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The Effect of the Launch of Bitcoin Futures on the Cryptocurrency Market: An Economic Efficiency Approach

David Vidal-Tomás [1,†], Ana M. Ibáñez [2,†] and José E. Farinós [2,*,†]

1 Department of Economics, Universitat Jaume I, Campus del Riu Sec, 12071 Castellón, Spain; dvidal@uji.es
2 Department of Corporate Finance, Universitat de València, Avenida de Los Naranjos S/N, 46022 Valencia, Spain; ana.m.ibanez@uv.es
* Correspondence: jose.e.farinos@uv.es
† These authors contributed equally to this work.

Abstract: We analyze the economic efficiency of the cryptocurrency market after the launch of Bitcoin futures by means of the Data Envelopment Analysis and Malmquist Indexes. Our results show that the introduction of Bitcoin futures did not affect the economic efficiency of the cryptocurrency market. However, we observe that Bitcoin obtained the highest risk-return trade-off due to its liquidity compared to the rest of cryptocurrencies. Therefore, our paper underlines the support of investors on Bitcoin to the detriment of the rest of cryptocurrencies.

Keywords: DEA; Malmquist Index; cryptocurrency; risk-return trade-off; economic efficiency

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1. Introduction

Bitcoin has been historically characterized by an explosive behavior due to its multiple bubbles since it was created by Nakamoto [1] in 2008. Some of the most relevant volatile periods were underlined by Phillips et al. [2], who observed three bubbles during 2011–2013, and Fry [3], who confirmed the existence of bubbles in Bitcoin during 2015–2018. However, this behavior is not only found on Bitcoin, since Corbet et al. [4] also observed bubbles in Ethereum, and Bouri et al. [5] highlighted the co-explosive phenomenon in the largest cryptocurrencies of the market.

The main drawback of this explosive behavior is the consequent crash that is driven by the fear of traders. The best example was observed in the last cryptocurrency bubble of 2017, which gave rise to a remarkable decrease in the market capitalization and price of most of the cryptocurrencies in 2018. This situation generated doubts about the plausible existence of cryptocurrencies in the long run, since most of them could disappear as a result of repetitive bubbles and crashes. In fact, the loss of power of Bitcoin, as demonstrated by Vidal-Tomás et al. [6] and Yi et al. [7] in favor of the other cryptocurrencies, could show an initial change of the influence of the largest virtual currencies in the cryptocurrency market given the effect of the explosive periods on their performance. However, despite the volatile behavior of Bitcoin and other cryptocurrencies, the institutions and investors keep trusting in these new assets. Proof of it is the introduction of Bitcoin futures in December 2017 by the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE), which could improve the performance of Bitcoin and the cryptocurrency market over time. In this regard, several studies [8–10] have sought to uncover the positive and negative effects of the introduction of the futures on Bitcoin. On the one hand, Hale et al. [9] contended that the decline in prices following the launch of futures on the CME is explained by the optimists' behavior, since investors bid up the price before derivatives are available to short the market ([11]), i.e., the introduction of futures gave rise to the crash of Bitcoin. However, on the other hand, Köechling et al. [10] observed positive consequences since Bitcoin returns are more efficient after the introduction of the futures. In addition to Koechling et al. [10] and Hale et al. [9], other scholars have also studied this point.

For instance, Yaya et al. [12] contended that the cryptocurrency market exhibited higher volatility persistence, and Kallinterakis and Wang [13], observed that herding behavior among cryptocurrencies decreases after the introduction of futures in 2017. Although there are few studies that examine this issue in the cryptocurrency literature, the impact of futures trading on the underlying asset volatility has been traditionally debated both in the economic literature and among practitioners, underlining the relevance of our analysis. For instance, Edwards [14] did not observe a significant increase in the S&P 500 index after the introduction of futures trading. Bologna and Cavallo [15] showed that the introduction of stock index futures in the Italian stock market gave rise to a decrease of the stock market volatility. Nevertheless, it is also possible to find other studies, more focused on the Asian market, in which the futures trading increases spot portfolio volatility such as in Chang et al. [16], who focused on the Nikkei 225 index, and Ryoo and Smith [17], who examined the KOSPI 200 index.

To shed more light on the effects of the introduction of Bitcoin futures on spot prices, in this research we employ an approach based on the economic efficiency that allows us to examine not only the effects on Bitcoin but also the impact on the cryptocurrency market as a whole. More specifically, unlike informational efficiency [18–22], the economic efficiency of the cryptocurrency market (or any financial market) seeks to measure how efficient the market is in relation to the risk-return trade-off, which is a key variable in the classic theory of risky financial asset selection, based on the theory of expected utility [23].

From this perspective, there are two general approaches for assessing economic efficiency: parametric and nonparametric. Parametric methods, such as the Stochastic Frontier Analysis (SFA), specify a parametric frontier, which accounts for stochastic error but require specific assumptions about the functional form on the frontier and the inefficiency term that may be inappropriate or very restrictive (such as half-normal or constant inefficiency over time). Incorporating a stochastic error, SFA allows for hypothesis testing. However, the disadvantage of this approach is the need of imposing an explicit functional form and distributional assumption of the error term. Hence, the SFA suffers from the problem of misspecification of the functional form, and potential inefficiency and multi-collinearity.

In contrast, the nonparametric model, such as the Data Envelopment Analysis (DEA) approach, does not impose a functional form on the frontier (the risk-return trade-off, in our case) and, hence, can accommodate wide-ranging behaviors. This method measures the efficiency as the quotient of outputs to inputs under the assumption that any economic agent wants outputs as high as possible and inputs as low as possible, giving rise to an increase of efficiency. In fact, one of the main advantages of DEA is the ability to deal with several inputs and outputs without demanding the precise relation between them, thus we can use a ratio of weighted outputs to weighted inputs. In this line, given that the usual variables in DEA are such that "more is better for outputs, and less is better for inputs" [24], the indicators preferred to have a greater value are treated as outputs, and the indicators with preferably small values are treated as inputs.

Considering these arguments, we employ the DEA technique for estimating the economic efficiency of a sample of cryptocurrencies and its change after the introduction of Bitcoin futures through the computation of Malmquist indexes. We follow classical financial theory to choose the appropriate comparison criteria in which the investors prefer higher returns and are risk averse [25], thus, variables connected with returns are outputs and variables connected with financial risk are inputs. In terms of DEA, the most efficient cryptocurrency will be the one that obtain a greater quotient of weighted outputs (returns) to weighted inputs (risk) compared to the rest of cryptocurrencies, i.e., the best risk-return trade-off.

As stated before, given that DEA is a non-parametric technique, it does not allow for random errors and does not have any statistical foundation, hence making it inadequate for testing statistical significance of the estimated distance functions. This inability to allow for random error has induced many authors to label it as deterministic. To solve this problem, Simar and Wilson [26] defined a statistical model which allows for the determination of the statistical properties of the non-parametric estimators in the multi-input and multi-output case, and hence for constructing confidence intervals for DEA efficiency scores. This possibility was first introduced by Efron [27] through the bootstrap technique (see also Efron and Tibshirani [28]), a computer-intensive technique essentially based on the idea of approximating the unknown statistic's sampling distribution of interest by extensively resampling from an original sample, and then using this simulated sampling distribution to perform inference in complex problems. In a later study, ref [29] demonstrated that the bootstrap technique can also be employed to estimate confidence intervals for Malmquist indices and its components. The most important practical implication of their conclusion is that statistical inference becomes possible for Malmquist indices. Therefore, we can evaluate whether the cryptocurency market significantly changed (improved) its economic efficiency after the launch of Bitcoin futures. In other words, it allows us to assess which cryptocurrencies provide investors with higher returns, given different measures of risk.

This paper makes several contributions to the literature. On the one hand, to the best of our knowledge, this is the first study that analyzes the economic efficiency in the cryptocurrency market, by means of the DEA approach, since other studies focused on different financial areas such as the management of public funds [30,31] or the measurement of mutual fund performance [32–34]. It is also possible to find different studies focused on traditional stock markets, such as Ismail et al. [35] (Malaysian stock market), Lim et al. [36] (Korean stock market) and Lopes et al. [37] (Brazilian stock market), which examined the effectiveness of DEA model on portfolio selection for investors.) On the other hand, compared to most of the literature on Bitcoin, which is focused on the informational efficiency [10,20], our study is based on the concept of economic efficiency. Finally, and related to Bitcoin futures literature [8,10], we observed that, despite the decrease in Bitcoin price after December 2017, Bitcoin is still the most robust cryptocurrency in terms of liquidity regardless of its bubbles and crashes, which could be related to the confidence of investors and institutions as a consequence of the launch of Bitcoin futures.

The rest of the paper is organized as follows. In Section 2, we describe the data and the variables considered as inputs and outputs of the model. In Section 3, we explain the methodology used to measure the economic efficiency of the cryptocurrency market. In Section 4, we report the results of our paper. Finally, we summarize the main contributions of this study in Section 5.

2. Data and Variables

The initial sample of cryptocurrencies (CCs hereafter) was sourced from BraveNewCoin database and consisted of 86 digital currencies that were trading from January 1, 2016 to November 30, 2018, i.e., we focused on long-lived cryptocurrencies. For all these virtual currencies we had daily exchange rates to dollar and the daily dollar volume. In order to examine whether there is a significant difference in the economic relative efficiency of the cryptocurrency market as a consequence of the launch of Bitcoin future market in December 2017, we employed two symmetric periods: a pre-launch period of 11 months from January 1, 2017 to November 30, 2017; and a post-launch period of 11 months from January 1, 2018 to November 30, 2018.

Concerning the selection of variables, the classical financial portfolio theory, which began with the mean-variance model proposed by Markowitz [25], states that the main determinant of asset performance is its level of risk, measured in this context by the variance of the assets' return. However, nowadays, due to the properties shown by the distribution functions of the returns, the use of alternative risk variables, other than variance, is expanding. Recent findings in risk theory suggest that quantile based measures are suitable for measuring risk. These measures behave properly for asymmetric distributions with both skewness and fat tails. Specifically, the Value-at-Risk (VaR) and the Conditional Value-at-Risk (CVaR), or Expected Shortfall, have increased in importance as risk measures since Basel II, being used in portfolio management models ([38–40] among others). For a given confidence level and a specific time horizon, the VaR of an investment is defined as the maximal loss expected to incur at the confidence level by holding the asset over a given time horizon. CVaR, otherwise, is defined as the conditional expectation of losses above VaR in a set period and at a given confidence level. In contrast to the VaR, which has shown certain properties that makes it an inconsistent measure of risk [41], the CVaR is currently presented as a coherent measure of risk.

In this line, there is also an increasing interest in the financial literature on the relationship between liquidity and asset returns. A great number of studies on asset pricing focuses on the illiquidity premium of stock returns. Some classic examples of this literature are Amihud and Mendelson [42] and Brennan and Subrahmanyam [43].

Given the existing literature, we chose four measures to describe the financial risk of CCs (inputs in DEA terminology), classified according to two types of risk: risk related to the distribution of returns and risk connected with illiquidity. The former type included the standard deviation (SD) for return volatility and Expected Shortfall (or CVaR) for probability of loss. The latter encompassed [44]'s illiquidity ratio (ILLIQ) and the number of days without trading with respect the total number of days in the time span (Zerovol). Finally, we measured returns (the output variable in DEA) as gross returns, since DEA models (and solvers) are developed for nonnegative data.

The gross return on day t for cryptocurrency i was computed as 1 plus the simple net returns on day t ($R_{i,t}$),

$$1 + R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}}, \tag{1}$$

where $P_{i,t}$ and $P_{i,t-1}$ are the price on day t an $t-1$ for cryptocurrency i, respectively. For each 11-month period under study we employed as output the average daily gross return.

The CVaR for CC i in the sample was computed by generating an empirical distribution function from the historical return data over each 11-month period under analysis using bootstrap. This empirical distribution function was derived by considering 2000 random draws from the 334 daily simple net returns for every period and cryptocurrency. From the empirical distribution function, the CVaR was calculated as the mean of all those returns that were not larger than the percentile 5 of the distribution function. CVaR is expressed in absolute terms.

The Amihud's illiquidity ratio for CC i ($ILLIQ_i$) was computed over each period as follows,

$$ILLIQ_i = \frac{1}{D}\sum_{t=1}^{D}\frac{|R_{i,t}|}{V_{i,t}} \tag{2}$$

where $V_{i,t}$ denotes the dollar volume on day t for cryptocurrency i, and D is the number of days with observations in each 11-month period. The illiquidity ratio is expressed multiplied by a scaling factor of 10^6.

Table 1 reports descriptive statistics for the cross-section of the initial sample of cryptocurrencies. According to Table 1, our initial sample of virtual currencies showed extreme values for some of the variables, particularly for those proxies of illiquidity risk (i.e., ILLIQ and Zerovol). Since the efficiency obtained from DEA is a relative efficiency score as compared to other DMUs (cryptocurrencies), it is sensitive to sampling variation. The deterministic nature of DEA models implies that efficiency measured using standard DEA models can be contaminated by outliers. As discussed by Stolp [45], the existence of outliers involves a problem for DEA in a similar way than in statistics or econometrics. In this context, as Table 1 shows extreme values for illiquidity proxies, we performed the median absolute deviation (MAD) procedure [46] for each of the proxies in order to detect (and remove) extreme observations.

Table 1. Descriptive statistics of variables used for the initial sample of 86 cryptocurrencies.

	Gross Return	SD	CVaR	ILLIQ	Zerovol
Panel A: First sub-period before the launch of Bitcoin futures					
Mean	1.0223	0.1799	0.2329	0.0014	0.0066
Median	1.0163	0.1320	0.1966	0.0000	0.0000
Standard Deviation	0.0210	0.1802	0.1062	0.0051	0.0271
Kurtosis	15.1467	27.9163	2.7805	23.8358	24.2520
Asymmetry	3.6192	4.7189	1.7711	4.7080	4.8666
Min	1.0012	0.0450	0.1035	0.0000	0.0000
Max	1.1377	1.4229	0.6027	0.0342	0.1737
Panel B: Second sub-period after the launch of Bitcoin futures					
Mean	1.0010	0.1290	0.2120	0.0010	0.0080
Median	0.9970	0.0850	0.1890	0.0000	0.0000
Standard Deviation	0.0190	0.1740	0.0840	0.0060	0.0280
Kurtosis	45.8410	50.2900	8.2490	66.0960	32.2040
Asymmetry	6.2210	6.6460	2.2890	7.8060	5.2880
Min	0.9910	0.0300	0.0500	0.0000	0.0000
Max	1.1480	1.5230	0.6460	0.0500	0.2070

After detecting and removing extreme observations, ILLIQ variable was the one that caused the greatest number of cryptocurrencies removals. Table 2 reports descriptive statistics for the cross-section of the final cryptocurrency sample after adjusting the sample size because of these outliers. Note that all the virtual currencies in the final sample traded at least 1 day in the periods under study, consequently Zerovol did not show variability. Therefore, we excluded this variable as an input in the analysis. The cryptocurrency final sample was made up of 43 currencies. This implies that 50% of the cryptocurrencies in the initial sample failed to provide enough liquidity, thus they could not be used as means of exchange.

Table 2. Descriptive statistics of variables used for the cryptocurrency final sample after outlier detection and removal. The final sample is made up of 43 currencies.

	Gross Return	SD	CVaR	ILLIQ	Zerovol
Panel A: First sub-period before the launch of Bitcoin futures					
Mean	1.0147	0.1107	0.1730	0.0000	0.0000
Median	1.0135	0.1060	0.1735	0.0000	0.0000
Standard Deviation	0.0051	0.0345	0.0265	0.0000	0.0000
Kurtosis	2.3971	10.1619	0.5257	5.0867	–
Asymmetry	1.3718	2.3628	−0.1273	2.3430	–
Min	1.0070	0.0450	0.1035	0.0000	0.0000
Max	1.0313	0.2694	0.2372	0.0000	0.0000
Panel B: Second sub-period after the launch of Bitcoin futures					
Mean	0.9959	0.0778	0.1708	0.0000	0.0000
Median	0.9956	0.0778	0.1722	0.0000	0.0000
Standard Deviation	0.0027	0.0151	0.0294	0.0000	0.0000
Kurtosis	0.9023	2.7633	1.2091	6.8919	–
Asymmetry	0.5675	0.8059	−0.0023	2.6496	–
Min	0.9908	0.0422	0.0984	0.0000	0.0000
Max	1.0038	0.1292	0.2580	0.0000	0.0000

3. Methodology

3.1. Measuring Efficiency Changes through the Malmquist Index

The Malmquist index, pioneered by Caves et al. [47] and developed further by Färe et al. [48] relies on distance functions. In particular, the output orientation Malmquist indices were used in this study.

To measure efficiency change between periods t_1 and t_2, consider a generic Decision Making Unit (DMU hereafter) that produces y outputs using x inputs over T time periods. In the DEA approach, a DMU in period t_1 employs input x_{t_1} to produce output y_{t_1}, whereas in period t_2 quantities of input and output are x_{t_2} and y_{t_2}, respectively. In our case, DMUs are the cryptocurrencies, so that in each 11-month period we analyse the return (output) achieved given a risk level (input) for every CC, that is, the change in CCs risk-return trade-off frontier.

Accordingly in the DEA method the production-possibilities set at period t is:

$$S_t = \{(x, y) \mid x \; can \; produce \; y \; at \; period \; t\}, \tag{3}$$

where x is an input vector, $x \in \mathbb{R}_+^n$ and y is an output vector, $y \in \mathbb{R}_+^m$ at period t. This can be described in terms of its sections. For example:

$$y_{t_2}(x_{it_1}) = \{y \in \mathbb{R}_+^m \mid (x, y) \in S_t\} \tag{4}$$

is its corresponding output feasibility set. Based on Shephard [49], the output distance function for a generic CC at period t_1 is:

$$D_{t_1}(x_{t_1}, y_{t_1}) = D_{t_1|t_1} = inf\{\theta \in \mathbb{R}{:}(x_{t_1}, y_{t_1}/\theta) \in S_{t_1}\} = \left(sup\left\{\theta \in \mathbb{R}{:}\left(x_{t_1}, \theta y_{t_1}\right) \in S_{t_1}\right\}\right)^{-1}, \tag{5}$$

where (x_{t_1}, y_{t_1}) is the vector in $\mathbb{R}_+^{n+m}$ made up of the generic CC inputs (risk measures) and outputs (gross return), and the quotient (product) in the vector $y_{t_1}/\theta\left(\theta y_{t_1}\right)$ is defined in relation to all its components. The same applies to $D_{t_2}(x_{t_2}, y_{t_2})$. Equation (5) refers to the output distance function, being the inverse of the Farrell [50] output-oriented measure of technical efficiency. Note that $D_t(x_t, y_t) \leq 1$ as long as $(x_t, y_t) \in S_t$, which holds for both t_1 and t_2.

Two additional distance functions are needed to be defined in order to compute the Malmquist index. Thus, distance in Equation (6) and distance in Equation (7) measure the maximum proportional change in outputs required to make (x_{t_2}, y_{t_2}) feasible in relation to the technology at t_1 and (x_{t_1}, y_{t_1}) feasible in relation to the technology at t_2, respectively.

$$D_{t_1}(x_{t_2}, y_{t_2}) = D_{t_1|t_2} = inf\{\theta \in \mathbb{R}{:}(x_{t_2}, y_{t_2}/\theta) \in S_{t_1}\} \tag{6}$$

$$D_{t_2}(x_{t_1}, y_{t_1}) = D_{t_2|t_1} = inf\{\theta \in \mathbb{R}{:}(x_{t_1}, y_{t_1}/\theta) \in S_{t_2}\} \tag{7}$$

Following Caves et al. [47], the Malmquist index between periods t_1 and t_2 ($t_1 < t_2$) can be defined as:

$$M_i(t_1, t_2) = \sqrt{\left(\frac{D_{it_1|t_2}}{D_{it_1|t_1}}\right)\left(\frac{D_{it_2|t_2}}{D_{it_2|t_1}}\right)} \tag{8}$$

which is the geometric mean of the output-based Malmquist indices for periods t_1 and t_2. If $M > 1$, there has been positive total factor change between periods t_1 and t_2. If $M < 1$, there have been negative changes in the total factor. $M = 1$ indicates no change.

As the possibility set S_t is never observed (Simar and Wilson [29]) all distances defined above are unobserved. Hence, the Malmquist index, Equation (8), is estimated with the nonparametric DEA method that uses linear programming to construct a piecewise frontier that envelops all data points (Charnes et al. [51]). DEA method avoids misspecification errors and allows investigating a multi-output, multi-input case simultaneously. Therefore, we considered the following linear programming model for cryptocurrency i ($i = 1, \ldots, L$):

$$\begin{aligned}
\left[\hat{D}_{it_1|t_1}\right]^{-1} &= \max\theta \; s.t. \\
\theta y_{imt_1} &\leq \sum_{j=1}^{L} \lambda_{jt_1} y_{mjt_1}, m = 1, \ldots, M \\
\sum_{j=1}^{L} \lambda_{jt_1} x_{jnt_1} &\leq x_{int_1}, n = 1, \ldots, N \\
\lambda_{it_1} &\geq 0, i = 1, \ldots, L
\end{aligned} \tag{9}$$

where $\lambda_{t_1} = \left(\lambda_{1t_1}, \ldots, \lambda_{Lt_1}\right)'$ is a vector of weights, which represent the weighting of each analyzed cryptocurrency in the composition of the efficient frontier. Linear programming model, Equation (9), calculates the distances $\hat{D}_{it_1|t_1}$, i.e., $\hat{D}_{it_1}\left(x_{it_1}, y_{it_1}\right)$. Substituting t_1 with t_2 in Equation (9), $\hat{D}_{it_2|t_2}$ is computed.

We estimated the mixed-period cases (Equations (6) and (7)) with two additional linear programming models. Thus, for each *i* cryptocurrency we compute the model from Equation (10).

$$\begin{aligned}
\left[\hat{D}_{it_1|t_2}\right]^{-1} &= \max\theta \; s.t. \\
\theta y_{imt_2} &\leq \sum_{j=1}^{L} \lambda_{jt_1} y_{mjt_1}, m = 1, \ldots, M \\
\sum_{j=1}^{L} \lambda_{jt_1} x_{jnt_1} &\leq x_{int_2}, n = 1, \ldots, N \\
\lambda_{it_1} &\geq 0, i = 1, \ldots, L
\end{aligned} \tag{10}$$

Thus, the reference to which $\left(x_{it_2}, y_{it_2}\right)$ is evaluated is constructed from observations in t_1. As in the model from Equation (9), $\hat{D}_{it_2|t_1}$ is computed reversing t_1 and t_2 in Equation (10). In this research we considered the Malmquist index in terms of constant-returns-to-scale (CRS) distance functions. An interesting feature of CRS is that results are invariable; the linear programming models are solved under either the input- or output-oriented approaches.

Finally, in terms of interpretation, $\hat{D}_{it|t} = 1$ indicates that *i*th cryptocurrency lies on the boundary of the virtual currency set of period *t* and is, therefore, efficient. The other cryptocurrencies with scores below unity ($\hat{D}_{it|t} < 1$) will be inefficient, achieving less output (return) at given input levels (risk).

3.2. *Constructing Confidence Intervals for the Malmquist Index*

In order to estimate the Malmquist index from the linear programming model for every cryptocurrency, Equation (10), we computed changes in the economic efficiency of the cryptocurrency market after the launch of Bitcoin futures, in December 2017. However, given our main aim, this information was not enough. We needed to know if those changes (if any) were statistically significant (or not). Therefore, we needed to construct confidence intervals at desired levels of significance. To do this, we used the bootstrapping method, which allowed us to resolve one important problem of DEA methodology. In particular, the shortcoming of DEA is that the results may be affected by sampling variation in the sense that distances to the frontier are underestimated if the best performers in the population are not included in the sample. To account for this, Simar and Wilson [26,29] proposed a bootstrapping method, allowing the construction of confidence intervals for DEA efficiency scores, which relies on smoothing the empirical distribution. The rationale behind bootstrapping is to simulate a true sampling distribution by mimicking a data-generating process, here the outputs from DEA. The procedure relies on constructing a pseudo data set and re-estimating the DEA model with this new data set. Repeating the process many times allows to achieve a good approximation of the true distribution of the sampling. At any rate, Simar and Wilson [52] highlighted that the biggest problem when bootstrapping in frontier models is that of consistently mimicking the data-generating process. The main reason underlying this problem is that distance estimation values are close to unity. As a result, resampling directly from the original data (naive bootstrap) will provide an inconsistent bootstrap estimation of the confidence intervals. To overcome this problem, Simar and Wilson [29,52] proposed a smoothed bootstrap procedure adapted from a univariate reflection method by Silverman [53]. This method is founded on the idea of "reflecting" the probability mass lying beyond unity where, in theory, no probability mass should exist.

Simar and Wilson [29] adapted the procedure to the case of Malmquist index derived using DEA in order to account for possible temporal correlation arising from the panel data characteristic. They proposed a consistent method using a bivariate kernel density estimate that accounts for the temporal correlation via the covariance matrix of data from adjacent years. The set of bootstrap Malmquist indices provided by this procedure allows to account for the bias and to construct confidence intervals. On the whole, this process can be summarized as follows:

1. Calculate the Malmquist index $\hat{M}_i(t_1, t_2)$ for each DMU i = 1, …, L, by solving the DEA programming models.
2. Compute a pseudo data set $\{(x^*_{it}, y^*_{it}); i = 1, \ldots, L; t = 1, 2\}$ to form the reference bootstrap technology using bivariate kernel density estimation and the adaptation of the reflection method proposed by Simar and Wilson [29].
3. Compute the bootstrap estimate of the Malmquist index for each DMU, $\hat{M}^*_{ib}(t_1, t_2)$, by applying the original estimators to the pseudo sample obtained in step 2.
4. Repeat steps 2–3 a large number of times (B) in order to provide a set of estimates $\{\hat{M}^*_{i1}(t_1, t_2), \ldots, \hat{M}^*_{iB}(t_1, t_2)\}$. Simar and Wilson [26] recommend a value of B = 2000.
5. Construct the confidence intervals for the Malmquist indices.

With the information provided in step 5, it is possible to observe whether growth (or decline) measured by the Malmquist index is significant, i.e., it is greater than (or less than) unity at the desired significance levels.

4. Results

Table 3 shows the results obtained from the 43 optimization programmes (one per cryptocurrency) in Equation (9), where the distances $\widehat{D}_{it_1|t_1}$, i.e., $\widehat{D}_{it_1}(x_{it_1}, y_{it_1})$, correspond to the pre-launch period and $\widehat{D}_{it_2|t_2}$, i.e., $\widehat{D}_{it_2}(x_{it_2}, y_{it_2})$, correspond to the post-launch period. When all the proxy measures to risk (standard deviation (SD), Expected Shortfall (CVaR) and Amihud's illiquidity ratio (ILLIQ)) were employed as inputs, we found that only 1 out of 43 cryptocurrencies was efficient in the post-launch period, i.e., Bitcoin was the only cryptocurrency that exhibited an efficiency score equal to 1. Therefore, Bitcoin formed the best practice frontier since we obtained the highest remuneration (return) given its level of risk, compared to the rest of cryptocurrencies.

As Bitcoin stood out for being a highly liquid cryptocurrency, we reran the above estimations but excluding our proxy for the illiquidity (the Amihud's illiquidity ratio) in order to remove any possible bias in the results. We observed the same outcome, thus, Bitcoin forms the best practice frontier.

In the post–launch period, we found that 2 out of 43 cryptocurrencies were efficient regardless of the risk proxies we employed as inputs, since Bitcoin and Unobtanium obtained efficiency scores equal to 1. This is an interesting result, as both cryptocurrencies exhibited the highest remuneration to their risk level compared to the other cryptocurrencies in our sample.

Table 3. DEA output oriented efficiency scores for cryptocurrencies.

	All Inputs		SD-CVaR Inputs			All Inputs		SD-CVaR Inputs	
Cryptocurrency	**Pre**	**Post**	**Pre**	**Post**	**Cryptocurrency**	**Pre**	**Post**	**Pre**	**Post**
Bitcoin	1	1	1	1	MaidSafeCoin	0.7289	0.6687	0.7289	0.6586
BitShares	0.5423	0.6553	0.5423	0.6371	MonaCoin	0.6675	0.6810	0.6675	0.6448
Blackcoin	0.5846	0.6536	0.5846	0.6186	Monero	0.6276	0.7889	0.6276	0.7627
Burst	0.6222	0.6249	0.6222	0.5995	Nav-Coin	0.6109	0.6731	0.6109	0.6388
Clams	0.5521	0.6654	0.5521	0.6654	NEM	0.6916	0.8059	0.6916	0.7397
CloakCoin	0.4463	0.6080	0.4463	0.5819	Nexus	0.5930	0.6034	0.5930	0.5354
Counterparty	0.5844	0.6101	0.5844	0.6000	Novacoin	0.6370	0.4097	0.6370	0.4097
Dash	0.7853	0.8369	0.7853	0.8086	Nxt	0.6381	0.7595	0.6381	0.7279
DigiByte	0.5783	0.7144	0.5783	0.6696	Omni	0.5709	0.5949	0.5709	0.5949
DogeCoin	0.5424	0.7617	0.5424	0.7059	Peercoin	0.7374	0.5264	0.7374	0.5191
Einsteinium	0.4924	0.6360	0.4924	0.6089	PotCoin	0.6846	0.6028	0.6846	0.6028
Emercoin	0.5993	0.6349	0.5993	0.6051	Primecoin	0.5249	0.5797	0.5249	0.5325
Ethereum	0.8619	0.8694	0.8619	0.8459	Ripples	0.7083	0.7327	0.7083	0.7007
Expanse	0.6175	0.6474	0.6175	0.6276	Siacoin	0.6503	0.6839	0.6503	0.6134
Factom	0.5720	0.5737	0.5720	0.5594	Stellar	0.5321	0.7706	0.5321	0.7124
Feathercoin	0.5260	0.5774	0.5260	0.5694	Synereo	0.6367	0.5740	0.6367	0.5715
FoldingCoin	0.6466	0.5513	0.6466	0.5513	SysCoin	0.5353	0.5967	0.5353	0.5668
GameCredits	0.5984	0.6288	0.5984	0.6190	Unobtanium	0.5277	1	0.5277	1
GoldCoin	0.5859	0.5452	0.5859	0.5452	Vericoin	0.4669	0.5375	0.4669	0.5081
Gridcoin	0.5690	0.5541	0.5690	0.5541	Vertcoin	0.5279	0.6069	0.5279	0.5859
Gulden	0.6818	0.7990	0.6818	0.7807	Viacoin	0.5086	0.6914	0.5086	0.6651
Litecoin	0.7389	0.9513	0.7389	0.8999					

In order to shed more light on the efficient (and inefficient) performance of the cryptocurrencies, we computed the market remuneration (return) for unit of risk (measured through our three proxies) for the pre– and post–launch periods, i.e., the ratio output to input (see Table 4). On the one hand, we observed that Bitcoin obtained the maximum ratio in the pre–launch period independent of the risk proxy used. On the other hand, in the post–launch period, we observed that Unobtanium showed the maximum ratio for CVaR, while Bitcoin still obtained the maximum remuneration per unit of risk when measuring by the standard deviation and the Amihud's illiquidity ratio.

Though revealing, Table 3 just shows a static picture of economic efficiency (that is, their risk-return trade-off) of our sample of the cryptocurrencies in the pre– and post–launch periods. Consequently, as the efficiency obtained from DEA is a relative efficiency score as compared to other cryptocurrencies, the fact that Bitcoin was efficient in the pre– and post–launch periods did not provide us with much information on the impact of the introduction of the futures market. Given this fact, we computed changes in the economic efficiency of the cryptocurrency market by estimating the Malmquist index from the linear programming model for every cryptocurrency, Equation (10). As stated before, the bootstrap method allowed us to construct confidence intervals at desired levels of significance.

Table 5 exhibits changes in efficiency measured through the Malmquist index and their statistical significance. Table 6 summarizes the results from Table 5. Around the 80% of the cryptocurrencies in our sample experienced a significant change in their risk-return trade-off from 2017 to 2018 regardless of the risk proxies used (34–35 out of 43). According to Table 6, the market paid a significantly higher return for unit of risk in 2018 compared to 2017 for 16 out of 43 cryptocurrencies (37%) and a significantly lower return for unit of risk in 2018 compared to 2017 for 19 out of 43 cryptocurrencies (42%). These results were quite similar when we excluded the illiquidity risk measure as an input (44% and 37%, respectively). Therefore, the introduction of the futures on Bitcoin did not seem to have had a wide effect on the cryptocurrency market.

Table 4. Ratio Gross Return/input for cryptocurrencies.

	Pre-Launch Period			Post-Launch Period		
Cryptocurrency	**SD**	**CVaR**	**ILLIQ**	**SD**	**CVaR**	**ILLIQ**
Bitcoin	22.41	9.74	1.98×10^{10}	23.62	8.81	2.17×10^{11}
BitShares	9.05	5.28	1.35×10^{7}	13.75	5.78	2.57×10^{8}
Blackcoin	8.94	5.70	2.53×10^{6}	12.14	5.80	3.19×10^{6}
Burst	9.70	6.06	1.16×10^{6}	12.20	5.55	2.90×10^{6}
Clams	10.55	5.38	1.39×10^{6}	13.75	6.12	4.83×10^{5}
CloakCoin	3.83	4.35	6.60×10^{4}	11.91	5.37	7.59×10^{6}
Counterparty	8.91	5.69	1.97×10^{6}	12.73	5.47	1.11×10^{6}
Dash	12.63	7.65	2.58×10^{8}	17.12	7.38	2.88×10^{9}
DigiByte	5.96	5.63	1.78×10^{6}	13.02	6.30	6.42×10^{7}
DogeCoin	11.42	5.28	2.23×10^{7}	13.33	6.71	2.71×10^{8}
Einsteinium	6.26	4.80	2.72×10^{5}	12.51	5.61	1.48×10^{7}
Emercoin	9.09	5.84	2.22×10^{6}	12.27	5.60	1.37×10^{7}
Ethereum	13.96	8.40	2.46×10^{9}	18.29	7.66	5.60×10^{10}
Expanse	10.10	6.02	1.54×10^{6}	12.61	5.83	9.33×10^{5}
Factom	11.90	5.57	3.05×10^{7}	12.08	5.07	6.80×10^{6}
Feathercoin	8.38	5.12	2.62×10^{5}	12.22	5.17	1.13×10^{6}
FoldingCoin	9.65	6.30	4.86×10^{5}	12.45	4.93	2.89×10^{5}
GameCredits	10.24	5.83	1.08×10^{7}	13.70	5.56	4.75×10^{6}
GoldCoin	8.90	5.71	9.17×10^{4}	10.64	5.12	1.30×10^{5}
Gridcoin	9.54	5.54	2.22×10^{5}	12.49	4.95	1.93×10^{5}
Gulden	9.54	6.64	9.45×10^{5}	16.56	7.12	2.36×10^{6}
Litecoin	12.77	7.20	1.24×10^{9}	17.94	8.38	1.07×10^{10}
MaidSafeCoin	14.87	7.10	2.47×10^{7}	14.76	5.90	3.06×10^{7}
MonaCoin	7.40	6.50	1.05×10^{5}	12.87	6.01	3.52×10^{7}
Monero	12.97	6.12	2.71×10^{8}	16.18	6.95	9.47×10^{8}
Nav-Coin	8.11	5.95	2.47×10^{6}	12.77	5.95	9.76×10^{6}
NEM	10.93	6.74	1.49×10^{7}	13.64	7.10	4.33×10^{8}
Nexus	9.64	5.78	7.82×10^{5}	9.11	5.32	1.71×10^{7}
Novacoin	9.00	6.21	4.56×10^{5}	7.77	3.89	1.09×10^{5}
Nxt	10.46	6.22	9.30×10^{6}	15.04	6.70	5.28×10^{7}
Omni	7.95	5.56	1.57×10^{5}	12.77	5.40	2.45×10^{5}
Peercoin	12.48	7.18	4.64×10^{6}	11.65	4.65	9.82×10^{6}
PotCoin	11.05	6.67	3.59×10^{6}	12.95	5.47	6.28×10^{5}
Primecoin	9.74	5.11	7.58×10^{5}	9.70	5.14	3.12×10^{6}
Ripples	7.63	6.90	4.30×10^{5}	14.40	6.46	1.20×10^{10}
Siacoin	9.26	6.34	7.11×10^{6}	10.71	6.03	1.33×10^{8}
Stellar	7.34	5.18	1.42×10^{7}	13.37	6.79	1.56×10^{9}
Synereo	10.40	6.20	2.54×10^{6}	12.67	5.14	1.20×10^{6}
SysCoin	9.40	5.22	3.35×10^{6}	11.39	5.27	1.46×10^{7}
Unobtanium	9.01	5.14	7.82×10^{4}	16.24	10.16	2.32×10^{5}
Vericoin	7.59	4.55	1.98×10^{5}	9.91	4.77	2.29×10^{6}
Vertcoin	7.65	5.14	8.12×10^{5}	12.33	5.36	1.36×10^{7}
Viacoin	8.92	4.96	3.79×10^{5}	13.82	6.11	1.03×10^{7}

Table 5. Changes in efficiency measured through the Malmquist index: pre vs post futures launch periods. ***/** denotes significance at the 1%/5%/ level.

Cryptocurrency	All Inputs	SD-CVaR Inputs	Cryptocurrency	All Inputs	SD-CVaR Inputs
Bitcoin	3.1450 ***	0.9945 **	MaidSafeCoin	0.8664 ***	0.8862 ***
BitShares	1.1126 **	1.1643 ***	MonaCoin	0.9915	0.9647 ***
Blackcoin	1.0186	1.0600 ***	Monero	1.1435 ***	1.1573 ***
Burst	0.9200 ***	0.9586 ***	Nav-Coin	1.0021	1.0439
Clams	1.1215 ***	1.1591 ***	NEM	1.0551	1.0820 ***
CloakCoin	1.3249 ***	1.2963 ***	Nexus	0.9329 ***	0.9251 ***
Counterparty	0.9628 ***	1.0202	Novacoin	0.6181 ***	0.6486 ***
Dash	0.9684 ***	1.0168	Nxt	1.0782 **	1.1227 ***
DigiByte	1.1240 ***	1.1622 ***	Omni	1.0283	1.0418
DogeCoin	1.2710 ***	1.2558 ***	Peercoin	0.6764 ***	0.7099 ***
Einsteinium	1.2048 ***	1.2286 ***	PotCoin	0.8228 ***	0.8755 ***
Emercoin	0.9634 ***	1.0054	Primecoin	1.0138	1.0036 ***
Ethereum	1.7295 ***	0.9782 ***	Ripples	0.9616 ***	0.9827 **
Expanse	0.9653 ***	1.0055	Siacoin	0.9530 ***	0.9677 ***
Factom	0.9249 ***	0.9390 ***	Stellar	1.3110 ***	1.3527 ***
Feathercoin	1.0488	1.0781 ***	Synereo	0.8547 ***	0.9049 ***
FoldingCoin	0.8321 ***	0.8740 ***	SysCoin	1.0119	1.0364
GameCredits	0.9865 ***	1.0344	Unobtanium	1.9483 ***	1.9483 ***
GoldCoin	0.9333 ***	0.9333 ***	Vericoin	1.0862 ***	1.0835 ***
Gridcoin	0.9684 ***	0.9856 **	Vertcoin	1.0526	1.0986 ***
Gulden	1.0850 ***	1.1378 ***	Viacoin	1.2589 ***	1.2724 ***
Litecoin	1.1646 ***	1.1964 ***			

Table 6. Summary of efficiency changes measured through the Malmquist index (see Table 5).

		All Inputs	SD-CVaR Inputs
Sample Size		43	43
Significant Changes		34	35
	over sample size	79.07%	81.40%
Significant increases		16	19
	over significant changes	47.06%	54.29%
	over sample size	37.21%	44.19%
Significant decreases		18	16
	over significant changes	52.94%	45.71%
	over sample size	41.86%	37.21%

When we focused on Bitcoin, some interesting results arose. Table 5 shows that Bitcoin obtained the largest and significant increase in its risk-return trade-off if all the risk proxies were taken into account, giving rise to a Malmquist index value equal to 3.145. Unobtanium obtained the second highest and most significant increase in our sample with a Malmquist index value of 1.948. Therefore, it seems that the introduction of the futures market did have a (significant) strong impact on Bitcoin's risk-return trade-off, improving it. It is interesting to highlight that, when we excluded the illiquidity risk measure as an input, Bitcoin's Malmquist index value turned from greater than 1 (3.145) to less than 1 (0.9945), both changes being statistically significant. In other words, instead of a significant increase in its risk–return trade-off when all the variables were taken into account, we found a significant decrease in its risk–return trade-off. This result gives support to the notion of a mix result for the introduction of the futures market in December 2017. On the one hand, the futures market gave rise to a crashed down of Bitcoin prices, as its value decreased more than 80% in 2018 (from its peak around $19,800 in December 2017 to a value around $3,700 at the end of 2018). Therefore, if one exclusively focused on the risk related to the distribution of returns, the obvious conclusion seems to be that the market penalized Bitcoin relative to the rest of cryptocurrencies in our sample. However, our analysis also showed that, when taking into account liquidity (i.e., the illiquidity risk), the introduction of Bitcoin's futures market boosted its risk–return trade-off in relation to the the rest of cryptocurrencies. This result supports the use of Bitcoin as a mean of exchange, instead of an asset, since the introduction of futures market brought it closer to the forex market in terms of liquidity.

5. Conclusions

The introduction of the futures market on Bitcoin in December 2017 put an end to a year in which its value increased more than 1000 percent until its peak around $19,800. However, the following year, its value decreased more than 80% (around $3700 at the end of 2018). In this research, we study the consequences of the introduction of trading futures on Bitcoin from the perspective of the economic efficiency. Unlike informational efficiency, with the economic efficiency of the cryptocurrency market we seek to measure how efficient the market is in relation to the risk-return trade-off, that is, how the market pays for unit of risk. We employ the Malmquist index using distance measures relative to Data Envelopment Analysis (DEA) frontiers in order to estimate changes in economic efficiency and its statistically significance through the bootstrap technique. Our final sample is made up of 43 currencies after removing the 50% of the cryptocurrencies from the initial sample as they failed to provide enough liquidity and, thus, they cannot be used as means of exchange. Our results show that the introduction of the futures on Bitcoin does not seem to have had a wide effect on our sample of cryptocurrencies as we find similar percentages of significant increases and decreases of risk-return trade-off changes. However, when we focus on Bitcoin, our results suggest that the introduction of Bitcoin's futures market boosted its risk-return trade-off, relative to the rest of cryptocurrencies, given its high liquidity. This outcome supports the view of Bitcoin as a mean of exchange instead of an asset, compared to the rest of the cryptocurrency market.

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Abbreviations

CME	Chicago Board Options Exchange
CBOE	Chicago Board Options Exchange
CVaR	Conditional Value at Risk (Expected Shortfall)
DEA	Data Envelopment Analysis
DMU	Decision Making Units
SD	Standard Desviation
VaR	Value at Risk

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