The Efficiency of Cryptocurrency Markets

Bachelor Thesis

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Abstract

This paper investigates the efficiency of cryptocurrency markets in two parts. Firstly, the weak form of the Efficient Market Hypothesis (Fama 1970) is tested using a set of powerful non-parametric tests. Secondly, the Adaptive Market Hypothesis is empirically tested through the use of the Adjusted Market Inefficiency Magnitude (Tran and Leirvik, 2019). The data used for this research consists of the returns and OHLC data for 12 Cryptocurrency assets. The results show that most cryptocurrencies excluding bitcoin do not satisfy the weak form of the EMH. Furthermore, all cryptocurrencies investigated exhibit large variations in levels of efficiency and, also, display signs of herding, positive-feedback trading and trend seeking.

Key words: Cryptocurrency, efficiency, herding

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1 Introduction

Over the last few years, the rapid expansion of the cryptocurrency markets has drawn the attention of governments, financial institutions and retail investors on a massive scale. On the one hand, retail investors have witnessed speculators and early supporters gain vast amounts of wealth by being involved in cryptocurrency markets. On the other, governments and regulators are tackling the issue of how to go about regulating this market and providing a reply to the 'decentralisation' movement that blockchain technology has brought about. We are witnessing the growth and development of an entirely new market, the likes of which have not been seen before. In that regard, the questions of how well the characteristics of these markets are understood and how they compare to pre-existing markets play an important role in the future development of the cryptocurrency market.

The reasons behind the explosion of interest in cryptocurrencies over the past few years are myriad. Primarily, the blockchain technology that represents the underlying foundation of all cryptocurrencies has gained the support of many that believe it to be a breakthrough in innovation that will disrupt the global economy on a scale similar to that of the invention of the internet (Zhao et al., 2016). Additionally, the decentralised aspects of the blockchain technology has facilitated the formation of Decentralised Autonomous Organisations (DAO's) that can be managed and run on a global scale through a group of individuals who coordinate on the direction the organisation takes through the use of consensus algorithms (Zheng et al., 2018). Financial transactions with no limit can be conducted from anywhere on the planet and executed within minutes. Moreover, A few characteristics of the cryptocurrency markets are akin to those found in frontier markets. The appeal of such markets is the promise of potential abnormal returns that are accompanied by risks that are not understood to their full extent. Such markets can, on occasion, be viewed as a tool for diversification into assets that are uncorrelated to more commonly accessed financial assets in order to mitigate the risks associated with financial crises. Several researchers have found that most cryptocurrency assets tend to be largely uncorrelated to other financial assets in the global economy (Wang et al., 2019). Thus, presenting another avenue for potential investments into cryptocurrencies such as bitcoin. A more extreme example of the mass adoption of cryptocurrencies can be seen in El Salvador, where bitcoin is on track to replace the nation's official currency (Chakravarthi et al., 2021). In essence, such an action would mean every person within the economy of El Salvador would be an investor in cryptocurrency markets that are completely unregulated.

It is clear from the perspective of regulators why cryptocurrencies represent a potential threat to the currently established systems within the global economy. As a start, many countries including China, India, Russia and Switzerland are working on developing and implementing their own state-run digital currencies known as Central Bank Digital Currencies (CBDC) (Kumhof and Noone, 2018) in combination with trying to mitigate the anonymity associated with cryptocurrency transactions through new legislations. From the perspective of market participants, it can be suggested that they are unaware of the mechanisms that govern this new market and may be exposing themselves to risks that may be hard to overcome if manifested. In order to begin developing an understanding for the aforementioned risk associated with this market, it is important to have an empirical foundation on the price mechanisms that govern it. As a contribution towards this goal this research aims to provide an analysis into the efficiency of the cryptocurrency markets.

As first delineated by Fama (1970) in his "Efficient Capital Markets: A Review of Theory and Empirical Work" the Efficient Market Hypothesis (EMH) represents the idea that publicly traded securities where all information regarding the same is publicly available must be priced efficiently and follow a price mechanism that follows a random walk. That is to say, all the information related to the market and the security is "priced-in" to the current price of any given security. An important implication of this theory is that it suggests that it should be impossible to make any accurate predictions about the value of securities in the long-run. Thus, the inefficiencies in a market may result in distortions between price and value that should converge over time. The EMH has had a profound impact on the way price mechanisms are understood and provided a foundation for modern risk-based asset pricing theories (Fama & French, 2004).

Cryptocurrencies, however, are said to not have any underlying asset value but may possess underlying value in their use or utility. This presents the issue of whether deviations from their underlying value can exist at all. Nevertheless, the efficiency of these markets may be assessed by virtue of these assets being traded on exchanges on a global scale and valued by the market as a whole in congruence with the flow of information regarding the underlying cryptocurrencies. This begs the question, "Does the EMH provide a reasonable estimate for the efficiency of cryptocurrency markets?"

A more recently developed theory for market efficiency is the Adaptive Market Hypothesis (AMH). First described by Andrew Lo (2004), the theory is based on the idea that market participants can exhibit both rationality and irrationality at the same time. For example, investors may behave irrationally during times of extreme volatility leading to anomalies in market outcomes while behaving rationally during other times. Moreover, the theory suggests that market participants through their irrationality make mistakes and overcome these mistakes by adapting and acting in a rational manner as time progresses. As such, it may be possible that an adaptive theory of market efficiency such as this one is better equipped to describe the mechanisms of the cryptocurrency markets. Hence, this research aims to answer the following question:

To what extent are cryptocurrency markets efficient on the basis of the Efficient and Adaptive Market Hypothesis?

This paper assesses the efficiency of the cryptocurrency market in two parts. Firstly, through the perspective of the weak-form of the Efficient Market Hypothesis by running a set of tests, such as the Ljung Box test, Runs test and Hurst exponent test on a variety of cryptocurrency assets in order to determine whether the price mechanism of the market follows a random walk as is necessitated by the weak form of the EMH. Secondly, the Adjusted Market Inefficiency Magnitude (AMIM) as described by Tran Leirvik (2019) is implemented to empirically measure the level of efficiency through time of the same set of diverse cryptocurrency assets on a daily basis starting from their inception till July of 2021. The overarching goal of this research is to provide an analysis into the efficiency of the cryptocurrency market that is more diverse and up to date than previous studies within this field.

From the first part of the research, the results from the non-parametric tests show that the cryptocurrency market is inefficient in that most assets do not satisfy the weak form of the Efficient Market Hypothesis. Other than the apparent inefficiency in this market, the results from the first part also delineate significant signs of herding, feedback-trading and positive serial correlation within the cryptocurrency markets. Surprisingly, the AMIM results in the second part of this study, used to quantify market efficiency and provide evidence that may support the Adaptive Market Hypothesis, show that the markets are largely efficient and show extreme variations in their levels of efficiency. Additionally, the results from this part of the research corroborate those from the first part as they confirm the presence of herding, feedback-trading and trend seeking behaviours within cryptocurrency markets.

The remainder of this research is structured as follows. The Theoretical Framework outlines the literature that is relevant to this research and provides an insight into what is to be expected from the results of the study. Secondly, the Data & Methodology provides details into the dataset used for the empirical analysis and outlines the methodological framework used for the same. Thirdly, the results are presented in detail and critically analysed in the Discussion. Finally, the conclusion provides a summary of the research and delineates shortcomings and potential avenues for future research.

2 Theoretical Framework

2.1 Literature Review

Several researchers and studies use the Efficient Market Hypothesis and Adaptive Market Hypothesis, as defined in the introduction, in order to come to conclusions about the efficiency of the cryptocurrency markets and specific cryptocurrencies. However, their results are largely contradictory. In that regard, this section will highlight some of the most important and relevant research done so far and draw some criticisms and insights from the same in order to develop a preliminary expectation of the results that this study will produce.

Andrew Urquhart (2016) conducted research into the efficiency of bitcoin grounded on the weak form of the EMH. The weak form of the EMH suggests that historical price performance cannot be used to make accurate predictions about the future price movements of an asset. As a result of the research, he indicates that by most standard measures of efficiency bitcoin is efficient during certain periods and inefficient during others. Moreover, Urquhart concludes that bitcoin may become more efficient over time.

Although Urquhart's research is solely on bitcoin, the results are complemented by the work of Noda (2019) wherein the author tests the applicability of AMH on three large cryptocurrencies using a GLS based time-varying model approach developed by Ito et al., (2016) to test for time-varying efficiency in Japanese securities markets. Noda postulates, based on the empirical results, that the efficiency in cryptocurrency markets varies over time and has evolved. Furthermore, he concludes that the efficiency of bitcoin is higher than most other cryptocurrencies. A potential explanation for these results can be drawn to the effects of liquidity on market efficiency.

The liquidity of a market refers to the ease with which assets within a market can be bought and sold without impacting the price of the assets (Pagano, 1989). As shown by Chordia et al., (2008) increases in liquidity lead to an increase in arbitrage activity. This, in turn, leads to more information being incorporated into markets and higher levels of market efficiency. Moreover, Chun Wei (2018) conducts an analysis of the level of liquidity of different cryptocurrency assets using the liquidity ratio and its effects on cryptocurrency market efficiency through return predictability. The author finds that cryptocurrencies with higher liquidity show higher efficiency and in that regard lower return predictability as arbitrage opportunities are more actively acted upon. Furthermore, suggesting that the liquidity of these assets plays a significant role in determining the efficiency of the same.

Contrary to the aforementioned research, Jiang et al., (2018) use a rolling window approach to assess the long-term memory of bitcoin. The authors find that bitcoin does not show any signs of improved efficiency over time. Additionally, bitcoin appears to display long-term memory and the author suggests that the inefficiency of the asset is likely due to the highly speculative nature of market participants within this market.

Finally, Tran and Leirvik (2019) have constructed a concrete measure for the time-varying efficiency of financial assets that is easier to implement than the complex process proposed by Ito et al., (2016) and implemented by Noda (2019). This novel measure has been termed the Adjusted Market Inefficiency Magnitude (AMIM) and involves creating a standardized set of the coefficients estimated for an autoregressive model in order to effectively calculate market efficiency over any time interval. Furthermore, the method can be implemented using a rolling window system or a batched system for the data providing further flexibility to the implementation of the AMIM.

2.2 Preliminary Expectations

The number of new cryptocurrency projects being developed is growing at an astounding rate. Within 2020 alone, a total of 2329 new cryptocurrency projects were launched (Statista, 2021). Thus, a lot of cryptocurrencies have extremely low levels of market capitalisation. However, the range of market capitalisation levels is very large as some cryptocurrencies have a total market value of a few hundred thousand U.S. dollars and some hundreds of billions of dollars. In such an extreme market environment it is seen that levels of liquidity can vary dramatically with the interest speculators have in this largely unregulated market (Amihud, 2002).

A primary expectation from the results of this study with respect to the AMH is that all cryptocurrencies will show time-varying efficiency. In addition to this, it makes intuitive sense from the aforementioned studies that cryptocurrencies that are relatively larger and older than most others will tend to show a decrease in market efficiency during times of extreme market interest as was seen in 2017 and more recently in 2021. Such a result would mirror the effects of financial distress on more developed markets such as the S&P 500. Conversely, it is expected that smaller and newer cryptocurrencies should depict increases in the level of efficiency described by the (AMH) during periods of high speculative interest and liquidity. This is a phenomenon often seen in emerging markets and follows the explanation described by Chordia et al., (2008).

With respect to the weak form of market efficiency (EMH), it is expected that most cryptocurrencies should not satisfy the requirements of market efficiency by traditional tests. The reason for this expectation is the idea that the market is relatively new and not yet fully developed and almost completely unregulated. It follows from this that there is a high amount of private information within the market. However, this notion may be affected by the decentralised aspects of the market which ensure that all transactions within cryptocurrency networks are made public in addition to most projects being worked on in a public environment thereby rendering private information redundant to a large extent.

3 Data & Methodology

3.1 Data

In this section, the acquisition of the dataset, its contents and the transformation of the data is outlined. The data collection section explains the data collection process. Secondly, the variables and data Transformation section delineates the process used to facilitate the implementation of the data for the empirical analysis. Finally, the Data Descriptives section illustrates the technical characteristics of the dataset.

3.1.1 Data Collection

The data used for this study is acquired through the implementation of a free to use API from the online cryptocurrency data site known as coingecko.com. The API is used in combination with 'google sheets' through the 'API Connector' add-on. This allows data to be accessed through the API, stored and adapted for further use.

The list of cryptocurrencies used for this research is taken based on the date of inception of the asset in such a manner as to include cryptocurrencies with more recent dates of inception and those that have been trading since 2010-2013 onwards. Using the ID of each currency used and the required data points in the API, it outputs the URL required to be included in the 'API Connector' add-on in order to access the data. The data collected was complete and did not contain any missing values. However, certain crypto-coins were removed and others added as per their availability. The final list of cryptocurrencies included was as follows: Bitcoin, Cardano, Chainlink, Cosmos, Dogecoin, EOS, Ethereum, Iota, Litecoin, Monero, NEM, Polkadot, Solana, Stellar, Tron, Uniswap and Ripple.

3.1.2 Variables & Data Transformation

The dataset used for this study contains the Open, High, Low, Close price data in addition to the volume and market capitalisation on a daily basis for each of the aforementioned cryptocurrencies in USD. In order for the price data to be used in the context of this research, a new variable containing the daily returns of each crypto-asset is calculated using the following formula: $\log(Price_t) - \log(Price_{t-1})$. This is the only transformation required for the data to be operational in the empirical analysis that follows. Additionally, the Market Inefficiency Magnitude and Adjusted Market Inefficiency Magnitude elaborated upon in the methodology section form the two remaining variables used in this study.

3.1.3 Data Descriptives

The number of assets used in this study is relatively larger than those used in other recent research. To that effect, the assets in question have been subdivided into three different sections on the basis of the length of time these assets have been trading. This is done based on the number of observations available for each asset in order to make the results section of this paper more comprehensible. Figure 1 below, depicts the average market capitalisation level and the number of observations since inception for each of the cryptocurrencies. The first category consists of three coins with the lowest number of observations (0 < Observations > 1000). This includes Cosmos, Polkadot and Solana. The second category consists of coins with observations less than 2000 (1000 < Observations > 2000) including the following coins: Cardano, EOS, Chainlink and Iota. The third category includes coins with observations greater than 2000 (2000 < Observations). This includes Bitcoin, Ethereum, Ripple, Monero, Stellar and Litecoin.

Figure 1: Market Capitalisation & Number of Observations

Note: This figure provides the average market capitalisation for each of the cryptocurrencies in the dataset. The y-axis on the left depicts the values for Market Capitalisation in U.S Dollars, the y-axis on the right indicates the number of observations. The x-axis lists each of the specific cryptocurrencies

Furthermore, the market capitalisation level of each asset is depicted in descending order. Most notably, Bitcoin has by far the largest market capitalisation amongst all the crypto-assets. Followed by Ethereum, Ripple and Cardano respectively.

Table 1. Below, outlines the descriptive statistics for the returns of each asset within the dataset, in addition to the results of the Augmented Dickey-Fuller test used to determine whether the data contains any unit roots. The null hypothesis for the test assumes non-stationarity. It is required, in order for further analysis of the data, that the time-series exhibits stationarity over time. The null hypothesis is rejected for each of the assets at the 1% significance level ($p < 0.001$). Thus, the returns are stationary over time.

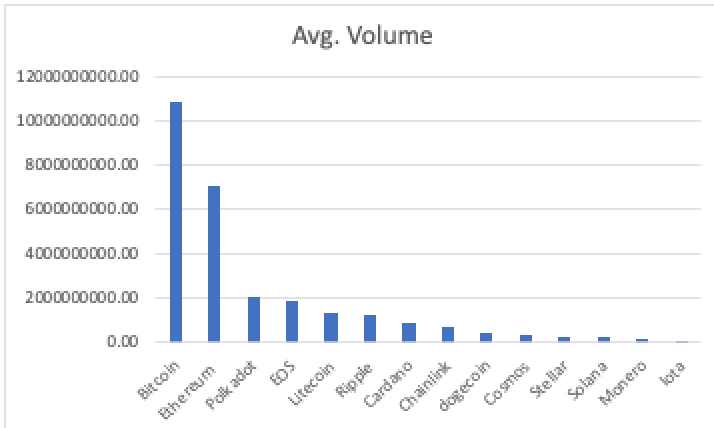
Table 1: Descriptive Statistics for Cryptocurrency Returns

Asset	**Obs**	**Mean**	**Std. Dev**	**Min**	**Max**	**ADF**
Dogecoin	2,759	.0025528	.0837581	-.5810523	1.516382	-49.716***
Ripple	2,892	.0016512	.0731831	-.6162879	1.027379	-52.071***
Cardano	1,373	.0029145	.07461	-.5036523	.8615429	-37.831***
ChainLink	1,384	.0034491	.0788526	-.6145769	.4806152	-38.702***
Cosmos	844	.0006655	.0736403	-.5901975	.2809294	-31.953***
EOS	1,465	.0002454	.0740446	-.5042275	.4395974	-41.217***
Ethereum	2,159	.0037214	.0620986	-.5507317	.4103353	-45.791***
Iota	1,483	.0003213	.0733395	-.543564	.3847659	-40.195***
Litecoin	2,990	.001156	.0637462	-.5145794	.8292592	-54.543***
Monero	2,601	.001793	.0681112	-.5341959	.584541	-53.571***
NEM	2,287	.0026471	.0785998	-.4227136	.9955766	-51.6***
Polkadot	319	.005409	.084095	-.476964	.4446069	-20.615***
Solana	451	.0083964	.0931687	-.4653544	.3871843	-23.9***
Stellar	2,526	.0018148	.0740457	-.4099526	.7230718	-47.786***
Tron	1,391	.0027447	.0846078	-.5231967	.7866696	-37.143***
Uniswap	291	.0040479	.0885633	-.4034739	.3803306	-19.151***
Bitcoin	2,990	.0018286	.0427583	-.4647303	.357451	-55.811***

*Note: This table provides a summer of the descriptive statistics for the returns of each asset in the dataset. Additionally, the dataset gives the results of the Augmented Dickey-Fuller test used to detect unit roots in the data. Significance levels are as follows: *p<0.1, **p<0.05, ***p<0.01.*

The standard deviation for the returns of each asset is relatively high. This can be attributed to the extreme volatility the cryptocurrency markets experience. The same is true for the minimum and maximum values for returns that are shown in the table. As these markets can display extreme changes in daily returns during times of large amounts of speculative interest, such high values are considered common-place in this market.

Figure 2: Average Volume



Note: This figure depicts the average trading volume for each asset in the dataset in descending order from left to right.

Figure 2. Above, illustrates the average daily trading volume for each asset in the dataset. In cryptocurrency markets, trading volume can be used as a good proxy for liquidity in order to compare different crypto-assets to each other. The values in the graph are in descending order and match up to those of the market capitalisation for each coin with a few exceptions. The variation of volume over time for each coin will provide useful insights in the discussion of the results as it will facilitate drawing conclusions on the effect liquidity may have on the level of efficiency for each cryptocurrency.

Finally, the dataset used for this research is vastly more expansive and up to date when compared to previous research conducted within the area of assessing market efficiency for cryptocurrencies. This should provide a good basis for drawing broader conclusions from the results that extend towards the cryptocurrency market as a whole.

3.2 Methodology

This section describes the methodological framework adopted for the analysis of the efficiency of cryptocurrency returns in two parts. In the first part, we will assess the efficiency of various cryptocurrency assets on the basis of the weak form of the EMH. This will be achieved through the use of various highly powerful tests for randomness. Furthermore, we will also test the assets in the dataset for long term memory. The second part of the analysis will test the efficiency of the cryptocurrency assets on the basis of the AMH using the Market Inefficiency Magnitude as illustrated by Tran and Leirvik (2019).

3.2.1 Tests for the weak form of the EMH

3.2.1.1 Ljung-Box test (Ljung and Box, 1978)

The Ljung-Box test is commonly used on time-series data as a test that determines if autocorrelation coefficients for a specified number of lags are different from zero. The null and alternative hypothesis for this test are as follows:

H_0: *No autocorrelation*
H_a: *Autocorrelation*

The number of lags for the test is based on the Akaike Information Criterion (AIC). Here the null hypothesis is rejected if no autocorrelation is present at the 5% significance level.

3.2.1.2 Runs test (Wald & Wolfowitz, 1940)

The Runs test is used to determine if the data generation process for a specific distribution has occurred as a random process. The test determines whether the number of runs observed in a series (sequence of price changes with the same sign) is statistically different from the expected number of runs. Moreover, the test also provides useful insights into whether the autocorrelation in the data is positive or negative. Too few runs indicates positive autocorrelation and too many runs indicates negative autocorrelation.

In the context of this research, the null hypothesis for the Runs test is as follows:

H_0: *Data generating process is random*
H_a: *Data generating process is non-random*

The test is conducted on the returns of each cryptocurrency and the null hypothesis is rejected if significant at the 5% significance level.

3.2.1.3 Hurst exponent (R/S Hurst) (Lo, 1991)

This test is used in order to measure the long-term time dependence of the data. In this context it refers to the tendency of the returns to exhibit reversion to some mean over a long period or the tendency of the price generation process to cluster or trend over time. The hypothesis for this test is as follows:

H_0: *Returns are not long-range dependent*
H_a: *Returns are long-range dependent*

This test outputs a t-statistic which is used in combination with the degrees of freedom from the data to generate a probability value which is used to evaluate the null hypothesis at the 5% significance level.

3.2.2 Quantifying the Adaptive Market Hypothesis

This subsection describes the steps taken to calculate the Market Inefficiency Magnitude and Adjusted Market Inefficiency Magnitude (Tran and Leirvik, 2019).

Step 1

An autoregressive model with an appropriate number of lags is required for each asset within the dataset. The autoregressive model will be used in combination with an appropriately sized rolling window to create a vector of autocorrelation coefficients (β) and a corresponding covariance matrix required for the standardisation of the coefficients determined by each model.

The autoregressive models implemented are of the following conventional AR(q) model form:

$$r_t = \alpha + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \ldots \beta_q r_{t-q} + \varepsilon_t$$

Wherein, α is a constant and ε_t represents the error term. The essential requirement of the Efficient Market Hypothesis is that the coefficients for each lag within the model are 0; thereby indicating that the price generation process is stochastic.

The number of lags chosen for each AR(q) model is based on the minimisation of the Akaike Information Criterion (AIC). Following the selection of an appropriate number of lags for each model, The AR(q) model is implemented in combination with a rolling window of 100 days. This model generates the vector of the aforementioned β estimates which are used to determine the covariance matrix needed to standardise the autocorrelation coefficients from the model in the following step.

Step 2

The β coefficients, by construction, will follow an asymptotic distribution of the following form:

$$\beta\ (Estimates) \sim N(\beta,\Sigma)$$

In the above equation, β(Estimates) represents the vector of estimated autocorrelation coefficients and Σ represents the covariance matrix of the estimated coefficients. We utilise Cholesky decomposition in order to separate the covariance matrix into two triangular matrix components such that Σ = LL'. Now, the vector of β(Estimates) is standardised by the following matrix multiplication:

$$\beta(Standardised) = L^{-1} * \beta(Estimates\ vector)$$

Where L^{-1} is the inverse of the lower triangle matrix calculated from the Cholesky decomposition. Additionally, β(Standardised) now follows a normal distribution N(0,I) wherein I is an identity matrix.

Through this process, we are able to use the β(Standardised) components reliably to calculate further measures as each component is independent, bringing us one step closer to the MIM measure.

Step 3

Now, we move on to the calculation of the Market Inefficiency Magnitude using the following formula:

$$MIM = \frac{\sum_{j=1}^{q} |\beta^{standardised}|}{1 + \sum_{j=1}^{q} |\beta^{standardised}|}$$

The use of absolute values in the formula is done in order to eliminate the possibility of sign effects on the MIM values. Moreover, the variation in the MIM values ranges from 0 to 1 due to the standard normal process implemented earlier. This implies that the β is positively related to the MIM. Values closer to 0 illustrate market efficiency and values closer to 1 indicate market inefficiency.

Step 4.

In the next step, we calculate the 95% confidence interval for the MIM for each *β(standardised)*. This is achieved by running a simulation under the null hypothesis that markets are perfectly efficient ($\beta = 0$). The confidence interval will be different for each number of lags used for each AR(q) model. Thus for each lag, we run a simulation of 100000 observations using a standard normal distribution for each *β(standardised)* from which the 95th percentile represents the 95% confidence interval for each Lag length.

Step 5.

Finally, the Adjusted Market Inefficiency Magnitude is calculated using the following formula:

$$AMIM = \frac{MIM - Rci}{1 - Rci}$$

Wherein, R_{CI} represents the 95% confidence interval. The AMIM measure indicates market inefficiency for AMIM > 0 and market efficiency for AMIM < 0.

3.2.3 Why AMIM

The use of the AMIM as a measure for market efficiency has several advantages over existing measures of time-varying degree of market efficiency (TIME) (Noda, 2019 & Ito et al., 2016). Firstly, the calculation of the measure is very straightforward and does not require as much computational power as is needed by the GLS-based time-varying autoregressive model implemented by ito et al., (2016). Thus, we are able to compute the degree of efficiency for a larger number of assets within the cryptocurrency market at a lower computational expense.

Secondly, the denominator of the TIME measure can equal zero by design. This causes the results to be subject to discontinuities that are avoided through the use of the MIM measure as described by Tran and Leirvik (2019).

Thirdly, as the results of the AMIM are adjusted using the confidence intervals of the coefficients of autocorrelation, they allow for easy inference of the results and provide a clear description of when markets are significantly inefficient. This inability of the TIME measure to address this issue is a shortcoming of the study conducted by Noda (2019) in the context of cryptocurrency markets.

4 Results

4.1 Results For EMH tests

Table 2: Results of Non-parametric tests

Coin	Ljung Box (Z)	runs test	hurst
Bitcoin	1.2965	2.34**	1.28
Cardano	30.1417***	2.08**	2.24**
Chainlink	2.2297	1.45	1.05
Cosmos	16.5598 ***	2.2**	1.22
Dogecoin	15.9527***	2.99***	1.43
EOS	10.1248***	4.36***	1.33
Ethereum	5.6067*	2.56**	1.89
Iota	8.3410*	4.44***	1.48
Litecoin	12.1560***	3.51***	1.29
Monero	5.1940***	3.75***	1.68*
Polkadot	3.4014*	0.73	1.26
Solana	6.4470***	0.8	1.33
Stellar	6.3126***	3.1***	1.48
Ripple	10.1302**	0.63	1.46

*Note: This table describes the results for Ljung-Box, Runs and Hurst exponent tests for each of the cryptocurrencies in the dataset. Significance levels are as follows: *p<0.1, **p<0.05, ***p<0.01*

4.1.1 Ljung-Box test (Ljung and Box, 1978)

Table 2 above, shows the Z-statistic values for the Ljung-Box test conducted on the return data for each asset within the dataset. For the cryptocurrencies Bitcoin and Chainlink the null hypothesis of no auto-correlation cannot be rejected at the 5% significance level ($p < 0.05$). This suggests that the price generating mechanism for these coins is stochastic in nature. Moreover, both of these assets satisfy the weak form of the EMH on the basis of this non-parametric test. Additionally, Ethereum, Iota and Polkadot reject the null hypothesis at the 10% significance level ($p > 0.1$). However, this result does not provide enough evidence to reject the null hypothesis of no-autocorrelation. Therefore, at the 95% significance level Ethereum, Polkadot and Iota satisfy the weak form of the EMH.

Finally, the remainder of the cryptocurrencies, namely: Cardano, Dogecoin, Cosmos, EOS, Litecoin, Monero, Solana and Stellar all reject the null hypothesis at the 1% significance level ($p < 0.01$) with ripple rejecting the null hypothesis at the 5% significance level ($p < 0.05$). These assets therefore exhibit significant autocorrelation and can be considered inefficient by weak form of the Efficient Market Hypothesis.

4.1.2 Runs test (Wald & Wolfowitz, 1940)

Column 3 of table 2. Depicts the Z-statistic values for the runs test for each cryptocurrency. From the table it can be seen that the null hypothesis that the data generating process is random cannot be rejected for the following cryptocurrencies at the 5% significance level ($p<0.05$): Chainlink, Polkadot, Solana and Ripple. As the value of the Z-statistic is positive, it is clear that the returns of these coins exhibit positive serial correlation, however, there is not enough evidence to suggest that the returns are not stochastic.

Bitcoin, Cosmos, Cardano and Ethereum reject the null hypothesis at the 5% significance level ($p<0.05$). Additionally, Dogecoin, EOS, Iota, Litecoin, Monero and Stellar; all reject the null hypothesis at the 1% significance level ($p<0.01$). Given that the values of the test statistic for these crypto-assets is positive and significant suggests that the number of runs observed is lower than the expected number of runs. As such, significant positive serial correlation is present and leads to inefficiencies in the pricing mechanism for these assets.

4.1.3 Hurst exponent (R/S Hurst) (Lo, 1991)

As depicted in Table 2. Cardano is the only cryptocurrency that rejects the null hypothesis of long-term dependence at the 5% significance level ($p < 0.05$). This indicates that cardano exhibits some long-term memory in returns with positive autocorrelation. Furthermore, high returns for this cryptocurrency are likely to be followed by more high returns. However, none of the other crypto-assets exhibit this characteristic.

4.2 Magnitude of market inefficiency

The AMIM measure indicates the magnitude of market inefficiency in combination with indicating the periods during which the market was significantly inefficient. Based on the computation of the AMIM measure one cannot reject the hypothesis that markets are efficient for AMIM values below zero (AMIM < 0). Additionally, AMIM values greater than 0 (AMIM > 0) indicate that the market is significantly inefficient. However, the primary objective of this measure is to indicate how the level of efficiency varies over time in accordance with the Adaptive Market Hypothesis.

Table 3: Descriptive Statistics for AMIM

Coin	Obs	Mean	St. Dev	Min	Max
EOS	1,367	-.4816659	.452948	-2.785671	.5667946
Cosmos	746	-.4805068	.531495	-3.253922	.447944
Cardano	1,275	-.6100865	.5958891	-2.875353	.5226684
Chainlink	1,275	-.1885635	.4287995	-1.81571	.681915
Ethereum	2,061	-.7020764	.5923546	-3.518413	.4013246
Polkadot	221	-.3476209	.0292066	-.397638	-.2933698
Ripple	2,793	-.5971249	.5940129	-3.429287	.4969569
Solana	353	-1.656908	.1950804	-1.954329	-1.234952
Iota	1,385	-.6701968	.5975753	-2.961334	.4359388
Bitcoin	2,892	-.8142661	.551797	-1.956504	.3978109
Stellar	2,428	-.8627044	.5642327	-1.956365	.4357939
Monero	2,504	-.8358263	.5601072	-1.957024	.4216547

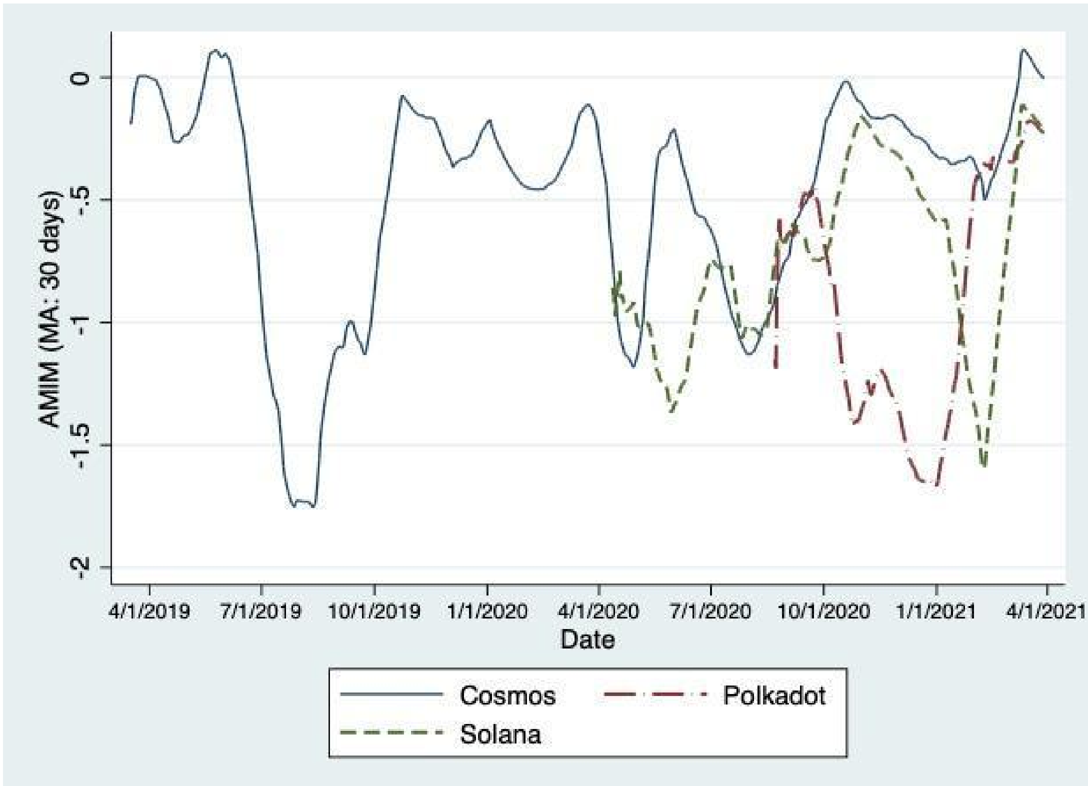
Note: This table provides the descriptive statistics with respect to the results of the AMIM calculation for each asset in the dataset.

Table 3 Above, highlights the average values for the AMIM measure retrieved from the dataset. It can be seen from the table that all the cryptocurrencies are, on average, efficient. This is indicated by the negative average values of AMIM for each cryptocurrency. The five most efficient cryptocurrencies within the dataset are Solana, Stellar, Monero, Bitcoin and Ethereum, respectively. The least efficient cryptocurrencies based on the average values of AMIM are Chainlink, Polkadot, Cosmos, EOS and Ripple, respectively.

The average value of AMIM may not effectively rank the efficiency of each crypto-asset. The reason for this is that the standard deviation for each asset within the dataset is 0.47, suggesting that the level of efficiency for each asset varies dramatically over different time periods. In that regard, the following subsections graphically delineate the variation of AMIM over time for each asset.

4.2.1 AMIM Small (observations < 1000)

Figure 3: AMIM (Observations < 1000)



Note: This figure depicts the variation of AMIM over time for all assets with a number of observations less than 1000. The y-axis contains the AMIM values. The x-axis contains the time variable. AMIM > 0 denotes significantly inefficient markets. AMIM > 0 cannot reject the hypothesis of market efficiency. Moreover, the level of AMIM is a measure for the level of market efficiency.

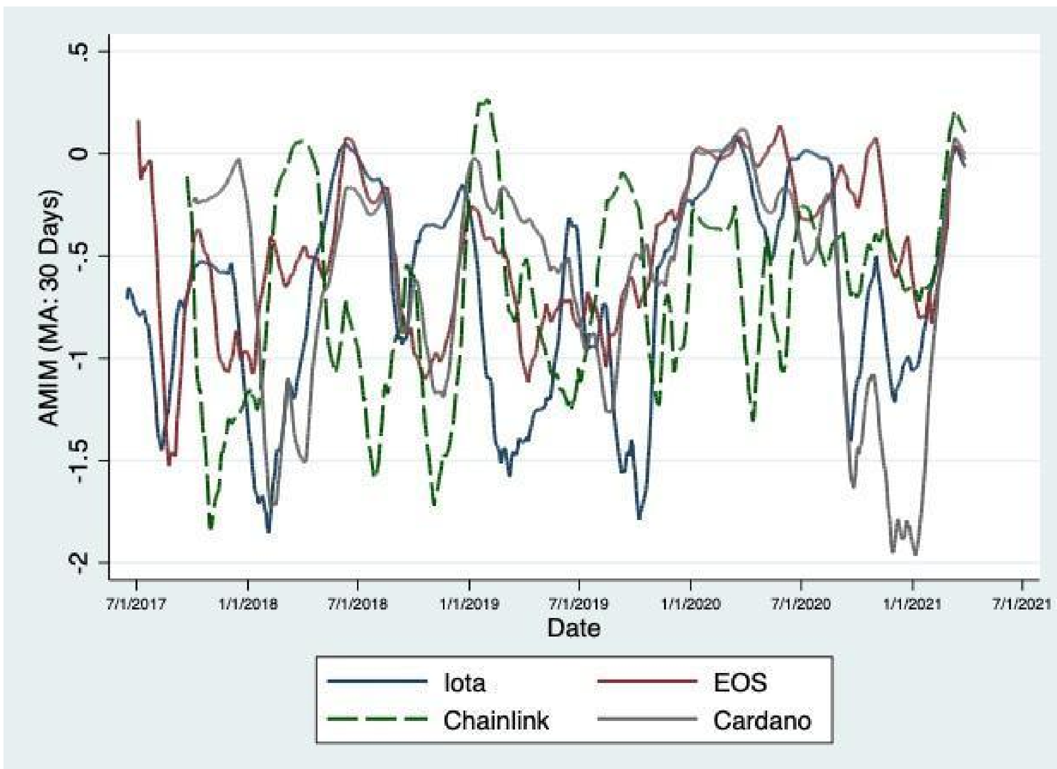
Figure 3 illustrates the variation of AMIM for Cosmos, Solana and Polkadot from their inception till the end of March 2021 on the basis of a moving average with a window of 30 days. It can be seen from the graph that all three cryptocurrencies exhibit large variations in their level of efficiency over time. This result supports the Adaptive Market Hypothesis.

It is also visible from the graph that cosmos experiences a spike in the level of market efficiency shortly after the cryptocurrency starts trading on exchanges globally. This spike indicates an event in the cryptocurrency markets wherein volumes rose dramatically and the market as a whole experienced a sharp downturn. The level of efficiency remains low and appears to be decreasing over time following this event. Furthermore, the crypto-asset experiences two peaks in AMIM wherein the market is significantly inefficient (AMIM > 0).

The level of efficiency for Polkadot and Solana follows a similar pattern to that observed in the early stages of Cosmos, with a peak in efficiency arising shortly after the inception of the coin followed by a drop in efficiency accompanied by a market wide decline. This drop is mirrored by Cosmos, but the drop in efficiency is less drastic in comparison. However, it is common for Solana and Polkadot that the market for these assets is not significantly inefficient at any point in time throughout the dataset.

4.2.2 AMIM Medium (1000 < observations < 2000)

Figure 4: AMIM (1000 < Observations < 2000)



Note: This figure depicts the variation of AMIM over time for all assets with a number of observations greater than 1000 and less than 2000. The y-axis contains the AMIM values. The x-axis contains the time variable. AMIM > 0 denotes significantly inefficient markets. AMIM > 0 cannot reject the hypothesis of market efficiency. Moreover, the level of AMIM is a measure for the level of market efficiency.

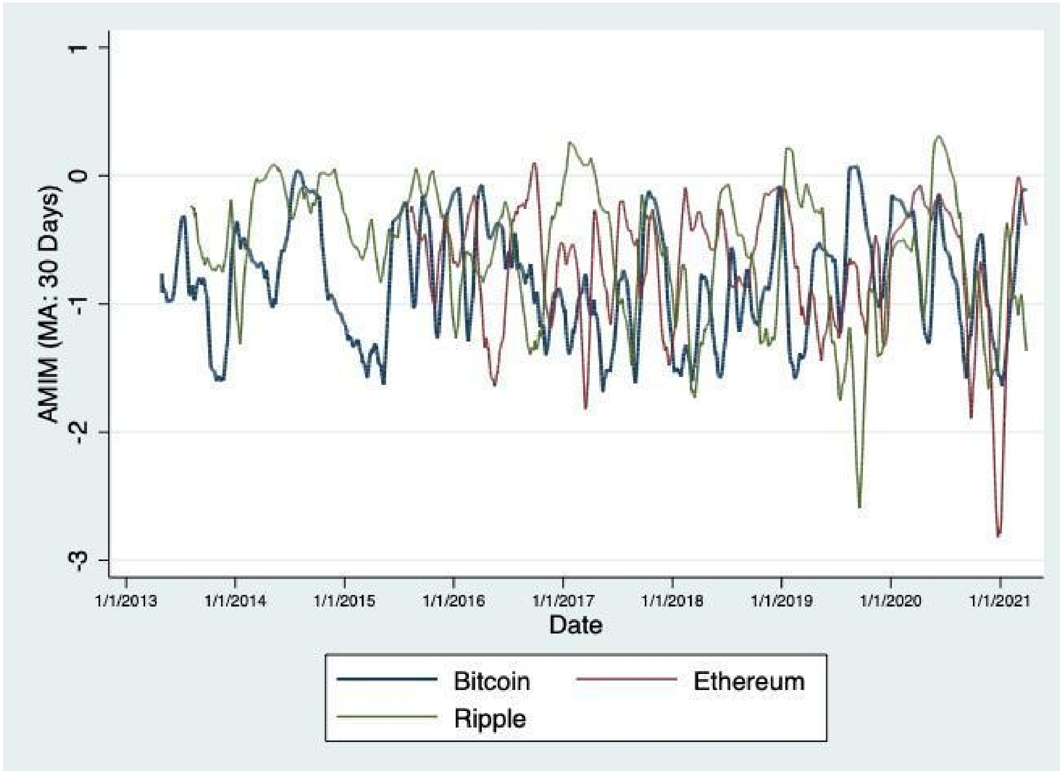
Figure 4 above, depicts the values of AMIM over a 30 day moving average for EOS, Iota, Cardano and Chainlink. From the figure it is apparent that each of the assets exhibits varying degrees of efficiency over time. Although the level of efficiency varies dramatically, it does not appear that the efficiency of the assets is improving or deteriorating over time for Iota, EOS and Cardano. Nevertheless, the efficiency of Chainlink is gradually reducing over the duration of the sample. In addition to this, it is interesting to note that after 2018, all of the assets in Figure 4 excluding chainlink show co-movement in relation to each other to a large extent.

Shortly before periods wherein the markets experiences dramatic increases in prices, spikes in the level of efficiency are observed. Following this, the markets experience periods of increased speculative interest in (As seen in 2018, 2019 & 2021), the level of efficiency drops drastically for all four cryptocurrencies. Additionally, during periods where speculative interest and liquidity are low, the efficiency of the market is higher. All of the assets experience 3 to 5 periods where markets are significantly inefficient, specifically when the volume of trading and, therefore, interest in this market is extremely high. This relationship is elaborated on further in the discussion section of this paper.

4.2.3 AMIM Large (2000 < observations)

As this section includes the results for five cryptocurrencies (Bitcoin, Ethereum, Ripple, Monero & Stellar), the information is depicted in two separate figures (Figure 5(a) & Figure 5(b)) with Bitcoin being used as a common cryptocurrency in both figures to allow for comparisons between the variation of AMIM values for each cryptocurrency.

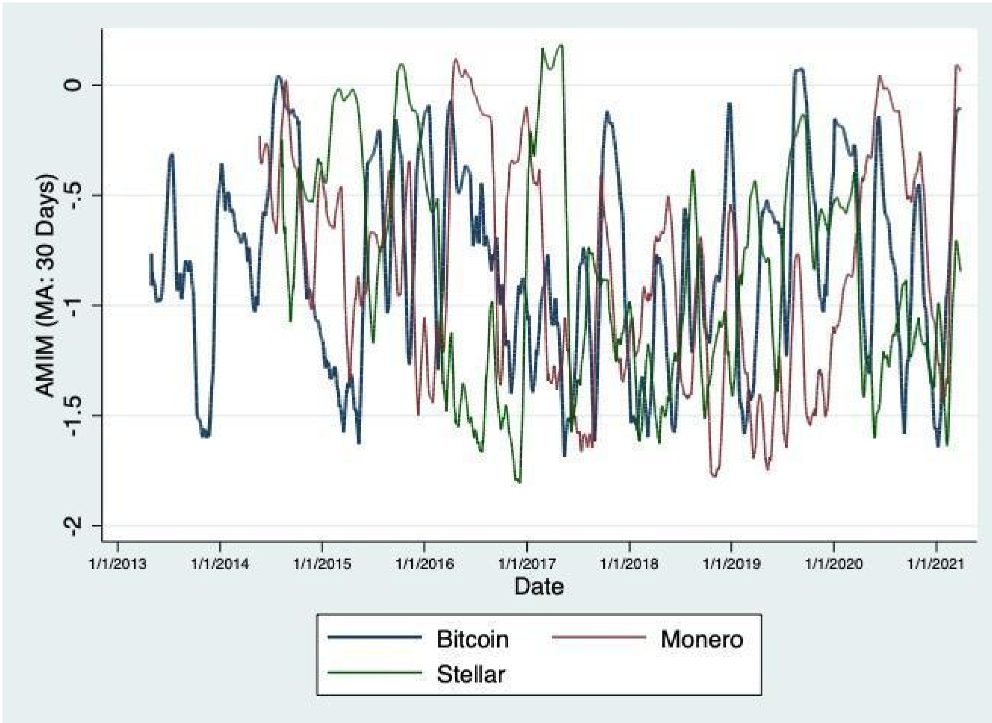
Figure 5(a): AMIM (Observations > 2000)



Note: This figure depicts the variation of AMIM over time for all assets with a number of observations greater than 1000 and less than 2000. The y-axis contains the AMIM values. The x-axis contains the time variable. AMIM > 0 denotes significantly inefficient markets. AMIM > 0 cannot reject the hypothesis of market efficiency. Moreover, the level of AMIM is a measure for the level of market efficiency.

From Figure 5(a) above, it can be seen that Bitcoin, Ripple and Ethereum all exhibit varying levels of efficiency over time. Out of the three cryptocurrencies depicted, ripple has the most instances of significant inefficiency (AMIM > 0). Furthermore, Bitcoin and Ethereum only show significant inefficiency in one instance - during 2019 and 2016, respectively. Another apparent feature of the results is the co-movement observed in the AMIM values for each of the respective cryptocurrencies. This is a recurring characteristic in each of the cryptocurrencies used in this study. Additionally, It is not clear that the level of efficiency for any of the crypto-assets is improving over time. However, the hypothesis that the cryptocurrencies are efficient cannot be rejected for the majority of the dataset. Conversely, Ripple exhibits several instances of significant inefficiency based on the figure. To that effect, it can be considered to be more inefficient than both Ethereum and Bitcoin.

Figure 5(b): AMIM (Observations > 2000)



Note: This figure depicts the variation of AMIM over time for all assets with a number of observations greater than 2000. The y-axis contains the AMIM values. The x-axis contains the time variable. AMIM > 0 denotes significantly inefficient markets. AMIM > 0 cannot reject the hypothesis of market efficiency. Moreover, the level of AMIM is a measure for the level of market efficiency.

In figure 5(b), the time-varying nature of the efficiency of Monero and Stellar can be observed clearly. In the period between 2015 and 2018 both Monero and Stellar depict periods of significant inefficiency. Moreover, there is relatively less co-movement between the AMIM values for these cryptocurrencies and Bitcoin before 2017. After which, the variation in levels of efficiency seem to be congruent in nature. This may be due to the increase in overall interest in the market and co-integration between alternative cryptocurrencies and Bitcoin. This notion will be expanded upon in the Discussion section of this research.

5 Discussion

5.1 Explain reasons for results in EMH

The results from the EMH section of this research show that most cryptocurrencies, aside from Bitcoin and Chainlink, are inefficient with respect to the weak form of the EMH. These results are to a large extent in line with those outlined in other studies, see Wei (2018), Al-yahyaee et al. (2018), Nadarajah and Chu (2017). It makes intuitive sense that Bitcoin, being the largest cryptocurrency by market capitalization and also the oldest cryptocurrency present on exchanges, is largely efficient on the basis of the on-parametric tests conducted in this study. A reason behind this finding can be attributed to the fact that efficiency in markets is attainable when there is enough liquidity present in the underlying asset allowing for arbitrage opportunities to be exploited and new information to be reflected in asset prices more actively (Chordia et. al, 2008) as is observed in the Bitcoin market. However, this intuition does not apply to what is observed in Chainlink. This cryptocurrency has a market capitalisation and average level of trading volume that is not significantly higher than most other cryptocurrencies. Nevertheless, it appears to be efficient in the weak form of the EMH. This result is juxtaposed by the results obtained from the AMIM measure suggesting that the efficiency of these markets is better explained by the Adaptive Market Hypothesis. This is elaborated on further under section 5.2.

A common result for all cryptocurrencies, observed from the runs test, is that there exists a significant amount of positive serial correlation in the returns of the assets considered in this study. This characteristic is a defining feature of the cryptocurrency markets as they stand today. This market has been shown to exhibit significant levels of herding and positive feedback trading (King & Koutmos, 2021 and Silva et al., 2019b). The cryptocurrency markets have seen extremely large amounts of retail investors entering the market over the past years who can be assumed to be largely uninformed, given the lack of clarity on the functioning of cryptocurrencies and, more specifically, cryptocurrency markets as whole. In combination with the ability to trade online with very few restrictions and access to leverage can be a possible reason for the high level of herding and trend following depicted by the results of this research. Furthermore, this reasoning is in line with the work of Barber and Odean (2001) wherein the authors outline that large volumes of uninformed market participants entering financial markets through the use of online trading leads to large amounts of feedback trading, volatility and trend seeking behaviours.

It follows from the notion of positive feedback trading and trend seeking behaviours being responsible for the high level of positive serial correlation in returns that this should in turn, affect the efficiency of markets as predictability of returns increases with the increase in the aforementioned market characteristics.

5.2 AMH discussion

All cryptocurrencies used for this research exhibited time-varying levels of efficiency while being significantly inefficient only for certain short periods within the dataset. These results are not in line with those found by Tran and Lerivik (2019) and Noda (2019), who find that the cryptocurrency markets are largely inefficient for the majority of the time-period used within their respective studies.

Moreover, some interesting characteristics can be identified from the figures pertaining to the time-varying nature of the AMIM measure for each asset considered. Primarily, most assets showed large degrees of co-movement in the level of efficiency over time. Specifically with respect to the movement of Bitcoin. This is illustrated clearly in figures 6, 7 and 8 in Appendix B. This co-movement often appears not within the exact same time frames, but rather, with a lag for certain coins see. A second characteristic made apparent by figures 9, 10, 11 in Appendix C is the link between the level of liquidity (Volume) and the level of efficiency observed over time for each cryptocurrency asset considered. It is seen that as the volumes of trades within a cryptocurrency increase, spikes in the level of efficiency are observed simultaneously. Moreover, these observations are more apparent during periods of high speculative interest and high returns within the market.

These observations are profound in that they are in line with the lead-lag effect and seesaw-effect observed with respect to cryptocurrency markets outlined by Wu et al. (2019) in combination with those of Chordia et al., (2008) linking increases in levels of efficiency with increases in liquidity and ease of trading. Wu et al. describe the seesaw-effect by illustrating how inflows of money are observed towards coins that have recently seen a large price increase and outflows are observed from coins that have recently experienced large price decreases. These findings serve as the basis for the explanation of the movements observed in the level of efficiency for each cryptocurrency over time.

Conversely, it is not observed for any cryptocurrency that the level of efficiency is improving over time as is originally suggested by the Adaptive Market Hypothesis. Nevertheless, the results presented in this study do not rule out this possibility. It can be argued that the cryptocurrency markets are still very new, being less than a decade old. In that regard, the improvements in efficiency over time may still require much longer than as the current time-frame can be considered short relative to those of more developed markets such as the US equities markets.

5.3 Comparison between research outcomes

On the one hand, the non-parametric tests used to analyse the Efficient Market Hypothesis in its weak form are well suited to describe the overall efficiency of the cryptocurrency markets with regard to the entire time-period that spans the dataset. On the other hand, it is clear that these tests do not provide insights into the time-varying nature of market efficiency in cryptocurrency markets that is highlighted by the implementation of the AMIM measure in line with the Adaptive Market Hypothesis. Moreover, it can be seen that the results of both, the tests for the weak form of EMH and the AMIM measure for AMH, suggest that markets show signs of herding and feedback trading that have significant effects on the efficiency of markets, see section 5.1 & 5.2. Taking the AMIM value as an average for each asset, one concludes overall efficiency in the cryptocurrency markets. This is juxtaposed by the non-parametric tests for EMH which depict inefficiency in the market overall.

To that effect, it can be suggested that both results are in line, as the AMIM is not a good measure for overall market efficiency when taken as an average. Rather, it is effective in illustrating the time varying efficiency of the cryptocurrency assets. Furthermore, the non-parametric tests for the weak form of EMH provide a better and more reliable insight into the overall efficiency of the markets but do not fully illustrate the time-varying aspects of efficiency or the different mechanisms that affect price generation in the cryptocurrency markets.

6 Conclusion

The aim of this paper is to determine the extent to which the up and coming cryptocurrency markets are efficient from the perspective of the Efficient Market Hypothesis (Fama, 1970 and 1991) and the Adaptive market hypothesis (Lo, 2004). Additionally, the paper aims to develop some insights into the nature of the price generating mechanisms that govern the cryptocurrency markets.

To conduct the analysis a large dataset consisting of approximately 26,300 data points for the returns of 12 cryptocurrency assets was subject to three powerful non-parametric tests to determine whether the markets satisfy the weak form of the Efficient Market hypothesis. Following this, a measure based on the work of Tran and Leirvik (2019), was derived to quantify the level of market efficiency over time for each asset. This facilitated inferences from the data regarding the time-varying nature of cryptocurrency market efficiency.

The results of the research provide an answer to the research question of, "To what extent are cryptocurrency markets efficient on the basis of the Efficient and Adaptive Market Hypothesis?" in that cryptocurrency markets were found to be, to a large extent, inefficient and display several characteristics of a market that is not yet fully developed. These include those of herding, feedback trading and trend seeking behaviours amongst investors within this market. These characteristics are akin to those found in emerging or frontier markets and have significant effects on the overall and transient levels of efficiency in the market. Finally, it was seen that the time-varying nature of market efficiency is very apparent in cryptocurrencies. These markets tend to see large spikes in levels of efficiency as liquidity and trading volumes shift from one asset to the other within the market.

However, this paper is subject to a number of limitations. Firstly, the model used for the construction of the Magnitude of Market Inefficiency is very new and is likely to be improved upon greatly over the coming years as researchers explore this field more actively. A second, very important limitation of this research stems from the nature of cryptocurrencies. An analysis into the efficiency of equities markets is supported by the fact that all equities are based on the same underlying principles and have the same purpose. That is to say, equity represents a percentage share of a firm. To the contrary, cryptocurrencies exist with vastly different purposes. For example, the cryptocurrency USDT aims to match the value of the US dollar consistently over time and claims to be a ‘Stable-Coin’. While the cryptocurrency YFI is used by the platform Yearn-Finance in order to optimise yield generation from other cryptocurrencies within the Decentralised-Finance (De-Fi) sector of the cryptocurrency markets. This variety in the utility of cryptocurrencies suggests that it is not ideal to combine a variety of different instruments into research which may only be relevant for a specific sector of the entire market. Finally, existing research within this field is likely to come to several different conclusions about the nature of these markets through the implementation of various analysis techniques over time. This in turn, affects the ability of current research to have concrete and lasting impacts on the understanding of the cryptocurrency markets. This effect is amplified by the fact that these markets have not yet fully matured. Nevertheless, the current research can provide a good insight into the markets as they stand today.

An important implication of this research on existing studies is that it presents empirical evidence that combines results from a variety of different studies regarding market efficiency and market behaviour and provides a link between them that has not yet been fully explored. In that regard, this research also presents an opportunity to explore these intertwined concepts more concretely in future studies in combination with the use of more data. Furthermore, research can be conducted in the direction of utilising the data from the underlying blockchain networks of cryptocurrencies in order to develop a better and more subjective understanding of the markets for specific crypto-assets.

Finally, from the perspective of social impact, this study highlights the idea that the regulation of these markets is going to be inhibited by the variety of different asset classes that exist within this market. In order for regulation to be effectively implemented, this market must first go through a process of being sectorised or organised in a manner that classifies each type of cryptocurrency effectively. Furthermore, speculative investors within this market are unlikely to understand the full extent of the risks and rewards they are faced with when participating in this market, this can have adverse effects on the outcomes of their participation in this market.

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8 Appendix

8.1 Appendix A

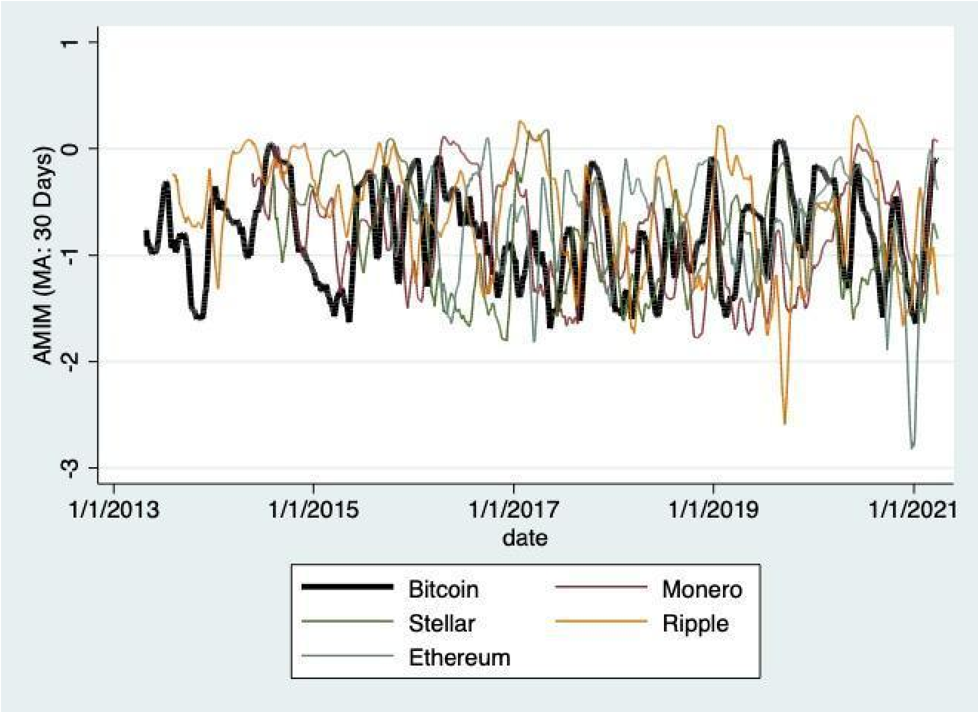
Table 4: Descriptive statistics MIM (8 assets)

Coin	Obs	Mean	St. Dev	Min	Max
EOS	1,367	.6451003	.1084935	.0932277	.8962354
Cosmos	746	.7666595	.0837681	.3295458	.9129913
Cardano	1,275	.61434	.1427318	.0717464	.885666
Chainlink	1,286	.5981166	.144988	.0479371	.8924474
Ethereum	2,061	.6783927	.1119254	.1462458	.8868803
Polkadot	221	.0841723	.0485378	.0010502	.1743309
Ripple	2,793	.698492	.1119714	.1646294	.9047264
Solana	353	.1016323	.0659616	.0010665	.2443063

Note: This table provides the descriptive statistics with respect to the results of the MIM calculation for each asset in the dataset.

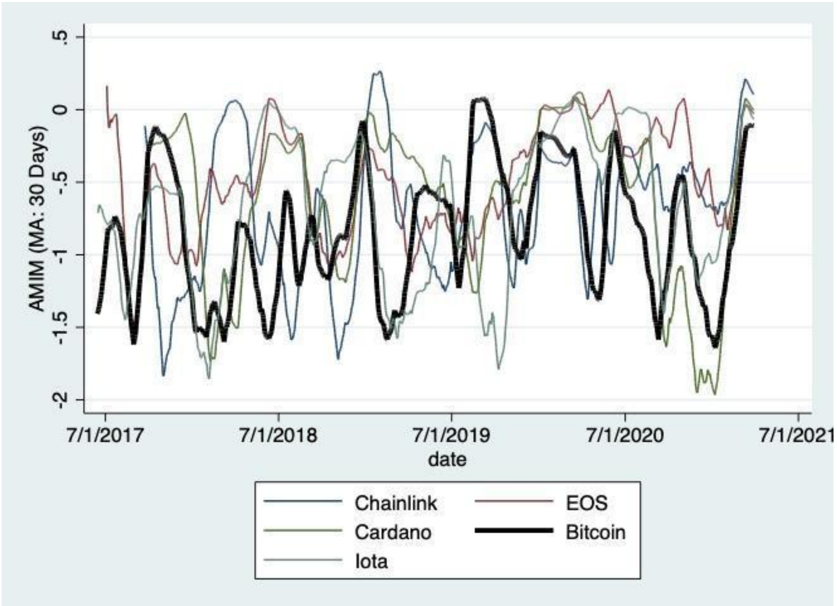
8.2 Appendix B

Figure 6: Bitcoin vs Large Coins



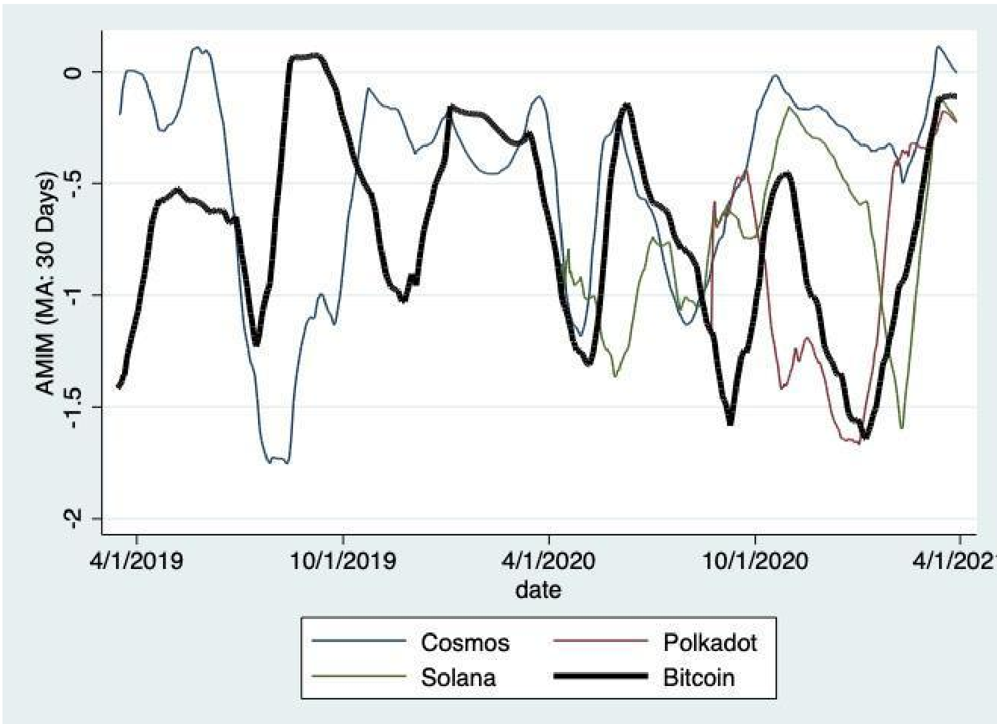
Note: This figure depicts the variation in AMIM values for bitcoin with respect to all coins with a number of observations greater than 2000.

Figure 7: Bitcoin vs Medium Coins



Note: This figure depicts the variation in AMIM values for bitcoin with respect to all coins with a number of observations less than 2000 and greater than 1000.

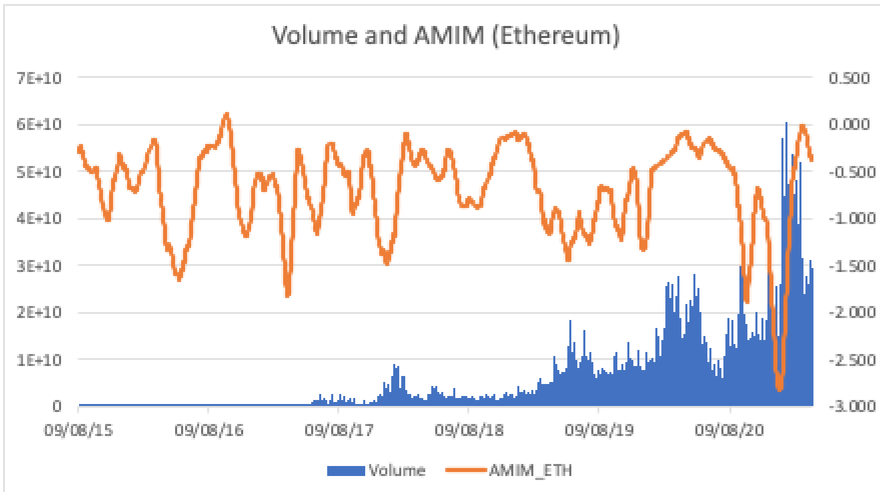
Figure 8: Bitcoin vs Small Coin



Note: This figure depicts the variation in AMIM values for bitcoin with respect to all coins with a number of observations less than 1000.

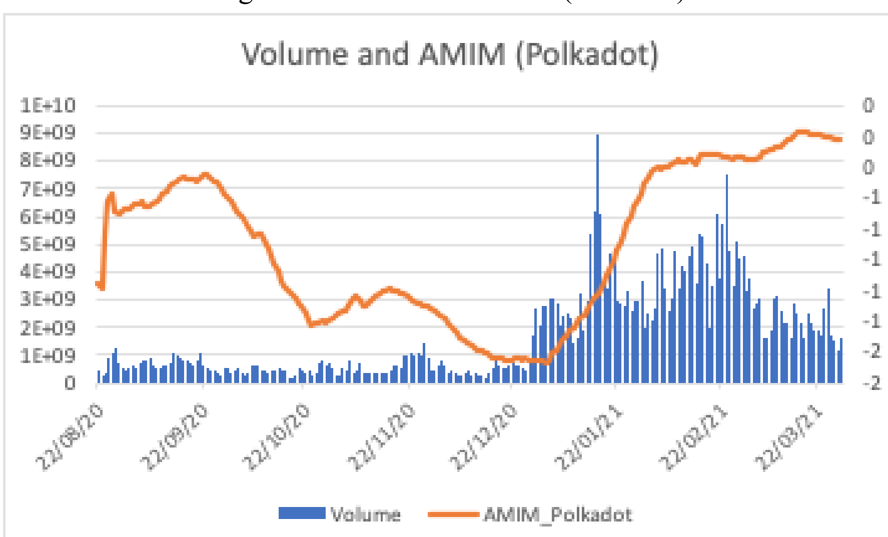
8.3 Appendix C

Figure 9: Volume vs AMIM (Ethereum)



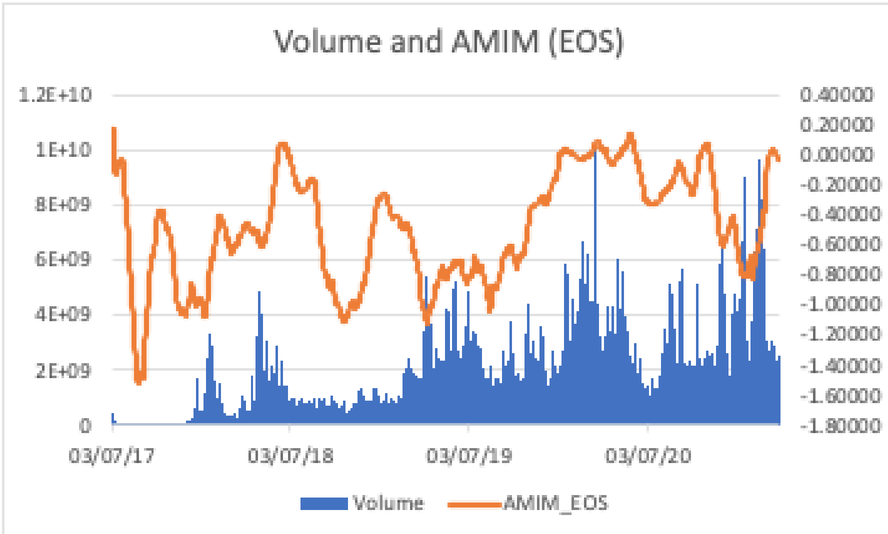
Note: This figure depicts the variation of volume (left y-axis) with AMIM (Right y-axis) over time For one of the cryptocurrencies in the 'Large' category (Observations > 2000)

Figure 10: Volume vs AMIM (Polkadot)



Note: This figure depicts the variation of volume (left y-axis) with AMIM (Right y-axis) over time For one of the cryptocurrencies in the 'small' category (Observations < 1000)

Figure 11: Volume vs AMIM (EOS)



Note: This figure depicts the variation of volume (left y-axis) with AMIM (Right y-axis) over time For one of the cryptocurrencies in the 'small' category (Observations < 1000)