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ARTICLE

Weak efficiency of the cryptocurrency market: a market portfolio approach

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ABSTRACT
Cryptocurrencies have attracted the attention of many investors and policymakers given the increase in popularity of Bitcoin. In this context, we analyse the cryptocurrency market by means of cap-weighted and equally weighted market portfolios that include all the altcoins available for three different periods (2015–2017, 2016–2017 and 2017). By using the most traditional tests of efficiency, we observe three main features of the cryptocurrency market: it is weak-form inefficient due to the behaviour of all the altcoins, it is more inefficient over time, especially in 2017, and the creation of new cryptocurrencies has not significantly changed the efficiency of the market.

KEYWORDS
Cryptocurrency; altcoin; Bitcoin; market efficiency

JEL CLASSIFICATION
G14; G15

I. Introduction

The Efficient Market Hypothesis is one of the main assumptions in Finance and a relevant aspect for investors and policymakers. This theory states that the current price of any stock includes all new information and, consequently, investors cannot earn abnormal returns. Despite previous studies in relation to this matter (Bachelier 1900; Cowles 3rd 1933), the Efficient Market Hypothesis was not recognized until 1965 with the seminal work written by Fama (1965). Given the relevance of this issue, the literature contains a large number of analyses connected with efficiency, and the Bitcoin market is no exception. In particular, most of the authors have focused on weak-form efficiency under the hypothesis that future returns cannot be predicted based on past information. By using a battery of tests, Urquhart (2016) contends that Bitcoin is characterized by informational inefficiency, although it was more efficient in the period 2013–2016. Nadarajah and Chu (2017) highlight the efficiency of Bitcoin by employing power transformations of daily returns. Given that inefficiency varies over time, Bariviera (2017) uses the Hurst exponent to show through a dynamic approach that Bitcoin was inefficient from 2011 to 2014, and was then white noise until 2017. By means of long-range dependence estimators, Tiwari et al. (2017) evaluate informational efficiency and state that Bitcoin is efficient with the exception of April–August 2013 and August–November 2016.

In the same vein, Jiang, Nie, and Ruan (2017) also analyse time-varying long memory by employing a new efficiency index, the result of which underlines the inefficiency of this digital currency. The interest in Bitcoin has given rise to many studies that analyse not only its efficiency but also its main properties (Katsiampa 2017) and economic implications, like management portfolio issues (Baek and Elbeck 2015) or its response to the measures of central banks (Vidal-Tomás and Iban˜ez 2018).

Given the strong performance of Bitcoin, most of the cryptocurrencies have increased their price and market capitalization. This fact has attracted the attention of more authors who are analysing a wide range of virtual currencies, also called altcoins (alternative virtual currencies). Phillip, Chan, and Peiris (2017) study the properties of 224 altcoins whose main features seem to be long memory and heteroscedasticity. Chen et al. (2016) examine the dynamics of the CRIX index (Trimborn and Härdle 2016), which includes 30 representative cryptocurrencies, observing leptokurtosis and volatility clustering. Ciaian and Rajcaniova et al. (2017) show evidence in favour

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of interdependency between Bitcoin and 16 altcoins in the short run. Gandal and Halaburda (2016) demonstrate the existence of strong network effects among six cryptocurrencies in 2014, Bitcoin being the predominant one. Osterrieder, Strika, and Lorenz (2017) show that the six main altcoins in 2014 are characterized by non-normal statistical properties with more volatility than fiat currencies. Brauneis and Mestel (2018) and Wei (2018) observe a positive relationship between cryptocurrencies' efficiency and liquidity.

Although Bitcoin seems to be generally weak-form inefficient, it is not possible to infer that the cryptocurrency market as a whole is weak-form inefficient, since it has not been studied from a general perspective. In this line, some authors (Brauneis and Mestel 2018; Wei 2018) have examined the efficiency of cryptocurrencies by performing a separate analysis for each one without considering the efficiency of the market as a whole. In order to fill this gap, we create market portfolios that describe the performance of the cryptocurrency market, thus we obtain an outcome related to the entire market of digital currencies instead of focusing on just one altcoin, as can be observed in the recent literature. Moreover, given that one of the main features of the cryptocurrency market is the creation of new altcoins each year (Wei 2018), it is relevant to take into account the fact that the creation of new cryptocurrencies can change the degree of efficiency over time. Therefore, the contribution of this paper is twofold: studying the efficiency of the cryptocurrency market through market portfolios and analysing the effect of new cryptocurrencies on the efficiency of the market. To do so, we examine the weak-form efficiency of six market portfolios, including all the cryptocurrencies available in the market, for three periods (2015–2017, 2016–2017, 2017), distinguishing between equally weighted and capitalization-weighted market portfolios.

II. Data

The source of the data used in this letter is BraveNewCoin (BNC 2018). This database provides us with information about a wide range of cryptocurrencies from April 2014; specifically, there are 492 daily global price indexes. The number of cryptocurrencies in the market is not surprising given the creation of new altcoins each year. To consider this issue, we analyse three sample periods with a constant number of cryptocurrencies[1] from 1 January 2015 to 31 December 2017, with 59 cryptocurrencies, from 1 January 2016 to 31 December 2017, with 81 cryptocurrencies, and from 1 January 2017 to 31 December 2017, with a total of 118 cryptocurrencies.[2] With this method, we can examine if new cryptocurrencies change the degree of efficiency over time, given that each period (2015–2017, 2016–2017, 2017) includes a different number of altcoins.[3] More specifically, the creation of new altcoins does not change the efficiency of the entire cryptocurrency market, if we observe that each year separately shows a similar degree of efficiency when comparing the three sample periods, regardless of the different number of altcoins.[4] In fact, we only compare the outcome in 2016 (results during 2015–2017 compared to 2016–2017) and 2017 (a comparison of the results of the three sample periods in 2017) given that 2015 only appears in the sample period 2015–2017, i.e. we cannot compare the results of 2015 to another time span.

In this line, it should be taken into account that the cryptocurrency market is characterized by considerable diversity in terms of market capitalization. As a matter of fact, the most traded cryptocurrencies (Bitcoin, Ethereum and Ripples) account for 83.73% of the total market capitalization in 2017. In order to consider this point, two types of market portfolios have been created. On the one hand, the equally weighted market portfolio includes all the cryptocurrencies with the same weight and, thus, each cryptocurrency has the same impact on the market;

[1]From 1 January 2014 to 31 December 2017 there are only 13 cryptocurrencies that have been trading the entire sample period. This period has not been analysed due to the scant number of digital currencies in comparison with the rest of the market portfolios.:

[2]We have only analysed those cryptocurrencies that have been trading for at least one year (2017) in order to obtain robust results. The list of the different cryptocurrencies is provided as supplementary material.

[3]Considering our data, during 2015–2017 there are 59 cryptocurrencies, in 2016 (sample period 2016–2017) there are 22 new cryptocurrencies, compared to 2015 (sample period 2015–2017), and in 2017 there are 37 new cryptocurrencies, compared to 2016 (sample period 2016–2017).

[4]Given that we are analysing three different periods, including different years (2015–2017, 2016–2017 and 2017), we cannot compare the test results of weak-form efficiency of these three sample periods since a different outcome could arise from a particular behaviour of the cryptocurrencies in one of the years that is not included in the rest of the sample periods. To avoid this issue, we focus on each year separately since the time span that we analyse is the same, i.e. one year. Therefore, the result will be related to the different number of altcoins rather than the sample period.

$$r_{m,t} = \frac{\sum_{i=1}^{N} r_{i,t}}{N} \quad (1)$$

where N is the number of cryptocurrencies, $r_{m,t}$ denotes the market return and $r_{i,t}$ denotes each cryptocurrency return, $r_{i,t} = (P_t - P_{t-1})/P_{t-1}$.[5] On the other hand, the capitalization-weighted market (cap-weighted market) portfolio includes all the cryptocurrency returns with their corresponding weights:

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t} \cdot r_{i,t} \quad (2)$$

where $w_{i,t}$ denotes the percentage of market capitalization on each day t, from the Coinmarketcap database (CMC 2018).

Considering the three different sample periods and the two types of market portfolios, there are six market portfolios for the analysis. The descriptive statistics are shown in Table 1, in which it is possible to observe an increase in the case of the mean and standard deviation, underlining the growth in popularity of this kind of asset in 2016 and 2017.

III. Methodology

The concept 'efficient capital market' has been used in the literature with several possible meanings (LeRoy 1989). However, most of the authors in the empirical literature connect market efficiency with tests of the martingale model, and also random walk hypothesis (Malkiel and McCue 1985; LeRoy 1989; Mills and Patterson 2009). The former is defined as a stochastic process (P_t) in which $E[P_t|P_{t-1}, P_{t-2}, \ldots] = P_{t-1}$. Given the simplicity of working with first differences, $Y_t = P_t - P_{t-1}$, we contend that Y_t follows a martingale difference sequence when $E[Y_t|Y_{t-1}, Y_{t-2}, \ldots] = 0$. In particular, for a real-valued stationary time series, the martingale difference hypothesis (MDH, hereafter) holds when $E[Y_t|Y_{t-1}, Y_{t-2}, \ldots] = \mu, \quad \mu \in \mathbb{R}$, or equivalently, $E[(Y_t - \mu)w(I_{t-1})] = 0$ where $I_t = \{Y_t, Y_{t-1}, \ldots\}$ denotes the information set at t and $w(I_{t-1})$ is a weighting function that represents any linear or nonlinear transformation of past prices. In the statistical literature, the MDH is called conditional mean independence, which states that past and current information are useless to forecast future prices (Escanciano and Lobato 2009b; Charles, Darné, and Kim 2011; Charles, Darné, and Fouilloux 2011).

On the other hand, the simplest definition of random walk is defined as $P_t = \mu + P_{t-1} + \epsilon_t, \quad \epsilon_t \sim \mathrm{IID}\mathcal{N}(0, \sigma^2)$, whose main assumption implies that ϵ_t is independently and identically distributed with mean 0 and variance σ^2.[6] The main difference of the martingale and random walk hypotheses is that the latter is more restrictive since the martingale rejects any dependence of the conditional expectations of price increments $(P_t - P_{t-1})$ while the random walk rejects this and also dependence involving the higher conditional moments of P_t (LeRoy 1989; Campbell, Lo, and MacKinlay et al. 1997; Lim and Brooks 2011; Charles, Darné, and Fouilloux 2011).[7]

Table 1. Descriptive statistics of the market portfolios.

Sample period	Type	N	Data	Mean	Std. Dev.	Kurtosis	Skewness
2015–2017	Equally weighted	59	1095	0.0032	0.0371	7.6732	−0.4651
2016–2017	Equally weighted	81	730	0.0052	0.0382	8.2896	−0.6160
2017	Equally weighted	118	364	0.0090	0.0477	6.0937	−0.8625
2015–2017	Cap-weighted	59	1095	0.0044	0.0317	8.9157	−0.1549
2016–2017	Cap-weighted	81	730	0.0064	0.0317	7.7328	−0.3723
2017	Cap-weighted	118	364	0.0104	0.0402	5.6686	−0.6435

[5]We use simple returns, instead of logarithm returns, in order to create properly the market portfolio since, mathematically, the logarithm of the sum is not equal to the sum of logarithms, i.e. it is not possible to create a market portfolio with logarithm returns. For robustness purposes, having calculated the returns of the market portfolio, we transform the simple market returns into logarithm market returns, $ln(1 + r_{m,t}) = r^l_{m,t}$, obtaining similar results (see Table A1 in the Appendix).

[6]This definition of random walk is the most restrictive one, which is denoted as random walk 1 by Campbell, Lo, and MacKinlay et al. (1997). We obtain the random walk 2 and 3 by relaxing the main assumptions. The random walk 2 includes processes characterized by independent but not identically distributed increments. On the other hand, for the random walk 3, we only hold the uncorrelated increments assumption, i.e. processes with dependent but uncorrelated increments (Campbell, Lo, and MacKinlay et al. 1997; Escanciano and Lobato 2009b).

[7]Despite the fact that there is not a strict connection between random walks and the Efficient Market Hypothesis (e.g. LeRoy (1973) and Lucas Jr (1978) show that the Efficient Market Hypothesis holds at the same time that prices do not follow random walks), in the empirical finance literature, authors are focused on the weak-form efficiency to examine whether future price changes are purely unpredictable based on the asset's price history (LeRoy 1973; Escanciano and Lobato 2009b).

To study the weak-form efficiency of cryptocurrencies, scholars employ in the recent literature on Bitcoin a battery of tests that evaluate assumptions of the random walk and also the MDH. In particular, we examine the weak-form efficiency of the market portfolios following the same tests as Urquhart (2016), Nadarajah and Chu (2017), Brauneis and Mestel (2018) and Wei (2018). We use the Ljung–Box test (Ljung and Box 1978) to detect serial dependence in the returns.[8] To test the non-linear correlations in our return series we employ the BDS test (Broock et al. 1996), whose null hypothesis is that the time series is characterized by being independent and identically distributed (i.i.d.).[9] We use runs test (Wald and Wolfowitz 1940) to analyse whether successive returns are independent of each other by studying the number of runs, and Bartels (1982) test to examine independence of returns. On the other hand, we employ the multiple variance ratio test (VRT) (Chow and Denning 1993), an extension to Lo and MacKinlay's (1988) variance ratio test, in order to test the random walk hypothesis. For no serial correlation, we employ the automatic portmanteau test (Escanciano and Lobato 2009a). To analyse long memory, we calculate the Hurst exponent of our time series by using Detrended Fluctuation Analysis (DFA), following Weron (2002). Finally, to study the MDH, we use the wild-bootstrapped automatic variance ratio test (AVR) (Kim 2009),which is based on linear measures of dependence, and the generalized spectral test (GS) (Escanciano and Velasco 2006), which is based on non-linear measures of dependence (Charles, Darné, and Kim 2011).

IV. Empirical results

All the test results are shown in Table 2 with the corresponding statistics and p-values for the six possible market portfolios. Given these test results, we can underline three main features of the cryptocurrency market. First, the market is weak-form inefficient for the three sample periods (2015–2017, 2016–2017 and 2017) regardless of the type of market portfolio (equally weighted or cap-weighted), since all the p-values reject the null hypothesis.[10] More specifically, regarding the cap-weighted market, weak-form inefficiency stems from the performance of the largest cryptocurrencies (Bitcoin, Ethereum and Ripples), but in regard to the equally weighted market, inefficiency arises from the behaviour of all the altcoins since this market includes all the digital currencies with the same weight. This outcome is in line with Chen et al. (2016) since they observe that the CRIX return series has an autocorrelation structure by

Table 2. Test results of weak market efficiency of the equally weighted and cap-weighted market portfolios.

	Ljung–Box	BDS	Runs	Bartels	Portmanteau	VRT	DFA	GS	AVR
Equally weighted market									
Crypto. 2015–2017	51.9420***	16.3066***	−4.267***	−6.6885***	14.7536***	3.9127***	0.6318***	0***	5.8054***
2015	15.8690***	4.3721***	−1.5088	−2.885***	4.081**	1.9916	0.6023	0.31	0.9601
2016	13.4011***	4.3941***	−2.3373**	−3.1247***	3.5086*	1.8255	0.5174	0.36	1.5144
2017	23.1735***	10.2183***	−3.5444***	−4.4379***	7.2234***	2.9297**	0.6604**	0***	4.5283***
Crypto. 2016–2017	41.5572***	17.8790***	−5.3975***	−6.6108***	9.4061***	3.7065***	0.6552***	0***	5.7180***
2016	15.1989***	4.8908***	−3.24***	−3.7228***	4.6299**	2.1496	0.5937	0.14	2.4469*
2017	21.4750***	10.3755***	−3.3022***	−4.5872***	6.1601**	2.7086**	0.6589**	0***	4.1358***
Crypto. 2017	19.0988***	10.8665***	−3.2588***	−4.4766***	4.984**	2.7970***	0.6794**	0.04**	3.7064***
Cap-weighted market									
Crypto. 2015–2017	57.3820***	17.6036***	−5.8219***	−7.5332***	15.7592***	3.9667***	0.5813*	0***	5.2588***
2015	17.6356***	7.3245***	−3.0962***	−4.0309***	2.267	1.5069	0.5542	0.13	1.1275
2016	20.7237***	6.9037***	−1.9795**	−2.8951***	3.6838*	1.9162	0.6265*	0.22	2.6756
2017	19.4934***	8.5979***	−3.4451***	−4.1386***	9.4733***	3.0704***	0.6425*	0.04**	3.8238***
Crypto. 2016–2017	36.3236***	17.1173***	−6.7053***	−6.7269***	11.5631***	4.0857***	0.6055*	0***	5.4284***
2016	16.7453***	7.6051***	−2.184**	−3.2837***	2.8344*	1.6853	0.6091	0.33	2.7461
2017	18.2787***	9.3630***	−2.9759***	−4.0566***	7.5127***	2.7369**	0.6778**	0.06*	3.8501***
Crypto. 2017	17.6069***	9.8104***	−3.0618***	−4.0925***	6.897***	2.7640**	0.6904**	0.06*	3.7802***

*** significance at the 1% level; ** significance at the 5% level; * significance at the 10% level.
Note: We report the Hurst exponent and p-values for DFA and GS, respectively. Statistics are reported for the rest of the tests.

[8]We test the joint hypothesis that all the autocorrelation coefficients (up to 3 lags) are simultaneously zero.
[9]Given that in the case of the BDS test it is necessary to choose the embedding dimensions, specifically from 2 to 5, in the results we show the average of the statistics and p-values.
[10]The only exception is found in the DFA test when analysing the sample period 2015–2017 for the cap-weighted market with logarithm returns (see Table A1 in the Appendix).

means of the Ljung–Box test. Second, if we study each year separately, we can observe that the test results of weak-form efficiency are not robust in 2015 and 2016. In particular, we do not detect long memory (DFA), and the random walk hypothesis, based on testing multiple variance ratios (VRT), and the MDH (GS, AVR) hold for the returns in 2015 and 2016. However, the cryptocurrency market is weak-form inefficient in 2017, since all the tests show evidence against the null hypothesis. Hence, we can state that the cryptocurrency market is more weak-form inefficient over time with some of the tests, especially in 2017. Third, the creation of new altcoins does not significantly change the degree of weak-form efficiency. On the one hand, in relation to the cap-weighted market, we observe in 2016 the same degree of efficiency in the sample period 2015–2017 as well as during 2016–2017. In this line, 2017 is characterized by being weak-form inefficient in the three cases: 2015–2017, 2016–2017 and 2017. On the other hand, regarding equally weighted markets, we can note a small change. In particular, if we compare the market portfolios during 2015–2017 and 2016–2017, it is possible to observe that 2016 is slightly more inefficient due to the Portmanteau and AVR tests. However, it does not seem to be a remarkable change given that we keep observing a similar degree of efficiency. Finally, in the same line as cap-weighted markets, all the market portfolios are weak-form inefficient in 2017. Therefore, we can state that the cryptocurrency market is more efficient in 2016 compared to 2017 regardless of the number of altcoins (59 cryptocurrencies during 2015–2017, 81 cryptocurrencies during 2016–2017, and 118 cryptocurrencies in 2017).

V. Conclusion

To the best of our knowledge, this paper is the first to examine cryptocurrency market efficiency as a whole by means of market portfolios. After applying a battery of robust tests, the results show that the market of digital currencies is weak-form inefficient. In particular, this market has become more inefficient due to the effect of the year 2017 on market returns, which can be related to the performance of Bitcoin itself as well as the other digital currencies. More specifically, we cannot state that weak-form inefficiency only arises from the behaviour of the largest cryptocurrencies (Bitcoin, Ethereum and Ripples) since the equally weighted market is weak-form inefficient, i.e. the inefficiency of the market stems from the behaviour of all the altcoins. Moreover, the creation of new altcoins does not significantly change the efficiency of the market since we observe a similar outcome when analysing each year separately regardless of the number of cryptocurrencies. Therefore, given these results, the cryptocurrency market could become more weak-form efficient with some of the tests in the near future due to a possible decrease in popularity of digital currencies. Consequently, in the coming years, we may observe a degree of efficiency similar to that of 2015 and 2016.

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Appendix

Table A1. Test results of weak market efficiency of the equally weighted and cap-weighted market portfolios. Logarithm returns.

	Ljung–Box	BDS	Runs	Bartels	Portmanteau	VRT	DFA	GS	AVR
Equally weighted market									
Crypto. 2015–2017	50.8659***	16.1977***	−4.1720***	−6.6884***	13.2827***	3.6290***	0.61960**	0***	5.3729***
2015	15.9208***	4.4451***	−1.7063*	−2.8849***	3.8679**	1.9391	0.60155	0.27	1.0002
2016	12.8526***	4.5149***	−2.1455**	−3.1247***	3.4947*	1.8219	0.5083	0.39	1.4988
2017	22.7351***	10.0707***	−3.5219***	−4.4379***	6.5918**	2.7357**	0.6421*	0***	4.1308***
Crypto. 2016–2017	40.4447***	17.6151***	−5.1401***	−6.6107***	8.3833***	3.1388***	0.64362**	0***	5.2547***
2016	14.7414***	4.8918***	−3.2467***	−3.7228***	4.5962**	2.1417	0.5874	0.16	2.4095**
2017	21.2382***	10.0516***	−3.0131***	−4.5872***	5.6776**	2.5029**	0.64094*	0***	3.7760***
Crypto. 2017	18.8459***	10.6667***	−2.7605***	−4.4766***	4.6068**	2.4559*	0.6647**	0.06*	3.35684***
Cap-weighted market									
Crypto. 2015–2017	57.0818***	17.4982***	−5.3062***	−7.5331***	15.2310***	3.8999***	0.5696	0***	4.9696***
2015	17.4617***	7.2298***	−2.8823***	−4.0308***	2.2498	1.5005	0.5532	0.09*	1.1032
2016	20.1816***	6.8770***	−2.0856**	−2.8950***	3.5996*	1.8941	0.6221	0.22	2.6844
2017	20.0604***	8.5180***	−3.1969***	−4.1386***	9.2620***	3.0363***	0.6326*	0.05**	3.5905***
Crypto. 2016–2017	37.0763***	17.0125***	−6.4739***	−6.7268***	10.8776***	3.6634***	0.5978*	0***	5.0379***
2016	16.1942***	7.5739***	−1.7244*	−3.2836***	2.7651*	1.6646	0.6057	0.32	2.7238
2017	18.9808***	9.2052***	−2.430**	−4.0565***	7.2444***	2.6880**	0.6665**	0.06*	3.5431***
Crypto. 2017	18.3338***	9.6850***	−3.2199***	−4.0924***	6.6488***	2.5658**	0.6825**	0.07*	3.4687***

*** significance at the 1% level; ** significance at the 5% level; * significance at the 10% level.
Note: We report the Hurst exponent and p-values for DFA and GS, respectively. Statistics are reported for the rest of the tests.