r_t \left( \frac{\text{BTC}}{\text{USD}} \right) = p_t \left( \frac{\text{BTC}}{\text{USD}} \right) - p_{t-1} \left( \frac{\text{BTC}}{\text{USD}} \right),
\]

\[
r_t \left( \frac{\text{altcoin}}{\text{RUB}} \right) = p_t \left( \frac{\text{altcoin}}{\text{RUB}} \right) - p_{t-1} \left( \frac{\text{altcoin}}{\text{RUB}} \right),
\]

\[
r_t \left( \frac{\text{altcoin}}{\text{INR}} \right) = p_t \left( \frac{\text{altcoin}}{\text{INR}} \right) - p_{t-1} \left( \frac{\text{altcoin}}{\text{INR}} \right),
\]

\[
r_t \left( \frac{\text{altcoin}}{\text{CNY}} \right) = p_t \left( \frac{\text{altcoin}}{\text{CNY}} \right) - p_{t-1} \left( \frac{\text{altcoin}}{\text{CNY}} \right)
\]

where \( r_t \) represents return rates of BTC and Altcoins, comprising ETH, LTC, XRP, BCH, USDT, and XLM.

**Correlation Metrics**

If two or more cryptocurrencies’ daily returns data are influenced by the same common characteristics, then these returns are expected to be strongly associated Burnie (2018). Such association is analyzed using a correlation metric. Particularly, Pearson’s product–moment correlation coefficient (PMCC), Spearman’s rho (SR), and Kendall’s tau (KT) are the most popular correlation metrics. Citing Xu et al. (2013), Burnie (2018) argued that the application of PMCC, which is primarily restricted in assessing linear relationships, holds under the presumption that cryptocurrency returns follow normal distributions—an assumption that previous studies have considered unreasonable (Chan et al., 2017; Osterrieder et al., 2017). Following the constraints of PMCC, evidence abounds supporting SR as being a more accurate measure of the association between series (in terms of mean square error), when the sample size is not large and true population correlation is assumed to be weak (Burnie, 2018).

Osterrieder et al. (2017) observed that the correlations between cryptocurrencies were typically small (except mostly for between BTC, LTC, and ETH) and the data set size is often limited. Against this backdrop, this article primarily employs the SR methodology to measure the association among selected cryptocurrencies’ daily returns series.

\[
SR(x, y) = \frac{\text{Cov}(\text{Rank}_x, \text{Rank}_y)}{\sigma_{\text{Rank}_x} \cdot \sigma_{\text{Rank}_y}}
\]

where \( \text{Rank}_i \) is the rank for the different values of variable \( i \). By dividing by the standard deviations of the ranked versions of \( x \) and \( y \), the covariance between the ranked versions of \( x \) and \( y \) is normalized.
Vector Error Correction (VEC) Model

This approach is employed to study the substitution and reinforcement effects among all analyzed cryptocurrencies. Recent existing digital finance literature adopted variants of the vector autoregressive approach to analyze the transmission between cryptocurrencies (Baçao et al., 2018; Huynh, 2019). Thus, we analyze the effects of all cryptocurrencies on all other ones in the USD market and across all the selected emerging markets economies. The choice of VEC is based on the outcome of stationarity test results, which indicate that our variables are all stationary at first difference. Moreover, in a system of variables, there could be a number of linearly independent cointegrating vectors. It follows that linear combinations of these vectors are also cointegrating vectors as linear combinations of stationary variables are stationary. The regression form for the VEC is represented as follows:

$$
\Delta y_t = c + \prod_{i=1}^{r} y_{t-i} + \sum_{i=1}^{r} \Gamma_i \Delta y_{t-i} + \varepsilon_t
$$

where $\Delta$ = differencing operator, $\Delta y_t = y_t - y_{t-1}$, $y_{t-1}$ = Vector of endogenous variable with 1st lag. $c$ = Vector residual. $c$ = Vector intercept. $\Pi = Matrix$ coefficient of cointegration ($\Pi = \alpha \beta^\prime$). $\alpha$ = Vector adjustment, matrix with order $(k \times r)$, and $\beta$ = vector cointegration. $\Gamma_i$ = Matrix with order $k \times k$ of coefficient of $i$th endogenous variable.

Results and Discussion

Preliminary Analysis

Trend analysis. Figure 1 presents a 486-day rolling window evolution of selected cryptocurrencies, namely, BTC, ETH, LTC, and USDT denominated in USD, RUB, INR, and CYN. The justification for the selected cryptocurrencies is that they are among the leading currencies in trading activities, with a market capitalization threshold of at least US$2 billion during the sample period. The figure reveals the constant increase in prices that mainly started from September 2017 and lasted until December 2017. Except for USDT, whose price was observed to be relatively stable throughout the sample, the other cryptocurrencies appeared to have some similarities in their fluctuations. Particularly, the Tether appeared to be consistently stable over the sample period and across all the markets. The stability shown seems to confirm the widely held opinion about the Tether (USDT) as “Stablecoin” characterized as the most stable compared with any other traded cryptocurrency as the USDT is designed to be stable, that is, 1:1 with the USD. Whereas other cryptocurrencies across the markets are fluctuating within some extreme bounds, the USDT is found to maintain a relative degree of stability at 1:1 with USD within the sample period.

However, the same stability and possible reinforcement influence of the USDT, as shown in the USD market, does not seem to be evident in the EMEs. The trend of the USDT in these markets does not portray stability and is relatively similar across the markets and with other selected Altcoins. This seems to be a reflection of the underlying strengths of the respective conventional currencies in the emerging markets in relation to the USD. Notably, the reason for comparing the USD denominated cryptocurrencies with those of the selected EMEs is to ascertain whether the price evolution follows a similar trend, or whether there are variations. This could have implications for cryptocurrency substitutions or reinforcements thereof, which underscore the goal of this article.

In Figure 2, the prices were transformed in return rates, using the traditional difference of price between two consecutive moments. Figure 2 shows that for each of the cryptocurrencies, except the USDT, associated return rates have similarities in fluctuations, with marginal differences in the degree of variations. In the USD-denominated market, the BTC, ETH, and LTC exhibited a strong fluctuation pattern compared with the USDT that seemed to be fairly stable during the period. The USDT did not show a significant association with BTC during the sample period, which is not surprising, as evident from the analysis in Figure 1. It should be noted that the popularity status of the USDT among traders is evidently explained by the fact that, at the end of a trading day, they normally exchange everything for tether, thereby having all cryptocurrencies in their book “frozen” and indirectly having them denominated in USD. The rationale for this action is that crypto-to-crypto transactions are cheaper than crypto-to-fiat transactions.

Statistical summary of return rate distributions. Visually, the boxplot in Figure 3 presents a statistical summary of distribution of prices as transformed in return rates. Figure 3 shows that the median of the data for all the digital assets was very close to zero. Moreover, the most important information embedded in the boxplots is the extent of extreme values that appear in all coins across the markets, both positive and negative, which is an indicative of the possibility of obtaining extreme gains or losses over time. To this effect, Huynh (2019) warned that digital coins often change negatively in terms of extreme values and could foreclose possibilities of extreme gains or losses. However, Figure 3 further showed that only the USDT/USD seemed to have identical outliers that could portend equal chances of gains or losses. USDT/CNY is also very distinct with the median of returns above zero and all outliers on the positive horizon, thus suggesting possibilities of extreme gains without a corresponding likelihood of extreme losses.

Correlations analysis. Table 1a represents a global evolution in cryptocurrencies, where cryptocurrencies are traded directly
for USD. The result shows that the highest correlation pairing is between ETH and LTC at .77 and the next is between BTC and ETH at .67. With the exception of USDT, cryptocurrency returns were positively and significantly correlated with each other. This outcome is in line with Burnie (2018) and provides evidence that the USDT is an outlier, being negatively (although weakly) correlated with the other cryptocurrencies. A weak association was expected as USDT, unlike the other cryptocurrencies, is fixed at 1 USDT equal to 1 USD. However, this correlation was consistently negative in value and statistically insignificant. A possible explanation, according to Burnie (2018) is that cryptocurrencies are often bought using USDT; for this reason, USDT is mostly sold at a time a cryptocurrency is being bought. This, therefore, appears to suggest that sudden increases in the demand for cryptocurrencies (which raises their prices) potentially correspond with...
sudden increases in the supply of USDT (bringing about decreases in the USDT price), which could explain the negative correlation observed.

Similarly, Table 1b explains the association between cryptocurrencies traded for the RUB where the highest correlation pairing is between ETH and LTC at .71, and the next is...
between BTC and ETH at .54. However, except for the XLM, all other cryptocurrencies were found to be positively and significantly correlated. The XLM was observed to be an outlier, being negatively associated with the other cryptocurrencies. For Tables 1c and 1d, where cryptocurrencies are traded for the rupee and the yuan, respectively, the highest correlation is between ETH and LTC at .90 and .88, respectively, and the next is between BTC and LTC at .92 and .91, respectively. There is, however, no strong evidence of outliers in both markets, with all cryptocurrencies being positively and strongly correlated with one another. This is in line with the findings in Aslanidis et al. (2018) and Songmuang et al. (2018), which suggest that, on average, correlation between digital assets in the cryptocurrencies ecosystem is positive. Supporting our finding, however, Stosic et al. (2018) found that the Altcoin community consists of some cryptocurrencies, with strong inverse correlations such as USDT. Burnie (2018) corroborated this aspect of our correlation results in his article, which found that with the exception of the USDT, there is a positive and statistically significant association between different analyzed cryptocurrencies.

Tables 2 to 5 present the VEC results and simultaneous equations that analyze the effects of all cryptocurrencies on all other ones traded in USD. Among the recent empirical

Figure 3. Boxplot graph of the returns on cryptocurrencies.

Note. BTC = Bitcoin; USD = U.S. dollar; ETH = Ethereum; LTC = Litecoin; RUB = Russian ruble; INR = Indian rupee; CNY = Chinese yuan.
studies, Bação et al. (2018), Smith (2015), and Huynh (2019) used variants of the vector autoregressive model, whereas Gandal and Halaburda (2016) employed the ordinary least squares (OLS) regression technique to examine interactions between cryptocurrencies. The results provide additional details and insights that could help to explain the degree of substitution and reinforcement effects in each market over time.

Table 2 represents VEC regression estimates based on the USD. When we considered the effect of BTC on the Altcoins, we observed that the BTC was negatively associated with ETH, LTC, XRP, and BCH, thereby suggesting reinforcement effect in favor of the BTC and also that the BTC holds a winner-takes-all advantage over these set of Altcoins. However, the results showed that the USDT and XLM were positively associated with the BTC, which is an indication of the substitution effect in favor of the USDT and XLM. In other words, the BTC was losing its competitive edge to the two Altcoins and appeared to be increasingly converted to (or substituted for) the USDT and the XLM. Moreover, when the Altcoins were regressed against the BTC, we found that, except for the BCH, all other cryptocurrencies exerted negative effect on BTC. This outcome points toward relative reinforcement effects in favor of ETH, LTC, XRP, USDT, and XLM, which contradicts a perception of the winner-takes-all advantage commonly ascribed to the BTC.

The results further showed that the USDT had the strongest winner-takes-all advantage over the BTC and all other Altcoins. This finding points to the fact that the USDT is having a competitive advantage and is high in demand
Table 2. Regression Analysis of the Effects of All Cryptocurrencies on All Other Ones Traded in USD.

| Regressors       | BTC/USD | ETH/USD | LTC/USD | XRP/USD | BCH/USD | USDT/USD | XLM/USD |
|------------------|---------|---------|---------|---------|---------|----------|---------|
| Adj. speed       | 0.207086| 0.078644| 0.059463| 0.127024| 0.125967| -0.038501| 0.118236|
| [1.51954]| [4.94206]**| [2.96876]**| [5.30546]**| [4.92369]**| [-16.8363]**| [4.17456]**|
| BTC/USD(-1)      | -0.375200| -0.065629| -0.000993| -0.061302| -0.255192| 0.035026| 0.141179|
| [-6.34414]**| [-0.95392]| [-0.01146]| [-0.59222]| [-2.30713]**| [3.54846]**| [1.15293]**|
| ETH/USD(-1)      | -0.022053| -0.540232| -0.125444| -0.021026| 0.039071| -0.035385| -0.100478|
| [-0.34166]| [-7.19479]**| [-1.32731]| [-0.18612]| [0.32366]| [-3.28461]**| [-0.75184]**|
| LTC/USD(-1)      | -0.071758| 0.018549| -0.449098| -0.145297| -0.145254| 0.024261| -0.136333|
| [-1.58255]| [0.35166]| [-6.76424]**| [-1.83081]| [-1.68063]| [3.20576]**| [-1.45429]**|
| XRP/USD(-1)      | -0.051446| -0.044436| -0.054818| -0.438896| -0.117595| -0.007182| -0.067214|
| [-1.71740]| [-1.27515]| [-1.24979]| [-8.37112]**| [-2.09897]| [-1.43652]**| [-1.08369]**|
| BCH/USD(-1)      | 0.005411| 0.072519| 0.082524| 0.095353| -0.214530| -0.011982| -0.015057|
| [0.20918]| [2.41005]**| [2.17892]**| [2.10621]**| [-4.43459]**| [-2.77554]**| [-0.28114]**|
| USDT/USD(-1)     | -0.353223| -0.882435| -0.793641| -2.422697| -1.845187| 0.046908| -0.372880|
| [-2.29755]**| [-2.78652]**| [-1.99108]| [-5.08479]**| [-3.62418]**| [1.01459]**| [-2.19417]**|
| XLM/USD(-1)      | -0.017819| 0.000993| 0.012807| -0.012422| 0.047104| -0.000103| -0.382817|
| [-0.34166]| [0.35122]| [-0.28499]| [0.32366]| [-3.28461]**| [-0.75184]**| [-0.100478]**|
| Intercept        | -0.071466| -0.03360| -0.02638| -0.01591| [0.05565]| [-0.01089]| [-0.02712]**|

*Note. The t-statistics are in parentheses. USD = U.S. dollar; BTC = Bitcoin; ETH = Ethereum; LTC = Litecoin; XRP = Ripple; BCH = Bitcoin cash; USDT = USD Tether; XLM = Stellar.*

The coefficient of determination (R-squared) could also have information about the association between the analyzed cryptocurrencies. In line with our earlier findings, R-Squared values (56.56%) for the USDT point toward a strong reinforcement effect in favor of the USDT. This entails that deviation from long-run equilibrium, only the coefficient of USDT possesses the right sign (−0.038501) and is significant. This entails that deviation from long-run equilibrium path for the “Stablecoin” is corrected at the speed of 3.85% on annual basis. Next to the USDT in the competitive advantage are the ETH (32.91%), XRP (32.39%), and BTC (29.39%). The BCH (22.84%), however, has the least R-Squared value, which further confirms the suggestions that it is the most substituted cryptocurrency among all other ones included in this analysis.

Table 3 presents the regression estimates of cryptocurrencies traded for the RUB. The results of the effects of Altcoins on the BTC showed that, with the exception of XLM, which is positively related to BTC (suggesting substitution effects in favor of BTC), ETH, LTC, BCH, XRP, and USDT hold fairly strong winner-takes-all advantage over the BTC. Moreover, when the effect of BTC on the Altcoins is estimated, the results revealed a reverse outcome where the BTC was negatively associated with all the analyzed Altcoins (suggesting a reinforcement effect in favor of the BTC), except for the BCH and XLM, which were positively related to the BTC and entails substitution effect in favor of BCH and XLM. This finding is supported by the coefficient of determination, which confirmed marginal competitive advantage in favor of the BCH and XLM although the level of competitiveness in the bourgeoning market seems to be evenly shared. Accordingly, we observed that 36.34% and 35.74% of changes in BCH and XLM, respectively, were explained by the variations in all other cryptocurrencies. This could be attributed to the fact that the BCH is closer in parity to the RUB in real market terms. A look at the price movements in the RUB-traded cryptocurrencies indicated
Table 3. Regression Analysis of the Effects of All Cryptocurrencies on All Other Ones Traded in RUB.

| Regressors     | BTC/RUB  | ETH/RUB  | LTC/RUB  | XRP/RUB  | BCH/RUB  | USDT/RUB  | XLM/RUB  |
|---------------|----------|----------|----------|----------|----------|-----------|----------|
| Adj. speed    | -0.38251 | 0.023073 | 0.512487 | 0.090264 | -1.089213 | 0.433756  | -0.193841|
| [−6.05744]**  | [0.30455]** | [5.76449]** | [0.67860]** | [−5.06380]** | [2.58288]** | [−7.50849]** |
| BTC/RUB (−1)  | -0.144230 | -0.133602 | -0.271522 | -0.126140 | 0.206167  | -0.088033 | 0.123729 |
| [-2.22991]**  | [-1.72170]** | [-2.98178]** | [-0.92586]** | [0.93578]** | [-0.51180]** | [4.66218]** |
| ETH/RUB(−1)   | -0.022428 | -0.471561 | -0.062687 | 0.090673  | 0.111270  | -0.100117 | -0.032001|
| [-0.37733]**  | [-6.61270]** | [-0.74911]** | [0.72421]** | [0.54958]** | [-0.63337]** | [-1.31690]|
| LTC/RUB(−1)   | -0.178502 | 0.074746  | -0.293068 | -0.070479 | -0.314723 | 0.081722  | -0.005772|
| [-3.80201]**  | [1.32699]** | [-4.43379]** | [-0.71267]** | [-1.96798]** | [0.65453]** | [-2.64520]**|
| XRP/RUB(−1)   | -0.036742 | -0.041050 | -0.039678 | -0.577185 | -0.116830 | -0.140445 | 0.008313 |
| [-1.56160]**  | [-1.45426]** | [-1.19785]** | [-11.6462]** | [-1.45776]** | [-2.24457]** | [0.86421]  |
| BCH/RUB(−1)   | -0.012503 | 0.003602  | -0.036052 | 0.033239  | -0.445811 | -0.067232 | 0.020281 |
| [0.91015]     | [0.21885]** | [-1.86413]** | [0.11195]** | [-9.52577]** | [3.61138]** |
| USDT/RUB(−1)  | -0.051488 | -0.016202 | 0.045883  | 0.039600  | -0.051001 | -0.322153 | -0.015318|
| [-2.39113]**  | [-0.62716]** | [1.51350]** | [0.86116]** | [-0.69534]** | [-5.62569]** | [-1.74005]|
| XLM/RUB(−1)   | 0.148481  | -0.129476 | -0.401588 | 0.776469  | 0.560470  | 0.370409  | 0.483941 |
| [1.33275]**   | [-0.96868]** | [-2.61726]** | [-1.99992]** | [2.04609]** | [-1.89168]** | [-8.13252]**|
| Intercept     | -0.021799 | -0.039777 | -0.013366 | -0.032616 | 0.013384  | -0.301099 | -0.002348|
| [-0.09444]**  | [-0.01436]** | [-0.04113]** | [-0.06709]** | [0.01702]** | [-0.50523]** | [-0.02489]**|
| R²            | 0.312250  | 0.283920  | 0.305516  | 0.326875  | 0.363358  | 0.214465  | 0.357387 |
| Adj. R²       | 0.298698  | 0.269810  | 0.291832  | 0.313611  | 0.350813  | 0.199866  | 0.344725 |
| Included obs. | 415       | 415       | 415       | 415       | 415       | 415       | 415      |

Note. The t-statistics are in parentheses. RUB = Russian rouble; BTC = Bitcoin; USD = U.S. dollar; ETH = Ethereum; LTC = Litecoin; XRP = Ripple; BCH = Bitcoin cash; USDT = U.S. dollar; XLM = Steller. **p < .01. *p < .05.
the USD crypto market. We observed that the USDT, while commanding a strong influence in the USD market, trailed all other analyzed cryptocurrencies that traded in RUB, INR, and CNY. In other words, whereas the USDT has “Stablecoin” status in the advanced wider market, it does not seem to have the same representation in the EMEs. This finding is supported by the results of the SR metric in Table 1 and corroborated by the trend analysis in Figures 1 and 2. This seems to be a reflection of the underlying strengths of the respective conventional currencies in the emerging markets in relation to the USD. In other words, converting cryptocurrencies into the USDT could invariably mean saving them in USD. Hence, the cryptocurrencies thus saved could be prone to fluctuations of the underlying conventional currencies relative to the USD. Therefore, if investor confidence in the primary currency is weak, they could be more inclined to choose any other cryptocurrency believed to offer stability relative to the underlying conventional currencies during or at the end of any trading day.

**Conclusion**

This article analyzed the association between cryptocurrencies in the global U.S. dollar–denominated market (where cryptocurrencies are traded directly for the USD) and in the EMEs of Russia, India, and China (where digital currencies are traded directly for the ruble, rupee, and the Yuan), with a view to ascertaining whether activities in both markets are predominantly shaped by reinforcement effect, due to the winner-takes-all phenomenon, or by substitution effect, occasioned by competition. Our analysis based on the relation between returns of cryptocurrencies in each of the markets over time suggests that, on average, correlation between digital assets in the cryptocurrencies environment is positive. This result is supported by findings in Aslanidis et al. (2018) and Songmuang et al. (2018), which confirmed that a majority of digital currencies in the cryptocurrency ecosystem are not unrelated. However, our results detected a case of an outlier with respect to the USDT in the global market, where the USDT was found to be negatively associated with all other cryptocurrencies. This is in line with the findings in Stosic et al. (2018), which argued that the digital assets community consists of some cryptocurrencies with strong inverse correlations such as USDT. This outcome is also in tandem with the finding of Burnie (2018), which found that the USDT is an outlier, being negatively correlated with the other cryptocurrencies traded in the USD. A weak association was expected as USDT, unlike the other cryptocurrencies, is fixed at 1 USDT = 1 USD. A possible explanation, according to Burnie (2018) is that cryptocurrencies are often bought

| Table 4. Regression Analysis of the Effects of All Cryptocurrencies on All Other Ones Traded in INR. |
|--------------------------------|
| Regressors | BTC/INR | ETH/INR | LTC/INR | XRP/INR | BCH/INR | USDT/INR | XLM/INR |
|--------------------------------|
| Adj. speed | -0.329882 | -0.344290 | -0.345237 | -0.314194 | -0.348773 | -0.324525 | -0.375518 |
| [-18.3541]** | [-15.9173]** | [-14.5488]** | [-10.7878]** | [-11.7894]** | [-10.2928]** | [-22.6037]** |
| BTC/INR(-1) | -0.389873 | -0.075989 | -0.043756 | -0.087031 | -0.195508 | 0.14004 | 0.042091 |
| [-4.87597]** | [-0.78696] | [-0.41448] | [-0.67169] | [-1.48551] | [1.00256] | [0.32596] |
| ETH/INR(-1) | -0.030137 | -0.495130 | -0.068560 | 0.081680 | 0.095172 | -0.043930 | -0.072642 |
| [-0.35909] | [-4.90219]** | [-0.61874] | [0.60059] | [0.68894] | [-0.29838] | [-0.93640] |
| LTC/INR(-1) | -0.026100 | 0.076160 | -0.403096 | -0.002748 | -0.003441 | -0.039937 | 0.046535 |
| [-0.42741] | [1.03634] | [-4.99980]** | [-0.02777] | [-0.53169] | [-0.36348] | [0.82444] |
| XRP/INR(-1) | -0.104186 | -0.119477 | -0.123458 | -0.575842 | -0.228760 | -0.170139 | -0.055934 |
| [-2.72949]** | [-2.60090]** | [-2.44977]** | [-9.30967]** | [-3.64104]** | [-2.54088]** | [-1.58535] |
| BCH/INR(-1) | 0.082973 | 0.138059 | 0.163076 | 0.115607 | 0.191480 | 0.036952 | 0.101147 |
| [2.45104]** | [3.38881]** | [3.64870]** | [2.10744]** | [-3.43646]** | [0.62224] | [3.23252]** |
| USDT/INR(-1) | -0.021678 | -0.026374 | -0.022586 | -0.030656 | 0.043326 | -0.049923 | 0.099871 |
| [-0.67156] | [-0.67890] | [-0.52995] | [-0.58607] | [0.81543] | [-7.23985]** | [0.33084] |
| XLM/INR(-1) | -0.577640 | 0.610431 | 0.588868 | 0.480234 | 0.676017 | 0.573603 | 0.162466 |
| [8.80365]** | [7.73056]** | [6.79764]** | [4.51666]** | [6.25946]** | [4.98339]** | [2.67881]** |
| Intercept | -0.011278 | -0.006740 | -0.015447 | -0.005412 | 0.110843 | -0.003242 | 0.012390 |
| [-0.03304] | [-0.01641] | [-0.03427] | [-0.00978] | [0.19768] | [-0.05412] | [0.03926] |
| $R^2$ | 0.694168 | 0.642518 | 0.612605 | 0.547312 | 0.480715 | 0.480269 | 0.737219 |
| 543 | 483 | 483 | 483 | 483 | 483 | 483 |
| Included obs. | 483 | 483 | 483 | 483 | 483 | 483 | 483 |

Note. The $t$ statistics are in parentheses. INR = Indian Rupee; BTC = Bitcoin; USD = U.S. Dollar; ETH = Ethereum; LTC = Litecoin; XRP = Ripple; BCH = Bitcoin cash; USDT = USD Tether; XLM = Stellar.

* $p < .05. ** $p < .01.
Table 5. Regression Analysis of the Effects of All Cryptocurrencies on All Other Ones Traded in CNY.

| Regressors       | BTC/CNY | ETH/CNY | LTC/CNY | XRP/CNY | BCH/CNY | USDT/CNY | XLM/CNY |
|------------------|---------|---------|---------|---------|---------|----------|---------|
| Adj. speed       | -0.911214 | -0.877526 | -0.633263 | -0.011363 | -0.987329 | -0.000640 | 0.001407 |
|                  | [-10.0452]** | [-8.17011]** | [-5.64017]** | [-1.11362] | [-7.12125]** | [-0.21874] | [0.24478] |
| BTC/CNY(−1)      | 0.122726 | 0.475321 | 0.413894 | 0.007629 | 0.328039 | 0.002259 | 0.003483 |
|                  | [1.47125] | [4.81245]** | [4.00875]** | [0.81307] | [2.57295]** | [0.83903] | [0.65907] |
| ETH/CNY(−1)      | -0.099620 | -0.382826 | 0.086120 | 0.007047 | 0.255937 | -0.000605 | 0.002698 |
|                  | [-1.15498] | [-3.74851]** | [0.80668] | [0.72631] | [1.94141] | [-0.21737] | [0.49369] |
| LTC/CNY(−1)      | -0.151433 | -0.039755 | -0.522058 | 0.002493 | -0.183474 | 0.001364 | 0.005197 |
|                  | [-2.15378]** | [-0.47754] | [-5.99889]** | [0.31515] | [-1.70732] | [0.60099] | [1.16699] |
| XRP/CNY(−1)      | -2.874818 | -3.193101 | -3.854588 | -0.439060 | -3.861069 | -0.054608 | -0.059314 |
|                  | [-3.79303]** | [-3.55812]** | [-4.10890]** | [-5.14988]** | [-3.33305]** | [-2.23223]** | [-1.23521] |
| BCH/CNY(−1)      | 0.057150 | 0.108671 | 0.110614 | 0.003263 | -0.231646 | 0.000993 | -0.00167 |
|                  | [1.49546] | [2.40161]** | [2.33851]** | [0.75901] | [-3.96589]** | [0.80537] | [-0.06893] |
| USDT/CNY(−1)     | 8.929182 | 7.715757 | 4.918922 | 1.180460 | 6.669691 | 0.133912 | 0.182757 |
|                  | [3.20588]** | [2.33962]** | [1.42684] | [3.76777]** | [1.56675] | [1.48958] | [1.03566] |
| XLM/CNY(−1)      | -8.128064 | -8.140300 | -9.046745 | -0.485629 | -5.146041 | -0.131693 | -0.610235 |
|                  | [-6.26609]** | [-5.30007]** | [-5.63473]** | [-3.32821]** | [-2.59580]** | [-3.14543]** | [-7.42531]** |
| Intercept        | -0.026612 | -0.017567 | -0.017808 | 0.001513 | 0.109882 | 0.001764 | 0.000223 |
|                  | [-0.06887] | [-0.03839] | [-0.03723] | [0.03480] | [0.18604] | [0.14141] | [0.09910] |
| $R^2$            | 0.695319 | 0.628365 | 0.60171 | 0.150805 | 0.50197 | 0.072291 | 0.21410 |
| Adj. $R^2$       | 0.690177 | 0.622092 | 0.593423 | 0.136473 | 0.498412 | 0.056633 | 0.200877 |
| Included obs.    | 483     | 483     | 483     | 483     | 483     | 483     | 483     |

Note. The t-statistics are in parentheses. CNY = Chinese yuan; INR = Indian rupee; BTC = Bitcoin; USD = U.S. dollar; ETH = Ethereum; LTC = Litecoin; XRP = Ripple; BCH = Bitcoin cash; USDT = USD Tether; XLM = Steller.

*p < .05. **p < .01.

Using USDT as it is considered the most stable currency. For this reason, USDT is mostly sold at a time a cryptocurrency is being bought. This, therefore, appear to suggest that sudden increases in the demand for cryptocurrencies (which raises their prices) potentially correspond with sudden increases in the supply of USDT (bringing about decreases in the USDT price), which could explain the negative correlation observed.

The results further showed that, whereas there is an outlier in the crypto RUB market with respect to the XLM, there is no strong evidence of outliers in the INR and CNY markets, with all cryptocurrencies being positively and strongly correlated with one another.

The regression results relatively corroborated our correlation metric results and revealed that, in the global cryptocurrency market, the reinforcement effect is in favor of the USDT contrary to findings of Gandal and Halaburda (2016), which argued that the BTC has a winner-takes-all advantage in the USD crypto market. We observed that the USDT, while commanding strong influence in the USD market, trailed all other analyzed cryptocurrencies traded in RUB, INR, and CNY. In other words, whereas the USDT has “Stablecoin” status in the advanced wider market, it does not seem to have the same representation in the EMEs. This seems to be a reflection of the underlying strengths of the respective conventional currencies in the emerging markets in relation to the USD. In other words, converting cryptocurrencies into the USDT could invariably mean saving them in USD. Hence, the cryptocurrencies thus saved could be prone to fluctuations of the underlying conventional currencies relative to the USD. Therefore, if investor confidence in the primary currency is weak, they could be more inclined to choose any other cryptocurrency believed to offer stability relative to the underlying conventional currencies during or at the end of any trading day.

Our findings have implication for existing and potential investors in the cryptocurrency market and would provide them some insight into market dynamics, which could be a guide in making investment decisions across different economies and digital assets.
Research Limitations

According to data availability at the time of this study, daily data set spanning the period from August 1, 2017, to November 30, 2018, reflecting daily closing prices at midnight GMT, was used. However, we consider the 486-day rolling window evolution as well as the adjusted period of observation relatively short. Second, the Altcoins examined were selected based on market capitalization of at least one billion U.S. dollars at the time of the study. This criterion essentially limited the number of Altcoins that could have been included in the analyses.

Suggestions for Future Study

Given that the cryptocurrency market has continued to witness unprecedented expansion, future research work could analyze digital assets at longer time periods while also considering varying time frequencies and a larger number of crypto assets for analysis. For further insights into the inter-relationships among competing cryptocurrencies, digital assets could be selected based on total supply, circulating supply, or trading volume.

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