Volatility Persistence in Cryptocurrency Markets Under Structural Breaks

Abstract:

This paper deals with the analysis of volatility persistence in 12 main cryptocurrencies (Bitcoin, Bitshare, Bytecoin, Dash, Ether, Litecoin, Monero, Nem, Ripple, Siacoin, Stellar and Tether) taking into account the possibility of structural breaks. Using fractional integration methods, the results indicate that both absolute and squared returns display long memory features, with orders of integration confirming the long memory hypothesis. However, after accounting for structural breaks, we find a reduction in the degree of persistence in the cryptocurrency market. The evidence of persistence in volatility imply that market participants who want to make gains across trading scales need to factor the persistence properties of cryptocurrencies in their valuation and forecasting models since that will help improve long-term volatility market forecasts and optimal hedging decisions.

JEL Classification: C22; C50; C60; G15; G11; G20
Keywords: Cryptocurrencies; volatility; long memory; fractional integration

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1. Introduction

Recent advances in empirical finance research on cryptocurrencies, leading to conclusions on them as a new class of financial assets (Bouri, Jalkh, Molnár, & Roubaud, 2017; Brandvold, Molnár, Vagstad, & Valstad, 2015; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Glaser, Haferkorn, Weber, & Zimmermann, 2014; Grinberg, 2012; Katsiampa, 2017; Nadarajah & Chu, 2017; Urquhart, 2016, 2017; Wu & Pandey, 2014; Giudici, Milne, & Vinogradov, 2020; Corbet, Lucey, Urquhart & Yarovaya, 2019; Aalborg, Molnar, & de Vries, 2019; Corbet, Larkin, Lucey, Meegan & Yarovaya, 2020; Platanakis, & Urquhart, 2019; Alexander & Dakos, 2020; Gil-Alana, Abakah, & Rojo, 2020), offer new opportunities for further comprehensive investigation on various aspects of cryptocurrencies yet to be explored. Since the inception of cryptocurrencies in 2009, research into various aspects of them has experienced increased growth suggesting the significant role of cryptocurrencies to the global financial system. Thus, for example, some papers have focused on the characteristics of cryptocurrencies following different forms of money and other well-known assets (Barber, Boyen, Shi, & Uzun, 2012; Wu & Pandey, 2014; etc.). Other papers have concentrated on price formation of cryptocurrencies (Buchholz, Delaney, Warren, & Parker, 2012; Dyhrberg, 2016; van Wijk, 2013, among others) and interconnections between cryptocurrencies and traditional financial asset class (Corbet et al., 2018). In addition, Gil-Alana, Abakah, & Rojo (2020) recently provided new evidence on the linkages between cryptocurrencies and stock market indices by showing evidence of no cointegration between cryptocurrencies and stock market indices, which clearly leaves room for further research on cryptocurrencies since they emerged to be decoupled from mainstream finance and economic assets. Interestingly, in spite of the comprehensive emerging literature on cryptocurrencies, a key question that remains unanswered is whether they follow the random walk theory, thus whether the behaviour of cryptocurrencies is predictable (Fama, 1970).

In finance and economic literature, a large stream of research modelling financial time series provides strong evidence of persistence in asset returns (Abuzayed, Al-Fayoumi, & Molyneux, 2018; Baillie & Morana, 2009; Caporale, Gil-Alana, Plastun, & Makarenko, 2016; Charfeddine, 2016; Giraitis, Kokoszka, Leipus, & Teyssière, 2003; Greene & Fielitz, 1977). This implies that the market does not respond immediately to information arriving into the financial system, but reacts to it gradually over time. As a result, past price changes can be used to predict future price changes. In this context, shocks to the volatility process tend to have long-lasting effects, thus, providing negative evidence as well as a new perspective to the Efficient Market Hypothesis (EMH). Additionally, a strand of prior studies in economics and finance have focused on estimating time-varying volatility. Indeed, an extensive literature has established the presence of non-constant and time dependent volatility in high-frequency asset returns. The main representatives of this class of model are the autoregressive conditional heteroscedasticity (ARCH) model (Engle, 1982) and its extensions including the generalised ARCH (Bollerslev, 1986) and the fractionally integrated generalised autoregressive conditional heteroscedasticity (FIGARCH) (Baillie, 1996; Baillie, Bollerslev, & Mikkelsen, 1996). These models explicitly recognise the difference between conditional and unconditional (or long run) variance, where the former is allowed to change over time and the latter remains constant.

Clearly understanding volatility changes in cryptocurrencies is important because, changes in volatility can affect the risk exposure of investors. These changes may alter their respective investments in cryptocurrencies. Thus, understanding volatility dynamics is important for decisions regarding valuation, hedging and investments in physical capital tied to cryptocurrencies. Although volatility fluctuates over time, a key question is to determine how persistent these changes are in volatility in prices. This study tries to answer this question. If changes are very persistent, then they will have a major impact on prices of assets that are tied to the price of cryptocurrencies. On the other hand, if changes in volatility are short lived (or less persistent), they should have little or no impact on market variables. Poterba & Summers (1984) make this point with their asset-pricing model that explicitly shows that the amount of persistence in volatility directly affects the price of an asset. In the current study, we examine volatility persistence in the cryptocurrency market using 12 major CCs, these being Bitcoin, Bitshare, Bytecoin, Dash, Ether, Litecoin, Monero, Nem, Ripple, Siacoin, Stellar and Tether, from 28th April 2013 until 29th March 2018 using fractional integration methods. However, following authors such as Diebold & Inoue (2001) who showed evidence that long memory and structural breaks are closely interrelated, and Granger & Hyung (2004) who found that long memory may be partially instigated by the presence of neglected breaks in the series, we additionally investigate the effects of structural breaks on volatility persistence in the 12 cryptocurrencies. We examine the effects of structural breaks because failure to incorporate them may result in an overstatement of the degree of persistence of variance or in spurious estimation of long memory (Lamoureux & Lastrapes, 1990).

The remaining part of the paper is organized as follows: Section 2 presents a brief overview of the cryptocurrency market along with a summary of the relevant empirical literature on cryptocurrencies. Section 3 describes the methodology adopted in the paper. Section 4 presents the data and the empirical findings, while Section 5 documents the concluding remarks and recommendations for further research.

2. Literature review

Cryptocurrencies have attracted a lot of attention since Bitcoin was first proposed by Nakamoto (2008). Unlike other financial assets, cryptocurrencies are not associated with any higher authority, are infinitely divisible, and their values are based on the security of an algorithm which is able to trace all transaction. The use of cryptocurrencies has grown dramatically in the last decade, mainly due to the low transaction costs, peer-to-peer system, and governmental free design, leading to a surge in trading volume, volatility and price of cryptocurrencies (Corbert et al., 2018). Although Bitcoin is the first decentralised digital currency and remains the cryptocurrency market leader, the number of them is still increasing, reaching 2864 cryptocurrencies traded in April 2020 with a market capitalization of $201 billion (www.investing.com). Therefore, research in these markets has increased rapidly in order to gain an understanding of several aspects which are key factors for investors to gauge the risks related to an investment in cryptocurrencies, such as, the dynamics of coin creation, competition and destruction in the cryptocurrency industry (Feder et al., 2018), price volatility (Dyhrberg, 2016; Katsiampa, 2017; Sovbetov, 2018), price clustering (Urquhart, 2017), speculation (Cheah and Fry, 2015 ; Yermack, 2015; Blau, 2017), transaction costs (Kim, 2017), the market efficiency (Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017; Vidal-Tomás, Ibañez and Farinos, 2018), market returns and volatility (Omane-Adjepong et al., 2019), robustness (Charles and Darné, 2019), and persistence in the cryptocurrencies market (Caporale et al., 2018, Bouri, 2018).

In particular, market efficiency of cryptocurrencies is a controversial issue. A market is said to be efficient with respect to an information set if the price would be unaffected by revealing the information set to all market participants (Malkiel, 1992). Economists consider investigating the efficiency of the cryptocurrency market in the sense of the Efficient Market Hypothesis (EMH), the classical definition due to Eugene Fama (1970), sorting the efficiency of the market into three segments: strong efficiency, semi-strong efficiency, and weak efficiency. Some authors support that cryptocurrency market, in particular Bitcoin market, is almost efficient (Urquhart (2016), Nadarajah & Chu (2017), Bariviera (2017), Khuntia & Pattanayak (2018), Tiwari (2018), Dimitrova (2019)), or inefficient depending on the sample size (Urquhart (2016). In contrast, other authors did not find conclusive evidence that the cryptocurrency market is inefficient, such as Caporale (2019) after examining the day of the week effect in the cryptocurrency market.

On the other hand, some authors showed that their empirical results do not support the EMH for this market. Lo (2004) proposed an alternative to the static view of market efficiency, proposing that the efficiency evolves over time. This is denoted the Adaptive Market Hypothesis (AMH). Urquhart and Hudson (2013), Ito et al. (2014), Noda (2016), Ito et al. (2016), Urquhart and McGroarty (2016) and Yaya et al (2019) investigates the market efficiency with methods derived with the AMH. Furthermore, Chu et al. (2019) investigates the AMH for the two largest cryptocurrencies, and found evidence that supports the hypothesis of a time varying market efficiency. Two approaches to examine the AMH have been adopted in the literature. One is based on conventional statistical test under the split samples or the rolling-window method (Urquhart (2016), Nadarajah and Chu (2017), Khuntia and Pattanayak (2018), Kristoufek (2018), Chu et al. (2019), Dimitrova et al. (2019), and Vidal-Tomás et al. (2019). However, these methods have the underlying empirical problem of choosing an optimal window width for the test statistics. Unlike these methods, a Generalized Least Square (GLS)-based time-varying model is an approach to examining the AMH, and has the superior property that it does not depend on sample size. In this approach, the degree of market efficiency is measured together with its statistical inference. Noda (2020) investigated whether the cryptocurrency markets (Bitcoin and Ethereum) evolve over time, based on Lo's (2004) AMH. The empirical results showed that cryptocurrency market efficiency varies with time, the market efficiency of the BTC is higher than that of the Ethereum in most periods, and the market has been evolving with high market liquidity.

On the other hand, Cheah et al. (2018) model cross market Bitcoin prices as long-memory processes and study dynamic interdependence in a fractionally cointegrated VAR framework. They find long memory in both the individual markets and the system of markets depicting non-homogeneous informational inefficiency. Moreover, Bitcoin markets are found to be fractionally cointegrated, where uncertainty negatively impacts this type of cointegration relationship. Caporale et al. (2018) employs two different long-memory methods (R/S analysis and fractional integration) in the four main cryptocurrencies (Bitcoin, Litecoin, Ripple, Dash) and show that these markets exhibit persistence, and that its degree changes over time. Such predictability represents evidence of market inefficiency and that trend trading strategies may be used to generate abnormal profits in the cryptocurrency market. Most recently, Tran & Leivirk (2019) have construct a simple measure to quantify the level of market efficiency, called Adjusted Market Inefficiency Magnitude (AMIM). The AMIM increases as market efficiency decreases, and decreases as market efficiency increases. They apply this measure to investigate the level of market efficiency and analyze its variation over time showing that the inefficiency depends also on the period of time and the cryptocurrency (Tran & Leivirk (*in press*)). They found that before 2017, cryptocurrency markets are mostly inefficient, but they become more efficient over time in the period 2017–2019. Also, on average, Litecoin is the most efficient cryptocurrency, and Ripple being the least efficient cryptocurrency.

A summary of the literature review on market efficiency of cryptocurrency is presented in Table 1.

Table 1: Cryptocurrency Market Efficiency Research

Authors (Year)	Methodology	Data source	Frequency	N	Observation
Urquhart and Hudson (2013)	Several Linear and nonlinear test	Not provided	Daily	>1500	- The linear dependence of stock returns varies over time but nonlinear dependence is strong throughout. - The AMH provides a better description of the behaviour of stock returns than the EMH
Urquhart (2016)	Hurst Exponent	bitcoinavarage	Daily	>1200	- Bitcoin in an inefficient market but may be in the process of moving towards an efficient market.
Nadarajah & Chu (2017)	Ljung-Box and others	Not provided	Daily	>2000	A power transformation of Bitcoin returns can be weakly efficient.
Baur et al (2017)	Means Test	Kaggle.com	Minutely	3045857	- No persistent patterns in returns. - Persistent patterns in volume, e.g. lower trading volume on weekends
Álvarez-Ramirez et al. (2018)	Detrended Fluctuation Analysis (DFA)	coindesk.com	Daily (2013 – 2017)	1435	- Bitcoin market exhibits periods of efficiency alternating with periods where the price dynamics are driven by anti-persistence. - Asymmetries and inefficiency are replicated over different time scales.
Caporale et al. (2018)	R/S analysis and fractional integration	coinmarketcap	Daily	>1000	- Cryptocurrency market exhibits persistence (there is a positive correlation between its past and future values), and that its degree changes over time. - Evidence of market inefficiency
Cheah et al. (2018)	Two-step Exact Local Whittle (ELW) Estimator	bitcoincharts	Daily	1057	Bitcoin markets are moderate to highly inefficient
Khuntia & Pattanayak (2018)	Linear and nonlinear dependence checked using rolling-window approach	coindesk.com	Daily	2714	- Market efficiency evolves with time - Validates the adaptive market hypothesis (AMH) in bitcoin market
Tiwari (2018)	Centred Moving Average	coindesk.com	Daily	2525	Bitcoin market is informational efficient

Yonghonga (2018)	Hurst Exponent	bitcoinaverage	Daily (2010-1017)	2551	- long-term memory exists in the Bitcoin market - high degree of inefficiency ratio - the Bitcoin market does not become more efficient over time
Caporale (2019)	Average Analysis, Student's t-test, ANOVA, the Kruskal–Wallis test, and Regression Analysis	coinmarketcap.com	Daily	>1500	- The market exhibits persistence (there is a positive correlation between its past and future values), and that its degree changes over time. - Evidence of market inefficiency
Noda (2020)	GLS-based time-varying autoregressive (TV-AR)	coinmarketcap.com	Daily	2346 (Bitcoin) 1515(Ethereum)	- The degree of market efficiency varies with time. - Bitcoin’s market efficiency level is higher than that of Ethereum
Tran &Leirvik (*in press*)	Adjusted Market Inefficiency Magnitude (AMIM) Model	coinmarketcap.com	Daily	2132 (Bicoin) 607 (EOS) 1301(Ethereum) 2132 (Litecoin) 2034 (Ripple)	- The cryptocurrency-markets become more efficient over time in the period 2017–2019. - Litecoin is the most efficient cryptocurrency, and Ripple being the least efficient cryptocurrency.

In the context of long memory and volatility in the Bitcoin series, Bariviera et al. (2017) found that the price volatility, measured as the logarithmic difference between intraday high and low prices, exhibits long memory, what reflects a different underlying dynamic process generating prices and volatility. Similarly, Omane-Adjepong et al. (2019) evidenced high persistence in volatility, so that market forecasters are required to account for such persistence characteristics in their forecasting models. This clearly might improve long-term volatility market forecasts and optimal hedging decisions. Moreover, Charfeddine & Maouchi (2019) questioned the true nature (true versus spurious) of the Long Range Dependence (LRD) behavior observed in the returns and volatility series of four cryptocurrencies. Using a robust approach, they showed that the LRD behavior exhibited by the returns and volatility series of Bitcoin, Litecoin, and Ripple is a true behavior, and not a statistical artifact. As for Ethereum, the results show that the LRD is only supported for the volatility series. Their results confirm the inefficiency of all the considered markets, with the exception of Ethereum. Still on this strand of the literature that examines persistence in cryptocurrency market, Yaya et al (2018) examined other popular alternative coins, by means of fractional integration to analyse persistence and also, using fractional cointegration in a VAR set-up to investigate dependency of the paired variables. Having segregated the series into periods before crash and those after the crash as determined by Bitcoin pricing, they document some interesting results. Thus, higher persistence of the shocks is observed after the crash due to speculation in the mind of cryptocurrency traders, and more evidence of non-mean reversion, implying chances of further price falls in cryptocurrencies. Cointegration analysis between Bitcoin and alternative coins exists during both periods, with weak correlation observed mostly in the post-crash period. In another recent study, Yaya et al (2019) investigated both market efficiency and volatility persistence in twelve cryptocurrencies during pre-crash and post-crash periods. Using robust fractional integration methods in linear and non-linear set-ups, they found that markets of

Bitcoin and most altcoins considered in their samples are efficient, and highly volatile, particularly in the post-crash sample. The different volatility methods mentioned in the introduction section are summarized in Table 2, and a brief summary of the volatility in cryptocurrency literature review, to the best of our knowledge, is summarized in Table 3.

Table 2: Volatility methods

Method	**Authors (Year)**
Autoregressive conditional heteroscedasticity (ARCH) model	Engle (1982)
Generalised ARCH (GARCH)	Bollerslev (1986)
Fractionally integrated generalised autoregressive conditional heteroscedasticity (FIGARCH)	Baillie (1996); Baillie, Bollerslev, & Mikkelsen (1996).

Table 3: Cryptocurrency Volatility Research

Authors (Year)	Methodology	Data source	Frequency	N	Observation
Gronwald (2014)	GARCH	Mt. Gov.	Daily	>500	- Bitcoin prices are strongly characterised by extreme price movements
Dyhrberg (2016)	GARCH	Coindesk.com	Daily	1769	Most aspects of bitcoin are similar to gold as they react to similar variables in the GARCH model, possess similar hedging capabilities and react symmetrically to good and bad news.
Bariviera (2017)	Hurst Exponent by means of the Detrended Fluctuation Analysis	bitcoincharts	Daily (2011 - 2017)	1404	- Bitcoin presents large volatility, but it is reducing over time. - long range memory is not related to market liquidity - Until 2014 the time series had a persistent behavior (H > 0.5), whereas after such date, the Hurst exponent tended to move around 0.5.
Lahmiri et al. (2018)	GARCH	bicoinity	Daily	>1300	Long-range memory in Bitcoin market volatility, irrespectively of distributional inference
Omane-Adjepong et al. (2019)	ARFIMA-FIGARCH		Daily	>900	- Efficiency and volatility persistence are dependent on scale and data variations

Yaya et al. (2019)	Fractional integration methods in linear and nonlinear set up	coinmetrics.io	Daily	>1100	- Evidence of random walk in returns of most cryptocurrencies including Bitcoin.

3. Methodology

In the paper we use long range dependence or long memory methods and in particular we focus on fractional integration. The idea that is behind this technique is that the number of differences required in a time series to convert it in stationary I(0) may be any real value, and thus, it may potentially include fractional numbers.

In a classical paper by Nelson and Plosser (1982) and using ADF (Dickey and Fuller, 1979) tests, these authors found that fourteen US macro series were integrated of order 1, or I(1), implying that first differences were required to convert them stationary I(0). However, fifteen years later, Gil-Alana and Robinson (1997) examined an updated version of the same dataset, and using fractional integration methods, they found that all except one of the series were in fact I(d) with the value of d constrained between 0 and 1. Since then, this technique has been widely employed in the analysis of aggregated economic and financial data (see, e.g., Lima and Xiao, 2010; Gil-Alana and Moreno, 2012; Mensi et al., 2014; Ben Nasr et al., 2016; Abbritti et al., 2016; Gil-Alana and Mudida, 2018; Merhrdoust and Fallah, 2020; etc.)

The estimation of the differencing parameter d is conducted by means of using a simple version of the tests of Robinson (1994). These tests are very general, including not only the standard case of fractional integration, but also allowing for seasonal and cyclical differentiation. The functional form of the version of the tests used in this work can be found in Gil-Alana and Robinson (1997).

4. Data and Empirical Results

The data for over 1500 cryptocurrencies was downloaded from CoinMarketCap.com. We followed the conventional literature to select the coins used in the study (e.g., Kaiser, 2019). For the purposes of the study, we included coins that are representative of the cryptocurrency market. First we considered only coins whose market capitalisation was more than the average market value of the cryptocurrency market and had over 850 observations over the period (i.e. the coin should have been in the market for at least for more than 2 years) to be included in the study. Aside, we further ensured the coins formed part of the top 20 cryptocurrencies by market capitalization as of March 31st 2018. Descriptive statistics for the coins are given across Tables 4 to 7.

[Insert Tables 4 – 7]

From Table 4 Bitcoin seems to be a determinant of the cryptocurrencies market since prices of the other cryptocurrencies peak after the BitCoin price. The standard deviation seems to be approximately twice the mean for most of them except Bytecoin and Tether. The mean returns are moderate for all them at 0.002 across the series. The series have more fat tails (the lowest kurtosis is Siacoin with 7.5 and Tether records the highest at 553). This shows that cryptocurrencies possess an element of heightened unexpected returns (positive/negative) when risk is involved. The best return given by Bitcoin in the market was 30%; Bytecoin however delivered the highest return at 160% (Table 2). The squared returns (Table 3) project a similar image

We start by estimating d for each cryptocurrency in the model given by

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

where y_t is the series of interest (absolute and squared returns), α is an intercept, and x_t is an I(d) process where d can be any real value. Thus, u_t is I(0) and it will be specified as a white noise process (in Table 7) and allowing for autocorrelation (in Table 8). In the latter case we use a non-parametric structure developed by Bloomfield (1973) that approximates ARMA models with very few parameters.

Starting with the case of no autocorrelation we observe that all the estimated values of d are positive and in the interval (0, 0.5) displaying thus a long memory pattern. For the absolute returns, the values of d range between 0.16 (Siacoin) and 0.32 (Ether), and for the squared returns the values are between 0.11 (Dash) and 0.37 (Ether).

[Insert Tables 7 and 8]

If autocorrelation is permitted, generally the same conclusion holds in favor of long memory, though in some cases, we cannot reject the null hypothesis of I(0) or short memory behavior. Thus, for the absolute returns, the estimates of d are all strictly positive except for Ether (d = -0.01), and for the squared returns short memory is found in the cases of Monero, Nem and Stellar, while for Ether the results support the hypothesis of anti-persistence (d < 0). In all the remaining cases, the values of d are once more strictly positive and supporting the long memory hypothesis.

Next we want to investigate if breaks are present in the data and if this is the case, if they have had any influence in the degree of persistence of the data. For this purpose, we use first the approach developed in Bai and Perron (2003) for detecting multiple breaks in time series, and then we also consider the methodology proposed in Gil-Alana (2008), which is basically an extension of Bai and Perron (2008) to the fractional case. The results were practically identical in the two cases the only difference being in the case of Bitshare with the squared returns where two breaks were detected with Bai and Perron (2003) and three with Gil-Alana's (2008) methodology. The number of breaks and the breaks dates for each case are presented in Table 9.

[Insert Table 9]

We observe in Table 9 that for the absolute returns, three breaks take place in the cases of Litecoin, Monero, Nem, Siacoin and Stellar; two breaks for Bitcoin, Bitshare, Bytecoin and Ripple; a single break occurs in case of Dash and Ether and no breaks are detected for Tether. For the squared returns, three break dates occur for Bitcoin, Monero and Stellar; two breaks for Bitshare, Bytecoin; on break in case of Dash, Ether, Litecoin and Nem, and no breaks in the remaining three series (Ripple, Siacoin and Tether). With respect to the break dates. Most of them occur at similar dates, namely, the end of 2014 and/or the beginning of 2015; middle or end of 2015 and middle of 2017.

Once the break dates have been determined, we examine the degree of persistence associated with each subsample, and here, based on the shorter sample sizes, we also consider the possibility of a linear trend. Thus, the model examined is now:

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

where α and β are the coefficients associated to the intercept and the linear time trend. We estimate d under three set-ups: i) when α and β are assumed to be 0 a priori, that is, imposing no deterministic terms in the model, ii) with β = 0 a priori, that is, allowing for an intercept, and iii) allowing for a linear time trend by estimating α and β freely from the data. The results in terms of the estimation of d for each of these three cases and each subsample are reported across Table 10 (absolute returns) and Table 11 (squared returns), and we have marked in bold in the tables the most adequate specification for each case according to the significance of the estimated coefficients of these deterministic terms.

Starting with the absolute returns, we observe in Table 10 that the time trend is required in a number of cases such as in the first subsamples for Dash and Litecoin, but also in the last subsamples for Bytecoin, Litecoin and Siacoin. Nevertheless, in the majority of the cases the intercept is sufficient to describe the deterministic part. Table 11 summarizes the estimates of d for each cryptocurrency and each subsample, and we observe that for the majority of the cases, there is a reduction in the degree of persistence as we move from one sample to another. This is noted in the cases of Bitcoin, Bytecoin, Dash, Ether, Ltecoin, Siacoin and Stellar; for Bitshare, Monero, Nem and Stellar, however, the degree of integration seems to be relatively stable, and only for Ripple do we observe an increase in the estimated value of d across the subsamples.

[Insert Tables 10 – 13]

Table 12 refers to the squared returns. Once more the time trend is required in a number of cases, at the beginning of the sample in the cases of Bitshare, Dash and Litecoin, and during the last subsamples for Bytecoin and Litecoin, and focussing on the estimated values of d, in Table 13, we notice a similar reduction as in the previous case in the degree of persistence in the cases of Bitcoin, Bytecoin, Etter and Nem. However, in other cases such as Dash and Litecoin, we observe a slight increase in the value of d.

5. Concluding comments

This paper uses fractional integration long-memory techniques and an extended form of Bai and Perron (2003) using fractional integration techniques to investigate the degree of persistence under structural breaks in twelve main cryptocurrencies (Bitcoin, Bitshare, Bytecoin, Dash, Ether, Litecoin, Monero, Nem, Ripple, Siacoin, Stellar and Tether). Succinctly, results obtained under the assumption of no autocorrelation indicate that all the estimated values of d are positive. For the case of autocorrelation, we obtain similar findings suggesting that for all cases the values of d are strictly positive, which clearly supports the long memory hypothesis. This further indicates that the cryptocurrency market is still inefficient implying that abnormal returns could be obtained by investors in the cryptocurrency market through technical trading strategies. After documenting the presence of persistence in the cryptocurrency market, we run further tests to investigate whether structural breaks in the data could have any effect on the extent of persistence, and provide some evidence indicating that the degree of persistence is somehow reduced when we take into account structural breaks. We recommend that further research must be carried out to consider the impact of non-linearity effects on the degree of persistence in the cryptocurrency market as expounded by prior studies that examined market efficiency in mainstream financial markets (see for instance, Masten, Coricelli and Masten, 2008; Clements, Franses and Swanson, 2004; Abakah, Alagidede, Mensah and Ohene-Asare, 2018). In fact, Robinson's (1994) tests used in this work impose linearity in the specification of the regression model, and though there exist some extensions of this method allowing for nonlinearities (Cuestas and Gil-Alana, 2016; Yaya et al., 2019a,b) they will be examined in future papers along with other approaches including for example the analysis of cyclical patterns in the context of fractional integration.

The findings documented in this study offer several implications for market participants, investors and policy markets as they seek to make gains, understand the long memory properties and regulate the cryptocurrency market respectively. First, our empirical findings surmise the significance of accounting for the long memory property in an empirical analysis that considers the economics and financial benefits of cryptocurrencies as optimal hedging estimation, risk portfolio management, and potential option valuation. Secondly, the evidence of high persistence in volatility suggests that, market analyst, participants and analysts who aim to make gains in the cryptocurrency market across trading scales need to factor the persistence properties of cryptocurrencies in their valuation and forecasting models since that will help improve long-term volatility market forecasts and optimal hedging decisions. Lastly, the findings also offer market participants and analysts an interesting opportunity to get benefits from the inefficiencies in the cryptocurrency market. As such, they can potentially improve the risk-adjusted performance of their portfolios by using long memory-based frameworks.

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Table 4: Descriptive statistics on the cryptocurrencies

Series	Average market Price	Highest Price		Lowest Price		St. dev	Skew.	Kurt.
		Amount	Date(s)	Amount	Date(s)			
Bitcoin	1,649.011	19,497.400	2017-12-16	68.430	2013-07-05	3,142.134	3.092	12.590
Ethereum	168.441	1,396.420	2018-01-13	0.435	2015-10-20	280.518	2.028	6.571

Ripple	0.114	3.380	2018-01-07	0.003	2014-07-06	0.334	5.121	35.356
Litecoin	23.799	1.160	2017-12-18	358.340	2015-01-14	52.081	3.489	15.474
Stellar	0.039	0.896	2018-01-03	0.001	2014-11-18	0.114	3.836	18.125
Monero	39.515	469.200	2017-12-20	0.224	2015-01-14	87.622	2.779	10.045
Dash	103.756	1,550.850	2017-12-20	0.315	2014-02-15	230.785	2.994	12.399
tether	1.000	1.210	2015-02-26	0.606	2015-03-03	0.022	-9.513	215.963
NEM	0.118	1.840	2018-01-07	0.000	2015-08-25	0.256	3.478	17.097
Siacoin	0.039	0.094	2018-01-06	0.000	2015-12-28	0.011	3.802	21.584
BitShares	0.056	0.892	2018-01-03	0.003	2016-01-08	0.120	3.544	17.633
Bytecoin	0.056	0.017	2018-01-06	0.000	2015-01-03	0.002	3.934	23.644

Table 5: Descriptive for the Absolute returns

Series	Start	Size	Mean	St. Dev.	Skew.	Kurt.	Min.	Max.
Bitcoin	28-Apr-13	1796	0.002	0.045	-0.193	10.872	-0.266	0.357
BitShare	21-Jul-14	1347	0.002	0.081	1.037	10.106	-0.392	0.520
Ripple	4-Aug-13	1698	0.003	0.080	2.025	29.884	-0.616	1.027
Bytecoin	17-Jun-14	1381	0.003	0.116	2.772	34.753	-0.629	1.598
Dash	14-Feb-14	1504	0.005	0.085	3.036	43.402	-0.468	1.271
Ethereum	7-Aug-15	965	0.005	0.084	-3.544	65.362	-1.302	0.412
Litecoin	28-Apr-13	1796	0.002	0.070	1.798	28.080	-0.514	0.829
Monero	21-May-14	1407	0.003	0.078	0.663	8.644	-0.378	0.585
NEM	1-Apr-15	1093	0.006	0.094	1.868	18.151	-0.361	0.996
Siacoin	26-Aug-15	945	0.006	0.114	0.943	7.519	-0.486	0.596
Stellar	5-Aug-14	1332	0.003	0.085	1.989	17.378	-0.366	0.723
Tether	25-Feb-15	1123	0.000	0.026	-10.147	553.236	-0.691	0.500

Table 6: Descriptive for the Squared Returns (daily)						
Series	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
Bitcoin	0.002	0.006	8.807	121.281	0.000	0.128
Bitshare	0.007	0.020	7.106	66.932	0.000	0.270
Ripple	0.001	0.035	19.154	510.493	0.000	1.055
Bytecoin	0.013	0.078	25.747	803.705	0.000	2.553
Dash	0.007	0.048	27.018	871.275	0.000	1.614
Ether	0.007	0.056	28.437	854.668	0.000	1.695
Litecoin	0.005	0.025	16.490	365.954	0.000	0.687
Monero	0.006	0.017	9.437	139.042	0.000	0.342
Nem	0.009	0.037	18.247	446.673	0.000	0.991
Siacoin	0.013	0.034	5.486	40.898	0.000	0.355
Stellar	0.007	0.030	11.340	161.430	0.000	0.523
Tether	0.001	0.016	26.563	740.428	0.000	0.477

Table 7: Estimates of d in a model under no autocorrelation

ABSOLUTE returns		**SQUARED returns**	
Series	**d (95% band)**	**Series**	**d (95% band)**
Bitcoin	0.21 (0.18, 0.25)	Bitcoin	0.15 (0.12, 0.19)
Bitshare	0.24 (0.21, 0.29)	Bitshare	0.17 (0.14, 0.23)
Bytecoin	0.20 (0.16, 0.25)	Bytecoin	0.12 (0.08, 0.17)
Dash	0.23 (0.20, 0.27)	Dash	0.11 (0.07, 0.15)
Ether	0.32 (0.24, 0.42)	Ether	0.37 (0.27, 0.52)
Litecoin	0.24 (0.20, 0.28)	Litecoin	0.16 (0.13, 0.20)
Monero	0.21 (0.17, 0.27)	Monero	0.28 (0.22, 0.35)
Nem	0.17 (0.13, 0.22)	Nem	0.06 (0.01, 0.11)
Ripple	0.27 (0.24, 0.30)	Ripple	0.18 (0.15, 0.22)
Siacoin	0.16 (0.12, 0.22)	Siacoin	0.16 (0.11, 0.23)
Stellar	0.25 (0.21, 0.31)	Stellar	0.14 (0.09, 0.20)
Tether	0.29 (0.25, 0.34)	Tether	0.17 (0.12, 0.22)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 8: Estimates of d in a model under autocorrelation			
ABSOLUTE returns		**SQUARED returns**	
Series	**d (95% band)**	**Series**	**d (95% band)**
Bitcoin	0.25 (0.21, 0.32)	Bitcoin	0.15 (0.11, 0.22)
Bitshare	0.23 (0.18, 0.28)	Bitshare	0.13 (0.07, 0.19)
Bytecoin	0.16 (0.11, 0.22)	Bytecoin	0.09 (0.02, 0.15)
Dash	0.17 (0.13, 0.23)	Dash	0.06 (0.02, 0.11)
Ether	-0.01 (-0.07, 0.07)	Ether	-0.15 (-0.19, -0.07)
Litecoin	0.25 (0.21, 0.31)	Litecoin	0.13 (0.09, 0.19)
Monero	0.15 (0.10, 0.22)	Monero	0.01 (-0.03, 0.08)
Nem	0.18 (0.12, 0.27)	Nem	0.05 (-0.02, 0.14)
Ripple	0.35 (0.30, 0.42)	Ripple	0.28 (0.22, 0.35)
Siacoin	0.17 (0.11, 0.25)	Siacoin	0.13 (0.07, 0.21)
Stellar	0.21 (0.15, 0.29)	Stellar	0.04 (-0.01, 0.12)
Tether	0.29 (0.24, 0.35)	Tether	0.10 (0.05, 0.16)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 9: Bai and Perron' s (2003) results for structural breaks

ABSOLUTE returns			SQUARED returns		
Series	**breaks**	**Break dates**	**Series**	**breaks**	**Break dates**
Bitcoin	2	15/04/2014; 30/06/2017	Bitcoin	3	18/12/2014; 17/12/2015 09/11/2016
Bitshare	2	03/02/2015; 15/12/2015	Bitshare	2	03/02/2015; 15/12/2015
Bytecoin	2	27/02/2014; 08/02/2016	Bytecoin	2	10/02/2015; 08/02/2016
Dash	1	04/12/2013	Dash	1	04/12/2013
Ether	1	10/10/2013	Ether	1	10/10/2013
Litecoin	3	23/01/2014; 24/07/2015 29/03/2017	Litecoin	1	23/01/2014
Monero	3	14/02/2014; 16/07/2015 09/02/2016	Monero	3	02/12/2013; 16/07/2015 14/07/2016
Nem	3	16/01/2014; 04/08/2014 29/04/2015	Nem	1	01/04/2014
Ripple	2	14/02/2014; 09/12/2016	Ripple	0	------
Siacoin	3	11/10/2013; 04/03/2014 07/11/2014	Siacoin	0	------
Stellar	3	08/11/2013; 15/10/2014 25/01/2016	Stellar	3	08/11/2013; 16/10/2014 01/09/2015
Tether	0	-----	Tether	0	-----

Table 10: Estimates of d for each subsample based on absolute returns

Series	*Subsamples*	*No terms*	*An intercept*	*A linear time trend*
Bitcoin	1st subsample	0.21 (0.14, 0.30)	**0.21 (0.14, 0.29)**	0.20 (0.14, 0.30)
	2nd subsample	0.22 (0.18, 0.27)	**0.21 (0.17, 0.26)**	0.21 (0.17, 0.26)
	3rd subsample	0.04 (-0.04, 0.17)	**0.05 (-0.05, 0.17)**	0.04 (-0.05, 0.17)
Bitshare	1st subsample	0.24 (0.17, 0.31)	**0.20 (0.14, 0.28)**	0.20 (0.14, 0.28)
	2nd subsample	0.18 (0.09, 0.29)	**0.16 (0.08, 0.27)**	0.16 (0.07, 0.27)
	3rd subsample	0.21 (0.11, 0.33)	**0.19 (0.10, 0.31)**	0.19 (0.10, 0.31)
Bytecoin	1st subsample	0.25 (0.16, 0.36)	**0.20 (0.13, 0.30)**	0.19 (0.12, 0.30)
	2nd subsample	0.18 (0.11, 0.26)	**0.18 (0.11, 0.26)**	0.18 (0.11, 0.25)
	3rd subsample	0.21 (0.12, 0.32)	0.17 (0.09, 0.27)	**0.16 (0.07, 0.27)**
Dash	1st subsample	0.21 (0.08, 0.38)	0.19 (0.07, 0.36)	**0.25 (0.10, 0.68)**
	2nd subsample	0.20 (0.16, 0.25)	**0.19 (0.15, 0.24)**	0.19 (0.15, 0.24)
Ether	1st subsample	0.41 (0.21, 0.71)	**0.41 (0.20, 0.78)**	0.45 (0.22, 0.80)
	2nd subsample	0.22 (0.16, 0.28)	**0.19 (0.14, 0.26)**	0.19 (0.14, 0.26)
Litecoin	1st subsample	0.25 (0.18, 0.35)	0.26 (0.19, 0.37)	**0.23 (0.14, 0.35)**
	2nd subsample	0.19 (0.13, 0.26)	**0.18 (0.12, 0.25)**	0.18 (0.12, 0.25)
	3rd subsample	0.21 (0.16, 0.28)	0.19 (0.13, 0.25)	**0.18 (0.12, 0.24)**
	4th subsample	0.20 (0.11, 0.31)	0.17 (0.08, 0.28)	**0.17 (0.08, 0.28)**
Monero	1st subsample	0.23 (0.14, 0.34)	**0.16 (0.10, 0.25)**	0.15 (0.09, 0.25)
	2nd subsample	0.20 (0.13, 0.29)	**0.20 (0.13, 0.28)**	0.19 (0.13, 0.28)
	3rd subsample	0.31 (0.19, 0.46)	0.26 (0.16, 0.41)	**0.25 (0.14, 0.42)**
	4th subsample	0.09 (0.02, 0.20)	**0.11 (0.02, 0.21)**	0.10 (0.01, 0.21)
Nem	1st subsample	0.14 (0.04, 0.29)	**0.13 (0.04, 0.25)**	0.13 (0.03, 0.28)
	2nd subsample	0.21 (0.12, 0.33)	**0.19 (0.11, 0.30)**	0.19 (0.11, 0.30)
	3rd subsample	0.15 (0.04, 0.29)	**0.14 (0.04, 0.27)**	0.13 (0.03, 0.26)
	4th subsample	0.13 (0.05, 0.23)	**0.12 (0.04, 0.22)**	0.12 (0.04, 0.22)
Ripple	1st subsample	0.24 (0.17, 0.33)	**0.21 (0.15, 0.29)**	0.20 (0.13, 0.29)
	2nd subsample	0.29 (0.23, 0.36)	**0.27 (0.21, 0.34)**	0.26 (0.20, 0.34)
	3rd subsample	0.28 (0.21, 0.36)	**0.28 (0.22, 0.36)**	0.28 (0.22, 0.36)
Siacoin	1st subsample	0.24 (0.09, 0.45)	**0.23 (0.09, 0.43)**	0.22 (0.08, 0.43)
	2nd subsample	-0.05 (-0.13, 0.10)	**-0.06 (-0.17, 0.10)**	-0.07 (-0.19, 0.10)
	3rd subsample	0.16 (-0.07, 0.42)	**0.11 (-0.04, 0.37)**	0.08 (-0.15, 0.36)
	4th subsample	0.11 (0.06, 0.17)	0.12 (0.07, 0.19)	**0.11 (0.06, 0.18)**

Stellar	1st subsample	0.27 (0.13, 0.47)	**0.24 (0.11, 0.42)**	0.25 (0.12, 0.42)
	2nd subsample	0.07 (-0.02, 0.18)	**0.07 (-0.02, 0.18)**	0.07 (-0.02, 0.18)
	3rd subsample	0.14 (0.06, 0.22)	**0.13 (0.06, 0.22)**	0.13 (0.06, 0.21)
	4th subsample	0.26 (0.15, 0.40)	**0.23 (0.13, 0.36)**	0.25 (0.14, 0.38)
Tether	No subsamples	0.29 (0.25, 0.33)	0.29 (0.25, 0.34)	**0.27 (0.22, 0.32)**

In parenthesis, the 95% confidence band of the non-rejection values of d. In bold, the significant models according to the deterministic terms.

Table 11: Estimated values for each series across the subsamples. Absolute returns

Series	*1st subsample*	*2nd subsample*	*3rd subsample*	*4th subsample*
Bitcoin	0.21 (0.14, 0.29)	0.21 (0.17, 0.26)	0.05 (-0.05, 0.17)	-----
Bitshare	0.20 (0.14, 0.28)	0.16 (0.08, 0.27)	0.19 (0.10, 0.31)	-----
Bytecoin	0.20 (0.13, 0.30)	0.18 (0.11, 0.26)	0.16 (0.07, 0.27)	-----
Dash	0.25 (0.10, 0.68)	0.19 (0.15, 0.24)	-----	-----
Ether	0.41 (0.20, 0.78)	0.19 (0.14, 0.26)	-----	-----
Litecoin	0.23 (0.14, 0.35)	0.18 (0.12, 0.25)	0.18 (0.12, 0.24)	0.17 (0.08, 0.28)
Monero	0.16 (0.10, 0.25)	0.20 (0.13, 0.28)	0.25 (0.14, 0.42)	0.11 (0.02, 0.21)
Nem	0.13 (0.04, 0.25)	0.19 (0.11, 0.30)	0.14 (0.04, 0.27)	0.12 (0.04, 0.22)
Ripple	0.21 (0.15, 0.29)	0.27 (0.21, 0.34)	0.28 (0.22, 0.36)	-----
Siacoin	0.23 (0.09, 0.43)	-0.06 (-0.17, 0.10)	0.11 (-0.04, 0.37)	0.11 (0.06, 0.18)
Stellar	0.24 (0.11, 0.42)	0.07 (-0.02, 0.18)	0.13 (0.06, 0.22)	0.23 (0.13, 0.36)
Tether	0.27 (0.22, 0.32)	-----	-----	-----

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 12: Estimates of d for each subsample based on squared returns

Series	*Subsamples*	*No terms*	*An intercept*	*A linear time trend*
Bitcoin	1st subsample	0.24 (0.18, 0.32)	**0.23 (0.17, 0.30)**	0.23 (0.17, 0.30)
	2nd subsample	0.07 (-0.03, 0.18)	0.05 (-0.02, 0.15)	**0.02 (-0.07, 0.14)**
	3rd subsample	0.12 (0.01, 0.28)	**0.12 (0.00, 0.26)**	0.12 (0.00, 0.27)
	4rd subsample	0.09 (0.02, 0.18)	**0.09 (0.02, 0.18)**	0.08 (0.02, 0.18)
Bitshare	1st subsample	0.23 (0.16, 0.29)	0.20 (0.14, 0.27)	**0.19 (0.14, 0.27)**
	2nd subsample	0.20 (0.11, 0.32)	**0.17 (0.09, 0.28)**	0.15 (0.05, 0.27)
	3rd subsample	0.21 (0.11, 0.33)	**0.19 (0.10, 0.31)**	0.19 (0.10, 0.31)
Bytecoin	1st subsample	0.24 (0.18, 0.32)	**0.22 (0.16, 0.29)**	0.20 (0.14, 0.28)
	2nd subsample	0.20 (0.12, 0.30)	**0.18 (0.11, 0.28)**	0.19 (0.11, 0.28)
	3rd subsample	0.07 (0.00, 0.13)	0.07 (0.00, 0.14)	**0.10 (0.00, 0.29)**
Dash	1st subsample	0.06 (-0.05, 0.13)	0.05 (-0.05, 0.19)	**0.11 (-0.02, 0.36)**
	2nd subsample	0.18 (0.13, 0.13)	**0.17 (0.12, 0.23)**	0.17 (0.12, 0.23)
Ether	1st subsample	0.38 (0.17, 0.69)	**0.38 (0.17, 0.73)**	0.41 (0.18, 0.77)
	2nd subsample	0.14 (0.08, 0.20)	**0.13 (0.08, 0.19)**	0.13 (0.08, 0.19)
Litecoin	1st subsample	0.15 (0.07, 0.25)	0.15 (0.07, 0.26)	**0.11 (0.02, 0.24)**
	2nd subsample	0.15 (0.11, 0.20)	**0.15 (0.11, 0.20)**	0.15 (0.11, 0.20)
Monero	1st subsample	0.15 (0.06, 0.27)	0.12 (0.04, 0.22)	**0.07 (-0.02, 0.18)**
	2nd subsample	0.19 (0.12, 0.26)	**0.18 (0.12, 0.26)**	0.18 (0.12, 0.26)
	3rd subsample	0.34 (0.22, 0.50)	**0.31 (0.20, 0.46)**	0.31 (0.20, 0.46)
	4rd subsample	0.02 (-0.08, 0.17)	**0.02 (-0.08, 0.16)**	0.03 (-0.07, 0.16)
Nem	1st subsample	0.14 (0.16, 0.25)	**0.25 (0.17, 0.37)**	0.25 (0.15, 0.38)
	2nd subsample	0.05 (-0.01, 0.20)	**0.05 (-0.01, 0.11)**	0.05 (-0.01, 0.12)
Ripple	No subsamples	0.18 (0.15, 0.22)	**0.18 (0.15, 0.22)**	0.18 (0.15, 0.22)
Siacoin	No subsamples	0.12 (0.17, 0.23)	**0.11 (0.16, 0.22)**	0.11 (0.16, 0.22)
Stellar	1st subsample	0.15 (0.03, 0.32)	**0.15 (0.03, 0.31)**	0.15 (0.03, 0.31)
	2nd subsample	0.06 (-0.02, 0.16)	**0.06 (-0.02, 0.16)**	0.06 (-0.02, 0.16)
	3rd subsample	0.22 (-0.14, 0.73)	**0.16 (-0.10, 0.55)**	0.22 (-0.08, 0.61)
	4rd subsample	0.13 (0.04, 0.24)	**0.13 (0.04, 0.24)**	0.13 (0.04, 0.24)
Tether	No subsamples	0.16 (0.12, 0.22)	0.17 (0.12, 0.22)	**0.15 (0.09, 0.21)**

Table 13: Estimated values for each series across the subsamples. Squared returns

SERIES	1ST SUBSAMPLE	2ND SUBSAMPLE	3RD SUBSAMPLE	4RD SUBSAMPLE
Bitcoin	0.23 (0.17, 0.30)	0.02 (-0.07, 0.14)	0.12 (0.00, 0.26)	0.09 (0.02, 0.18)
Bitshare	0.19 (0.14, 0.27)	0.17 (0.09, 0.28)	0.19 (0.10, 0.31)	-----
Bytecoin	0.22 (0.16, 0.29)	0.18 (0.11, 0.28)	0.10 (0.00, 0.29)	-----
Dash	0.11 (-0.02, 0.36)	0.17 (0.12, 0.23)	-----	-----
Ether	0.38 (0.17, 0.73)	0.13 (0.08, 0.19)	-----	-----
Litecoin	0.11 (0.02, 0.24)	0.15 (0.11, 0.20)	-----	-----
Monero	0.07 (-0.02, 0.18)	0.18 (0.12, 0.26)	0.31 (0.20, 0.46)	0.02 (-0.08, 0.16)
Nem	0.25 (0.17, 0.37)	0.05 (-0.01, 0.11)	-----	-----
Ripple	0.18 (0.15, 0.22)	-----	-----	-----
Siacoin	0.11 (0.16, 0.22)	-----	-----	-----
Stellar	0.15 (0.03, 0.31)	0.06 (-0.02, 0.16)	0.16 (-0.10, 0.55)	0.13 (0.04, 0.24)
Tether	0.15 (0.09, 0.21)	-----	-----	-----