CRYPTOCURRENCIES AND STOCK MARKET INDICES. ARE THEY RELATED?

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Abstract

In this paper, we investigate the stochastic properties of six major cryptocurrencies and their bilateral linkages with six stock market indices using fractional integration techniques. From the univariate analysis, we observe that for Bitcoin and Ethereum, the unit root null hypothesis cannot be rejected; for Litecoin, Ripple and Stellar, the order of integration is found to be significantly higher than 1; for Tether, however, we find evidence in favour of mean reversion. For the stock market indices, the results are more homogeneous and the unit root cannot be rejected in any of the series, with the exception of VIX where mean reversion is obtained. Concerning bivariate results within the cryptocurrencies and testing for cointegration, we provide evidence of no cointegration between the six cryptocurrencies. Along the same lines, testing for cointegration between the cryptocurrencies and the stock market indices, we find evidence of no cointegration, which implies that the cryptocurrencies are decoupled from the mainstream financial and economic assets. The findings in this paper indicate the significant role of cryptocurrencies in investor portfolios since they serve as a diversification option for investors, confirming that cryptocurrency is a new investment asset class.

Keywords: Cryptocurrencies; stock market indices; fractional integration; fractional cointegration

JEL Classification: G11, G19, G32, C59

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1.   Introduction

Cryptocurrencies are a globally spreading phenomenon that is frequently and also prominently addressed by the media, venture capitalists, financial and governmental institutions alike (Glaser et al., 2014). The recent emergence of cryptocurrencies as a new class of financial assets consequently offers a new opportunity to investigate several as yet unexplored aspects of cryptocurrencies. In empirical finance, the role of cryptocurrency markets has grown rapidly in recent years gaining a lot of attention from among academic scholars, the media, government institutions and the finance industry. The upsurge in cryptocurrencies and rapid development of cryptocurrency markets have been attributed to the recent sharp increase in Bitcoin trading volume leading to a comprehensive literature on cryptocurrency markets (Hileman and Rauchs, 2017). Since Bitcoin was first proposed by Nakamoto (2008), several studies have been conducted on Bitcoin, focusing on market efficiency (Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017; Vidal-Tomás and Ibañez, 2018), price volatility (Dyhrberg, 2016; Katsiampa, 2017), price clustering (Urquhart, 2017), speculation (Cheah and Fry, 2015) and transaction costs (Kim, 2017). Consequently, the introduction of different kinds of cryptocurrencies in recent years has resulted in the rapid increase of market size of the cryptocurrency markets. Some key studies have examined some cryptocurrencies properties such as market returns and volatility (Omane-Adjepong et al., 2019), herding behaviour in cryptocurrency markets (Bouri, Gupta and Rouband, 2018), portfolio diversification across cryptocurrencies (Liu, 2018), regime shifting models (Mensi, Al-Yahyaeeb and Kang, 2018; Bouri, Gil-Alana, Gupta and Roubaud, 2019; Omane-Adjepong, Alagidede and Akosah, 2019), return-volume relationship (Bouri et al., 2018), or speculation (Yermack, 2015; Blau, 2018).

Recently, a strand of the literature on cryptocurrencies has focused on stylized facts and technical aspects of cryptocurrencies. For example, Katsiampa (2017) and Vandezande (2017)

conclude that high volatility in cryptocurrencies may be the reason for the high returns in cryptocurrencies. Bariviera et al. (2017) established that cryptocurrencies are characterized by anonymity and are susceptible to speculative bubbles (Cheah and Fry, 2015). According to Yarovaya et al. (2016), the speculative bubbles in the cryptocurrency markets may in turn spread contagion and weaken financial stability. The past few years have also witnessed considerable research concerning the importance of adding cryptocurrency to a portfolio with equity and with other assets classes (Briere et al. 2015; Eisl et al. 2015; Bouri et al. 2017, Omane-Adjepong et al., 2019; Stensas et al., 2019; etc.). Despite the popularity of cryptocurrencies, there are fewer academics works assessing cryptocurrencies from the economic-finance perspective, leading to the conclusion that research on cryptocurrency markets is still in its infancy (Urquhart, 2016). Even though a number of studies have investigated the connectedness between the same type of asset classes (Aftab et al. 2015; Tiwari et al. 2018) and the linkages between different asset classes (Corbet et al. 2018), the scant empirical work addressing connectedness within the cryptocurrencies, and other asset classes, is the motive for this study.

Succinctly, this paper contributes to the literature on cryptocurrency markets and its role in investment finance decisions. Our objective is to provide empirical relations between cryptocurrency markets and other stock market indices to show the patterns of return and volatility transmission among these markets to aid investment decisions. Specifically, we study the stochastic properties of the bilateral linkages between the largest cryptocurrencies and other financial assets. Thus, we contribute to studies that focus on the technical aspects and stylized facts of cryptocurrency markets. We investigate the statistical properties of the cryptocurrencies and the stock market prices from a fractionally integrated viewpoint, testing the degree of persistence for each series using alternative methods. Then, in a multivariate

framework, we look at bivariate relationships, firstly, with the cryptocurrencies themselves, and then, between the cryptocurrencies and each stock market, in a vis-à-vis relation, testing the degree of integration of such relationships. A study of this nature is crucial for investment decisions since it establishes the patterns of information transmission across cryptocurrency markets and other financial assets. In this work, we discuss the largest investable sample of cryptocurrencies, and conditionally measure some important stylized facts using fractional integration and cointegration methods. To the best of our knowledge, this is the first study to examine stochastic properties of cryptocurrencies using a robust methodology based on fractional integration and cointegration.

We contribute to the literature in two ways. First, we investigate the level of connectedness between cryptocurrencies and other financial assets using fractional integration and cointegration techniques. We provide evidence of no linkages between cryptocurrency markets and stock market indices confirming the findings of Corbet et al. (2018). Our findings show that the cryptocurrency markets are decoupled from the main financial and economic asset class, hence offering diversification benefits to investors. Second, we examine the linkages between the selected cryptocurrencies, again using I(d) methods, and the results confirm that there exist no bilateral linkages between the selected cryptocurrencies, which is not in consonance with the findings of Corbet et al. (2018) who established that cryptocurrencies are connected.

The structure of the paper is as follows: Section 2 provides a brief overview of the cryptocurrency market since its inception in 2009. Section 3 outlines the empirical methodology, while Section 4 documents the data and the main empirical results. In Section 5, we provide some concluding remarks.

2.   Literature review

Although Bitcoin can be considered relatively new (from 2008, as mentioned above), the last ten years have witnessed the spectacular development of cryptocurrencies in the market. In fact, a total of 2520 cryptocurrencies were being traded in January 2019 (www.investing.com) with a market capitalization of $113 billion. This is partially due to the support of some countries, such as Japan and South Korea, that recognised Bitcoin as a legal method of payment (Bloomberg, 2017; Cointelegraph, 2017), as well as a large number of banks and companies that created the Enterprise Ethereum Alliance (https://entethalliance.org/) to make use of the cryptocurrencies and the related technology called blockchain (Forbes, 2017).

The evolution of Bitcoin and other flowering cryptocurrencies in the market has been analysed in detail during this decade. In particular, from 2013 when the value of Bitcoin increased rapidly from around $150 in mid-2013 to over $1000 in late 2013, which is known as the 2013 bubble. Brown (2014) provided evidence of short-term price predictability of the Bitcoin. Gandal and Halaburda (2014) analysed competition in the cryptocurrency market, but most of the researchers focused on the price volatility, showing that this market is more volatile than others (Cheung et al., 2015; Dwyer, 2015; Bouoiyour and Selmi, 2015). In fact, some authors, such as Glaser et al. (2014) and Baek and Elbeck (2015) stated that Bitcoin is mostly used for speculative purpose, due to the extreme volatility and bubbles.

After the Bitcoin price fell dramatically to $200 by 2016, many researchers were interested in analysing the efficiency of the Bitcoin market (Bartos, 2015; Urquhart, 2016) and the negative bubbles and shocks in cryptocurrencies markets by using, among others, econophysical models (Fry and Cheah, 2016). In 2017, things changed abruptly. Bitcoin began rising again and by early 2017, the value of bitcoin was again more than $1000 and reached a

maximum of more than $10000 in December 2017. This phenomenon caused a huge impact in the cryptocurrency market. Feder et al. (2018) analysed in detail the rise and fall of cryptocurrencies, in particular the dynamics of coin creation, competition and destruction in the cryptocurrency industry. They concluded that, unlike the end of the 2013 bubble, some alternative cryptocurrencies continued to flourish after the fall of Bitcoin. In fact, the number of new digital coins increased impressively, from 22 cryptocurrencies in August 2017, to 2520 in January 2019 (www.investing.com). Other authors also analysed the anomalies in cryptocurrency market (Kurihara and Fukushima, 2017; Caporale and Plastun, 2018; Caporale et al., 2018), and the extreme volatility (Dyhrberg, 2016; Corbet et al., 2018, Hafner, 2018). Catania and Grassi (2017) evaluated Bitcoin volatility by using GAS models, and Phillip et al. (2018) used a stochastic volatility model. Bouri et al. (2017) showed, among other things, a negative relation between the US implied volatility index (VIX) and Bitcoin volatility, and Bariviera (2017) tested the presence of long memory in Bitcoin series from 2011 to 2017.

During the last few years, more efforts have been made to analyse the risk-return, volatility and benefits for investors. For example, Corbet et al. (2018) explored the dynamic relationships between cryptocurrencies and other financial assets, showing that cryptocurrencies may offer diversification benefits for investors with short investment horizons. Phillip et al (2018) explored the properties of 224 cryptocurrencies and found that, in general, they have several unique properties including leverage effects and Student- error distributions. Liu and Tsyvinski (2018) established that the risk-return trade-off of cryptocurrencies (Bitcoin, Ripple, and Ethereum) is distinct from those of stocks, currencies, and precious metals. In addition, they created an index of exposures to cryptocurrencies of 354 industries in the US and 137 industries in China. More recently, Kapar and Olmo (2019) suggested that the Bitcoin futures market dominates the price discovery process and found that

both prices are driven by a common factor that is given by a weighted combination of the futures and spot market. On the other hand, the effects of the geopolitical risks on Bitcoin returns and volatility have been analysed by Aysan et al. (2019), showing that Bitcoin can be considered as a hedging tool against global geopolitical risks.

3.   Empirical methodology

As mentioned earlier we use techniques based on fractional integration and cointegration (see, Gil-Alana and Hualde, 2009). Fractional integration generalizes the case of unit roots to the fractional case. In other words, a process is said to be integrated of order d if it requires d-differences to render the series stationary I(0). The usual value for d is 1, and first differencing has become a standard practice to remove the nonstationarity in time series. However, the number of differences, d, may not necessarily have to be restricted to an integer value (i.e., 0, 1 or 2) but may be any real value, including thus fractional numbers. Thus, we say that $\{x_t, t = 0, \pm1, …\}$ is integrated of order d, and denoted as I(d) if it can be represented as:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, ..., \qquad (1)$$

where L is the backshift operator ($Lx_t = x_{t-1}$) and u_t is I(0) indicating a covariance stationary process with a spectral density function that is positive and bounded at all frequencies in the spectrum. Note that if u_t is an ARMA(p, q) process, x_t is then said to be a fractionally integrated ARMA, i.e., ARFIMA(p, d , q) process (Beran, 1994). Thus, it includes the classical ARMA and ARIMA models as particular cases of interest if d = 0 and 1 respectively. The polynomial $(1 - L)^d$ in equation (1) can be expressed in terms of its Binomial expansion, such that, for all real d,

$$(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \cdots,$$

and thus,

$$(1 - L)^d x_t = x_t - dx_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \cdots,$$

implying that equation (1) can be expressed as

$$x_t = dx_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \cdots + u_t.$$

Thus, if d is a fractional value, x_t depends on all its past history and the higher the value of d is, the higher the level of dependence between the observations is. Moreover, the differencing parameter d is quite relevant from different perspectives. Thus, if d = 0, x_t is short memory or I(0), while d > 0 implies long memory behaviour, so-named because of the strong degree of association between observations far distant in time.[1] From a statistical viewpoint, 0.5 is another relevant point: if d < 0.5, x_t is covariance stationary, while d ≥ 0.5 implies nonstationarity (in the sense that the variance of the partial sums increases in magnitude with d); finally, from an economic viewpoint d = 1 is also relevant: d < 1 indicates mean reversion, with shocks disappearing in the long run, while d ≥1 shows a lack of mean reversion with shocks persisting forever.

4.   Data

In this study, we use a cryptocurrency dataset for the time period from 07-May-2015 to 05-October-2018, with 826 trading days in total. We obtained data for cryptocurrencies from cryptocompare.com. We focused on the top six largest cryptocurrencies assets with market capitalisation value over \$1b as of end of 5th October 2018 with enough data available to achieve the objective of the study, these being Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Tether. The combined market capitalisation of the selected cryptocurrencies constituted 80.22% of the top 100 cryptocurrencies by market capitalisation value as at end of 5th October

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[1] We use a "broad" definition of long memory by saying (in the time domain) that a process is long memory if the infinite sum of the autocovariances (or pseudo-autocovarainces) is infinite. Alternatively, in the frequency domain, a process is long memory if the spectral (or pseudo-spectral) density funtion has at least one pole or singularity in the spectrum. These definitions apply for all I(d, d > 0) processes.

2018. For the other traditional assets, a number of strands informed our choice. Corbet et al. (2018) examined the relationships between three popular cryptocurrencies and a variety of financial assets including S&P 500 Composite, S&P GSCI Commodity Total Return, VIX, S&P Bond Index, S&P GSCI Gold Total Return and US Nominal Dollar Broad Index. With a similar objective, we work with these six major financial asset class with data obtained from DataStream.

Following the non-synchronicity of trading days between the stock markets indices and cryptocurrencies and the objective of the study which is to test for the linkages between the well-known traditional finance and economic asset class and the digital currencies, we synchronised the data and consider trading days from Monday to Friday. We ignore weekend trading days for the digital currencies because, the results remained unchanged when included in the model in estimating the pairwise relationship between the asset class in our sample.

[Insert Table 1 and Figure 1 about here]

Table 1 and Figure 1 display some descriptive statistics of the six cryptocurrencies and the six stock market indices. We observe that the cryptocurrencies have higher returns but much higher volatility than the stock market indexes. In particular, Tether shows about 10^4 differences between the minimum and maximum values, in comparison to the stock market indices. Moreover, the coefficient is dramatically higher in the cryptocurrencies (between 0.01 for Stellar, and 1.66 for Litecoin) than in the stock market indices (between 0.02 and 0.3), indicating a great dispersion in the cryptocurrency values.

5.   Empirical results

We start this section by considering the following model,

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad (1 - L)^d x_t = u_t, \qquad t = 0, 1, ..., \qquad (2)$$

where y_t refers to each of the time series we observe (in logs), β_0 and β_1 refers respectively to the intercept and a linear time trend; x_t is supposed to be I(d) and thus, u_t is I(0), and d is a real value that is estimated from the data.

Across Tables 2 – 7 we report the estimates of d using the Whittle function in the frequency domain (Dahlhaus, 1989). Based on the nonstationary nature of the data examined, the analysis was conducted in the first differenced data, adding then the value 1 to obtain the estimated value of d. Moreover, we present in the table the interval of values of d where the null hypothesis of d being equal to a given value (say, d_o) cannot be rejected at the 5% level using a version of the tests of Robinson (1994), which is valid even in nonstationary contexts.

Table 2 displays the estimates of d and the associated 95% confidence bands, in the model given by (2) under the assumption that u_t is a white noise process. We display the results for the three common cases of i) no regressors, i.e., imposing that β_0 and β_1 are both equal to zero; ii) an intercept (i.e., with β_1 equal to 0); and iii) an intercept with a linear time trend (i.e., β_0 and β_1 estimated from the data), and mark in bold in the table the selected models according to these deterministic terms. Note that under the null hypothesis: $d = d_o$, equation (2) can be expressed as:

$$(1\text{-}L)^{d_o} y_t = \beta_0 (1\text{-}L)^{d_o} 1 + \beta_1 (1\text{-}L)^{d_o} t + u_t; \qquad t = 0, 1, ..., \qquad (3)$$

and since u_t is I(0) by construction, t-tests apply on the coefficients β_0 and β_1. We see that for the cryptocurrencies, only the Bitcoin requires a linear time trend, and for the stock prices, the time trend is only required in the case of Standard and Poor (S&P). In all other cases, the intercept is sufficient to describe the deterministic terms. Focusing on the estimated values of d, and starting again with the cryptocurrencies, we observe that for Bitcoin and Ethereum, the unit root null hypothesis (i.e., d = 1) cannot be rejected; for Litecoin, Ripple and Stellar, the value of d is found to be significantly higher than 1, and for Tether we get evidence in favour of mean reversion (i.e., d < 1).[2] For the stock market, however, the results are more homogeneous and the unit root hypothesis cannot be rejected in any of the series with the exception of VIX where mean reversion is obtained. The evidence of mean reversion in the cases of Tether and VIX indicate that random shocks in these series have transitory though long lasting effects.

[Insert Tables 2 and 3 about here]

Table 3 extends the analysis to the case of autocorrelated errors. Here, instead of imposing a parametric ARMA model, we use a non-parametric approach due to Bloomfield (1973) that produces autocorrelations decaying exponentially as in the autoregressive (AR) case. One advantage of this model is that it is stationary for all its values unlike the AR case, and it accommodates very well in the context of fractional integration (Gil-Alana, 2004). Evidence of unit roots is now found in most of the cryptocurrencies; Bitcoin, Ethereum, Litecoin and Stellar; d > 1 is obtained for Ripple, and d < 1 (mean reversion) in the case of Tether, which is consistent with the results reported above for the white noise case. The findings on Tether is not surprising because, Tether (UST) mostly depicts a flat top price

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[2] Note that Tether is 1:1 to the US dollar and has mostly shown a flat-top price development, being this potentially an argument to explain the mean reverting result.

development since is only 1:1 to the US dollar. Hence the evidence of mean reversion (shock transitory) property was expected. For the stock market, the I(1) behaviour is found in all cases except Standard and Poor (S&P 500) and VIX where the estimated value of d is significantly below 1.

We can summarize the results across these two tables by saying that evidence of unit roots is found in [3]the majority of the series, and the only support of mean reversion is found in the cases of Tether for the cryptocurrencies, and VIX for the stock market prices.

Next we move to the multivariate work and look at the potential long run relationships between the cryptocurrencies, first by looking at vis-à-vis relationships between the variables. We consider two approaches here. First, we look at the differences in the log-values between the cryptocurrencies. We then conduct OLS regressions on each of the cryptocurrencies against the others, and estimate the value of d in the regression errors. The results are displayed respectively in Tables 4 and 5, and in both cases we consider the two cases of uncorrelated and autocorrelated errors.

[Insert Tables 4 and 5 about here]

Starting with the log-differences across the cryptocurrencies, in Table 4, we only observe a single case with evidence of mean reversion (d < 1), this being the one corresponding to the difference between Ripple and Stellar. In all the other cases, the estimates of d are in the I(1) intervals, finding evidence of no cointegration. Table 5 displays the estimates of the regression errors. We see that under no autocorrelation, mean reversion occurs in three cases related with Tether. This is not surprising, noting that Tether was the only cryptocurrency where mean reversion took place in the results displayed across Tables 2 and 3. If the errors

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[3] Thus, in both cases we test for (fractional) cointegration, assuming known values (1, -1) in the long run relationships in the first case, and estimating freely the coefficients in the second case. In the latter we use the approach in Engle and Granger (1987) though extended to the fractional case as in Cheung and Lai (1993) and Gil-Alana (2003).

are autocorrelated, (Table 5) there are three more cases, dealing with Ripple, Litecoin and Stellar, though, in general, the orders of integration are relatively high and close to 1, implying once more, high degrees of persistence among the cryptocurrencies. The vast dispersion within the cryptocurrencies reported in this study could be accounted for using the findings of Osterrieder et al. (2017). These authors investigated statistical similarities and extreme value behavior of six virtual currencies. Their results suggest that the virtual currencies exhibit non-normal statistical properties for those which share the same underlying technology. Accordingly, we surmise that the disconnections among cryptocurrencies could be as a result of the above reason. In addition, we link our findings of interdependence among cryptocurrencies to the fact that prices of cryptocurrencies fluctuate considerable wider than those of the standard fiat currencies (Dong et al., 2016). Our research suggests a role for cryptocurrencies in an investor portfolio, they being highly disconnected to each other and other mainstream assets. However, per the nature and price formation process of cryptocurrencies, the cryptocurrency market contains its own idiosyncratic risk that is extremely difficult to hedge against.

Next we focus on the relationships between the cryptocurrencies and the stock markets indices (Tables 6 and 7). As before, we look first at the differences in the log-values between the cryptocurrencies and the stock market prices following by OLS regressions of each of the variables against the others, and estimate the value of d in the regression errors. Results indicates that there is very little evidence of cointegration between the cryptocurrencies and the stock markets indices, which is consistent with Kurka (2017), Corbet et al. (2018), Liu and Tsyvniski (2018) and others.

[Insert Tables 6 and 7 about here]

If we start with the log-differences, we observe that under no autocorrelation there is very little evidence of mean reversion, taking place only in case of the differences between Tether and the six stock market indices: Bond (0.76), Dollar (0.82), Gold (0.92), GSCI (0.93), S&P (0.89), VIX (0.91). If the errors are autocorrelated, estimates of d significantly below 1 are observed in the differences between Bitcoin and VIX (0.90) and in the differences of Tether with Bond (0.76), Dollar (0.82).

For the case of the regression models, with the results reported across Table 7, we observe some more cases of mean reversion, though once more the estimated values of d are relatively close to 1. If there is no autocorrelation, we observe mean reversion in the regressions of Bitcoin against S&P (0.93) and VIX (0.90); also with Ethereum against VIX (0.91); Litecoin against VIX (0.92) and in all cases with Tether against the six stock indices. With autocorrelation, mean reversion occurs in the same cases as before along with Ethereum against S&P (0.91), Litecoin against S&P (0.92) and Ripple against VIX (0.92). The above results connotes that cryptocurrencies and the selected financial and economic assets are disconnected. This suggests that for the period under study, financial market conditions influences cryptocurrencies less than structural conditions related to the design, price formation, operation and clearing of cryptocurrencies.

As a robustness method, and following the works by Mensi et al. (2018), Omane-Adjepong et al. (2019), Bouri et al. (2019) and others, the possibility of structural breaks is also taken into account, noting that the high levels of persistence obtained in the data could be a consequence of breaks which have not been taken into account (Diebold and Inoue, 2001; Granger and Hyung, 2004; etc.). Here, we focus on the six cryptocurrencies and examine the

possibility of a single break in the data by using both Bai and Perron's (003) and Gil-Alana's (2008) methods, the latter being an extension of the former for the fractional case.

[Insert Tables 8 and 9 about here]

The results were identical in the two cases and the break date took place in all cases in 2017 at the time of the financial crisis, the specific dates ranging from 13 March 2017 (Ethereum) to 22 May 2017 (Tether). The results, however, were very similar to those presented above, finding evidence of unit roots in practically all cases, and the only evidence in favour of mean reversion is found in the cases of Stellar (during the first subsample) and Tether (especially during the second subsample). Based on these break dates, we reconduct the analysis among the cryptocurrencies and between the cryptocurrencies and the stock prices and the results were very similar to those obtained under no breaks, finding evidence of no cointegration in the majority of the cases.

6.   Summary and Concluding comments

In this paper, we have examined the stochastic properties of six major cryptocurrencies and the bilateral linkages between six selected popular cryptocurrencies and six stock market indices, using daily prices. For the purposes of the study, we used a long memory approach based on fractionally integrated and cointegrated models. We adopted this approach to investigate the dependence between the selected markets since it allows for much richer dynamics than the classical models employed in recent studies on cryptocurrencies that focus exclusively on integer degrees of differentiation, and are thus based on the $I(0)/I(I)$ dichotomy.

The results from the univariate analysis indicate evidence of unit roots in most of the cryptocurrencies; Bitcoin, Ethereum, Litecoin and Stellar; $d > 1$ is obtained for Ripple, and $d < 1$ (mean reversion) in the case of Tether. Thus, only for this cryptocurrency will shocks have

a transitory nature. For the stock market, I(1) behaviour is found in all cases except Standard and Poor (S&P 500) and VIX, where the estimated value of d is found to be significantly below 1. Nevertheless, the values are very high in all cases, supporting the evidence of high degrees of persistence. The fact that orders of integration close to 1 are found in the majority of the cases does not invalidate our results noting that they have been obtained under fractional alternatives rather than with the classical AR ones as is the case in all standard unit root methods. From the bivariate analysis, we document evidence of no cointegration between the six cryptocurrencies and very little evidence is found for cointegration between the cryptocurrencies and the selected stock markets indices. We document a very low level of connectedness between the six popular cryptocurrencies. We conclude that the cryptocurrency market is proving to be a more relevant phenomenon for financial markets than previously believed, due to the diversification option it offers investors because of the low level of connectedness with the traditional asset class.

The findings of this paper may have implications to investors, market participants and regulators. First, the low level of bilateral linkages between cryptocurrency market and stock indices found in this study may have implications on investor's choice of asset class to invest in, due to price independence. From a portfolio perspective, since price movements in the traditional asset class have no direct influence in the cryptocurrency market, investors or market participants can take capital and somehow invest in cryptocurrencies due to its inevitability benefits. The investability of cryptocurrencies and their accessibility around the world might drive more liquidity in the cryptocurrency markets than assets situated within boarders. Based on Bitcoin exchange trading volume averaging $1 billion a day through the first quarter of 2016, we conclude that, in the coming years, liquidity in the cryptocurrency market will be compared more with traditional assets class since investors and market

participants may be compelled to hold a cryptocurrency than an equity in a listed traded company. Second, focusing on the risk-reward profile shown in Table 1, what we see is that the traditional asset class recorded high level of risk and this implies that even though these markets may offer high returns to investors, due to their volatile nature, investors may be getting fewer returns for the risk they take on. Regarding the cryptocurrencies, they can be interpreted as independent financial instruments that pose little to no systematic risk, which may add to their attractiveness for investors. Third, concerning the connectedness within the cryptocurrency market, our findings of no cointegration within the cryptocurrencies provide insights for regulators and potential international investors. Owing to findings of this paper on the disparity among cryptocurrencies and disconnections between cryptocurrency and the traditional finance and economic asset class, what investors can do differently to cement the diversification benefits associated with their investments in cryptocurrencies is to call for policy makers and regulators to enact measures that will deepen the dispersed structural relations within the cryptocurrency market and with the rest of the traditional finance and economic asset class to ensure investors benefits with the diversification returns that comes with the disparity between cryptocurrency and stock market indices. As the literature grows, there are different valuation techniques to model and analysis the bilateral linkages between cryptocurrencies and traditional asset classes. Recently the use of copula to analyse financial markets data have become very popular. Hence, in future, we recommend the application of copula to uncover the connections between the studied asset classes in this study and provide grounds for further research since research on cryptocurrencies is at the experimental stage and requires more rigorous econometric techniques to establish stylized facts in the market.

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Table 1: Descriptive statistics

	Max.	Min.	Mean	Std. Dev.
Cryptocurrency Markets				
BITCOIN	3490,0955	4002,46481	19114,2	210,49
ETHEREUM	47,6523608	66,510549	358,34	2,63
LITECOIN	0,24499567	0,40626048	3,2	0,00409
RIPPLE	0,08696606	0,14483281	0,896227	0,001444
STELLAR	0,99970524	0,0105739	1,08	0,913595
TETHER	214,180368	282,52745	1299,74	0,434829
Stock Market Indices				
BOND	2359,26414	297,162205	2930,75	1829,08
DOLLAR	2397,70915	234,867302	2956,024	1860,66
GOLD	14,5994915	4,55763708	40,74	9,14
GSCI	113,812594	2,2477448	118,768	109,0196
S&P	664,321065	2,88546641	736,56	566,41
VIX	121,982824	38,5801712	129,0778	115,2109

Figure 1: Descriptive statistics of the Cryptocurrency and Stock Market Indices.

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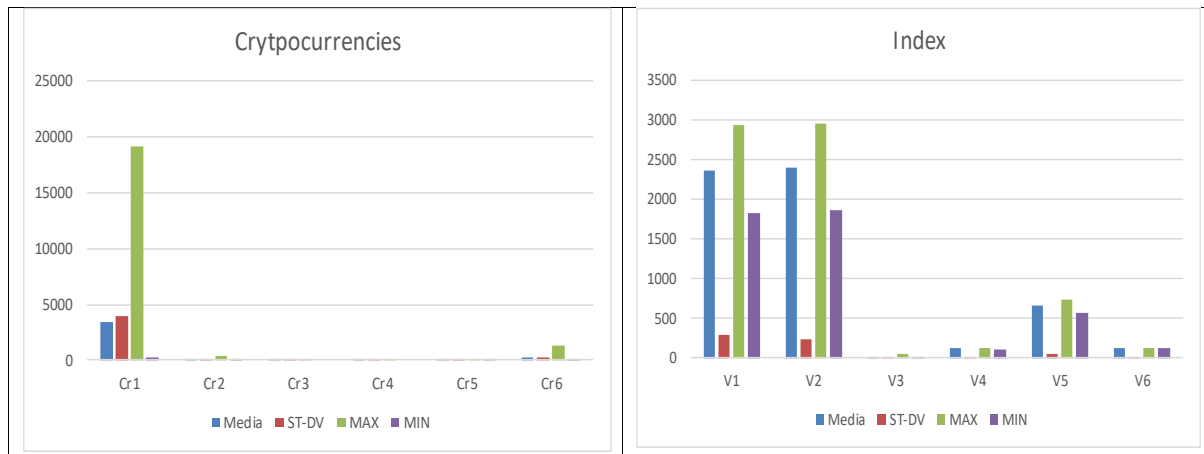
Table 2: Estimates of d based on uncorrelated (white noise) errors

i) Cryptocurrencies

	No terms		An intercept		A linear time trend	
BITCOIN	0.98	(0.94, 1.04)	1.03	(0.98, 1.08)	**1.03**	**(0.98, 1.08)**
ETHEREUM	0.94	(0.90, 0.97)	**1.01**	**(0.97, 1.06)**	1.01	(0.97, 1.06)
LITECOIN	1.02	(0.98, 1.08)	**1.06**	**(1.02, 1.11)**[+]	1.06	(1.02, 1.11)
RIPPLE	1.03	(0.99, 1.08)	**1.14**	**(1.10, 1.20)**[+]	1.15	(1.10, 1.20)
STELLAR	1.01	(0.97, 1.06)	**1.05**	**(1.01, 1.10)**[+]	1.05	(1.01, 1.10)
TETHER	0.71	(0.66, 0.78)	**0.71**	**(0.66, 0.78)**[*]	0.71	(0.66, 0.78)

ii) Stock market Indices

	No terms		An intercept		A linear time trend	
BOND	0.99	(0.95, 1.05)	**0.97**	**(0.93, 1.01)**	0.97	(0.93, 1.01)
DOLLAR	1.00	(0.95, 1.05)	**1.01**	**(0.96, 1.06)**	1.01	(0.96, 1.06)
GOLD	1.00	(0.95, 1.05)	**0.99**	**(0.95, 1.04)**	0.99	(0.95, 1.04)
GSCI	1.00	(0.95, 1.05)	**0.98**	**(0.94, 1.03)**	0.98	(0.94, 1.03)
S&P	0.99	(0.95, 1.05)	0.95	(0.89, 1.01)	**0.95**	**(0.90, 1.01)**
VIX	0.99	(0.94, 1.04)	**0.91**	**(0.85, 0.98)**[*]	0.91	(0.85, 0.98)

In bold the significant cases according to the deterministic terms. +: evidence of d > 1. *: evidence of mean reversion, i.e., d< 1.

Table 3: Estimates of d based on autocorrelated (Bloomfield) errors

i)   Cryptocurrencies

	No terms	An intercept	A linear time
BITCOIN	0.98 (0.91, 1.08)	1.04 (0.96, 1.12)	**1.04 (0.96, 1.11)**
ETHEREUM	1.05 (0.99, 1.12)	**1.01 (0.96, 1.07)**	1.01 (0.96, 1.07)
LITECOIN	1.00 (0.93, 1.09)	**1.02 (0.96, 1.10)**	1.02 (0.96, 1.10)
RIPPLE	1.05 (0.98, 1.14)	**1.15 (1.08, 1.26)[+]**	1.16 (1.08, 1.26)
STELLAR	1.02 (0.96, 1.10)	**1.04 (0.98, 1.11)**	1.04 (0.98, 1.11)
TETHER	0.67 (0.57, 0.81)	**0.67 (0.57, 0.81)[*]**	0.67 (0.57, 0.81)

ii)   Stock market indices

	No terms	An intercept	A linear time
BOND	0.98 (0.92, 1.07)	**1.05 (0.98, 1.13)**	1.05 (0.98, 1.13)
DOLLAR	0.99 (0.92, 1.08)	**0.98 (0.92, 1.06)**	0.98 (0.92, 1.06)
GOLD	0.99 (0.92, 1.08)	**1.04 (0.96, 1.13)**	1.04 (0.96, 1.13)
GSCI	0.99 (0.92, 1.08)	**1.02 (0.93, 1.10)**	1.02 (0.93, 1.10)
S&P	0.98 (0.92, 1.08)	0.88 (0.81, 0.97)	**0.86 (0.78, 0.97)[*]**
VIX	1.01 (0.93, 1.09)	**0.78 (0.67, 0.88)[*]**	0.78 (0.67, 0.88)

In bold the significant cases according to the deterministic terms. +: evidence of d > 1. *: evidence of mean reversion, i.e., d< 1.

Table 4: Estimates of d based on the differences between log-cryptocurrencies

i)   No autocorrelation

	BITCOIN	ETHEREUM	LITECOIN	RIPPLE	STELLAR	TETHER
BITCOIN	---	1.01 (0.97, 1.07)	1.04 (0.99, 1.10)	1.15 (1.10, 1.21)	1.02 (0.98, 1.07)	1.02 (0.97, 1.06)
ETHEREUM	---	---	1.01 (0.96, 1.07)	1.03 (0.98, 1.10)	0.99 (0.93, 1.05)	1.01 (0.97, 1.06)
LITECOIN	---	---	---	1.02 (0.96, 1.07)	1.00 (0.95, 1.06)	1.05 (1.01, 1.11)
RIPPLE	---	---	---	---	1.02 (0.97, 1.09)	1.14 (1.10, 1.18)
STELLAR	---	---	---	---	---	1.05 (1.01, 1.10)

ii)   With autocorrelation

	BITCOIN	ETHEREUM	LITECOIN	RIPPLE	STELLAR	TETHER
BITCOIN	---	0.97 (0.93, 1.04)	0.94 (0.88, 1.02)	1.08 (1.02, 1.14)	0.98 (0.93, 1.06)	1.02 (0.96, 1.1)
ETHEREUM	---	---	0.94 (0.88, 1.01)	0.93 (0.87, 1.01)	0.94 (0.89, 1.01)	1.01 (0.96, 1.07)
LITECOIN	---	---	---	0.92 (0.85, 1.01)	0.92 (0.84, 0.99)	1.03 (0.97, 1.11)
RIPPLE	---	---	---	---	0.86[*] (0.80, 0.94)	1.15 (1.08, 1.24)
STELLAR	---	---	---	---	---	1.03 (0.98, 1.11)

[*]: Evidence of mean reversion at the 5% level.

Table 5: Estimates of d based on the regression errors of log-cryptocurrencies market prices

i)   No autocorrelation

	BITCOIN	ETHEREUM	LITECOIN	RIPPLE	STELLAR	TETHER
BITCOIN	---	1.03 (0.97, 1.08)	1.03 (0.98, 1.08)	1.11 (1.06, 1.17)	1.00 (0.96, 1.06)	0.80[*] (0.76, 0.85)
ETHEREUM	---	---	1.02 (0.97, 1.10)	1.04 (0.98, 1.12)	0.99 (0.95, 1.05)	0.89[*] (0.86, 0.93)
LITECOIN	---	---	---	0.97 (0.93, 1.04)	1.00 (0.95, 1.06)	0.89[*] (0.83, 0.93)
RIPPLE	---	---	---	---	1.03 (0.97, 1.10)	0.97 (0.93, 1.02)
STELLAR	---	---	---	---	---	0.87[*] (0.81, 0.92)

ii)   With autocorrelation

	BITCOIN	ETHEREUM	LITECOIN	RIPPLE	STELLAR	TETHER
BITCOIN	---	0.96 (0.91 1.03)	0.93 (0.86, 1.01)	1.03 (0.96, 1.11)	0.94 (0.87, 1.02)	0.82[*] (0.77, 0.89)
ETHEREUM	---	---	0.94 (0.88, 1.01)	0.94 (0.85, 1.01)	0.94 (0.89, 1.01)	0.96 (0.90, 1.02)
LITECOIN	---	---	---	0.85[*] (0.77, 0.94)	0.88[*] (0.82, 0.97)	0.95 (0.87, 1.01)
RIPPLE	---	---	---	---	0.86[*] (0.80, 0.95)	0.99 (0.92, 1.05)
STELLAR	---	---	---	---	---	0.89[*] (0.81, 0.97)

*: Evidence of mean reversion at the 5% level.

Table 6: Estimates of d based on the differences between log-cryptocurrencies and log-stock market prices

i)   No autocorrelation

	BOND	DOLLAR	GOLD	GSCI	S&P	VIX
BITCOIN	1.02	1.02	1.03	1.03	1.01	0.98
	(0.98, 1.07)	(0.98, 1.07)	(0.99, 1.08)	(0.98, 1.08)	(0.97, 1.06)	(0.93, 1.04)
ETHEREUM	1.01	1.01	1.00	1.01	1.01	1.00
	(0.97, 1.06)	(0.97, 1.06)	(0.96, 1.05)	(0.97, 1.06)	(0.96, 1.06)	(0.95, 1.06)
LITECOIN	1.06	1.06	1.06	1.06	1.05	1.03
	(1.01, 1.11)	(1.02, 1.11)	(1.02, 1.12)	(1.01, 1.11)	(1.01, 1.11)	(0.98, 1.09)
RIPPLE	1.14	1.15	1.14	1.14	1.14	1.07
	(1.10, 1.20)	(1.10, 1.20)	(1.10, 1.19)	(1.10, 1.19)	(1.10, 1.20)	(1.02, 1.12)
STELLAR	1.05	1.05	1.05	1.05	1.05	1.02
	(1.01, 1.10)	(1.01, 1.10)	(1.01, 1.10)	(1.01, 1.10)	(1.00, 1.10)	(0.97, 1.07)
TETHER	0.76^*	0.82^*	0.92^*	0.93^*	0.89^*	0.91^*
	(0.72, 0.81)	(0.77, 0.87)	(0.88, 0.97)	(0.89, 0.98)	(0.83, 0.94)	(0.85, 0.98)

ii)   With autocorrelation

	BOND	DOLLAR	GOLD	GSCI	S&P	VIX
BITCOIN	1.03	1.03	1.05	1.02	1.02	0.90^*
	(0.97, 1.12)	(0.97, 1.11)	(0.97, 1.12)	(0.96, 1.10)	(0.96, 1.10)	(0.83, 0.99)
ETHEREUM	1.01	1.02	1.01	1.01	1.01	0.97
	(0.96, 1.07)	(0.97, 1.08)	(0.96, 1.07)	(0.96, 1.07)	(0.96, 1.06)	(0.92, 1.04)
LITECOIN	1.03	1.03	1.03	1.03	1.02	0.96
	(0.96, 1.09)	(0.98, 1.11)	(0.96, 1.11)	(0.96, 1.10)	(0.96, 1.09)	(0.90, 1.06)
RIPPLE	1.17	1.16	1.16	1.15	1.17	1.04
	(1.10, 1.26)	(1.08, 1.26)	(1.09, 1.25)	(1.08, 1.25)	(1.10, 1.25)	(0.96, 1.13)
STELLAR	1.04	1.04	1.05	1.03	1.03	0.98
	(0.98, 1.11)	(0.98, 1.11)	(0.98, 1.13)	(0.96, 1.11)	(0.97, 1.11)	(0.92, 1.07)
TETHER	0.79^*	0.85^*	0.98	0.98	0.86^*	0.78^*
	(0.71, 0.89)	(0.77, 0.95)	(0.90, 1.09)	(0.87, 1.05)	(0.77, 0.95)	(0.67, 0.89)

*: Evidence of mean reversion at the 5% level.

Table 7: Estimates of d based on the regression errors of log-cryptocurrencies on log-stock market prices

i)   No autocorrelation

	BOND	DOLLAR	GOLD	GSCI	S&P	VIX
BITCOIN	1.03	1.04	1.02	0.99	0.93*	0.90*
	(0.99, 1.08)	(0.99, 1.10)	(0.97, 1.07)	(0.95, 1.05)	(0.88, 0.98)	(0.85, 0.96)
ETHEREUM	1.02	0.96	0.95	0.99	0.95	0.91*
	(0.97, 1.06)	(0.91, 1.02)	(0.91, 1.01)	(0.95, 1.04)	(0.89, 1.00)	(0.85, 0.97)
LITECOIN	1.06	1.04	1.02	1.00	0.96	0.92*
	(1.01, 1.10)	(0.98, 1.10)	(0.97, 1.08)	(0.96, 1.06)	(0.91, 1.02)	(0.87, 0.97)
RIPPLE	1.10	1.06	1.04	1.04	1.03	0.97
	(1.06, 1.15)	(1.01, 1.11)	(1.00, 1.09)	(0.99, 1.09)	(0.98, 1.09)	(0.92, 1.03)
STELLAR	1.03	1.02	1.02	0.99	0.98	0.97
	(0.98, 1.08)	(0.97, 1.07)	(0.98, 1.07)	(0.95, 1.05)	(0.93, 1.03)	(0.93, 1.03)
TETHER	0.71*	0.71*	0.71*	0.71*	0.71*	0.71*
	(0.66, 0.78)	(0.66, 0.78)	(0.66, 0.78)	(0.66, 0.77)	(0.66, 0.78)	(0.66, 0.77)

ii)   With autocorrelation

	BOND	DOLLAR	GOLD	GSCI	S&P	VIX
BITCOIN	1.06	0.97	1.06	1.00	0.87*	0.79*
	(1.00, 1.13)	(0.89, 1.07)	(0.99, 1.17)	(0.94, 1.09)	(0.79, 0.94)	(0.69, 0.88)
ETHEREUM	1.03	0.92	1.00	1.02	0.91*	0.81*
	(0.98, 1.08)	(0.87, 1.01)	(0.92, 1.09)	(0.96, 1.08)	(0.85, 0.98)	(0.70, 0.89)
LITECOIN	1.05	0.94	1.05	1.01	0.92*	0.84*
	(1.00, 1.12)	(0.83, 1.02)	(0.97, 1.13)	(0.95, 1.10)	(0.85, 0.99)	(0.79, 0.92)
RIPPLE	1.13	1.05	1.08	1.05	1.00	0.92*
	(1.06, 1.21)	(0.97, 1.14)	(1.01, 1.18)	(0.98, 1.12)	(0.93, 1.08)	(0.82, 0.99)
STELLAR	1.04	0.97	1.08	1.00	0.91*	0.93
	(0.97, 1.11)	(0.86, 1.04)	(1.01, 1.16)	(0.93, 1.10)	(0.84, 0.99)	(0.87, 1.01)
TETHER	0.68*	0.67*	0.67*	0.68*	0.67*	0.67*
	(0.56, 0.80)	(0.57, 0.80)	(0.57, 0.79)	(0.57, 0.80)	(0.57, 0.80)	(0.57, 0.80)

*: Evidence of mean reversion at the 5% level.

Table 8: Estimates of d under the presence of a single break. White noise errors

	Break date	1st sub-sample	2nd sub-sample
BITCOIN	01 – 05 – 2017	0.96 (0.89, 1.04)	1.05 (0.98, 1.12)
ETHEREUM	13 – 03 – 2017	0.93 (0.88, 1.01)	1.07 (1.01, 1.15)
LITECOIN	03 – 04 – 2017	0.96 (0.89, 1.04)	1.08 (1.01, 1.17)
RIPPLE	31 – 03 – 2017	1.05 (0.97, 1.14)	1.12 (1.06, 1.19)
STELLAR	28 – 04 - 2017	0.83* (0.77, 0.91)	1.08 (1.02, 1.16)
TETHER	22 – 05 – 2017	1.09 (0.98, 1.22)	0.42* (0.35, 0.51)

*: Evidence of mean reversion at the 95% level.

Table 9: Estimates of d under the presence of a single break. Autocorrelated errors

	Break date	1st sub-sample	2nd sub-sample
BITCOIN	01 – 05 – 2017	0.90 (0.89, 1.04)	1.06 (0.96, 1.17)
ETHEREUM	13 – 03 – 2017	0.93 (0.86, 1.01)	1.04 (0.95, 1.14)
LITECOIN	03 – 04 – 2017	0.94 (0.76, 1.12)	0.98 (0.89, 1.10)
RIPPLE	31 – 03 – 2017	0.98 (0.86, 1.14)	1.21 (1.10, 1.35)
STELLAR	28 – 04 - 2017	0.78* (0.69, 0.91)	1.03 (0.94, 1.16)
TETHER	22 – 05 – 2017	0.63* (0.52, 0.77)	0.38* (0.26, 0.57)

*: Evidence of mean reversion at the 95% level.