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Article

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Malaysian management journal

Provided in Cooperation with:
Universiti Utara Malaysia

Reference: Abdul-Rahim, Ruzita/Ling, Pick Soon et. al. (2021). Assessing the predictability of cryptocurrency prices. In: Malaysian management journal 25 S. 143 - 168.
http://mmj.uum.edu.my/images/vol25july2021/143-168.pdf.
doi:10.32890/mmj2021.25.6.

MALAYSIAN MANAGEMENT JOURNAL
http://e-journal.uum.edu.my/index.php/mmj

How to cite this article:

Abdul-Rahim, R., Ling, P. S., & Mohd Khalid, M. A. S. (2021). Assessing the predictability of cryptocurrency prices. *Malaysian Management Journal*, *25*(July), 143-168. https://doi.org/10.32890/mmj2021.25.6

ASSESSING THE PREDICTABILITY OF CRYPTOCURRENCY PRICES

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Received: 6/5/2020 Revised: 7/3/2021 Accepted: 16/3/2021 Published: 9/7/2021

ABSTRACT

The predictability of asset prices works against the notion of an efficient market where asset prices reflect all available and relevant information. This paper examined the predictability of Bitcoin and 51 other cryptocurrencies that have been classified into the following five categories: Application, Payment, Privacy, Platform, and Utility. Two market efficiency tests (Ljung-Box autocorrelation and Runs tests) were run on the daily returns of the 52 unique cryptocurrencies and the MSCI World index from 28 April 2013 to 30 June 2019. The results showed that Bitcoin was consistently efficient, whereas most of the other cryptocurrencies and even the MSCI World index were not, implying that their prices were predictable. Categorically, Payment altcoins were the most consistent in showing inefficiency. Since altcoins in this category also recorded the third highest risk-adjusted returns, investors with advanced technical trading strategies had a great chance of exploiting the market information to make extremely high abnormal returns.

Keywords: Cryptocurrency market efficiency, cryptocurrency predictability, cryptocurrency types, Payment altcoins, Platform altcoins.

INTRODUCTION

An efficient market is when prices quickly and fully reflect available and relevant information (Fama, 1970). The implication of an efficient market on investment is significant because investors cannot exploit the information to outsmart the market and make abnormal returns. However, several conditions have to be in place to create an efficient market; namely, 1) there are a large number of profit-oriented investors participating in the market, 2) information is available widely, and at minimum search costs, 3) information is generated randomly, and 4) prices are not influenced by a small group of investors. In the cryptocurrency market, these conditions can be met faster than conventional financial assets. That is because cryptocurrency is a universal and internet-based asset that gives it easier access to a large pool of investors. However, there is also a notable grey area in the cryptocurrency market for several reasons. Market information is available in real-time, but that is only as far as it goes. Investors are deprived of information about the foundation and purpose of the individual cryptocurrency because this asset generally lacks track records. This disadvantage makes cryptocurrency a precarious investment mainly because it is still not regulated in most markets. Investors are daunted by the limited understanding of the economic and financial properties of cryptocurrencies. The complexity of the digital asset and its underlying technology does not help much in investment decision either.

The bewildering grey area and the remarkable development in the cryptocurrency market have quickly gained the attention of financial scientists. As a result of its importance on investment, a stream of studies began rapidly and was focused on the efficiency of the cryptocurrencies, starting with Bitcoin (e.g., Urquhart, 2016; Bariviera, 2017; Kurihara & Fukushima, 2017; Kristoufek, 2018; Lahmiri et al., 2018; Zargar & Kumar, 2019; Vidal-Tomas et al., 2019). Bitcoin, the first digital currency initiated from a white paper written by Nakamoto (2008), has become the largest by market capitalization, the most covered by exchanges, and consequently could offer the kind of data that empirical studies required. Bitcoin has proved its presence in the market as this newly created asset has evolved from being an alternative method of payment (Demir et al., 2018) to become a mainstream investment tool (Katsiampa, 2017) that could offer commodity characteristics (Selgin, 2015; Ammous, 2018). Unlike traditional financial assets, cryptocurrencies tended to have different investment characteristics (Troster et al., 2018; Corbet et al., 2018) that would offer great diversification benefits for the investors. Phillip et al. (2018) explained that cryptocurrency could provide other features such as crowdsourcing and peer-to-peer networking while at the same time was not subjected to any control from the authorities. It utilized cryptographic features that allowed it to have high liquidity, lower transaction costs and anonymity, to name just a few (Chan et al., 2017). These features differentiate cryptocurrencies from conventional or fiat currencies, which function mainly as a medium of exchange while being controlled by the central banks.

More financial scientists have begun to examine cryptocurrency market efficiency in response to the increasing popularity of cryptocurrency among speculators and investors. They have examined whether this digital financial asset's price was formed randomly or could be predictable. Evidence of market efficiency has a significant implication on an investment decision because an efficient market disqualifies any analytical attempt to make abnormal returns. The cryptocurrency market has a short history. It lacks the authority that will enable it to monitor, regulate, and control the market. Investment platforms and exchanges trading the cryptocurrencies are about all that can be relied upon for information about this digital asset. These issues present another explanation for the surge of empirical studies focusing on the cryptocurrency market's efficiency in its weak form based on past prices. For instance, Kochling et al. (2018) investigated Bitcoin and Bitcoin Cash's efficiency after Bitcoin's futures were introduced. Caporale et al. (2018) and Zhang et al. (2018) examined a number of cryptocurrencies in their study. Others took a different approach to investigating cryptocurrency market efficiency. For instance, Bundi and Wildi (2019) studied the effectiveness of technical trading strategies in Bitcoin trading. It is important to note that no technical trading strategies can generate an abnormal return when the tested asset market is already efficient. Aharon and Qadan (2019), Mbanga (2018) and Ma and Tanizaki (2019) examined the day-of-the-week effect in Bitcoin prices, expecting that if such an anomaly existed in the cryptocurrency market, then there would still be an opportunity to exploit it for abnormal returns.

This study could contribute to the scant literature on this newly created but rapidly expanding cryptocurrency market by offering new insights on market efficiency. For example, by associating market efficiency with the category or type of digital assets. This move was similar to that in categorizing companies by sectors. Investors could select more efficiently by focussing on some cryptocurrencies in a specific category rather than screening from the vast universe of the cryptocurrencies market. This study has classified cryptocurrencies that were readily available off the shelf into the following five categories: Payment, Privacy, Platform, Application, and Utility. Bitcoin was treated as the benchmark for those categories of altcoins (cryptocurrencies other than bitcoin) because of several reasons; namely, 1) it was the oldest cryptocurrency, 2) it was the largest cryptocurrency (accounted for 65 % of total market capitalization as reported in coinmarketcap.com), and 3) it had the broadest coverage. This study has included the MSCI World Index to gauge these cryptocurrency markets' performance and efficiency against a stock market representing the riskiest investment before the era of digital assets.

The rest of this paper has been organized in the following manner. The next section reviewed previous related literature. Then, the research methodology section explained the data, sample, estimation models and statistical method. Section 4 presented and then discussed the empirical results, and finally the last section discussed the implications and ended with the conclusion.

LITERATURE REVIEW

The grey area in the cryptocurrency market has quickly gained the attention of the financial economists. A surge of studies started to investigate its efficiency, implying the predictability of cryptocurrency prices, especially that of Bitcoin. Among the notable empirical studies, Urquhart (2016), Bariviera (2017) and Kurihara and Fukushima (2017) reported that the Bitcoin market was inefficient in the full sample studied from August 2010 to July 2016. However, these same studies also obtained results which showed that Bitcoin was becoming more efficient toward the later study period. Bariviera (2017), using the Hurst exponent of DFA and R/S methods found supporting evidence for Urquhart (2016) in that Bitcoin gradually became efficient after 2014 and this lasted until 2017. Kurihara and Fukushima (2017) tested the presence of weekly price anomalies in Bitcoin from July 2010 until December 2016. Their results suggested that the Bitcoin market was expected to become more efficient gradually in the later period.

Despite evidence suggesting Bitcoin was becoming more efficient in the later period, several other studies such as Kristoufek (2018) and Lahmiri et al. (2018) still found evidence indicating the inefficiency of the Bitcoin market. Kristoufek (2018) found further evidence when the focus was on the USD and CNY prices of Bitcoin from 2010 until 2017. An exception was when the test was done on the cooling-down period after the bubble-like price had surged. Meanwhile, Lahmiri et al. (2018) conducted their study using the nonlinear patterns of the time-varying volatility. The volatility was estimated using the fractionally integrated generalized autoregressive conditional heteroscedastic (FIGARCH) model. The results seemed to suggest market inefficiency, since past information was useful in predicting the future volatility of Bitcoin in seven Bitcoin markets, specifically in BITX, CEX.IO, COINBASE, EXMO, GEMINI, HITBTC and KRAKEN. The Lahmiri et al. (2018) study found a significant long-range behaviour in all volatility series, indicating the dependencies between distant volatility trajectories. The study also found that most Bitcoin markets were highly disordered and risky, and therefore they did not serve as viable hedging instruments. Cheah et al. (2018) also examined the long-memory processes and the dynamic interdependence of Bitcoin prices in five developed markets, namely in Europe, United States of America, Australia, Canada, and the United Kingdom. These markets started quoting Bitcoin prices in November 2011 and it was continued until March 2017. The results showed that Bitcoin prices followed a long-memory process. The study by Cheah et al. (2018) also discovered that the interdependency of Bitcoin markets was significantly affected by the movement of stochastic shocks, which negatively impacted the Bitcoin markets.

Caporale et al. (2018) further reaffirmed the inefficiency of the cryptocurrency market in a study which covered the period from 2013 until 2017. They found evidence of persistent behaviour in the four oldest and largest cryptocurrencies (BitCoin, LiteCoin, Ripple and Dash). The study had employed the following two long-memory methods: rescaled range (R/S) analysis and fractional integration. Zhang et al. (2018) applied 13 tests on nine cryptocurrencies, namely Bitcoin, Ripple, Ethereum, NEM, Stellar, Litecoin, Dash, Monero and Verge. They found evidence that, in general, supports the inefficiency of the cryptocurrency market. Verge was the most inefficient, Dash and Monero were relatively efficient, and five out of 13 tests still indicated that Bitcoin was also inefficient. Using the Hurst exponent MF-DFA, they found time-varying behaviour in the cryptocurrency composite index. This finding served to add more evidence supporting the inefficiency of the cryptocurrencies. Vidal-Tomas et al. (2019) adopted several traditional efficiency tests for the study period from January 2015 to December 2017. They divided the sample cryptocurrencies into three sub-periods; 59 for sub-period 1, 81 cryptocurrencies for sub-period 2, and 118 cryptocurrencies for sub-period 3. The results generally indicated that the cryptocurrency market was still inefficient in all sub-periods, but the inefficiency result was not as robust in 2015 and 2016.

The evidence that has been presented so far seemed to support the inefficiency of the cryptocurrency market. However, some results supported just the opposite view. For instance, the findings in Nadarajah and Chu (2017) indicated that Bitcoin behaved efficiently after its return series were transformed into an odd integer. The authors argued that transforming the return series into an odd integer avoided the loss of information in the returns. The results were robust, given that eight different tests consistently failed to reject the null hypothesis of efficient behaviour, except for the Runs test and Bartels's test. Tiwari et al. (2018) also reported that the Bitcoin market was efficient except for the months of April and August 2013, and between August and November 2016. The study had employed various computationally efficient long-range dependence estimators (CMA-1, CMA-2, DFA, GPH, MLE, Periodogram-LAD & Periodogram-LS).

Zargar and Kumar (2019) tested the efficiency of Bitcoin in very high-frequency data ranging from 15, 30, 60, and 120 minutes, as well as daily data from January 2013 until January 2018. Through different variance ratio tests, they found evidence that the inefficient behaviour only prevailed at higher frequency data (15, 30 and 60 minutes), but not in the lower frequency of 120 minutes and daily data. Zargar and Kumar (2019) explained that the results were such because the cryptocurrency markets were still emerging. In this regard, reliable information was scarce such that the inefficiency could be attributed to endogenous factors of an emerging market and the lack of fundamental traders.

Aharon and Qadan (2019) examined the day-of-the-week effect in Bitcoin returns and volatility. They used the following two methods; Ordinary Least Squares (OLS) and generalized autoregressive conditional heteroscedastic (GARCH). They found evidence that showed returns and volatility tended to be higher on Mondays. Their study also claimed that Bitcoin moved independently from other financial speculative market factors such as capital, bond and commodity, although these financial instruments seemed to have similar features with Bitcoins. Similar findings were reported by Ma and Tanizaki (2019), who discovered the day-of-the-week effect on Monday from January 2013 to December 2018. Mbanga (2018) also studied the day-of-the-week pattern in Bitcoin prices from February 2011 until May 2018. Still, unlike the studies by Aharon and Qadan (2019) and Ma and Tanikazi (2019), the Mbanga (2018) study found no evidence to support the weekend effect in Bitcoin price. However, price clustering on Fridays appeared stronger than on other weekdays. Furthermore, Corbet et al. (2019) found that specific technical rules were profitable in Bitcoin trading, providing more support for cryptocurrency market inefficiency. Bundi and Wildi (2019) also found evidence that rejected the EMH in the Bitcoin market. They found that the Bitcoin market was positively and serially correlated and the selected trading strategies such as momentum, moving average and neural nets provided significant returns.

Previous studies have tested the market efficiency of cryptocurrencies without associating it with a specific event. Unlike the majority of these studies, Kochling et al. (2018) examined the effect of the introduction of Bitcoin's futures in December 2017, more specifically on the market efficiency of Bitcoin and Bitcoin Cash over the period from August 2017 to April 2018. The results showed that the Bitcoin market was inefficient in seven out of eight tests conducted before the launch of the Bitcoin futures. In contrast, no tests reported significant inefficiency after the launching of the Bitcoin futures. For Bitcoin Cash, the study found evidence for efficient Bitcoin Cash in some of the tests before and after the launch of the Bitcoin futures. Wei (2018) examined the link between market efficiency and liquidity of 456 cryptocurrencies. Using various traditional efficiency tests, they found evidence that cryptocurrencies with high market liquidity tended to be more efficient than those with low liquidity. Overall, empirical studies on the market efficiency of the cryptocurrency market were still focused on only Bitcoin. Only a few involved the largest cryptocurrencies, and rarely were there studies that used a large sample. Except for a few cases, the results generally indicated that the Bitcoin market was still inefficient, but moving toward becoming efficient later. This conclusion was in line with the meta-analysis and the result of the study conducted by Kyriazis (2019). With more altcoins, that is other cryptocurrencies making their way into the mainstream, the present study was of the view that it was crucial to provide insights into their price behaviour. Kochling et al. (2018) tested their large cryptocurrency sample by categorizing them based on their liquidity. This study differed from the others because it proposed categories that could serve as the the various sectors representing the primary function or purpose of the cryptocurrencies.

METHODOLOGY

In light of the extensive discussion by Danial (2019) of investdiva.com, which also separated cryptocurrencies into several categories, the present study has adopted the following three categories, namely Payment, Privacy and Platform introduced in investdiva.com, and another category that of Application from medium.com. On top of that the present study also made use of another category called Utility, representing cryptocurrencies designed for specific purposes such as gaming/gambling, exchange, legal and property, content and social media, and supply chain. Like Stellar (XLM), some of these cryptocurrencies served more than one purpose, for example as payment, platform, and utility. For this study, they would be analyzed in every category they fell into. More details of the description and examples of the cryptocurrency categories are provided in the Appendix.

The present study selected cryptocurrency that met the group description in the Appendix and had at least 1,000 daily prices from coinmarketcap.com. With these criteria, Augur was the last cryptocurrency that made it to the list of the sample cryptocurrencies as it was listed on coinmarketcap.com on 4 October 2016, the latest date to provide 1,000 days before the study ended on 30 June 2019. The earliest data were collected from 28 April 2013, representing the listing date for Bitcoin and three other altcoins on coinmarketcap.com. Three of these cryptocurrencies, namely Bitcoin, LiteCoin, and NameCoin met the selection criteria, and they provided maximum observations of 2,255 daily prices. Overall, the selection criteria employed in the present study generated a total of 52 unique cryptocurrencies. Bitcoin was set as the benchmark among cryptocurrencies for several reasons. These were as follows: 1) the oldest, 2) the largest with approximately 65 percent of total cryptocurrency market capitalization, 3) most covered by digital currency exchanges, and 4) by far the most expensive cryptocurrency. Meanwhile, data on the MSCI World Index's daily price were also collected so that the cryptocurrencies were also benchmarked against common stocks that used to be the riskiest among financial assets before digital assets were introduced.

The sample cryptocurrencies and the MSCI World Index were tested individually for their market efficiency using the daily return data. The prices in USD were transformed using the total return method ($\frac{P_t - P_{t-1}}{P_{t-1}}$) into daily returns ($R_t$). The predictability of the cryptocurrency prices was tested using the efficiency tests of Ljung-Box autocorrelation (Urquhart, 2016; Nadarajah & Chu, 2017; Brauneis & Mestel, 2018; Jiang et al., 2018; Phillip et al., 2018; Wei, 2018; Kochling et al., 2018) and the non-parametric Runs test (Urquhart, 2016; Nadarajah & Chu, 2017; Wei, 2018). The Ljung-Box autocorrelation test examined the relationship between a returns series and its previous values at different lags, as expressed in Equation (1):

$$Q_{Ljung-Box} = n(n+2)\sum_{t=1}^{k} \frac{\psi^2(t)}{n-t} \tag{1}$$

where n represents the sample size, k represents the number of autocorrelation lags, and $\psi^2(t)$ represents the correlation coefficient at lag t. The null hypothesis that the return series had no autocorrelation was rejected if the Q-statistic of Ljung-Box was significantly different from zero, which implied the predictability in the movement of the return series. Since financial time series data usually were not normally distributed, the present study concurred with Fauzel's (2016) argument that non-parametric tests such as the Runs test was more useful than the autocorrelation test. The Runs test examined the independency of returns series on changes of its successive returns series, as in Equation (2).

$$Z = \frac{r-\mu_r}{\sigma_r} \sim N(0,1) \tag{2}$$

where $\mu_r = \frac{2(N_+)(N_-)}{N} + 1$ and $\sigma_r = \sqrt{\frac{2(N_+)(N_-)(2(N_+)(N_-)-N)}{N^2(N-1)}}$ respectively represent the sample mean and standard deviation, N_+ represents the positive runs and (N_-) represents the negative runs, while N is the total runs in the return series. The observed number of runs in the returns series should be close to the expected number of runs in the random series data.

RESULTS AND DISCUSSION

Table 1 summarizes the characteristics of the sample cryptocurrencies by their types and the MSCI World Index. In this study, Bitcoin was presented as a stand-alone category as it served as the cryptocurrency benchmark. With a maximum supply of 20 million BTCs, Bitcoin offered the scarcity feature of a medium of exchange. It was still a small market (0.0011%) relative to the MSCI World Index (USD41.25 quadrillion), but Bitcoin had been selling at an average price of USD2,570 over the study period. This price was by far higher than any altcoin and also higher than the MSCI World Index, which had an average price of USD1,810. The average prices for the other altcoins were subtler, with the cheapest being recorded among Utility altcoins, which also recorded the largest units circulating in the economy. Other altcoins were larger (units) and indicated equal chances of being mineable, except for Platform altcoins that mostly were not. Other than Bitcoin, Payment and Platform altcoins recorded the most exchanges, and therefore, they were expected to have less illiquidity risk.

Table 1

Profiles of Cryptocurrencies by Types and MSCI World Index

Type	N	Price (USD)	MktCap (USD)	Crltg Units	Mineable	#Exch
Payment	19	12.00	1.24E+11	1.04E+10	0.67	136
Application	6	6.28	7.68E+08	1.22E+08	0.50	21
Platform	15	21.49	3.14E+10	1.46E+09	0.36	115
Utility	6	0.37	2.87E+10	7.67E+10	0.57	12
Privacy	12	0.87	2.18E+10	2.50E+10	0.50	13
Bitcoin	1	2,570.41	4.61E+10	1.79E+07	1.00	1,000
MSCI World	1,650	1,810.26	4.13E+16	-	-	-

Note: N = number of cryptocurrencies in the subsample, MktCap = market capitalization, #Exch = number of exchanges trading the cryptocurrencies, and Crltg = circulating. The total of Ns is 59 because six altcoins fall in two categories and 1 in three. From MSCI World Index (30 September 2019) at https://www.msci.com/documents/10199/149ed7bc-316e-4b4c-8ea4-43fcb5bd6523, https://www.investing.com/indices/msci-world-historical-data

Table 2 presents the descriptive statistics of the five subsamples of cryptocurrencies, Bitcoin and the MSCI World Index. The results show that Utility cryptocurrencies recorded the highest average daily returns of 1.44 percent (equivalent to 525.6 % per annum). Next is Privacy cryptocurrencies with average daily returns of 1.21 percent (441.65 % annum). Note that the yearly return equivalence was calculated by multiplying the daily return with the standard number of trading days, which was 360 days for cryptocurrencies and 250 days for stock. Interestingly, Bitcoin recorded the lowest average daily returns of 0.29 percent (equivalent to 72.50 % per annum). This finding seemed to suggest that even the least profitable cryptocurrency recorded returns about ten times higher than the return on stocks. The MSCI World Index recorded an average daily return of 0.03 percent (equivalent to 7.5 % per annum). Consistent with the "risk-return" trade-off theory, Utility, the most profitable cryptocurrency, also recorded the highest risk. However, the risk-return relationship was not monotonous across all sub-samples as riskier cryptocurrency type also happened to record lower returns. That said, Bitcoin appeared to be the least risky cryptocurrency with the least mean return, supporting the "risk-return" trade-off explanation.

Table 2

Descriptive Statistics

N	Bitcoin	Application	Payment	Platform	Privacy	Utility	MSCI World
	1	6	20	12	15	11	
Mean daily	0.003	0.008	0.007	0.008	0.012	0.014	0.000
Maximum	0.430	1.542	0.872	1.542	3.265	3.653	0.031
Minimum	-0.234	-0.585	-0.264	-0.585	-0.278	-0.309	-0.049
Std. Dev	0.044	0.090	0.060	0.082	0.108	0.123	0.007
Unc.Vol'ty	0.039	0.074	0.047	0.064	0.103	0.126	0.007
Skewness	0.498	4.328	3.045	4.856	14.256	16.785	-0.692
Kurtosis	12.715	59.139	41.368	78.836	386.323	454.476	7.288
Jarque-Bera	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sharpe ratio	0.066	0.084	0.111	0.096	**0.112**	**0.117**	0.040

Note: N = number of cryptocurrencies in each sub-sample. Sharpe = Sharpe ratio = Mean/Std Dev, and Unc.Vol'ty = unconditional volatility.

The tremendous return offered by cryptocurrencies was undeniably an attractive property that appealed to speculators and investors. However, this abnormally high return came with the kind of risk that could threaten their wealth, particularly speculators who traded by following the *herd*. Fundamental traders and investors whose objective was to profit from long-term growth should observe the behaviour of the prices of the cryptocurrencies before making an investment decision. Figure 1 illustrates the volatility of these cryptocurrencies relative to Bitcoin. Note that in each of the panels in Figure 1, the sub-sample returns were always plotted on the secondary axis (right pane) and Bitcoin on the primary axis (left pane). The volatility patterns reflected the standard deviation reported in Table 2, in that all cryptocurrency categories were more volatile than Bitcoin. Specifically, the most volatile altcoins were Utility and Privacy. The former also recorded the highest maximum daily return of 415 percent, which happened on 10 March 2014, whereas their lowest returns were 31 percent. The worst skid was 58 percent which was reported for Application and Platform. Overall, all altcoin categories recorded higher volatility measures (standard deviation and unconditional volatility) than Bitcoin, which recorded the highest return of 43 percent and the lowest of 23 percent.

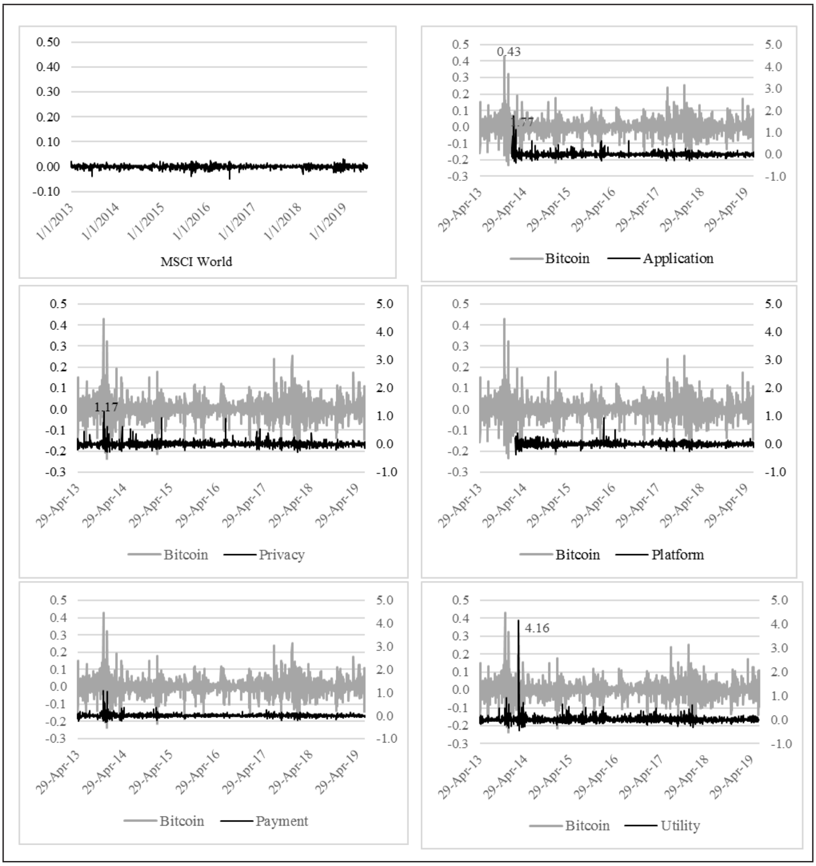
Standardized valuation given by the Sharpe ratio has provided interesting results. Despite reporting the lowest standard deviation and showing the smallest volatility over the study period, Bitcoin recorded the lowest Sharpe ratio (0.0664) among all cryptocurrency categories. Another measure of volatility that is easier to interpret is unconditional volatility which is also reported in Table 2. Saiti and Noordin (2018) explained that volatility had a value between 0 and 1.0. Returns series are less volatile if the volatility value is closer to 0, while the reverse is true if the volatility value is closer to 1.0. Just like the standard deviation, the unconditional volatilities were highest among Utility and Privacy altcoins. Therefore, it could be surmised that they were the most volatile among groups of cryptocurrencies. Bitcoin remained the least volatile cryptocurrency with a value of 0.0393. However, Bitcoin was still six times more volatile than the MSCI World Index, which recorded an unconditional volatility of 0.0069. This result could have an important implication for investors. Being risk-averse, rational investors would be better off investing in altcoins such as Utility, Privacy and Payment categories because, in general, they would provide about twice as high a return per unit of risk than Bitcoin. Bitcoin's low Sharpe ratio seemed to suggest that the largest and oldest cryptocurrency was approaching the maturity stage.

Surprisingly, the result also showed that the MSCI World Index recorded the lowest Sharpe ratio, i.e., even lower than that of Bitcoin. This condition was most probably because the index was a very-well diversified portfolio. After all, the index contained 1,650 component stocks from 23 developed countries. In other words, the index return was low because the fluctuation in the component stock prices had been stabilized through the diversification process. The index return was also low because its components were large and mid-cap stable stocks in the 23 markets. However, like any portfolio, the diversification effect could only eliminate the idiosyncratic risks, but not the market risks. Meanwhile, the skewness and kurtosis values of the cryptocurrencies indicated that positive daily returns dominated their returns and the distribution of these daily returns were fat-tailed. Like other financial assets, a cryptocurrency's daily returns were also not normally distributed, as was shown by the significant Jarque-Bera values.

The discussion in this section proceeds with the results from the tests on the predictability or efficiency of Bitcoin and each of the sample altcoins that was analyzed in their respective categories. The present study followed Urquhart (2016) and Wei (2018) for the Ljung-Box autocorrelation test. It focused on the results of the average *p*-values of lags 2 until 5 to determine the efficiency of the cryptocurrencies. The results of both market efficiency tests reported in Table 3 and Table 4 consistently showed that the Bitcoin market was already efficient. This result seemed to suggest that Bitcoin prices moved randomly and, therefore, could not be predicted. This finding also seemed to imply that attempts to time the Bitcoin market were not likely to generate abnormal returns consistently. This result therefore, supported that of Zhang et al. (2018), which revealed that Bitcoin was efficient in eight out of 13 tests, Nadarajah and Chu (2017), found evidence that Bitcoin returns were transformed into an odd integer.

Figure 1

Volatility of Altcoins versus Bitcoin



Note: MSCI World index is not plotted against cryptocurrencies because they have different trading days. Stocks are traded in about 220 days a year, whereas cryptocurrencies are traded continuously.

Similarly, in Tiwari et al. (2018) and Zargar and Kumar (2019) who employed various long-range dependence estimators. The latter study found evidence that Bitcoin was efficient in daily data, although it was still inefficient in minutely and hourly data. Surprisingly, both tests consistently showed that the MSCI World Index was inefficient. Although the stock index had already existed far longer than Bitcoin and received wide coverage and offered in multiple ETFs, the price index movement was still predictable.

For the other cryptocurrencies, Table 3 and Table 4 show the results of the market efficiency tests for the individual altcoin under its respective category. Such information could be of great advantage in an investment decision. The present study has computed for each category its overall efficiency by considering all sample altcoins (Efficient1) and when excluding altcoins with multiple categories (Efficient2). The Ljung-Box tests results in Table 3 show that the efficient cryptocurrency percentage was at most 50 percent, as was reported for Application altcoins.

Meanwhile, altcoins in the Payment category reported the least percentage of efficient cryptocurrencies, in that only 16 percent of them was efficient (Efficient1). Utility altcoins reported a slightly higher percentage of efficiency, and excluding multipurpose altcoins (Efficient2) reduced the percentage to zero, indicating that all purely Utility altcoins were still inefficient. The results also show that two of the earliest altcoins (Namecoin and Litecoin) and three other major altcoins (Ethereum, Ripple, and Litecoin) were also inefficient. Therefore, their prices could be predicted based on their past movements.

The results of the Run tests in Table 4 were mostly in support of the Ljung-Box autocorrelation results. The difference was that the highest percentage of efficient cryptocurrencies came from the Platform category while the least was among Privacy altcoins. This conclusion remained the same even after excluding the multipurpose altcoins from the specific categories. Utility altcoins recorded 33.33 percent efficiency in both counts of Efficient1 and Efficient2. Meanwhile, Payment altcoins were subtler as they reported the second-lowest efficiency after Privacy altcoins. Overall, the results gathered from both tests seemed to suggest that altcoins in the Payment categories were more likely to be inefficient and, therefore, offered price predictability that was important for investment purpose.

Table 3

Results (p-values) from Ljung-Box Autocorrelation Test (average of lags 2-5)

Benchmark		Utility (6)		Application (6)		Privacy (12)		Platform (15)		Payment (19)	
Bitcoin	0.994	SiaCoin	0.096[c]	Augur	0.709	Aeon	0.000[a]	BitShares	0.000[a]	Dash	0.072[c]
MSCI World	0.000[a]	Stealth	0.746	DigiByte	0.440	ByteCoin	0.029[b]	Blocknet	0.000[a]	Decred	0.000[a]
		Steem	0.000[a]	GridCoin	0.000[a]	CloakCoin	0.000[a]	Burst	0.255	Diamond	0.000[a]
		Stellar	0.000[a]	Nxt	0.024[b]	Dash	0.072[c]	C'terParty	0.000[a]	DigiByte	0.440
		SysCoin	0.000[a]	Radium	0.349	D'talNote	0.281	D'talNote	0.281	DigixDAO	0.074[c]
		Ripple	0.000[a]	VertCoin	0.000[a]	I/Ocoin	0.000[a]	E'steinium	0.400	DogeCoin	0.000[a]
		Efficient1	16.73%	Efficient1	50.00%	Monero	0.481	Ethereum	0.019[b]	FeatherCoin	0.702
		Efficient2	0.00%	Efficient2	50.00%	Namecoin	0.008[a]	Factom	0.459	GroestlCoin	0.000[a]
						NavCoin	0.000[a]	HiCoin	0.086[c]	Gulden	0.001[a]
						PIVX	0.118	Lisk	0.000[a]	LEOCoin	0.000[a]
						Stealth	0.746	NEM	0.000[a]	Litecoin	0.036[b]
						Verge	0.000[a]	Nxt	0.024[b]	Monero	0.481
						Efficient1	33.33%	Shift	0.027[b]	Nexus	0.000[a]
						Efficient2	11.11%	Stellar	0.000[a]	ReddCoin	0.000[a]
								Waves	0.064[c]	Stellar	0.000[a]
								Efficient1	26.67%	Tether	0.000[a]
								Efficient2	25.00%	Unobtanium	0.000[a]
										ViaCoin	0.000[a]
										XRP	0.000[a]
										Efficient1	15.79%
										Efficient2	6.67%

Note: Superscripts [a], [b], and [c] respectively indicate significance at 1%, 5%, and 10% levels. Efficient1 is counted as a percentage of ALL sample in the category, and Efficient2 is estimated while excluding the multipurpose altcoins (Dash, DigiByte, DigitalNote (D'talNote), Monero, Nxt, Stealth and Stellar). Efficient2 is 57.14%.

Table 4

Results (p-values) from the Runs Test

Benchmark		Utility (6)		Application (6)		Privacy (12)		Platform (15)		Payment (19)	
Bitcoin	0.663	SiaCoin	0.334	Augur	0.049^{b}	Aeon	0.014	BitShares	0.072^{c}	Dash	0.118
MSCI World	0.008^{a}	Stealth	0.001^{a}	DigiByte	0.000^{a}	ByteCoin	0.000^{a}	Blocknet	0.000^{a}	Decred	0.392
		Steem	0.874	GridCoin	0.000^{a}	CloakCoin	0.018^{b}	Burst	0.002^{a}	Diamond	0.006^{a}
		Stellar	0.034^{b}	Nxt	0.444	Dash	0.392	C'terParty	0.000^{a}	DigiByte	0.000^{a}
		SysCoin	0.084^{c}	Radium	0.002^{a}	D'talNote	0.000^{a}	D'talNote	0.000^{a}	DigixDAO	0.000^{a}
		Ripple	0.043^{b}	VertCoin	0.215	I/Ocoin	0.001^{a}	E'steinium	0.007^{a}	DogeCoin	0.001^{a}
		Efficient1	33.33%	Efficient1	33.33%	Monero	0.052^{c}	**Ethereum**	0.168	FeatherCoin	0.052^{b}
		Efficient2	33.33%	Efficient2	16.67%	**Namecoin**	0.021^{a}	Factom	0.283	GroestlCoin	0.661
						NavCoin	0.001^{a}	HiCoin	0.000^{a}	Gulden	0.119
						PIVX	0.071	Lisk	0.031^{b}	LEOCoin	0.040^{b}
						Stealth	0.001^{a}	NEM	0.170	**Litecoin**	0.038^{b}
						Verge	0.000^{a}	Nxt	0.444	Monero	0.027^{b}
						Efficient1	8.33%	Shift	0.157	Nexus	0.052^{c}
						Efficient2	0.00%	Stellar	0.034^{b}	ReddCoin	0.000^{a}
								Waves	0.173	Stellar	0.000^{a}
								Efficient1	40.00%	Tether	0.034^{b}
								Efficient2	33.33%	Unobtanium	0.000^{a}
										ViaCoin	0.000^{a}
										Ripple	0.018^{b}
										Efficient1	21.05%
										Efficient2	20.00%

Note: Superscripts ^{a}, ^{b}, and ^{c} respectively indicate significance at 1%, 5%, and 10% levels. Efficient1 is counted as a percentage of ALL sample in the category, and Efficient2 is estimated while excluding the multipurpose altcoins (Dash, DigiByte, DigitalNote (D'talNote), Monero, Nxt, Stealth and Stellar). Efficient2 is 28.57%.

Recall from Table 2 that Payment was the third of the three categories Utility (0.117), Privacy (0.112) and Payment (0.111), which recorded the highest daily risk-adjusted returns (Sharpe ratios). This cryptocurrency category offered the best investment consideration criteria because taking risks in these predictable altcoins was worth the very high returns they offered, which was about 237.6 percent per annum. The inefficiency of these cryptocurrencies would suggest that investors had a great chance to outsmart the market and could enjoy abnormal returns from these altcoin markets. However, they had be equipped with technical and analytical knowledge and skills. The results generally indicated that the cryptocurrency markets were still largely inefficient. This finding is seen as lending strong support for Zargar and Kumar (2019). They attributed the inefficiency of the cryptocurrency markets to an emerging market's endogenous factors and the lack of fundamental traders. The results also show that except for Ethereum (in the Runs test), the other earliest and/or major altcoins, namely Namecoin, Ripple, and Litecoin were still inefficient. The findings seemed to imply that being the earliest and most covered cryptocurrency were not good enough reasons as compared with Bitcoin's efficiency.

CONCLUSION

This study has examined the efficiency of cryptocurrencies in five categories, namely Application, Payment, Privacy, Platform, and Utility. The study covered the period from 28 April 2013 until 30 June 2019. Daily data of 52 unique cryptocurrencies, including Bitcoin, were examined, along with the MSCI World index which represented a common stock that used to be considered the riskiest financial asset. The results showed that total returns were highest among Utility and Privacy altcoins and lowest for Bitcoin. However, the risk-adjusted returns revealed that Privacy, Utility and Payment altcoins generated the highest return per unit of risk. The efficiency tests showed that the same altcoin categories recorded the highest percentage of inefficient altcoin markets. However, payment altcoin was the most consistent.

The results of this study have several important implications. For investment purpose, these inefficient altcoin markets have suggested that the movement in their prices could still be predicted. This finding seemed to imply that specific technical trading strategies could be useful for generating abnormally high returns. Payment altcoins represented the best investment candidates because they appeared to have the best combination of the highest risk-adjusted returns and predictability. Privacy altcoins were the least efficient through the Runs test, and they also recorded the second mean daily return and risk-adjusted return. However, investors should take extra caution investing in Privacy altcoins since they were often associated with illegal dealings and were likely to face additional scrutiny by the authority. Although Utility altcoins might appeal the most to investors for recording the highest mean daily returns, a further test was warranted because this category did not fare well in the Runs test.

Meanwhile, investors interested in Bitcoin should consider this cryptocurrency for long-term growth. Bitcoin provided the lowest total return, the lowest total risk, and the lowest risk-adjusted return relative to the altcoins. However, its performance was still better than that of the stock market (MSCI World Index). On the other hand, the MSCI World Index was the better choice compared to Bitcoin for trading because the latter was efficient, suggesting that its past prices and volume could not be exploited to predict its future price movement. The opposite was the case with the MSCI World Index and probably also with the various exchange-traded funds (ETFs) based on the stock index.

Overall, the findings of this study have added insights into the behaviour of the cryptocurrency market. Understanding this digital asset has become all the more important since its presence in major Finance and Investment platforms such as Yahoo.Finance and Investing.com. It was clearly an acknowledgement of its role as an important investment tool. This development could threaten uninformed investors who had joined the bandwagon for fear of lost opportunity (FOMO) to make great returns from the digital assets. As underscored in the empirical findings of the present study, cryptocurrencies were far riskier than common stock used to represent the riskiest financial assets. However, the risks could be reduced by choosing cryptocurrencies whose market behaviour could be predicted. This study has shown that there were ample cryptocurrencies with such features to choose from, particularly those that belong to the payment category. In brief, because cryptocurrencies were extremely risky and unregulated in most countries, investors needed to apply additional screening criteria to protect their capital. Future studies could address some of these criteria, including refining the identification of cryptocurrencies into reasonably tricky categories due to the complexity of the assets and the limited information. More tests would improve the robustness of the results, and high-frequency data might be more relevant to investors, given the volatility of these digital assets.

ACKNOWLEDGMENT

This work was supported by a Finance and Investment Research Grant scheme (EP-2018-010) from the Yayasan Tun Ismail Mohamed Ali (YTI-UKM).

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APPENDIX

Description of Types of Cryptocurrencies

Category and Description	Examples of Cryptocurrencies
Payment	
- Its primary use is as a store of value, transaction, and payments, just like fiat currencies. It is created to remove central authority control and cut out the middlemen in the daily transactions. Blockchain technology allows payment using cryptocurrencies to be more efficient and safe.	- Bitcoin, Litecoin, Bitcoin Cash, OmiseGo, Dash, Ripple, Tether, Bitcoin Cash, Bitcoin Gold, Stellar Lumens, Ripple, GameCredits, ReddCoin, Digix DAO, Nexus, SmartCash, Monacoin, Dogecoin, Tether, Monero, Dash, IOTA, Nano, Decred, Aeternity, Bitcoin Atom, Dogecoin, Digibyte, Bitcoin Diamond, Stellar Lumens, and Request Network
Application	
- These cryptocurrencies provide plenty of applications, and each of them based on their development and operation on other smart contracts platform.	- Ox Project, Zilliqa, DeepBrain Chain, Skycoin, Status, Gnosis, Enigma, Emercoin, Nebulas, Nxt, FunFair, Komodo (KMD), dIGIbYTE, Augur, TRON, and EOS.
Platform	
- Referred to as a decentralized application, protocol cryptocurrencies, smart contract cryptocurrencies or a hybrid of all three. - Built on a centralized blockchain platform, developers use them as a platform for building decentralized applications.	- Ethereum, NEO, Lisk, EOS, Icon, Qtum, VeChain, Ark, Substratum, Achain, Chainlink, Aeternity, Bytom, Factom, Dragonchain, Waltonchain, VeChain, Waves, Ethereum Classic, Cardano, NEO, Ethereum, NEM, Ethereum Classic, NEO, EOS, Lisk, Chainlink, Waves, Stratis, Cardano, Stellar, Zilliqa, QTUM, Icon, Rchain, Ardor, Ontology, Bytom, Nxt, Straits, Status, Ark, Neblio, Bancor, Dragonchain, and Skycoin.
Utility	
- It is designed for a specific purpose such as; - Fintech facilitates creating a financial system that provides services like cryptocurrency bank accounts, trading, and loan. - Exchange: introduced and used mainly by the cryptocurrency exchanges as incentives like token and discount coupon to bring people to their exchange platform.	- Siacoin, Storj, Byteball, Siacoin, Maidsafecoin and Storj, Ripple, Stellar Lumens, Piopulous - Fintech: Bancor, Bancera, Crypterium, Ripple, Stellar Lumens, Populour, OmiseGo, Quoine, Bancor, and Crypto.com - Exchange: Binance Coin, KuCoin Shares, BiBox Token, COSS Coin, Binance token, Huobi token, Kucoin Shares, Republic Protocol, and 0x project

(continued)

Category and Description	Examples of Cryptocurrencies
Privacy - Mainly focus on providing security and anonymity in a transaction. - A bit controversial because it is seen as an illicit tool for illegal activities such as money laundering.	- Monero, Zcash, CloakCoin, Dash - Monero, ZCoin, Zclassic, Bytecoin, Verge, ZCash, Dash, Bitcoin Private, Komodo, PIVX, Enigma and Navcoin.

Notes: From each type of cryptocurrencies, the description and examples are gathered from various sources:

https://cryptflix.com/cryptocurrencies-by-category/

https://cryptoverze.com/cryptocurrency-categories/

https://masterthecrypto.com/breakdown-of-cryptocurrency-market/

https://medium.com/cryptolinks/5-1-major-cryptocurrency-categories-where-should-you-invest-in-6af800465613

https://www.investdiva.com/investing-guide/top-cryptocurrency-categories-investment/

https://www.iris.xyz/learn/equities/5-top-cryptocurrency-categories-your-investment-portfolio