

Chapter 22

The Efficiency of Futures Markets on Cryptocurrencies



Radu Lupu  and Catalina Maria Popa 

Abstract From the launch of Bitcoin till the present moment, cryptocurrency market had expanded continuously, gaining more and more influence over the global economy with each passing year. Yet, the events of 2020 marked a new phase for the cryptocurrency ecosystem, which has experienced a significant increase in size and complexity. The third halving cycle that led to an increase in cryptocurrency prices, the beginning of pandemic, and afterward inflation and economic uncertainty made Bitcoin an attractive asset for both retail and institutional investors. Although the liquidity of the cryptocurrency assets increased, their volatile nature is still persistent, causing mixed views on its status. While crypto-enthusiasts are perceiving it as a worthwhile investment with novel economic properties, the more skeptic participants consider it only a speculative asset with a transitory presence. The absence of a consensus on this topic has attracted the interest of the academic community, which aims to analyze whether cryptocurrencies display economic properties. A keystone characteristic for considering cryptocurrency an economic asset is the lack of price manipulation. In this respect, numerous papers have investigated the efficiency of the cryptocurrency market. Even though the results are mixed, a large body of studies indicate that the efficiency of the crypto-assets market varies, increasing from period to period. However, most of the papers focus on testing information efficiency only on the spot market. Thus, the objective of this study is to analyze whether the futures cryptocurrency market is efficient. In this regard, the futures prices for Bitcoin from 2018 to 2022 are used. On them, a battery of tests is applied, which investigate several statistical properties that can assess the efficiency hypothesis. Furthermore, under the assumption of efficient market hypothesis the spot and future prices are supposed to move together. In the contrary case, the

R. Lupu (✉)

Bucharest University of Economic Studies, Bucharest, Romania

e-mail: radu.lupu@rei.ase.ro

C. M. Popa

Bucharest University of Economic Studies, Bucharest, Romania

Institute for Economic Forecasting, Romanian Academy, Bucharest, Romania

efficient market hypothesis is rejected. Thus, the property is evaluated from a double perspective by using statistical tests and evaluating the relation between the spot and the future price.

Keywords Cryptocurrency market · Cryptocurrency efficiency · Bitcoin · Efficient market hypothesis · Spot market · Futures market · Cointegration test

22.1 Introduction

Over the years, the impact of the cryptocurrency market on the global economy has increased. The debate concerning whether cryptocurrency has the potential to change the monetary and financial system has raised the attention of the regulatory institutions. Their main concerns target the financial stability and the risk that the investors are exposing to. Under this context, the study of the economic properties of the crypto-coins is mandatory for understanding their compartment and the risks associated with it. For deciding if the cryptocurrencies are more than a speculative asset, the efficiency of the cryptocurrency market was highly studied in the literature. Yet, an exceedingly number of papers have investigated the efficient market hypothesis on spot level, neglecting the futures market. The aim of this paper was to fill this gap, by applying two methods. First, a battery of tests was applied on Bitcoin future prices, which investigates the statistical properties needed to confirm EMH. Secondly, the Engle-Granger co-integration test was applied for studying if the spot and futures prices move together.

22.2 Literature Review

In the last years, the popularity of cryptocurrencies has considerably increased both among retail and institutional investors. Their increased participation and the strengthened role of the cryptocurrency in world's economy raised the question of whether the crypto-coins are more than a speculative asset or not. This dilemma raised the attention of the research community whose aim is to analyze whether the cryptocurrency displays some economic properties, similarly to other financial assets. Thus, a large body of studies that concern this topic have emerged. The investigated properties concern the volatile nature of the crypto coins (Baur, 2018; Katsiampa et al., 2019; Bouri et al., 2019a), their safe-haven capabilities (Corbet et al., 2018, 2020), bubbles (Bouri et al., 2019b; Bubbles and crashes in cryptocurrencies: Interdependence, 2022), and herding behavior (Bouri et al., 2019c; Mnif et al., 2020).

Another studied property is the efficiency of the crypto-market. Introduced by Fama (1970), the efficient market hypothesis infers that financial assets display all the information available, which makes them impossible to be consistently

predicted. The incapacity of price manipulation under EMH would change the perspective over the cryptocurrency market, possibly implying that is stable and mature enough to invest in. On the contrary, the invalidation of EMH would suggest a speculative character. These implications motivate the large number of studies developed in this area. However, the results are still mixed. On one hand, some scholars reject EMH on cryptocurrency market (Vidal-Tomás et al., 2019; Jiang, 2018). On the other hand, other studies show that the efficiency of the cryptocurrency market fluctuates in time, becoming more efficient over the years (Urquhart, 2016). Although many factors have been considered when the efficiency was studied (comparing the efficiency of different exchanges, at different time frequencies, between different cryptocurrencies), many studies have targeted the spot market, neglecting the futures market.

Introduced by Chicago Mercantile Exchange in 2017, the futures contracts on Bitcoin have represented a milestone moment for the cryptocurrency market. Later, the contracts were launched for other currencies as well, like Ethereum, Polygon, Cardano, and Tezos. The presence of futures contracts issued through a standardized process supported by CME represents a vote of confidence for the cryptocurrency market. In this respect, several studies analyze the impact of future introductions on the market. Shaen Corbet (2018) suggests that the volatility spiked after the introduction of Bitcoin futures. Kochling et al. (2018) show that the efficiency of the spot cryptocurrency market showed signs of improvement after the introduction of Bitcoin. Godinh (2020) argues that Bitcoin futures may be a proper instrument for hedging. Other studies discussed the price discovery of Bitcoin (Fassas et al., 2019; BurcuKapara, 2019; Corbet et al., 2019). Yet, the efficiency of the cryptocurrency futures market was not frequently discussed by the academic community. The aim of this study was to complete this gap.

22.3 Methodology

In respect to the scope of this paper, the efficiency of the cryptocurrency futures market was analyzed using two approaches.

Firstly, the literature indicates that the returns respect certain statistical properties if the market is efficient. For testing this assumption, a battery of tests was applied. Secondly, under EMH the spot and future prices are presumed to move together. Thus, the Engle-Granger cointegration test was used.

In respect to the first approach, the historical CME Futures Daily Roll Index prices of Bitcoin have been used. The index is a gauge for the return that stems from rolling a long position in two Bitcoin futures contracts that have the closest maturity and are traded on the Chicago Mercantile Exchange. This indicator is developed with the purpose to capture the performance of Bitcoin futures market within a day. The analyzed period was from December 18, 2017, when the futures contracts for Bitcoin were introduced to November 18, 2022. During this period, several events, such as the beginning of the pandemic, the economic uncertainty generated by it,

and the third halving cycle of Bitcoin, have significantly impacted the cryptocur-
 rency market. To investigate the impact of these milestone moments over the effi-
 ciency of the futures market, the data were divided into three subsets named base
 period (December 18, 2017–November 20, 2020), ATH 1 (November 30,
 2020–November 10, 2021), ATH 2 (November 11, 2021–November 18, 2022). The
 periods were selected based on the newest all time high of Bitcoin which, after the
 third halving cycle, was first hit on November 30, 2020, and lastly achieved on
 November 11, 2021. Thus, ATH 1 set is marked by an ascending trend (a bull
 period), while ATH 2 is mostly characterized by a descending trend (the beginning
 of the bear period). The dynamic is depicted in Fig. 22.1.

For all the periods, the Bitcoin futures prices were transformed in logarithmic
 returns by applying the formula: $r_t = \ln(P_t/P_{t-1})$, where P_t represents the price at
 the moment t , P_{t-1} represents the price at $t - 1$, and r_t represents the return at
 moment t . The efficiency was analyzed by applying six statistical tests proposed by
 (Urquhart, 2016) Under EMH, the returns cannot be autocorrelated to assure that
 the future returns cannot be predicted based on the past ones. To evaluate this prop-
 erty, the Ljung-Box test (Ljung & Box, 1978) was applied. The statistics is defined
 by the formula:

$$(a) Q_k = n(n+2) \sum_{j=1}^k \frac{c_j^2}{n-j} \tag{22.1}$$

where the sample size is depicted by n , the number of lags tested is captured by k ,
 and the sample autocorrelation at lag j is expressed by c_j^2 .

Another property is the independence of returns, which was investigated by
 applying the Runs test (Wald & Wolfowitz, 1940) and the Bartels test (Bartels,
 1982). The Runs test presumes that any element of a sequence is independent and is
 computed by the formula:

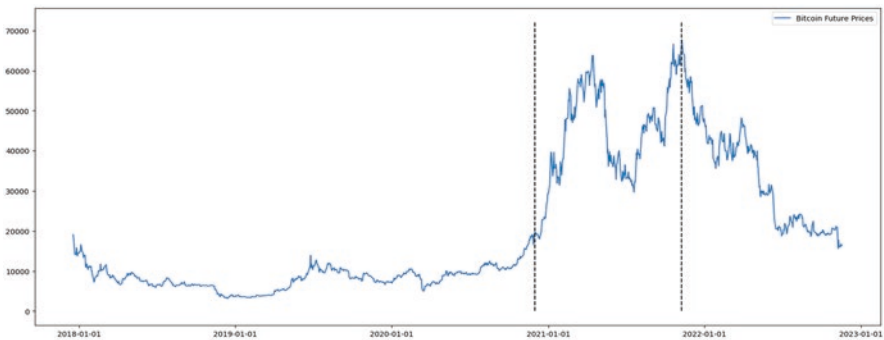


Fig. 22.1 BTC Future Prices Dynamic—Sampling. (Source: Author’s calculations)

$$(b) Z = \frac{R - \mu_R}{\sigma_R} \tag{22.2}$$

where R is used to represent the number of runs, μ_R stands for the expectation for the number of runs, which is captured by the formula: $\mu_R = \frac{2N_+N_-}{N} + 1$ and σ_R depict the standard deviations expressed as $\sigma_R = \sqrt{\frac{2N_+N_-(2N_+N_- - N_+ - N_-)}{(N_+N_-)^2(N_+ + N_- - 1)}}$. N_+ , N_- are the count of positive and negative elements contained in a sequence. The second test applied for evaluating the independence property is defined by the formula:

$$(c) RVN = \frac{\sum_{i=1}^{T-1} (R_i - R_{i+1})^2}{\sum_{i=1}^T (R_i - \bar{R})^2} \tag{22.3}$$

where the rank for the i th observation in a sequence of T observations is depicted by R_i . Given that the size of the sample exceeds 100 in both cases ($T > 100$), the p -value was approximated by using the formula $\sim N\left(2, \frac{20}{5T + 7}\right)$.

Besides the lack of autocorrelation and the property of independence, the returns have to follow a random walk process under EMH. To evaluate this property, the variance ratio test (Lo & MacKinley, 1988) was used, whose null hypothesis states that the returns follow a random walk. The test is computed as:

$$(d) Z^*(q) = \frac{\sqrt{ng}VR(q)}{\sqrt{\hat{\theta}(q)}} \sim N(0,1) \tag{22.4}$$

where n denotes the count of observations, q stands for the number of lags, VR is the variance ratio, and $\hat{\theta}(q)$ depicts the heteroscedasticity estimator of $\theta(q)$.

For investigating whether the returns are serial dependent, the BDS test (Broock, 1996), whose null hypothesis states the returns are independently identically distributed, was applied. The test is defined as:

$$C_{m,T}(\epsilon) = T^{1/2} \frac{[C_T(\epsilon) - C_1(\epsilon)^m]}{\sigma_{m,\tau}(\epsilon)} \tag{22.5}$$

where $C_{m,\tau}(\epsilon)$ represents the correlation integral, m the embedding dimension, τ designates the time delay, ϵ is the threshold distance indicator, and σ represents the variance.

For analyzing whether the returns present long-term memory, the rescaled Hurst Exponent (Taylor, 1971) was applied. The statistics is computed as:

$$(e) E \left[\frac{R(n)}{S(n)} \right] = Cn^H, asn \rightarrow \infty \quad (22.6)$$

where we consider $R(n)$ to be the range of the first n cumulative standard deviations, we use $S(n)$ to represent the standard deviation, and we employ C for a constant and n to capture the span.

The second approach started from the assumptions that the spot and future prices move together. To test this assumption, Engle-Granger test (Engle, 1987) is applied, which assumes that the time series do not drift apart. In this respect, two data sets have been used. The first one was the historical spot prices of Bitcoin, and the second one was the historical futures prices. Both of the series had daily frequency and were analyzed between December 18, 2017, to January 14, 2022. On this, the Engle-Granger co-integration test was used, whose null hypothesis assumes that the time series are not co-integrated. The test is expressed mathematically as:

$$S_t = \alpha + \beta F_{t-i} + \epsilon_t \quad (22.7)$$

where S_t represents the spot price at moment t and F_{t-i} denotes the future price at moment $t - i$.

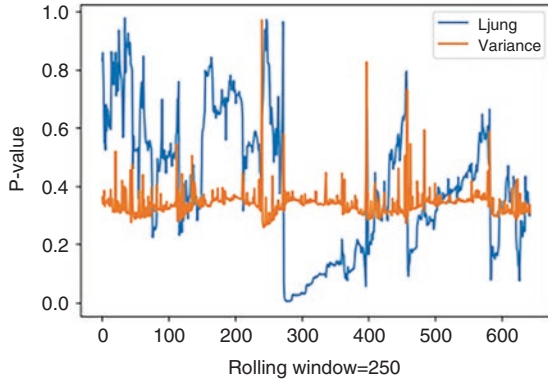
22.4 Analysis/Result Interpretation

Figures 22.2, 22.3, and 22.4 depict the dynamic in time of the p -values corresponding to each efficiency test. According to the results presented in Fig. 22.2, the Ljung-Box test tends to be constant and above the significance level (0.05) for all the periods, meaning that returns tend to not be autocorrelated. Moreover, the variance ratio test varies along the periods, but in most of the cases, the values exceed the level of significance, implying that returns are following a random walk process.

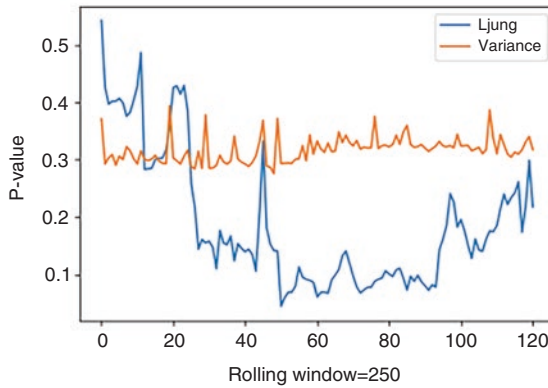
However, during ATH 1 period the market tends to be less efficient according to both tests. The Runs and Bartels tests exhibited in Fig. 22.3 are also fluctuating in time, although in most of the cases the p -values are beyond the level of significance, suggesting that the returns tend to be independent.

Similarly, to the previous tests, Runs and Bartels' corresponding p -values display a lower level of efficiency during ATH 1 period. The BDS test is depicted in Fig. 22.4. Although the p -values vary in time, there are no major differences between data sets. The majority of the p -values are above the significance level inferring that the returns are independently identically distributed most of the time.

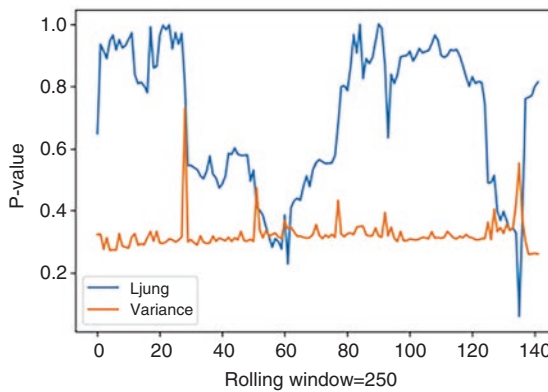
The Hurst exponent is displayed in Fig. 22.5. For all three samples, the rescaled Hurst is under 0.5, indicating an anti-persistent behavior. This mean-reverting tendency implies that a period of decrease will be followed by a period of increase and the other way around. Otherwise the future returns tend to go toward a long-term mean.



(a) Base Period (18/12/2017-20/11/2020)



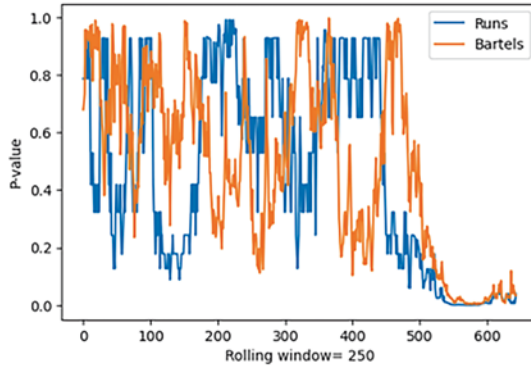
(b) ATH 1 Period (30/11/2020 - 10/11/2021)



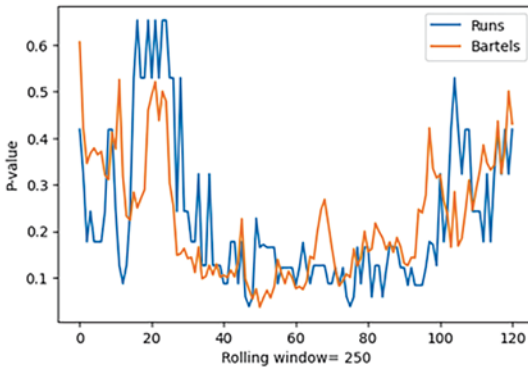
(c) ATH 2 Period (11/11/2021 - 18/11/2022)

Source: Author’s calculations

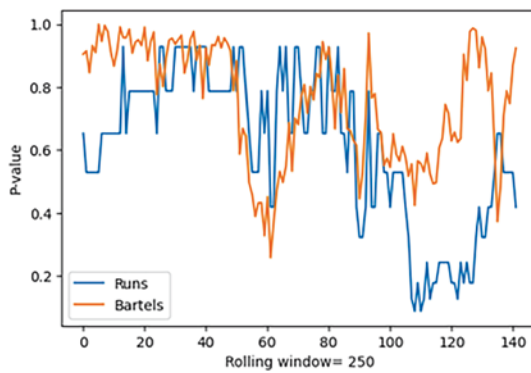
Fig. 22.2 P-values of Ljung-Box test and variance ratio test. (a) Base period (18/12/2017–20/11/2020). (b) ATH 1 Period (30/11/2020–10/11/2021). (c) ATH 2 period (11/11/2021–18/11/2022)



(f) Base Period (18/12/2017-20/11/2020)
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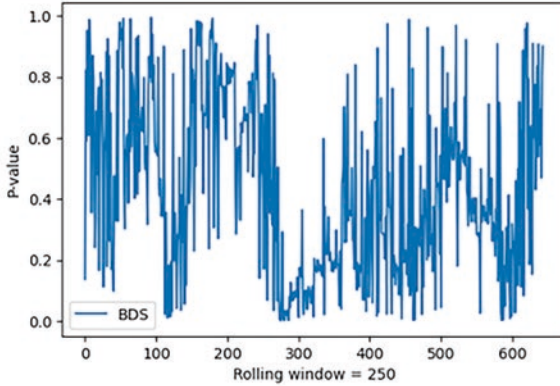


(g) ATH 1 (30/11/2020 - 10/11/2021)

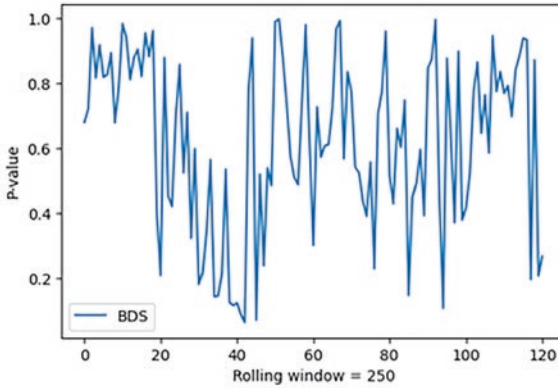


(h) ATH 2 (12/11/2021 - 18/11/2022)

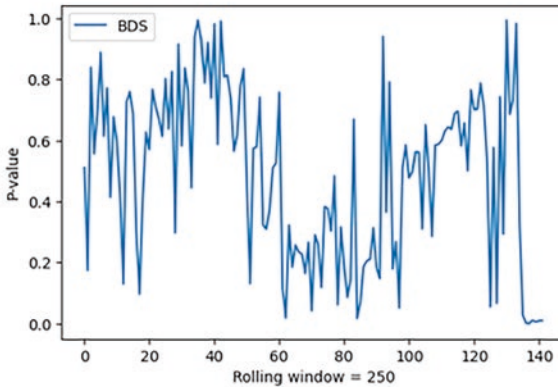
Fig. 22.3 *P*-values of Runs and Bartels test. (a) Base Period (18/12/2017–20/11/2020). (b) ATH 1 (30/11/2020–10/11/2021). (c) ATH 2 (12/11/2021–18/11/2022). (Source: Author’s calculations)



(a) Base Period (18/12/2017-20/11/2020)

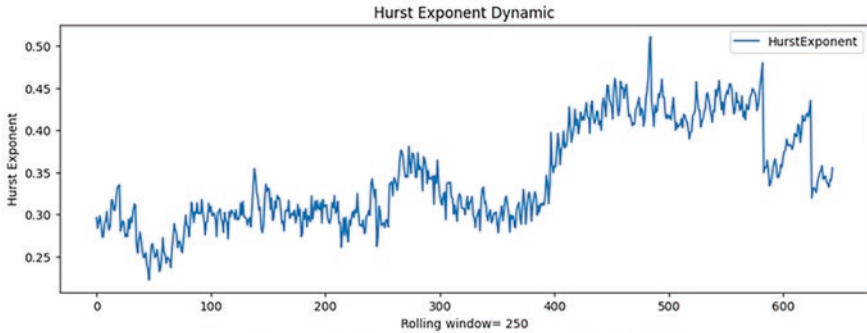


(b) ATH 1 (30/11/2020 – 10/11/2021)

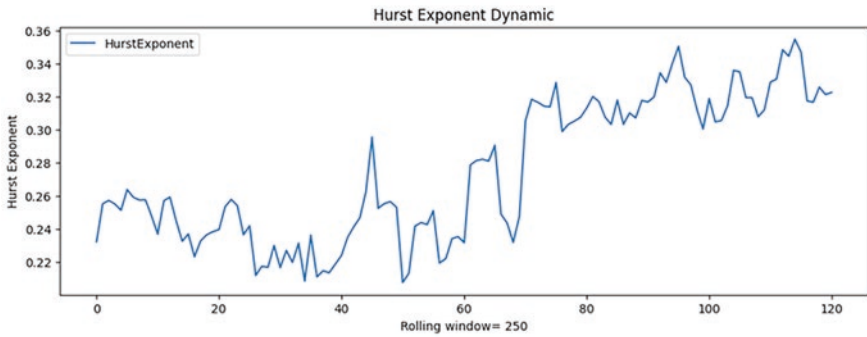


(c) ATH 2 (11/11/2021 – 18/11/2022)

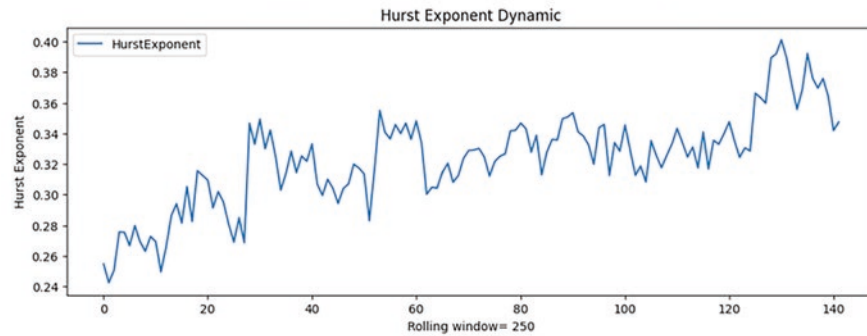
Fig. 22.4 *P*-values of BDS Test. (a) Base period (18/12/2017–20/11/2020). (b) ATH 1 (30/11/2020–10/11/2021). (c) ATH 2 (11/11/2021–18/11/2022). (Source: Author’s calculations)



(a) Base Period (18/12/2017 – 20/11/2020)



(b) ATH 1 (30/1/2020 – 10/11/2021)



(c) ATH 2 (11/11/2021 – 18/11/2022)

Fig. 22.5 Hurst exponent. (a) Base period (18/12/2017–20/11/2020). (b) ATH 1 (30/1/2020–10/11/2021). (c) ATH 2 (11/11/2021–18/11/2022). (Source: Author’s calculations)

Overall, the cryptocurrency future market tends to be efficient, yet the level of efficiency tends to decrease during the ATH 1, having even some short moments of inefficiency. The fact that this behavior is displayed during ATH 1 may suggest that the market tends to be more predictable when is on an ascending trend, with investors expecting the prices to further increase.

Nevertheless, the tendency of the cryptocurrency futures market to be efficient is supported by the Engle-Granger test, whose null hypothesis that states that the time series are not co-integrated has been rejected. Thus, future prices are an indicator for the future spot prices. In other words, the EMH assumptions are validated, and the future prices are the best indicator of spot prices.

22.5 Conclusions

The efficiency of the cryptocurrency market is necessary to be studied in order to understand if the prices are manipulated or not. Thus, a large body of studies emerged. However, most of them have analyzed the efficiency on the spot market, neglecting the futures market. In this respect, the scope of this chapter was to investigate whether the cryptocurrency market is efficient using two approaches. Firstly, a battery of tests was applied on CME Daily Bitcoin Futures prices between December 18, 2017, and November 20, 2020. The data were divided in three sets, cut based on the all-time high dates. Overall, the tests indicate that the cryptocurrency futures market tends to be efficient, although during ATH 1 the level of efficiency decreased. This might suggest that during the ascending periods, the market leans to be more predictable, possibly due to the over-optimistic expectations of the investors. Secondly, the Engle-Granger co-integration test was used on Bitcoin spot prices and futures prices from December 18, 2017, to January 14, 2022. The test indicated that the spot and future prices are co-integrated, which implies that the spot and future prices do not deviate from one another. This result sustains the efficiency of the cryptocurrency futures market. Further studies may consider the usage of different cryptocurrencies at a more detailed frequency (hourly, minute). This approach may extend the knowledge on this topic, providing an exhaustive view.

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