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# UNVEILING THE LINKAGES BETWEEN EMERGING STOCK MARKET INDICES AND CRYPTOCURRENCIES

**Wajid Shakeel Ahmed*, Ahsan Mehmood, Talha Sheikh, and Allah Bachaya**

*Department of Management Sciences, COMSATS University, Islamabad, Pakistan*

*Corresponding author: wajid_shakeel@comsats.edu.pk

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## ABSTRACT

*This paper investigated the relationship between cryptocurrencies and emerging stock market indices using fractional integration and co-integration technique. Particularly, fractional integration is applied to examine stochastic properties of individual assets and fractional cointegration to analyse bivariate connectedness. Our findings unveil the absence of mean reversion in majority cases which indicates high persistence in series. Furthermore, bivariate analysis reveals disconnection between cryptocurrencies prices and stock indices. Surprisingly, a different picture emerges on using conditional volatility instead of prices. Like, conditional volatility-based estimation uncovers evidence of mean reversion in univariate analysis as expected. There is some evidence of cointegration on volatility grounds between cryptocurrencies and emerging stock market indices. Our findings implies that investment decision regarding digital currencies should be taken cautiously. As cryptocurrencies are extremely volatile with high degree of persistence which can make them counterproductive.*

**Keywords:** emerging market indices, cryptocurrencies, price uncertainty, autoregressive fractionally integrated moving average, generalised autoregressive conditional heteroskedasticity

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## INTRODUCTION

Bitcoin and other flowering digital currencies are being warmly embraced as an alternate avenue of investment (Fang et al., 2020). As cryptocurrencies offer abnormal returns (Bouri et al., 2017; Liu & Tsyvinski, 2018) relative to conventional assets owing to extreme volatility (Aysan et al., 2019). Given their complex and decentralised nature digital currencies are also regraded isolated and detached from traditional financial systems (Härdle et al., 2019). Consequently, researchers have intriguingly explored the dynamics of cryptocurrencies in multifarious manner. A line of research has focused on stochastic characteristics of cryptocurrencies such as market efficiency (Tran & Leirvik, 2019), price clustering (Urquhart, 2017), transaction cost mechanism (Kim, 2017), price formation and drives (Ciaian et al., 2016; Kristoufek, 2015), and another branch of research that examined volatility with spectacular interest such as Bouri et al. (2020b), Cerqueti et al. (2020), Dyhrberg (2016a), and Katsiampa (2017).

Apart from decentralised nature, financial liberalisation is also contributing factor in amplifying attraction of cryptocurrencies. Conventional stock markets of emerging market economies and developed economies have become substantially integrated and interconnected in the last two decades (see Aftab et al., 2021; Arouri & Foulquier, 2012; Dooley & Hutchison, 2009; Narayan et al., 2014). The economic integration has led investor to seek alternate diversification opportunities. Moreover, the turbulent times of global financial crisis has exposed the vulnerabilities of liberalised financial system. Therefore, cryptocurrencies emerge as a natural choice and strong contender to supersede conventional investment vehicles. Subsequently, this financial role of cryptocurrencies is immensely studied, and some interesting facts are uncovered. Unfortunately, research relating to linkages between cryptocurrencies and conventional assets is bifurcated and ambiguous because crypto-market is still premature and unregulated (Qureshi et al., 2020). For instance, a plethora of studies contended that Bitcoin can act as safe haven and hedge against conventional assets like Aslanidis et al. (2019), Bouri et al. (2020), Corbet et al. (2018), Gil-Alana et al. (2020), Goodell and Goutte (2021), Shahzad et al. (2019), and Symitsi and Chalvatzis (2018). However, a strand of literature undermines the role of Bitcoin and other currencies as a hedge tool. Charfeddine et al. (2020) concluded that cryptocurrencies are weak hedging instruments given their lower hedging effectiveness index. Similarly, Klein et al. (2018) argued that Bitcoin cannot act as strong hedging tool for developed markets because there are some notable periods of shocks transmission between Bitcoin market and traditional stocks (Kurka, 2019). Furthermore, Zhang et al. (2021) has provided evidence for downside risk-spillover between equities and Bitcoin. Likewise, some distinct studies viewed cryptocurrencies as a speculative vehicle

(Baek & Elbeck, 2015; Baur et al., 2018; Cheah & Fry, 2015; Tan et al., 2020) on high volatility grounds (Chu et al., 2017; Härdle et al., 2019). These contradictory findings evidently show scepticism surrounding cryptocurrency's financial role and necessitates further analysis to refine the findings.

This paper contributes to existing literature on cryptocurrencies and financial contagion on several fronts. Firstly, motivated by Gil-Alana et al. (2020) we have analysed the stochastic properties such as presence of long memory and persistence in cryptocurrencies prices and emerging stock market indices using fractional integration and cointegration technique. Bitcoin dominance has been challenged by so-called altcoins, as their market share is upsurged to almost 40% and which is not negligible. The second novelty is investigation of bivariate (long-run equilibrium) interdependence among cryptocurrencies using a large sample of seven leading cryptocurrencies. Third and most notable contribution is extension of Gil-Alana et al. (2020) work in global perspective, specifically in context of emerging market economies. As we have examined the bivariate (long-run equilibrium) relationship between emerging stock market indices and cryptocurrencies which has far reaching implication for investors. As emerging markets are becoming more economically integrated with advance economies, so investment opportunities are scarce. Such study is rare in literature and more importantly any such research gap is worth exploring, it can provide new perspectives[2]. Finally, we extend the literature on volatility connectedness by testing the existence of cointegrating relationship in conditional volatility of cryptocurrencies and stock indices extracted from Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model. Hence, the main purpose of this study is to analyse the cryptocurrencies and emerging stock market indices by employing fractional integration and cointegration technique from univariate (individual) and bivariate perspective.

We initially explore both assets' classes at individual level. The findings from univariate analysis corroborates the existing literature (Abakah et al., 2020; Caporale et al., 2018; Gil-Alana et al., 2020) finding that cryptocurrencies and stock indices exhibit high persistence and long-memory behaviour. Then, bivariate analysis is conducted which yield some interesting findings. As per evidence, emerging stock indices and cryptocurrencies prices are disconnected and as there is no evidence of mean reversion which is line with Corbet et al. (2018) and Gil-Alana et al. (2020) studies. Contrastingly, cryptocurrencies are found to be cointegrated, but evidence is inconclusive. As far as volatility connectedness is concerned, additional evidence of mean reversion is obtained but with high degree of persistence.

## LITERATURE REVIEW

The arrival of cryptocurrencies has sparked a new discourse in finance. There is burgeoning literature dedicated towards exploring the various characteristics of cryptocurrencies. Halaburda and Gandal (2014) has studied the competitiveness of cryptocurrencies market. Bouoiyour and Selmi (2015) unveil that crypto-market is exposed to extreme volatility. Therefore, Bitcoin is a sophisticated instrument for speculators expecting abnormal returns (Baek & Elbeck, 2015; Glaser et al., 2014). Bitcoin market is adversely effected by market stocks (Härdle et al., 2019). This drive researchers to study market dynamics of cryptocurrencies, particularly to assess market efficiency (Bartos, 2015; Cheah & Fry, 2015; Urquhart, 2016) and anomalies (Caporale et al., 2018a; Caporale & Plastun, 2019; Kurihara & Fukushima, 2017). Besides market dynamics, some distinct studies have analysed the stochastic properties of cryptocurrencies such as long memory and persistence in prices (Abakah et al., 2020; Bariviera, 2017; Caporale et al., 2018a; Gil-Alana et al., 2020) and volatility (Bouri et al., 2019; Fakhfekh & Jeribi, 2020).

Global financial has uncover the dwindling investment opportunities in conventional financial markets Therefore, investors are eagerly hunting for alternate avenues that can alleviate their exposure to risk. The alternate avenue must play a multifaceted role. Precisely, the alternate avenue must act as a diversifier, hedge, and predominantly a safe haven against conventional assets[3].The launch of Bitcoin in the twilight of global financial crisis has lay the foundation of digital currencies as an alternate asset class. Since then, cryptocurrencies linkages with other assets classes especially stock markets have received a vast attention in literature. For example, Phillip et al. (2018) investigation of more than 200 cryptocurrencies reveals a distinguishable risk-return trade-off in cryptocurrencies comparative to traditional assets. Corbet et al. (2018) contended that digital currencies can offer some diversification benefits for investors with short investment horizon. In a similar context, some studies have shed light on cryptocurrencies weak connectedness with stock markets (Aslanidis et al., 2019; Baur et al., 2018; Bouri, Gupta, et al., 2017; Brière et al., 2015; Dyhrberg, 2016b; Guesmi et al., 2019). Likewise, Bouri et al. (2020a) and Shahzad et al. (2019) have pointed out diversifier and hedging role for cryptos respectively. More recently, Gil-Alana et al. (2020) has tested the existence of cointegration between stock market indices and cryptocurrencies and concluded that cryptocurrencies are decoupled from stocks in long run. The aforementioned literature highlights the potential financial role of cryptocurrencies in offsetting losses from equities. Therefore, Bitcoin can also play a pivotal role in magnifying portfolio performance (Hu et al., 2020; Kajtazi & Moro, 2019).

The finance literature is ambiguous regarding hedging capabilities of cryptos. Because a nexus of research challenges the notion that cryptocurrencies are safe assets. Rather than it advocates that, Bitcoin market and conventional assets are interconnected. As Klein et al. (2018) argued that Bitcoin did not resembles to gold and lack the ability to act as hedge or diversify for developed markets. Moreover, according to Kurka (2019), Bitcoin propagate shocks to others assets such commodities and stocks which question its hedging capability. In parallel, Zhang et al. (2021) uncover presence of downside risk spillover from Bitcoin to stocks. Similarly, Charfeddine et al. (2020) findings also undermine the cryptocurrencies role as hedging tool. These contradictory and inconsistent results indicate the scepticism about cryptocurrencies financial role. This ambiguity justifies the need for more rigorous and detail analysis to dispel the confusion and which will further refine the existing literature.

## METHODOLOGY

### Model Specification

### AutoRegressive Fractionally Integrated Moving Average (ARFIMA) (*p*, *d*, *q*)

A plethora of studies has discovered presence of long memory and high degree of persistence in cryptocurrencies (Abakah et al., 2020; Caporale et al., 2018b; Gil-Alana et al., 2020). Thus following the work of Gil-Alana et al. (2020), our empirical specification is based on fractional integration and co-integration process, which makes series stationary with fractional differencing. First differencing is widely accepted benchmark to make series stationary. Nonetheless, number of differences could be any real value even fractional number. Hence ($x_t$, $t = 0, \pm 1$) is integrated in order of $d$ and represented as:

$$(1-L)^d x_t = u_t, t = 1, 2\ldots\ldots, \qquad \text{Eq. 1}$$

$L$ is the back-shift operator ($Lx_t = x_{t-1}$) and $u_t$ is $I$ (0) referring towards covariance stationary process with spectral density function and positive. If $u_t$ is ARIMA ($p, q$) process, $x_t$ will be considered as fractionally integrated ARIMA, i.e., ARFIMA ($p$, $d$, $q$) (Beran, 1994). Thus, it includes ARIMA and ARFIMA particularly. The polynomial $(1–L)^d$ in Equation 1 can be expressed as binomial expansion, for all real values of $d$:

$$(1-L)^d = \Sigma_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - \mathrm{d}L + \frac{d(d-1)}{2} L^2 -,,,, \qquad \text{Eq. 2}$$

Hence,

$$(1-L)^d x_t = x_t - dx_{t-1} + \frac{d(d-1)}{2} x_{t-2} -,,,,,, \qquad \text{Eq. 3}$$

Equation 1 can be written as follow:

$$x_t = dx_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \ldots + u_t. \qquad \text{Eq. 4}$$

Therefore, if the differencing parameter ($d$) is a fractional value and $x_t$ is correlated with past values, then a larger value of $d$ indicates higher level of dependence between values. Additionally, $d$ has dynamic relevance. Thus, in case $d = 0$, $x_t$ is short memory or $I$ (0) and if $d > 0$, $x_t$ exhibit long-memory behaviour. Long memory implies far distant association between values. The point 0.5 is quite relevant statistically, as if $d < 0.5$, $x_t$ is covariance stationary. However, $d \geq 0.5$ implies nonstationary (in a way that variance of partial sums increases in magnitude of $d$). Predominantly, threshold - ($d = 1$) is more relevant economically, because $d < 1$ indicate mean reversion, shocks mitigating in long run while $d > 1$ shows no mean reversion with persistence in stocks[4].

## GARCH (1, 1)

As ARCH effects are found in mostly series which indicates volatility clustering. Each series is estimated using GARCH model to compute conditional variance:

Series are estimated as first order autoregressive AR (1) process:

$$Y = \alpha + \beta Y_{-1} + \mathcal{E}_t.$$

Here $Y$ is dependent variable (market prices of respective series) estimated by its first lag $Y_{-1}$ and $\mathcal{E}_t$ is error term.

Now we use GARCH (1,1) estimation based on maximum likelihood to estimate conditional variance.

$$h_t = \alpha + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1}.$$

$h_t$ is conditional variance, $u_{i,t-1}^2$ is previous year squared residuals and $h_{i,\ t-1}$ is variance from model.

## DATA EXPLORATION

### Cryptocurrencies

The study sample time covers 7 August 2015 to 25 May 2020. There are 1,252 trading days in sample time[5]. Cryptocurrencies closing prices are retrieved from coinmarketcap.com. Sample selection is based on market capitalisation and data availability. Accordingly, top 20 cryptocurrencies by market capitalisation are selected then cryptocurrencies with minimum data coverage of five year are considered in sample. Finally, we ended up with the following seven cryptocurrencies: Bitcoin, Ethereum, Litecoin, Monero, Ripple, Stellar, and Tether.

### Emerging Stock Market Indices

Dataset on stock indices is sourced from Morgan Stanley Capital International (MSCI) index. Morgan Stanley provides daily data on emerging stock market indices[6]. Stock indices are computed on country and region levels as prime focus of study is to examine the mutual connectedness of cryptocurrencies with emerging market. Stock indices for individual countries could also be considered but it would have reduced the generalisability of findings. We have selected regional indices as it will enhance the generalisability of findings. Consequently, selected MSCI regional indices are as follow:

| Stock indices | Abbreviation | Definition and construction |
|---|---|---|
| MSCI EM EMEA (Europe, Middle East, and Africa) Index | EM Europe | This Index consists of the following 10 emerging market country indexes: Czech Republic, Greece, Hungary, Poland, Russia, Turkey, Egypt, South Africa, Qatar, and United Arab Emirates. |
| MSCI Asia ex Japan Index | EM Asia | The MSCI AC (All Country) Asia ex Japan Index is a free float-adjusted market capitalisation. Weighted index that is designed to measure the equity market performance of Asia, excluding Japan. The MSCI AC Asia ex Japan Index consists of the following 10 developed and emerging market country indexes: China, Hong Kong, India, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand. |

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(*continued*)

| Stock indices | Abbreviation | Definition and construction |
|---|---|---|
| MSCI Emerging Markets Index | EM (Overall) | MSCI Emerging Markets Index is a free float-adjusted market capitalisation index that is designed to measure equity market performance of emerging markets MSCI classification of 23 emerging market country indexes: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey, and United Arab Emirates. |
| MSCI BRIC Index | BRIC | It is a free float-adjusted market capitalisation weighted index that is designed to measure the equity market performance of the following four emerging market country indexes: Brazil, Russia, India, and China. |
| MSCI World Index | World indices | It is a free float-adjusted market capitalisation weighted index that is designed to measure the equity market performance of developed markets. The MSCI World Index consists of the following 23 developed market country indexes: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. |

Table 1
*Descriptive statistics*

| | Mean | Max | Min | Stdv | Skew. | Kurt. | J.B Prob |
|---|---|---|---|---|---|---|---|
| Bitcoin | 4775.65 | 19114.20 | 210.49 | 3970.72 | 0.55 | 2.58 | 0.00 |
| Ethereum | 202.25 | 1299.74 | 0.43 | 231.79 | 1.84 | 6.79 | 0.00 |
| Litecoin | 52.19 | 358.34 | 2.63 | 56.36 | 1.85 | 7.45 | 0.00 |
| Monero | 70.54 | 469.20 | 0.37 | 82.09 | 1.98 | 7.29 | 0.00 |
| Ripple | 0.26 | 3.20 | 0.00 | 0.33 | 3.49 | 22.94 | 0.00 |
| Stellar | 0.09 | 0.90 | 0.00 | 0.12 | 2.07 | 8.24 | 0.00 |
| Tether | 1.00 | 1.08 | 0.91 | 0.01 | −2.34 | 28.05 | 0.00 |
| BRIC | 113.43 | 150.80 | 73.59 | 17.35 | −0.29 | 2.06 | 0.00 |
| EM (Overall) | 110.94 | 143.84 | 77.79 | 14.01 | −0.14 | 2.18 | 0.00 |
| EM Asia | 113.97 | 147.91 | 81.26 | 15.33 | −0.14 | 2.01 | 0.00 |
| EM Europe | 108.69 | 137.87 | 71.30 | 12.91 | −0.15 | 2.59 | 0.00 |
| World indices | 111.64 | 139.35 | 84.06 | 12.85 | −0.12 | 1.97 | 0.00 |

*Note:* This table provides descriptive statistics of all financial assets in sample. EM refers to Morgan Stanley Capital International Emerging Market Classification with respective regional indices. Moreover, it is quite visible from values of mean and standard deviation that cryptocurrencies are highly volatile relative to emerging stock markets. Bitcoin standard deviation is enormously large as compared to other currencies.

## EMPIRICAL RESULTS

Following the work of Gil-Alana et al. (2020), *d* is estimated using whittle function in frequency domain (Dahlhaus, 1989). We started with conducting ADF unit root test, which reveals that data is plagued with non-stationarity. Therefore, differencing parameter estimates are obtain using first difference of respective series. Then, one is added to differencing parameter to compute desired value.

### Univariate Analysis

As discussed earlier, numerous studies have discovered presence of long memory and persistence in cryptocurrencies. Therefore, investigation of individual asset stochastic and statistical behaviour become indispensable. The techniques like fractional integration can play an instrumental role in uncovering hidden patterns that previous literature left unexplored. Consequently, we initiated the analysis by estimating differencing parameter for all individual series. Univariate estimations are extracted using three regression model[7] for each time series. The first regression model is estimated with sole inclusion of *d*. In Second model, intercept is added along with *d*. Finally, linear time trend is incorporated in third model to observe the variation in *d.*

Estimates of *d* computed using original series (cryptocurrencies prices and stock indices) are tabulated in Table 2. As per empirical evidence in Table 2, all cryptocurrencies (except Monero & Tether) have unit root as value of *d* is greater than or equal to one in majority cases. Such higher values of differencing parameter indicate greater persistence and dependence in cryptocurrencies. Predominantly, these findings suggest lack of mean reversion in leading cryptocurrencies like Bitcoin, Ethereum, Litecoin, and Stellar. However, evidence of mean reversion is observed for Tether[8] and Monero only as differencing parameter is less than one in both cases. As far as stock market indices are concerned, approximation unveils strong evidence for lack of mean reversion in all regional stock indices. As *d* is substantially greater than one for all indices. In line with cryptocurrencies, emerging stock indices also exhibit long memory behaviour and high level of persistence.

Table 2
*Estimates of d using market prices*

| | No term | An intercept | Linear time trend |
|---|---|---|---|
| Cryptocurrencies | | | |
| Bitcoin | 1.013 | 1.012 | 1.021 |
| Ethereum | 1.034 | 1.034 | 1.062 |
| Litecoin | 1.115 | 1.115 | 1.067 |
| Ripple | 1.175 | 1.175 | 1.197 |
| Monero | **0.947** | **0.947** | **0.947** |
| Stellar | 1.012 | 1.012 | 1.012 |
| Tether | **0.629** | **0.629** | **0.629** |
| Stock Markets | | | |
| BRIC | 1.075 | 1.075 | 1.076 |
| EM (Overall) | 1.105 | 1.105 | 1.105 |
| EM Asia | 1.074 | 1.074 | 1.058 |
| EM Europe | 1.067 | 1.067 | 1.042 |
| World indices | 1.013 | 1.013 | 1.144 |
| Model specification | $\Delta Y = d + \mathcal{E}_t$ | $\Delta Y = \alpha + d + \mathcal{E}_t$ | $\Delta Y = \alpha + d + \textit{time trend} + \mathcal{E}_t$ |

*Note:* This table report estimated value of *d* for first difference of original series based on uncorrelated White Noise errors with 5% significance level. The computation is made for three cases as described above. If the value of *d* is less than 1 it indicates mean reversion and value of *d* greater than 1 implies that series are non-stationary with no mean reversion. The value in bold refers to mean reversion.

Interestingly, greater persistence and long memory characteristics enhance the likelihood of predicting future price using historical prices. Now extending empirical inference to Table 3 which reports differencing parameters estimates derived from conditional volatility. Contrast to original series, mean reverting behaviour is observed in cryptocurrencies volatility as Table 3 shows. But *d* for Bitcoin is almost equal to one and greater than one for Litecoin which suggest lack of mean reversion in conditional volatility. Similar is the case with stock indices volatility as EM Europe, world indices and EM (overall) has mean reversion[9] and lack of mean reversion is found in BRIC and EM Asia indices.

Table 3
*Estimates of d using conditional volatility*

| | No term | An intercept | Linear time trend |
|---|---|---|---|
| Cryptocurrencies | | | |
| Bitcoin | 1.000 | 1.000 | 1.000 |
| Ethereum | 0.899 | 0.899 | 0.899 |
| Litecoin | 1.208 | 1.208 | 1.208 |
| Ripple | 0.719 | 0.719 | 0.719 |
| Monero | 0.961 | 0.961 | 0.961 |
| Stellar | 0.928 | 0.928 | 0.928 |
| Tether | 0.944 | 0.944 | 0.944 |
| Stock Market indices | | | |
| BRIC | 1.009 | 1.009 | 1.009 |
| EM (Overall) | 0.974 | 0.974 | 0.974 |
| EM Asia | 1.104 | 1.104 | 1.104 |
| EM Europe | 0.987 | 0.987 | 0.987 |
| World indices | 0.897 | 0.897 | 0.897 |
| Model specification | $\Delta Y = d + \mathcal{E}_t$ | $\Delta Y = \alpha + d + \mathcal{E}_t$ | $\Delta Y = \alpha + d + \textit{time trend} + \mathcal{E}_t$ |

*Note:* This Table reports estimated value of *d* for first difference of conditional volatility based on uncorrelated white noise errors with 5% significance level. If the value of *d* is less than 1 it indicates mean reversion and value of *d* greater than 1 implies that series are non-stationary with no mean reversion. The value in bold refers to mean reversion.

## Bivariate Analysis

This section focuses on the long run relationship between the sample cryptocurrencies and stock markets. This section is conducted in two phases, first phase deals with investigation of long-run dependence of each cryptocurrency with all peer-currencies in sample. This detail analysis is displayed across Table 4 and Table 5. Then, second phase emphasises on uncovering the stochastic mutual long-run relationship and cointegration properties of each stock market indices with each cryptocurrency. These findings are reported in Table 6 and Table 7.

## Cryptocurrencies connectedness

For estimating *d* original series, i.e., market prices and conditional volatility are used. The findings are shown in Table 4 and Table 5, respectively. The *d* estimates based on prices have provided little evidence of cointegration among cryptocurrencies except for Monero and Tether. Moreover, these findings

(Table 4) corroborate the Gil-Alana et al. (2020) conjecture that cryptocurrencies are disconnected. Contrarily, when conditional volatility is used to estimate *d* it unveils more cases of mean reversions. Especially, Ethereum, Bitcoin, Stellar, and Ripple are cointegrated with other digital currencies. However, value of *d* is close to one in many cases, which is indication of high degree of persistence and possibility of shocks. Volatility connection among cryptocurrencies is obvious as a line of research (Liu & Serletis, 2019; Symitsi & Chalvatzis, 2018; Yi et al., 2018) has discover interdependence and integration between digital assets.

Table 4
*Market price connectedness (cryptocurrencies vis-à-vis cryptocurrencies)*

| Dependent Variables | Regressors | | | | | | |
|---|---|---|---|---|---|---|---|
| | Bitcoin | Ethereum | Litecoin | Ripple | Monero | Stellar | Tether |
| Bitcoin | – | 1.024 | – | 1.025 | 0.937 | – | – |
| Ethereum | 1.048 | – | 1.068 | 1.036 | 1.038 | – | 1.034 |
| Litecoin | 1.137 | 1.156 | – | 1.126 | 1.087 | 1.119 | 1.114 |
| Ripple | 1.201 | 1.207 | 1.193 | – | 1.187 | 1.087 | 1.174 |
| Monero | 0.857 | 0.936 | 0.866 | 0.923 | – | – | 0.949 |
| Stellar | – | 0.970 | 1.013 | 0.876 | 1.006 | – | 1.013 |
| Tether | 0.627 | 0.629 | 0.628 | 0.63 | 0.632 | 0.628 | – |

*Notes:*
Model spesification is as follow:
$\Delta$Cryptocurrency (prices) = $\alpha + \beta\Delta$ Cryptocurrency (prices) + $d + \mathcal{E}$
$\Delta$ denotes first difference of respective series.
This table provide estimates of *d* using Market Prices (original series) obtain through regressing each cryptocurrency with other one at 5% significance level based on uncorrelated white noise errors. The (–) refers towards insignificant estimates of *d*. If the value of *d* is less than 1 it indicates mean reversion. This mean reversion implies that respective series are cointegrated and connected in long run. In case of value of *d* greater than 1 implies lack of mean reversion and series are disconnected in long run. The value in bold refers to mean reversion cases.

Table 5
*Conditional volatility connectedness (cryptocurrencies vis-à-vis cryptocurrencies)*

| Dependent Variables | Regressors | | | | | | |
|---|---|---|---|---|---|---|---|
| | Bitcoin | Ethereum | Litecoin | Ripple | Monero | Stellar | Tether |
| Bitcoin | | 0.887 | 0.837 | 0.850 | 0.850 | 0.852 | 0.847 |
| Ethereum | – | | – | 0.980 | 0.980 | 0.979 | – |
| Litecoin | 0.974 | – | | 0.947 | 0.982 | 0.976 | 0.929 |
| Ripple | 0.812 | 0.819 | 0.817 | 0.813 | | 0.813 | 0.813 |

*(continued on next page)*

Table 5: (*continued*)

| Dependent Variables | Regressors | | | | | | |
|---|---|---|---|---|---|---|---|
| | Bitcoin | Ethereum | Litecoin | Ripple | Monero | Stellar | Tether |
| Monero | 0.728 | 0.735 | 0.657 | | 0.731 | 0.753 | 0.733 |
| Stellar | 0.902 | 0.900 | 0.898 | 0.926 | 0.900 | | 0.901 |
| Tether | 0.953 | 0.960 | 0.899 | 0.960 | 0.955 | 0.954 | – |

*Notes:*
Model spesification is as follow:
$\Delta$Cryptocurrency (volatility) = $\alpha + \beta\Delta$ Cryptocurrency (volatility) + $d + \mathcal{E}$
$\Delta$ denotes first difference of respective series.
This table provide estimates of *d* using GARCH estimated (Conditional volatility) obtain through regressing each cryptocurrency with other with 5% significance level based on uncorrelated white noise errors. The (–) refers towards insignificant estimates of *d*. If the value of *d* is less than 1 it indicates mean reversion. This mean reversion implies that respective series are cointegrated and connected in long run. In case of value of *d* greater than 1 implies lack of mean reversion and series are disconnected in long run. The value in bold refers to mean reversion cases.

## Stock markets and cryptocurrencies connectedness

Now moving towards relationship between cryptocurrencies and emerging stock market indices. At first, the prices-based estimates are computed by regressing each stock indices on individual cryptocurrency. And the results uncover absence of cointegration for all stock indices. The *d* values are greater than or close to one in all cases. Therefore, emerging markets stock indices are not cointegrated with cryptocurrencies. Hence, cryptocurrencies are isolated and decoupled from stock indices offering investment opportunities. In a similar fashion, Corbet et al. (2018) and Gil-Alana et al. (2020) has concluded that cryptocurrencies are detached from stock market indices.

However, the conditional volatility-based estimates uncover contrasting evidence of cointegration. As per empirical evidence in Table 7, emerging market stock indices, world indices, and BRIC are cointegrated with digital currencies. Interestingly, Asian stock indices and BRIC are found to be disconnected with value of *d* greater than one. But the *d* is quite close to one in cointegrating cases and its clear indication of high persistence in long run. This implies that stock indices volatility and cryptocurrencies volatility might move together in long-run but it cannot be surmised that stock indices are strongly connected with digital currencies on volatility ground as cryptocurrencies are extremely volatile (Hafner, 2018) and exhibit erratic price movements (Caporale et al., 2018b) which is not the case with conventional stock indices.

Table 6
*Market price connectedness (cryptocurrencies vis-à-vis stock indices)*

| Dependent variables | Regressors | | | | | | |
|---|---|---|---|---|---|---|---|
| | Bitcoin | Ethereum | Litecoin | Ripple | Monero | Stellar | Tether |
| Emerging Market | 1.104 | 1.101 | 1.104 | 1.103 | 1.105 | 1.101 | 1.109 |
| Asia | 1.074 | 1.070 | 1.073 | 1.072 | 1.074 | 1.070 | 1.076 |
| EM Europe | 1.063 | 1.063 | 1.065 | 1.065 | 1.065 | 1.064 | 1.070 |
| BRIC | 1.074 | 1.069 | 1.074 | 1.073 | 1.074 | 1.070 | 1.078 |
| World indices | – | – | – | – | – | – | 1.020 |

*Notes:*
Model spesification is as follow:
$\Delta$Emerging Market (EM) Stocks (MSCI index) = $\alpha + \beta\Delta$ Cryptocurrency (Prices) + $d + \mathcal{E}$
$\Delta$ denotes first difference of respective series.
This table provide estimates of $d$ using Market Prices (original series) obtain through regressing each cryptocurrency with each emerging stock market indices with 5% significance level based on uncorrelated white noise errors. The (−) refers towards insignificant estimates of $d$. If the value of $d$ is less than 1 it indicates mean reversion. This mean reversion implies that respective series are cointegrated and connected in long run. In case of value of $d$ greater than 1 implies lack of mean reversion and series are disconnected in long run. The value in bold refers to mean reversion cases.

Table 7
*Conditional volatility connectedness (cryptocurrencies vis-à-vis stock indices)*

| Dependent variables | Regressors | | | | | | |
|---|---|---|---|---|---|---|---|
| | Bitcoin | Ethereum | Litecoin | Ripple | Monero | Stellar | Tether |
| Emerging Market | **0.975** | **0.973** | **0.974** | **0.974** | **0.974** | **0.974** | **0.966** |
| Asia | 1.109 | 1.103 | 1.104 | 1.104 | 1.104 | 1.104 | 1.103 |
| EM Europe | **0.994** | – | **0.987** | **0.987** | – | – | **0.975** |
| BRIC | 1.008 | – | 1.009 | 1.009 | – | – | **0.998** |
| World indices | **0.894** | **0.895** | **0.897** | **0.897** | **0.897** | **0.897** | **0.859** |

*Notes:*
Model spesification is as follow:
$\Delta$Emerging Market Stocks (volatility) = $\alpha + \beta\Delta$ Cryptocurrency (volatility) + $d + \mathcal{E}$
$\Delta$ denotes first difference of respective series.
This table provide estimates of $d$ using GARCH estimated (Conditional volatility) obtain through regressing each cryptocurrency with emerging market indices with 5% significance level based on uncorrelated white noise errors. The (−) refers towards insignificant estimates of $d$. If the value of $d$ is less than 1 it indicates mean reversion. This mean reversion implies that respective series are cointegrated and connected in long run. In case of value of $d$ greater than 1 implies lack of mean reversion and series are disconnected in long run. The value in bold refers to mean reversion cases.

## CONCLUDING REMARKS AND IMPLICATIONS

This study has explored the linkages between Morgan Stanley emerging stock market indices and seven leading cryptocurrencies using fractional integration and cointegration approach. We initiated the estimations with individual level analysis, which unveil presence of persistence and long memory in majority cases for both asset classes. However, on extending univariate analysis to conditional volatility, more cases mean reversion are observes relative to prices base analysis. In second stage, bivariate analysis is conducted to test for existence of long-run equilibrium relationship between two distinct asset classes. At first, we analysed the linkage among sample cryptocurrencies. The differencing term estimates reveals that sister cryptocurrencies prices movements are not cointegrated therefore no mean reversion (see Table 8). But volatility-based estimation narrates a different story because as per empirical evidence all sample cryptos cointegrated with each other. Secondly, emerging stock indices are subjected to check for cointegration against cryptocurrencies. Bivariate analysis suggests that both asset classes price movements are detached from each other because *d* values are greater than one in almost all cases. Contrarily, a slightly different picture emerged on testing existence of cointegration on volatility ground. Notably, some degree of connectedness is found between stocks and cryptos as *d* values are less than but close to one in majority cases. But as *d* values are substantially lying around one, we cannot contend that cryptocurrencies are connected on volatility grounds. Because cryptocurrencies are extremely volatile and exposed to certain kind of idiosyncratic which is not the case the conventional stock indices.

Our findings have great implications for market participants. We have found that cryptocurrencies and stock indices price movements are not cointegrated, but some level of volatility connectedness is observed. More importantly, fractional integration approach has exposed the volatile nature of assets as well as high degree of persistence. These finding implies that investors should gauge the risk return trade-off cautiously. Predominantly, high persistence and lack of mean reversion could lead to some unexpected market shocks which could make any kind of investment strategy to hedge or diversify counterproductive. Therefore, hedging emerging market equities with cryptos can be lucrative avenue if crypto market nuances and subtleties are observed carefully.

Table 8
*Overall results snapshot*

| Table No. | Connected cases | Disconnected cases | Significant cases | Total cases | Mean reverting % of total | Mean reverting % of significant |
|---|---|---|---|---|---|---|
| Table 4 (CC vs CC) | 12 | 24 | 36 | 49 | 24 | 33 |
| Table 5 (CCV vs CCV) | 38 | 0 | 38 | 49 | 78 | 100 |
| Table 6 (SM vs CC) | 0 | 29 | 29 | 35 | 0 | 0 |
| Table 7 (SMV vs CCV) | 19 | 10 | 29 | 35 | 54 | 66 |
| Grand total | 69 | 63 | 132 | 168 | 41 | 52 |

*Notes:* This table summarises the results presented in empirical results sections. Connected Cases refers to the number of cases in each table with mean reversion and disconnected cases columns is sum of all cases where series are not cointegrated i.e., no mean reversion is found for each table.
Mean reverting cases as % of significant cases is computed as follow:
(Connected cases /Significant cases) x 100,
Mean reverting cases as % of total cases is computed as follow:
(Connected cases / Total cases) x 100
CC stands for cryptocurrencies prices, CCV stands for cryptocurrencies volatility, SM stands for Stock market indices, SMV stands for Stock market indices volatility.

## NOTES

1. To the best of our information this study is very first attempt with particular focus on emerging stock market indices and cryptocurrencies.
2. Because emerging market economies are considerably more volatile relative to advance economies (Ayub et al., 2015).
3. Baur and Lucey (2010, p. 219) has defined hedge as an asset that is uncorrelated or negatively correlated with another asset or portfolio on average, diversifier as an asset that is positively (but not perfectly correlated) with another asset or portfolio on average, and safe haven is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil.
4. Beran (1994) and Gil-Alana and Hualde (2009) are recommended for additional technical details.
5. As stock markets are closed on weekend whereas cryptocurrencies are traded 24/7. Therefore, we have considered only five trading days per week (Monday to Friday) to achieve synchronicity between series.
6. For more details on index definition and methodology, see https://www.msci.com/documents/1296102/1339060/MSCI+Index+Definitions+2015.pdf/8a3896c1-7a2f-4a7b-acd8-3bea6fd151c4 and https://www.msci.com/index-methodology

7. Regression models are estimated using ARIMA model estimated with maximum likelihood, which assume that error term is a white noise process with no autocorrelation.
8. Tether is classified as stable coin as its value is pegged to United States Dollar as 1:1. So mean reversion is expected (Gil-Alana et al., 2020).
9. Mean reversion is expected in condition volatility as GARCH (1,1) approximates condition variance as a stationary process with restriction on sum of all three parameters being equal to one in variance equation.

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