RESEARCH ARTICLE

Financial Market Efficiency: Equity Versus Cryptocurrency Before and After Covid-19 Pandemic

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Abstract

The Covid-19 pandemic outbreak may generate differential impacts on global financial markets causing some markets to be more efficient than the others. This paper employs Hurst Exponent as a methodology for measuring financial market efficiency. The literature focused largely on the equity markets such as the stock markets. There is a paucity of studies on the evolving cryptocurrency markets such as Bitcoins and Ethereum. There is also a paucity of studies examining how asset market efficiencies are influenced by the pandemic. We therefore develop testable efficiency market hypotheses for both equities and cryptocurrencies against the backdrop of a global pandemic. We also provide a new perspective in addition to those in the literature for explaining our empirical findings. Our results show that the efficiency levels of the cryptocurrency markets are lower than the stock markets, and the efficiency levels for the cryptocurrency and stock markets decline after the onset of the covid-19 pandemic.

Key Words: *Efficient market; Cryptocurrency; Equity; Theoretical model; Empirical test; Covid-19 pandemic*

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1. Introduction

Various financial assets show unusual price movements during the Covid-19 pandemic (hereafter pandemic). This phenomenon raises a new concern on the traditional concept of market efficiency. This paper first tests and compares the efficiencies of the stock markets and the cryptocurrency markets. In contrast to stocks, there is a paucity of theoretical and empirical studies of market efficiency on cryptocurrency. There is also a paucity of studies on how the pandemic affects the efficiency levels of financial assets. This paper bridges the gaps in the literature [1, 2]. It provides an original analysis of how efficiencies of the equity and cryptocurrency markets are influenced by the pandemic. The equity market is represented by the stock market while the cryptocurrency market is represented by Bitcoin and Ethereum. Prior to conducting the empirical studies on the market efficiencies of these markets, we provide a theoretical review of the literature (on cryptocurrency market efficiency) and a new perspective which may be used to explain for the changes in market efficiencies generated by the pandemic. Our study has practical implications for investments in these types of financial assets/securities.

Empirical tests of market efficiency are often classified into three broad categories. First, weak-form tests of efficient market models focus on the information subset, which is just historical price or return sequences, including tests of return predictability. Second, strong-form tests of efficient markets models are concerned with whether current prices "fully reflect" all publicly available information. Third, strong-form tests of efficient markets model are concerned with whether all available information is fully reflected in prices in the sense that no individual has higher expected trading profits than the others by dint of his or her monopolistic access to some information, including private information. Our paper is developed along these market efficiency concepts. However, there is a potential deviation from the above concepts due to peculiar price movements and information flows caused by the pandemic. We therefore embellish the above market efficiency concept in this paper.

For our empirical analysis, we first use the daily close prices of Bitcoin, Ethereum, S&P 500, and CSI 300 from Oct 1, 2018 to Dec 31, 2019, representing the price changes before the onset of the pandemic. We then compare these results (before the pandemic with the daily close prices of Bitcoin, Ethereum, S&P 500, and CSI 300 from Jan 1, 2020 to Mar 31, 2021, representing the price movements after the pandemic outbreak. To compare how the market efficient levels change before and after the pandemic, we use Hurst Exponent as the instrument for the measurement.

Efficiencies of the cryptocurrency and the stock markets may be attributed to the following reasons: (a) investors are not fully rational and have strong cognitive biases; markets have restrictions on short-selling and arbitrage; (b) existence of transaction costs and costs of information gathering; (c) market participants have disagreements on the current prices and also on the distribution of the future price for each asset; and (d) the possibility that the prediction of future price movement is less accurate than the prediction of future cash flow. There is a large literature explaining the first three reasons. Our contribution in this paper is due to the fourth reason, which we think is more aptly targeted at analyzing the difference in efficiency between cryptocurrency and stock markets and the difference in efficiency before and after a pandemic.

Cryptocurrencies are more restricted on short-selling and arbitrage than stocks. Cryptocurrencies have higher transaction costs than stocks. Since cryptocurrencies have no information on the future cash flow generated, any investment of a cryptocurrency would be based on prediction of its future price movement, which is a lot more difficult than prediction of future cash flow (available more readily in the stock market). In view of these observations, we propose two hypotheses as follows:

(a) The inefficiency level of cryptocurrency markets will be higher than stock markets. (b) The inefficiency level of cryptocurrency markets and stock markets will increase during the pandemic. The results of our empirical tests appear to corroborate with our two hypotheses above.
Our paper provides an alternative perspective for understanding (a) the differences in market efficiencies between the stock and the cryptocurrency markets and (b) changes in market efficiencies of the assets before and after the pandemic. For the financial market investments, the interactions between investors in real life are complicated, and hence the conditions of market efficiency proposed by Fama are often violated. Our paper also explains how investors may think about the asset payoffs based on conditional information.

2. Literature Review

2.1. Efficient market hypothesis

Efficient Market Hypothesis (EMH) is a milestone of contemporary finance theory. The development of financial theory based on EMH with the debate around it became a most popular theme in the 1970s . In 1900s, a French mathematician, Louis Bachelier, published his thesis, *Theorie de la Speculation* [3], which explained price movements of stocks as a random process. However, the paper was ignored for half a century but rediscovered in the 1950s by Leonard Savage. [4] had begun to circulate [3]'s work among economists around 1960s and published a proof in 1973 showing that properly anticipated prices fluctuate randomly. [2, 5-6, 4] provide clear reviews on historical developments of EMH.

[7] Defined an "efficient" market for the first time in his seminal empirical analysis of stock market prices and concluded that they followed a random walk. [8] explained how the theory of random walks in stock market prices presents important challenges to the proponents of both technical and empirical analyses. Given the different information set, [9] proposed a three-level market efficiency. The first level is called the weak-form efficient market that can reflect all information contained in historical prices. The second level is called the semi-strong-form efficient market that can reflect all information which is publicly available. The third level is called the strong-form efficient market that reflect all public including private information. Empirical test of weak-form efficient market can be approximately classified into statistical tests of "random walk model". If the coefficients of information variables used to forecast future returns are not significantly different from zero, one concludes the market is efficient [10].

Shiller showed that stock prices move too much to be justified by subsequent changes in dividends and raise considerable doubt on efficient markets model in 1981 [11-12]. In 1985, [13] discovered that stock prices tend to overreact, pointing to the evidence of weak-form market inefficiencies. 14] wrote a sequel called "Efficient Capital Markets II" in 1991. He reviewed the empirical findings along the three levels of efficient markets. [15] found that "the random walk model is rejected for the entire sample period (1962–1985) for a variety of aggregate returns indexes and size-sorted portfolios". [16] Questioned EMH in 2009 and broke down the hypothesis into two connotations, which are "price is right" and "no free lunch".

There are two major approaches to evaluating the EMH. One is to evaluate its deductive application through empirical evidences. The other one is to evaluate its methodological foundation by logical reasoning [17]. "Price is right" is the central idea of the EMH, which is emphasized in Fama's 1970 seminal paper [9]. The first critique of "price is right" connotation is so natural that even Fama admits it in his 1970 paper and calls it "Joint Hypotheses Problem" [9], which means that if you want to test market efficiency, you must test it jointly with an equilibrium pricing model. Fama persistently uses "Joint Hypotheses Problem" to argue against his critics [see 14, 18]. It does not seem like a theoretical "problem" to him but a theoretical "merit". He argued against the evidences of market inefficiency that other researchers found for the reason that they use a problematic pricing model [14, 10].

The second critique on "price is right" connotation is proposed by behavioural economists [11, 16]. Financial markets are composed by investors and financial instruments. Because various cognitive biases are found in ordinary investors, such as overconfidence, representative bias, and framing effect, financial markets would systematically deviate from efficiency. The third critique on "price is right" connotation is raised by [19] in 1980. Since gathering and processing information is costly, financial markets would never become fully efficient, otherwise investors will become a free rider of information rather than gather and process information to make markets efficient.

Another simple critique is: If the current price accurately equals its expected value and every investor agrees with it, why do investors buy from and sell to each other in the market? If no transaction would occur under the strong-form condition, Efficient Market Hypothesis will become Efficient No-Market Hypothesis. It is quite different from equilibrium market of goods and services, because buyer and seller have enough reason to trade in equilibrium point in order to consume the goods and services. However, if a rational investor wants to buy a unit of financial instrument and another rational investor also want to sell it to him, the valuation of the unit of financial instrument must be different between the two investors assuming they have a same risk-averse level, which is often the assumption in equilibrium pricing model.

Identical valuation and strategy of market participants would form a "seemingly efficient market" that no other valuation and strategy could outperform the overwhelming identical one, because arbitrage against it may lead you to bankruptcy in the short run. This "seemingly efficient market" doesn't necessarily "fully reflect" all available information of future cash flow, yet it looks "efficient".

The price seeking in financial markets is everlasting if we agree there is no such mysterious function that could accurately predict the future like a crystal ball. The impossibility of accurate prediction come from different sources. [17] Re-emphasized the idea of fallibility and reflexivity regarding the philosophy of social science.

Many empirical papers in asset pricing use "hard to beat" phenomenon as a strong evidence that supports the EMH, but the problem is: if we use the return of a so-called naïve "buy-and-hold" strategy as the market return, the hardness to beat the return is not a sufficient condition of market efficiency. Assuming a market only contains one stock; risk-free rate and transaction cost are both zero; the stock price always "fully reflects" all available information of future cash flow:
Case 1: The stock price goes up 1% each day for a month due to genuine news. In this case, the "buy-and-hold" strategy is mathematically the optimal, no strategy could outperform it without leverage.
Case 2: The stock price goes down 1% each day for a month due to genuine news. In this case, the "buy-and-hold" strategy is mathematically the worst, any other strategy could outperform it without leverage.
Case 3: The stock price first goes up 100% in total for half a month and then goes down 50% in total for half a month due to genuine news. In this case, the "buy-and-hold" strategy get 0%, and the above average investors will have a very good chance to choose another strategy (e.g. buy in the

beginning and sell when the price goes down for 10%) within the month outperforming the "buy-and-hold" strategy because of the huge fluctuation.
Case 4: The stock price remains unchanged each day for a month due to no genuine news. In this case, all strategies get a same 0% return and no strategy will outperform any other strategy.

In the four cases above, the easiness or hardness to beat the "buy-and-hold" return is not determined by how efficient the market is, but the mathematical structure of the price movement.

The empirical hardness to beat the "buy-and-hold" return is a representation of high competitiveness of market participants, but high competitiveness of market participants does not necessarily lead to market efficiency. Highly similar strategy and valuation of market participants will lead to the high competitiveness of market, but this highly similar strategy and valuation will not necessarily "fully reflect" all available information of future cash flow.

2.2. Market Efficiency of Cryptocurrency: A Recent Review

There is a paucity of studies on cryptocurrency's efficiency as it is still pretty recent as compared to other forms of financial assets or securities. Past paper showed that cryptocurrencies are much more volatile than other markets [20, 21, 23]. The inefficiency of the Bitcoin market is documented by [24], reporting that this market immediately reacts to the arrival of new information and can therefore be characterised as efficient [10]. [23] analyses correlations in daily closing prices. The above review shows that there is a paucity of research on cryptocurrency's efficiency before and after a pandemic.

[1] Examines the day of the week effect in the cryptocurrency market using a variety of statistical techniques including Average Analysis, Student's t-test, ANOVA, Kruskal–Wallis test, and regression analysis with dummy variables. Their results showed that most cryptocurrencies such as Litecoin, Ripple, and Dash are found not to exhibit this anomaly (the day of the week effect) except Bitcoin for which returns on Mondays are significantly higher than those on the other days of the week, pointing to an exploitable arbitrage profit opportunity in Bitcoin market. However, most of their empirical results are not significantly different from the random ones and therefore should not be seen as conclusive evidence against market efficiency.

[24] represents the most recent paper investigating the effects of cryptocurrencies on market efficiency. They examined the herding biases by quantifying the self-similarity intensity of cryptocurrency returns. Their empirical results showed that covid-19 has a positive general impact on the cryptocurrency's market efficiency. In contrast to their research, our paper focuses specifically and exhaustively on Bitcoin and Ethereum and compares their efficiency levels before and after the covid-19 pandemic. In addition, we provide practical explanations on why market efficiency of cryptocurrency (especially the Bitcoin market) has declined after the pandemic outbreak.

3. Methodology, Theory and Hypotheses

The Hurst Exponent can be calculated by the rescaled range analysis (R/S analysis). For time series $X = X_1, X_2, \dots Xn$, the R/S analysis method is elucidated as follows:

- Calculate mean value m.

$$m = \frac{1}{n}\sum_{i=1}^{n} X_i$$

- Calculate mean adjusted series Y

$$Y_t = X_t - m, \quad t = 1, 2, \ldots, n$$

- Calculate cumulative deviate series Z

$$Z_t = \sum_{i=1}^{t} Y_i, \quad t = 1, 2, \ldots, n$$

- Calculate range series R

$$R_t = max(Z_1, Z_2, \ldots, Z_t) - min(Z_1, Z_2, \ldots, Z_t)$$
$$t = 1, 2, \ldots, n$$

- Calculate standard deviation series S

$$S_t = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(X_i - u)^2} \quad t = 1, 2, \ldots, n$$

Here u is the mean value from X_1 to X_t.

- Calculate rescaled range series (R/S)

$$(R/S)_t = R_t/S_t \quad t = 1, 2, \ldots, n$$

Note that $(R/S)_t$ is averaged over the regions $[X_1, X_t]$, $[X_{t+1}, X_{2t}]$ until $[X_{(m-1)t+1}, X_{mt}]$ where m=floor(n/t). In practice, to use all data for calculation, a value of t is chosen that is divisible by n. Hurst found that (R/S) scales by power-law as time increases, which indicates:

$$(R/S)_t = c*t^H$$

Here c is a constant and H is called the Hurst Exponent. To estimate the Hurst exponent, we plot (R/S) versus t in log-log axes. The slope of the regression line approximates the Hurst Exponent. If the Hurst exponent equals to 0.5, it indicates the time series doesn’t possess property of long-term memory and it is undistinguishable from Brownian motion. Thus, the market is viewed as efficient if Hurst exponent equals to 0.5.

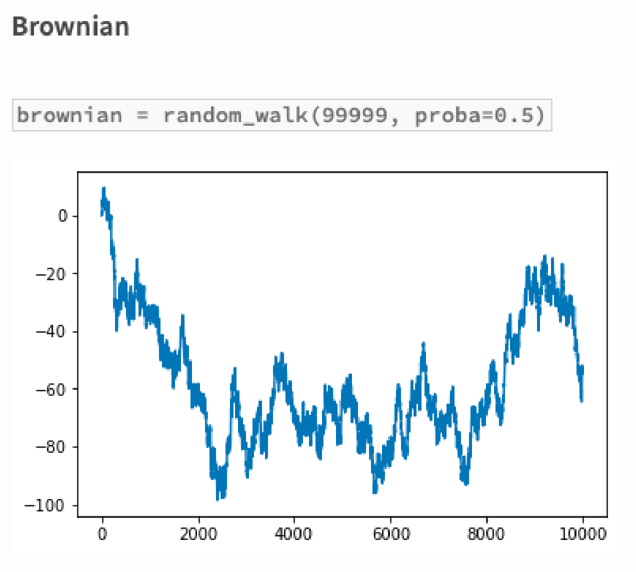

Figure 1: *Illustration of Brownian Motion Time Series.*

Notes: $Hurst = 0.5$. Source: Python 3.9.2

Hurst exponent smaller than 0.5 indicates that the time series possesses property of anti-persistent and is distinguishable from Brownian motion. Thus, the market is viewed as inefficient if Hurst exponent is smaller than 0.5.

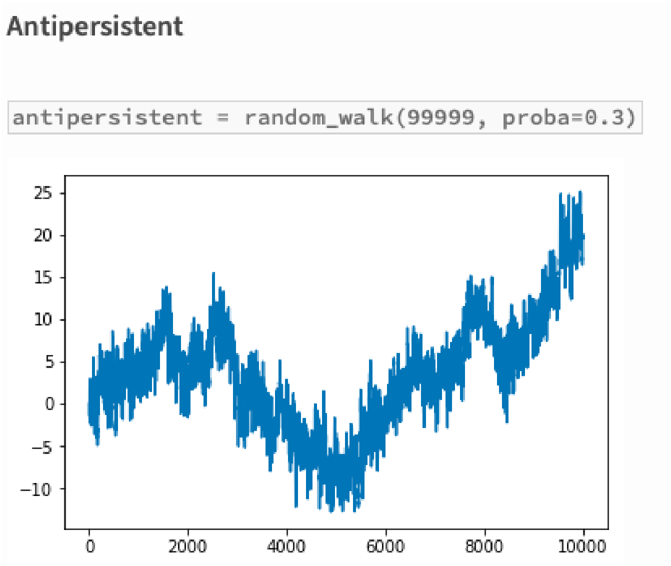

Figure 2: *Illustration of Anti-persistent Time Series***.**

Notes: $Hurst = 0.3$. Source: Python 3.9.2

Hurst exponent bigger than 0.5 indicates that the time series possesses property of persistent and is distinguishable from Brownian motion. Thus, the market is seen as inefficient if Hurst exponent is bigger than 0.5.

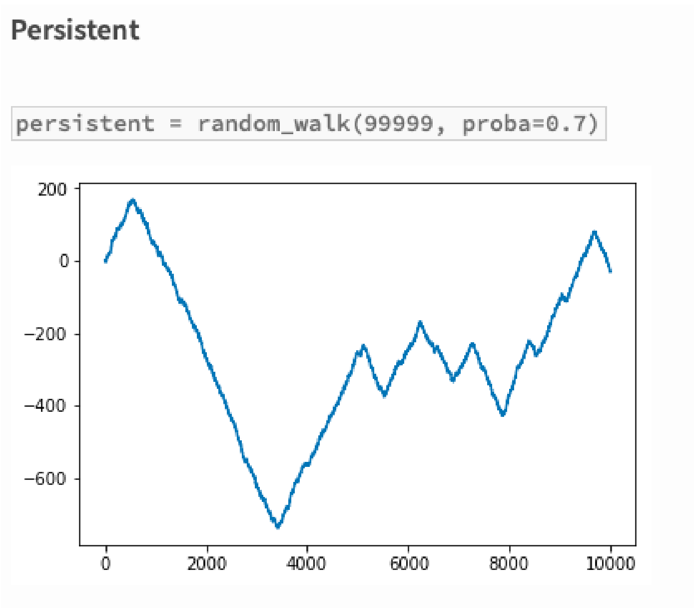

Figure 3: *Illustration of Persistent Time Series.*

Notes: $Hurst = 0.7$. Source: Python 3.9.2

The inefficiency of cryptocurrencies and stock markets may emanate from the following five reasons: (a) Investors are not fully rational and have strong cognitive biases; (b) Markets have restriction on short-selling and arbitrage; (c) Transaction costs and costs of gathering information exist; (d) Market participants have disagreement on the implications of current information for the current price and distributions of future prices of each asset; and (e) Prediction of future price movement is less accurate than prediction of future cash flow. There is a large volume of literature in explaining the first four reasons. However, the fifth reason, despite its paucity, is considered by us to be more appropriate for analysing the difference in (i) inefficiency between cryptocurrency and stock markets and (ii) the change in market efficiency of these assets before and after a pandemic.

In classical microeconomic theory, if a buyer is willing to spend P_{t_0} amount of cash to exchange for a good and a seller accepts, the buyer's utility function values more for the good than P_{t_0} amount of cash and the seller is the opposite. The good may be durable and not be consumed immediately. In this case, the utility calculation of the buyer or seller is a sum of their utility that generated at different time later but discounted back to the time of this transaction. If we assume investors only generate utility from the payoff of an asset, the transaction of goods is analogous to transaction of assets.

Contemporary asset pricing theory shares this idea as well. The following formula appears almost in every asset pricing textbook

$$p_0 = E(m x_1)$$

More specifically, it appears in consumption-based asset pricing model as following:

$$p_t = E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1}\right]$$

Because m and x_t are both viewed as random variable, m is deemed as the stochastic discount factor (SDF). Recent literature in asset pricing focuses more on discussing m. As real market participants, they normally pay more attention on x_t before conducting an investment in financial markets.

If we use f_{P1} to denote the prediction function of payoff x_1, and θ_0 to denote the personal available information of a market participant at t_0. It can be described as:

$$x_1 = f_{P1}(P_0/\theta_0)$$

The well-known mean-variance framework created by Markowitz in 1956 is about the final step of real investment. The biggest problem in practical investment is how to estimate the mean and variance of the expected return of a specific asset. In order to estimate return at t_1, we have to estimate x_1 or p_1 and d_1 individually.

$$E(x_1) = E(p_1 + d_1 - P_0) = E(r_1 P_0)$$

$$Var(x_1) = Var(p_1 + d_1 - P_0) = Var(r_1 P_0)$$

In practice, a market participant is not accessible to all relevant information Θ_0 at t_0 and individual investors have to use their personal information θ_0 to estimate the prediction function f_{p1} of x_1.

$$x_1 = f_{P1}(P_0|\theta_0)$$

However, f_{P1} is very complicate and could vary over time. Normally, investors will try to decompose f_{P0}, f_{P-1}, f_{P-2}... first and use them as a reference in order to estimate f_{P1} thereafter. Let me use f_{P0} as an illustration to show the decomposition process.

$$X_0 = P_0 + D_0 = f_{P0}(P_{-1}/\theta_{-1})$$

The common decomposition factors of market pricing function can be the asset profitability, liquidity level of the market, risk-averse level of the market etc. The profitability of asset, denoting as π_t gives guidance to asset picking. Market liquidity level, denoted as l_t, and risk-averse level denoted as a_t affect timing of trading.

$$x_0 = f_{P0}[p_{-1}, (\pi_{-1}, l_{-1}, a_{-1}, \ldots)/\theta_{-1}]$$

$$p_0 + d_0 = f_{P0}[p_{-1}, (\pi_{-1}, l_{-1}, a_{-1}, \ldots)/\theta_{-1}]$$

For each individual factor, we could conduct this decomposition process again. For example, the profitability of asset can be decomposed as business condition of the company being denoted as b_t, the development of the industry i_t, and macroeconomic circumstance e_t, etc.

$$\pi_{-1} = f_\pi(b_{-1}, i_{-1}, e_{-1}/\theta_{-1})$$

$$x_0 = f_{P0}[p_{-1}, (b_{-1}, i_{-1}, e_{-1}, l_{-1}, a_{-1}, \ldots)/\theta_{-1}]$$

Obviously, the interaction between those decomposed factors could be complex and non-linear, but if we use a linear approximation to illustrate this pricing function, it may look like the following:

$$x_0 = c_{b_0} b_{-1} p_{-1} + c_{i_0} i_{-1} p_{-1} + c_{e_0} e_{-1} p_{-1} + c_{l_0} l_{-1} p_{-1} + c_{a_0} a_{-1} p_{-1} + \ldots$$

However, in reality, the interaction between those decomposed factors is opaque mathematically. Factors may overlap each other and have high correlations. Even if you run a regression using a linear or a more sophisticated model, the result is often highly unreliable because the interaction between those factors is substantially determined by aggregated investment behavior of market participants which is variable over time. Thus, both the coefficients and factors may change from t_0 to t_1. Besides, some significantly relevant information regarding market atmosphere or business condition may not be properly transformed to a standard numerical value.

Therefore, even most informed professional investors are somehow walking in the dark when conducting an investment in reality. Because the intrinsic complexity of aggregated investment behavior in financial markets is inevitable, investors have to rely on a manageable principle in order to conduct investment in practice, and we name it as the Principle of Ignorance, which is a principle that if you don't have enough information to infer how a coefficient or a factor will change from t_0 to t_1, you assume it remains stable. Based on the Principle *of* Ignorance, we are able to focus on coefficients and factors which we have relatively more information to infer from t_0 to t_1, leaving others to remain stable. However, the more you apply the Principle of Ignorance; your prediction will become more unreliable given the predictive time span. You may have to shorten the predictive time span to reach the same confidence level of your prediction.

For coefficients and factors, which we have information to infer from t_0 to t_1, there are two layers of prediction that depend on how much relevant information you have. The first layer predicts if a coefficient or factor will be more likely to go up or down from t_0 to t_1. The second layer predicts how much a coefficient or factor will go up or down from t_0 to t_1. The second layer requires more relevant information than the first layer. In practice, different factors would affect the prediction over different time span (like macroeconomic circumstance factor e, relevant information from the government statistical bureau, usually updated quarterly) The reasonable prediction time span will be months or even quarters. It is not able to guide daily prediction.

On the assets we are assessing, cryptocurrencies are more restricted on short selling and arbitrage than stocks. Cryptocurrencies have higher transaction costs than stocks. Since cryptocurrencies have no future cash flow generated, any investment of cryptocurrencies will be solely based on the predictions of future price movements, which are more difficult than the predictions of future cash flows. The pandemic causes uncertainty of payoffs to rise both for cryptocurrencies and stocks, because it increases economic and political uncertainty exogenously which will affects both assets. In view of these observations, we are able to propose two hypotheses as follows:

Hypothesis 1*:* The inefficiency levels of the cryptocurrency markets are higher than that of the stock markets.

Hypothesis 2*:* The inefficiency levels of the cryptocurrency markets and the stock markets increase after the outbreak of the Covid-19 pandemic.

4. Data and Results

This paper uses daily close prices of Bitcoin, Ethereum, S&P 500, and CSI 300 from Oct 1, 2018 to Dec 31, 2019, representing the price movements before the pandemic outbreak. The relevant summary statistics are presented in (Table 1).

TABLE 1: *Summary statistics: prices of bitcoin, ethereum, S&P and CSI300 in USD before covid-19 pandemic.*

	Bitcoin	Ethereum	S&P500	CSI300
Mean	6915.92	176.7891466	2870.47	3638.19
Standard Error	121.54	2.390291964	9.53	18.73
Median	7127.01	174	2885.57	3767.16
Standard Deviation	2598.19	51.09860588	169.17	326.50
Sample Variance	6750577	2611.067523	28619.58	106603.18
Kurtosis	-1.15	0.034850296	-0.05	-1.08
Skewness	0.19	0.63065642	-0.22	-0.63
Range	9744.44	251.86	888.92	1155.77
Minimum	3183	83	2351.1	2964.84
Maximum	12927.44	334.86	3240.02	4120.61
Count	457	457	315	304

Source: Wind Financial Database.

We then compare our results with the daily close prices of Bitcoin, Ethereum, S&P 500, and CSI 300 from Jan 1, 2020 to Mar 31, 2021, representing the price movements after the pandemic outbreak. The post-pandemic summary statistics are provided in (Table 2).

TABLE 2: *Summary statistics: prices of bitcoin, ethereum, S&P and CSI300 (USD) after covid-19 pandemic.*

	Bitcoin	Ethereum	S&P500	CSI300
Mean	17859.54	550.85	3343.27	4570.31
Standard Error	691.30	24.53	21.84	32.77
Median	10675.53	352.84	3345.78	4691.24
Standard Deviation	14762.23	523.87	386.44	568.56
Sample Variance	2179235	274438.31	149338.11	323254.81
Kurtosis	1.19	0.82	-0.30	-1.06
Skewness	1.59	1.51	-0.37	0.08
Range	56321.4	1847.38	1737.14	2277.41
Minimum	4857.1	110.3	2237.4	3530.31
Maximum	61178.5	1957.68	3974.54	5807.72
Count	456	456	313	301

Source: Wind Financial Database.

We use January 1, 2020 as the cut-off date because Wuhan Municipal Health Commission first publicly announced the existence of pneumonia in the city on December 31, 2019 according to "Notification of Wuhan Municipal Health Commission on the Current Situation of Pneumonia in Our City". The local office of World Health Organization (WHO) in China also reported the situation to WHO on the same date. The differences of data count between assets are because of different market opening days during the chosen period. Both the data from (Tables 1 and 2) are taken from Wind Financial Database.

We use the R/S method to calculate the Hurst Exponents. To calculate the Hurst Exponents, we first take the Log return to de-trend the time series of the price movements. The results of our empirical tests are summarized in (Table 3).

TABLE 3: *Hurst exponent and market inefficiency.*

	Bitcoin/USD	Ethereum/ USD	S&P 500	CSI 300
Hurst Before	0.6105	0.5371	0.553	0.5471
Hurst After	0.6339	0.6002	0.5565	0.5689
Inefficiency Before	0.1105	0.0371	0.053	0.0471
Inefficiency After	0.1339	0.1002	0.0565	0.0689
Inefficiency Change	0.0234	0.0631	0.0035	0.0218

Notes: The algorithm codes are available from the authors upon request.

As seen from the empirical results reported in (Table 3), the inefficiency levels of Bitcoin and Ethereum are found to be higher than S&P 500 and CSI 300. Besides, the inefficiency levels of Bitcoin, Ethereum, S&P 500 and CSI 300 have significantly increased after the pandemic (compared to before the pandemic outbreak). The results of the empirical tests corroborate with our two proposed hypotheses. In what follows, we provide a new perspective which may be used to explain for the changes in market efficiencies generated by the pandemic.

5. Discussion and Explanation

As mentioned earlier, the inefficiency of the cryptocurrency and the stock markets may emanate from the following reasons:

- **a** Investors are not fully rational and have strong cognitive biases.
- **b** Markets have restriction on short selling and arbitrage.
- **c** Transaction costs and costs of gathering information exist.
- **d** Market participants have disagreement on the implications of current information for the current price and distributions of future prices of each asset.
- **e** Prediction of future price move is less accurate than prediction of future cash flow.

Investors would get different payoffs at different points in time based on their estimated prediction function:

$$x_1 = f_{P1}(P_0|\theta_0);\, x_2 = f_{P2}(P_0|\theta_0);\, x_3 = f_{P3}(P_0|\theta_0)\ldots$$

The mean and variance of predicted payoffs can be shown as:

$$E(x_1) = E\left[f_{P1}(P_0|\theta_0)\right];\, E(x_2) = E\left[f_{P2}(P_0|\theta_0)\right];\, E(x_3) = E\left[f_{P3}(P_0|\theta_0)\right]\ldots$$

$$Var(x_1) = Var\left[f_{P1}(P_0|\theta_0)\right];\, Var(x_2) = Var\left[f_{P2}(P_0|\theta_0)\right];\, Var(x_3) = Var\left[f_{P3}(P_0|\theta_0)\right]\ldots$$

We could then draw a mean-variance-time line by connecting these dots of prediction. The following graph and all hypothetical numbers is used in our typical illustration.

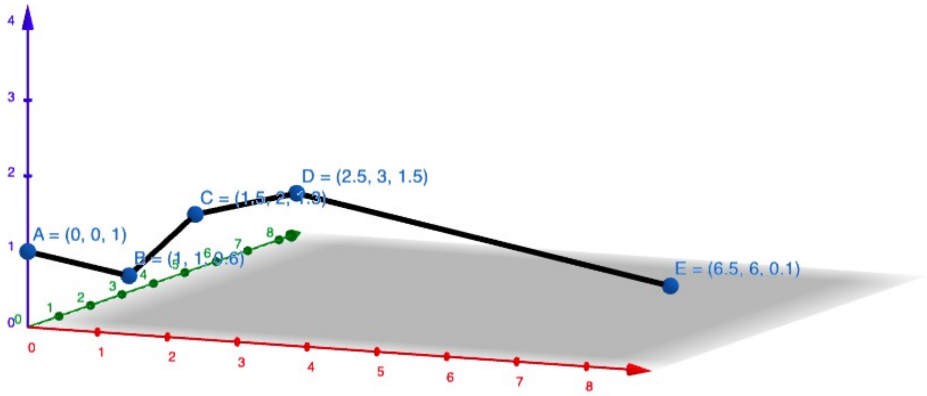

Figure 4: *Mean-Variance-Time Line.*

Notes: Visualization with hypothetical numbers. Source: Geo Gebra.

The red x-axis is the personal estimated variance of expected return of a given asset. The blue z-axis is the personal estimated mean of expected return of a given asset. The green y-axis is the timeline.

Personal estimated variance of expected return tends to increase when time increases. Given the information available to you, the farther the time you are going to predict, the less accurate your prediction will be. In some cases, your available information and pricing function are very suitable in predicting expected returns at one specific point in time. The estimated variance could be smaller than the prediction at a closer point of time. Personal estimated mean of expected return varies on different point in time depended on your available information and pricing function as well. When we put aside the timeline, it transforms to a mean-variance line. Each point is personal estimated mean-variance combination in discrete time.

The above illustration is for a normal individual investor who possesses only personal information of a given asset, but even for a representative agent who possesses all relevant information Θ_0, the process to get the estimated mean and variance of expected payoffs is the same:

$$x_1 = F_{P1}(P_0|\Theta_0)$$

$$E(x_1) = E[f_{P1}(P_0|\Theta_0)]; E(x_2) = E[f_{P2}(P_0|\Theta_0)]; E(x_3) = E[f_{P3}(P_0|\Theta_0)]\ldots$$

$$Var(x_1) = Var[f_{P1}(P_0|\Theta_0)]; Var(x_2) = Var[f_{P2}(P_0|\Theta_0)]; Var(x_3) = Var[f_{P3}(P_0|\Theta_0)]\ldots$$

In SDF pricing model, we have:

$$p_{01} = E(m x_1); p_{02} = E(m x_2); p_{03} = E(m x_3)\ldots$$

Different estimated payoffs on different points of time will generate a different legitimate pricing at t_0 for a given asset. Shiller wrote in his 1981 seminal paper: "The efficient markets model can be described as asserting that $P_t = E_t(P_t^*)$is the mathematical expectation conditional on all information available at time t of P_t*(21). In other words, P_t is the optimal forecast of P_t*." And in his 2003 review: "Different forms of the efficient markets model differ in the choice of the discount rate, but the general efficient market model can be written just as $P_t = E_t(P^*_t)$."

Fama reiterated the following in his 2014 Nobel lecture: "The implicit model of market equilibrium is that equilibrium expected returns are constant (10):

$$E\left(R_{t+1}\middle|\Theta_{tm}\right)=E(R).$$

If the market is efficient so that $E\left(R_{t+1}\middle|\Theta_{tm}\right)=E\left(R_{t+1}\middle|\Theta_{t}\right)$ holds, then

$$E\left(R_{t+1}\middle|\Theta_{t}\right)=E(R).$$

However, given the personal available information and pricing function of a market participant, the rational investment choice of the participant will be on his estimated mean-variance-time line. Thus, different pricing of a given asset could both be reasonable because of different investment time span. If we assume $E(R)$ is constant, $E\left(R_{t+1}\middle|\Theta_{t}\right)=E(R)$ will not hold because $E\left(R_{t+i}\middle|\Theta_{t}\right)$ is changeable such as $E\left(R_{1}\middle|\Theta_{0}\right)$ may not equal to $E\left(R_{2}\middle|\Theta_{1}\right)$.

6. Conclusions

This paper tests and compares the efficiencies of the stock markets (S&P500 and CSI300) with the cryptocurrency markets (Bitcoin and Ethereum). It also investigates how the efficiency levels of these asset markets change from before the pandemic to those after the pandemic. There are paucities of studies on (i) cryptocurrency's market efficiency and (ii) how the pandemic affects the efficiency levels of financial assets. Our theoretical analysis and our empirical results bridge the gaps in the literature.

Before we conduct the empirical analysis, we provide a theoretical review of the literature on market efficiency and a new perspective which may be used to explain the relative inefficiencies of the cryptocurrencies under investigation as well as to account for the changes in the market efficiencies wrought by the pandemic. For our empirical analysis, we use the daily close prices of Bitcoin, Ethereum, S&P 500, and CSI 300 from Oct 1, 2018 to Dec 31, 2019, representing the price movements before the Covid-19 pandemic, and we compare the results with the daily close prices of Bitcoin, Ethereum, S&P 500, and CSI 300 from Jan 1, 2020 to Mar 31, 2021, representing the price movements after the pandemic. Following the literature, we use Hurst Exponent as the instrument for measuring the level of financial market inefficiency. The inefficiency levels of Bitcoin and Ethereum are reported in this paper to be higher than the inefficiency levels of S&P 500 and CSI 300 after the pandemic. Besides, the inefficiency levels of Bitcoin, Ethereum, S&P 500 and CSI 300 have both gone up after the pandemic relative to before the pandemic.

Financial market inefficiency may be attributed to (a) investors are not fully rational and markets have restriction on short-selling and arbitrage, (b) transaction and information gathering costs, (c) market participants have disagreements on the implications of current information on the current price and on the distributions of future prices for each asset, and (d) prediction of future price movement is less accurate than prediction of future cash flows. The first three reasons are often cited in the literature for explaining the market efficiency phenomenon. The merit of this paper lies in using the fourth reason for analysing the differences in the efficiency levels between the cryptocurrency and the stock markets, and also the differences in the efficiency levels of these assets before and after the pandemic.

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