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Efficiency in the markets of crypto-currencies

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ABSTRACT

We show that the level of market-efficiency in the five largest cryptocurrencies is highly time-varying. Specifically, before 2017, cryptocurrency-markets are mostly inefficient. This corroborates recent results on the matter. However, the cryptocurrency-markets become more efficient over time in the period 2017–2019. This contradicts other, more recent, results on the matter. One reason is that we apply a longer sample than previous studies. Another important reason is that we apply a robust measure of efficiency, being directly able to determine if the efficiency is significant or not. On average, Litecoin is the most efficient cryptocurrency, and Ripple being the least efficient cryptocurrency.

1. Introduction

In this paper we analyze the market efficiency of the five largest cryptocurrencies.¹ We find that the markets for these five currencies are currently mostly efficient, but has been significantly inefficient in the past. The market for cryptocurrencies has received much attention the last three years, both from regulators, the public, and traders. The trading volume in the largest such currencies has grown exponentially, and with this increase in liquidity, the prices increased as well. We analyze how this increased interest and trading volume affects the efficiency of the cryptocurrency markets. We find that the efficiency increases significantly during 2017 and remains efficient midway through 2018. Our results also shows that these markets are sensitive to various events. For example, in June 2016 the DAO hack leads to a separation of Ethereum into Ethereum and Ethereum Classic, which caused increased uncertainty in the market. The level of efficiency dropped significantly following this event. The markets also stayed highly inefficient for several months, before stabilizing at weakly inefficient in late 2016 and early 2017.

Market efficiency has received much attention since Fama (1970) and the follow-up paper by Fama (1991). In the papers, the Efficient Market Hypothesis (EMH) is introduced and the author sorts the efficiency of the market into three segments: strong efficiency, semi-strong efficiency, and weak efficiency. Furthermore, the author argues that financial markets are, to a large extent, strongly efficient. This implies that all available information is reflected in the price of the security. The challenge was for a long time to quantify market efficiency. Lo and MacKinlay (1989) proposed a method to test if markets are efficient or not. Furthermore, Lo (2004) proposed an alternative to the static view of market efficiency, proposing that the efficiency evolves over time. This is denoted the *Adaptive Market Hypothesis*, (AMH). The papers by Urquhart and Hudson (2013), Ito et al. (2014), Noda (2016), Ito et al. (2016), and Urquhart and McGroarty (2016) investigates the market efficiency with methods derived with the AMH in mind. Furthermore, Chu et al. (2019) investigates the AMH for the two largest cryptocurrencies, and find evidence that supports the hypothesis of a time-varying market efficiency. However, some specific measures of market efficiency has potential challenges. For example, the efficiency

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¹ The size is measured by market capitalization as of Feb 28th, 2019. The currencies includes Bitcoin (BTC), Ethereum(ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). The market capitalization varies substantially over time, so other currencies might be larger in other periods.

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estimator can be given as a fraction, where the denominator can be zero, or fluctuate between positive, zero, and negative. This can lead to discontinuities in the estimates, yielding unreliable estimates, and implies crucial challenges for applications in testing market efficiency. We apply a novel measure of the level of market efficiency, derived in [Tran and Leirvik \(2019\)](#). This measure allows for any values for both nominator and denominator. The estimator is continuous for all input parameter values.

The cryptocurrency market, and in particular the market for Bitcoin, is found to be largely inefficient, see, for example, [Urquhart \(2016\)](#); [Vidal-Tomás and Ibañez \(2018\)](#); [Jiang et al. \(2018\)](#); [Wei \(2018\)](#); [Hu et al. \(2019\)](#); [Caporale et al. \(2018\)](#); [Zargar and Kumar \(2019\)](#); [Al-Yahyaee et al. \(2018\)](#), and [Nan and Kaizoji \(2019\)](#). However, the cryptocurrency market can be efficient in certain periods as well, see, for example, [Kristoufek \(2018\)](#); [Kristoufek and Vosvrda \(2019\)](#), or a power transformation of Bitcoin return can be weakly efficient [Nadarajah and Chu \(2017\)](#). Other studies such as [\(Omane-Adjepong and Alagidede, 2019\)](#); [Omane-Adjepong et al., 2019](#); [Sifat et al., 2019](#); [Antonakakis et al., 2019](#); [Katsiampa et al., 2019](#)) also show that cryptocurrencies are strongly interlinked reflecting by volatility spill-over, volatility co-movement, lead-lag effect, market co-movement. The systematic risks involved in such markets are also thoroughly investigated in [Corbet et al. \(2019\)](#). One reason for risks and inefficiencies can be that the markets has been difficult to trade in, and hence liquidity has been relatively low compared to other markets. The ease of trading one cryptocurrency can be significantly different from the ease of trading another such currency, thus the liquidity in various such currencies varies substantially, see [Phillip et al. \(2018\)](#). Liquidity and market efficiency is closely related, and different markets show different levels of liquidity, see for example [Amihud \(2002\)](#); [Chordia et al. \(2008\)](#); [Leirvik et al. \(2017\)](#); [Wei \(2018\)](#); [Brauneis and Mestel \(2018\)](#), and [de la Horra et al. \(2019\)](#). In this paper we show that the level of market efficiency is varying over both time and individual currencies. In particular, we show that the Bitcoin market is largely inefficient until early 2017. In contrast with other cited studies, we find that Bitcoin becomes significantly efficient after 2017. The other currencies under investigation shows similar time-varying patterns.

2. Data

The markets for cryptocurrencies is relatively new, and our sample covers the period April 29th, 2013 through February 28th, 2019. Bitcoin, Litecoin and Ripple enter the sample from the very beginning (2013). Some of the currencies has been developed after April 29th, 2013 (Ethereum from 2015; EOS from 2017), but has shown to rely on a solid technology compared to other currencies, and has quickly become some of the largest currencies by market capitalization. We apply freely available data from [Coinmarketcap.com](#), and import all available data via a statistical package named “crypto” in the software R. The data is at daily frequency which contains open, high, low, close prices, volume, and market capitalization.² [Table 1](#) shows the descriptive statistics for the simple returns of the five currencies we analyze. We use simple returns because log-returns might give unreliable estimates for assets with extremely high volatility. In fact, for our sample the minimum daily log-return is -130.2% .³ This is clearly not economically sound. To eliminate the chance of using uneconomic reasonable estimates for returns, we exclusively use simple returns as inputs to our calculations.

Not surprisingly, there is a significant variation between the various cryptocurrencies. The differences seems to be very heterogeneous. [Fig. 1](#) shows time series plots of the normalized prices (Panel a) and trading volume in Billions USD of the five currencies (Panel b) during the last 3 years. As is evident from those illustrations, the price and volume increases tremendously at the end of 2017, with significant variation over time. This exceptional rise in prices and the corresponding high volatility has attracted much attention in media. We will analyze whether the prices can be considered efficient, and whether the level of efficiency varies over time.

3. Methodology

To estimate the level of efficiency, we apply a recently derived method to quantify the level of market efficiency, see [Tran and Leirvik \(2019\)](#). In this paper, the authors derive a measure for the level of Adjusted Market Inefficiency Magnitude (AMIM). In short, to compute the AMIM, we start with representing the returns of a currency as

$$r_{i,t} = \beta_0 + \beta_1 \cdot r_{i,t-1} + \beta_2 \cdot r_{i,t-2} + \dots + \beta_q \cdot r_{i,t-q} + \varepsilon_{i,t}. \quad (1)$$

If markets are efficient then the coefficients $(\beta_1, \beta_2, \dots, \beta_q)$ should be zero, or at least insignificantly different to zero. If not, the β coefficients are (significantly) non-zero. [Lo \(2004\)](#) used the first auto-regressive coefficient to characterize the inefficiency level. One can argue that the Efficient Market Hypothesis (EMH) is based on a random walk or martingale dynamics of the price or the log-price. This has a direct implication in which the future price differences and log-price differences (log-returns) cannot be predicted. In this study, we mainly use the simple return, not log-returns. That can potentially be problematic. However, it turns out that if price follows a RW process then the future simple return cannot be predicted either.⁴ Hence a regression of simple return on its lag should

² By the end of Feb.2019, the market capitalization of the top 5 crypto-currencies in billions USD are: BTC (67.70), ETH (14.37), XRP (13.03), EOS (3.21), LTC (2.81). Just after the top 5 are Bitcoin Cash (2.33 Billions USD) and Tether (2.04 Billions USD).

³ Reader can find the summary statistics using log return in the appendix.

⁴ Consider a RW process: $y_{t+1} = y_t + \varepsilon_{t+1}$. Where ε_{t+1} is a shock at time $t+1$ in the future which cannot be predicted, hence $E[\varepsilon_{t+1}] = E_t[\varepsilon_{t+1}] = 0$, and ε_{t+1} is independent with y_t . The simple return at time $t+1$ is: $r_{t+1} = \frac{y_{t+1}}{y_t}$. We will show that $E[r_{t+1}] = E_t[r_{t+1}] = 0$, which means both the conditional and unconditional expectation of simple returns cannot be predicted. First, it is clear that $E_t[r_{t+1}] = \frac{E_t[y_{t+1}]}{y_t} = 0$. Second $E[r_{t+1}] = E[E_t(r_{t+1})] = E[E_t(\varepsilon_{t+1})]$. $E[1/y_t] + \text{cov}(E_t[\varepsilon_{t+1}], 1/y_t)$. With $E[\varepsilon_{t+1}] = E_t[\varepsilon_{t+1}] = 0$, in addition ε_{t+1} is independent with y_t hence we can believe that $\text{cov}(E_t[\varepsilon_{t+1}], 1/y_t) = 0$. Therefore $E[r_{t+1}] = 0$.

Table 1

Summary Statistics of daily *simple returns* for the 5 crypto-currencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). The sample is from 29 April 2013 to 28th February 2019. *n* is the number of observations, *mean* is the sample average of the returns, *sd* is the sample standard deviation of the returns, *min* and *max* are the minimum and maximum daily returns, respectively. *skew* is the skewness of returns, *kurtosis* measures the thickness of the tails of the return distributions, and *se* is the standard error of the means.

Crypto	<i>n</i>	mean	sd	median	min	max	skew	kurtosis	se
BTC	2132	0.25%	4.36%	0.18%	-23.37%	42.97%	0.50	9.94	0.00
EOS	607	0.70%	11.28%	-0.20%	-31.96%	168.32%	5.99	80.83	0.00
ETH	1301	0.58%	7.29%	-0.09%	-72.80%	51.03%	0.27	13.13	0.00
LTC	2132	0.35%	7.34%	0.00%	-40.19%	129.10%	4.77	65.90	0.00
XRP	2034	0.51%	8.75%	-0.29%	-46.00%	179.37%	6.12	99.47	0.00

yield a non-significant coefficient if the market is efficient.

We estimate Eq. (1) and use the Akaike information criterion (AIC) to choose the number of lags. We denote $\hat{\beta}$ is the vector of these autocorrelation coefficients and $\Sigma = LL'$ is the asymptotic co-variance matrix of the estimated vector. The sum of the absolute value of the autocorrelation coefficients, after being standardized ($\hat{\beta}^{standard} = L^{-1}\hat{\beta}$), are divided by the sum of absolute values of parameter estimates plus one. This measures the Market Inefficiency Magnitude (*MIM*), and is related to the measure applied in Noda (2016) and Ito et al. (2016). Specifically, the *MIM* is given by:

$$MIM_t = \frac{\sum_{j=1}^q |\hat{\beta}_{j,t}^{standard}|}{1 + \sum_{j=1}^q |\hat{\beta}_{j,t}^{standard}|} \quad (2)$$

As Eq. (2) sums up the standardized auto-regression coefficients of Eq. (1), it should be statistically equal to zero in a strongly efficient market. To reduce the impact of insignificant parameter estimates, we subtract the range of the confidence interval under the null hypothesis of efficient market from the *MIM* and divide by one minus the range of the confidence interval under the null hypothesis of efficient market. We call this the *AMIM*. The measure is thus robust against insignificant autocorrelation. In short, we estimate the *AMIM* for any financial asset price by the estimator

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}} \quad (3)$$

The R_{CI} is the range of the confidence interval for the *MIM* under the null hypothesis of efficient market. For further explanations and derivations, the reader is encouraged to read the article by Tran and Leirvik (2019).

Because the *MIM* is constrained between zero and one, the $R_{CI} < 1$. Thus, Eqs. (2) and (3) makes sure that both *MIM* and *AMIM* are continuous functions. Accounting for Eq. (3), the $AMIM_t$ cannot be larger than one. It can, however, be zero, or negative. A positive value, i.e. $AMIM_t > 0$, indicates an inefficient market. If $AMIM_t$ is less than zero, i.e. $AMIM_t \leq 0$, then the market is efficient. Hence, the measure is simple to compute, and very easy to interpret. In addition, it is also very easy to use *AMIM* to compare the level of efficiency for different assets in different points in time. Another quality of *AMIM* that we want to exploit is that it reflects very well economic events influencing the assets.

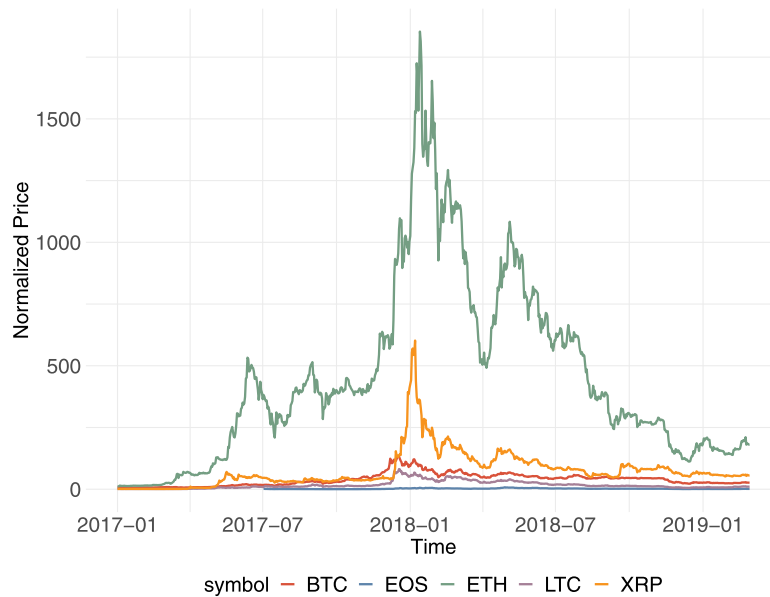
4. Empirical results

Table 2 shows some descriptive statistics of the estimation of Eq. (3). In our study we have applied daily observations of cryptocurrency prices. We largely follow Tran and Leirvik (2019) by estimating the *AMIM* daily using over-lapping window data of 1 year. Tran and Leirvik (2019) shows that the non-overlapping and overlapping window approaches give the same *AMIM* results.

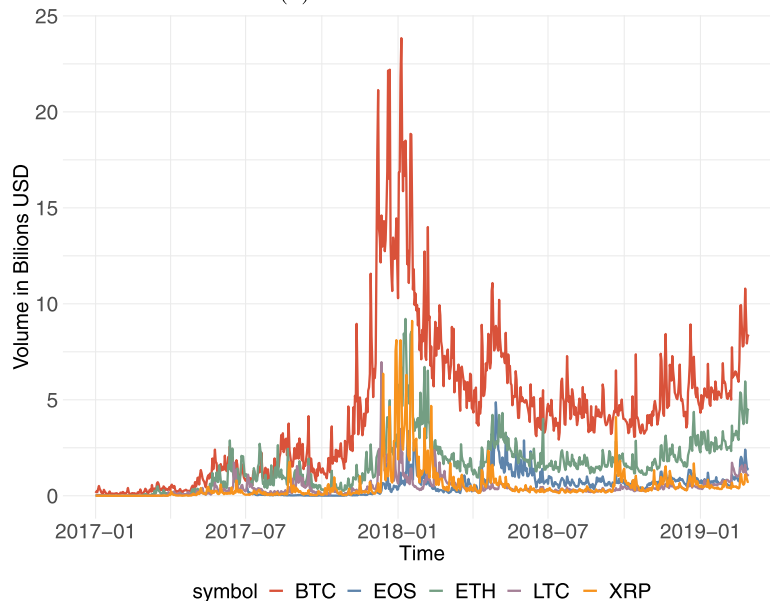
Table 2 shows that on average the prices for BitCoin, EOS, Ethereum, Litecoin, and Ripple are all inefficient ($\overline{AMIM} > 0$). This is statistically significant, as seen by the small size of the standard error. The median, however, is zero for BTC, ETH, and LTC. This indicates that the efficiency of these currencies experiences substantial periods of efficiency.

Fig. 2 shows a time series plot of the *AMIM* for all cryptocurrencies. For a clearer illustration of the trend of *AMIM*, we calculate a 30-day Moving Average (MA) of *AMIM*. As one can see from this graph, the level of market efficiency varies substantially over time. In particular, in the early stage of the sample period, the prices of all currencies we analyze are relatively inefficient. Ripple has a bump in efficiency in early 2015, which corresponds to the timing of some large banks announcing that they would apply this currency in new real-time international transactions. Moreover, the creator of XRP was fined by US authorities in late 2015 for violations of the Bank Secrecy Act. The price inefficiency saw an immediate spike in the last quarter of that year.

The Bitcoin (BTC) efficiency level also varies substantially, and follows various market events. For example in the end of 2013 and beginning of 2014, the *AMIM* for BTC increases significantly. This is due to a lot of uncertainty in markets when accusations of illegal activities (drug trading, money laundering, etc.) was related to BTC. For example, on early October 2013 the Federal Bureau of Investigation (FBI) arrest Ross Ulbricht and shuts down Silk Road, a black market trading illicit goods using BTC.



(a) Normalized Price



(b) Volume

Fig. 1. Trading Volume in Billions USD and Normalized Price of the top 5 crypto-currencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). We normalize the price for each crypto-currency by dividing the actual price to the first observed price in our data sample.

At the end of Q1 2014, Mt. Gox, one of the largest BTC exchanges, files for bankruptcy protection in Japan. Mt. Gox reports that 744,000 Bitcoin (about 350 millions USD) is stolen.⁵ In addition, around the same time, there were also a lot of uncertainty about whether China would ban Bitcoin or not.⁶ These events led *AMIM* of BTC spiked again in Q2 2014. In June 2016, the hack on the DAO project of Ethereum casted doubt on crypto-currencies. *AMIM* of Bitcoin did not raise significantly in this period. However, as expected, the *AMIM* of Ethereum shows a significant increase following this event. The *AMIM* is very high but does not last long because Ethereum community responded very quickly to eliminate doubt and uncertainty. Indeed, to save Ethereum from the hack,

⁵ Details: See [BBC \(2014\)](http://www.bbc.com/news/technology-25233230) MtGox Bitcoin exchange files for bankruptcy <http://www.bbc.com/news/technology-25233230>

⁶ Details: See [Coin-Desk \(2014\)](https://www.coindesk.com/price-bitcoin-remains-500-amid-china-uncertainty/) Price of Bitcoin Falls Under 500 USD Amid Uncertainty in China <https://www.coindesk.com/price-bitcoin-remains-500-amid-china-uncertainty/>

Table 2

Summary Statistics of AMIM for 5 crypto-currencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). The AMIM is computed daily with one year overlapping data using *simple return*. The sample is from 29 April 2013 to 28th February 2019. n is the number of observations, \overline{AMIM} is the sample average of AMIM, sd is the sample standard deviation of AMIM, min and max are the minimum and maximum AMIM, respectively. $skew$ is the skewness of AMIM, $kurtosis$ measures the thickness of the tails of the AMIM distributions, and se is the standard error of the mean.

Crypto	n	\overline{AMIM}	sd	median	min	max	skew	kurtosis	se
BTC	1933	0.083	0.132	0.000	-0.349	0.370	0.532	-0.609	0.003
EOS	408	0.086	0.089	0.110	-0.200	0.195	-0.839	-0.201	0.004
ETH	1102	0.061	0.095	0.000	-0.305	0.281	0.700	-0.202	0.003
LTC	1933	0.011	0.117	0.000	-0.324	0.434	0.090	0.458	0.003
XRP	1835	0.251	0.151	0.268	-0.250	0.535	-0.705	0.298	0.004

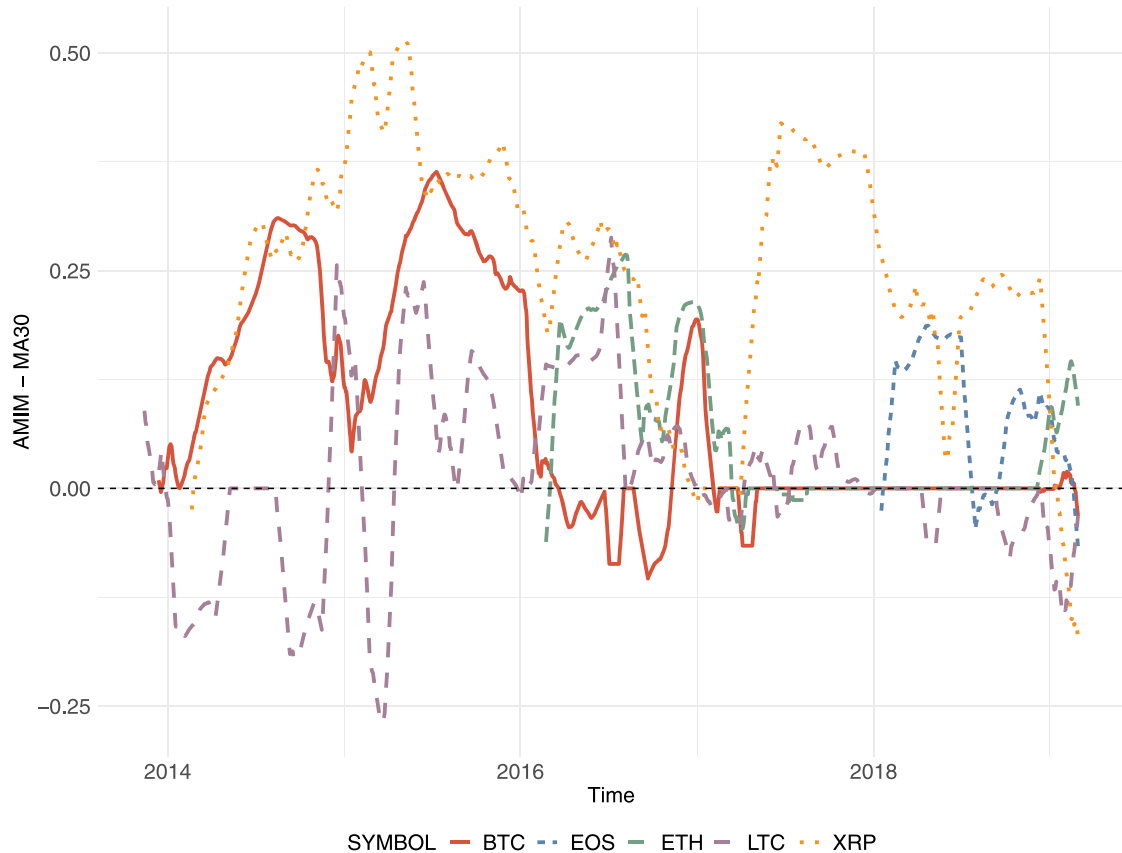


Fig. 2. The time series plot of Moving-Average 30 days (MA30) of AMIM for 5 crypto-currencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). The AMIM is computed daily with 1 year overlapping data using *simple return*.

the Ethereum community decided to “hard-fork”, which are upgrades to the programming code that add new rules to the Ethereum software that are incompatible with earlier versions. Basically, the Ethereum community rewrote the ledger, which is the common transaction book, to eliminate all the hacked transactions.⁷

All in all, many of the spikes and drops in market inefficiency, as shown in Fig. 2, can be related to idiosyncratic events. This is particularly true for the time early in the sample period of each cryptocurrency. In the later stages of our sample period, all currencies show a significant improvement in efficiency, as shown by a negative estimate of the *AMIM*. This means that the currencies are significantly efficient. However, it seems that the prices are turning less efficient in the last half of Q1-2018, and the first half of Q2-

⁷ This process violates the core motivation of using blockchain technology which prevents any modification of past information. This process requires a lot of computing power and is a collective work. Therefore debates were going at that time. This leads to a separation of Ethereum into Ethereum and Ethereum Classic. The Ethereum Classic does not accept the hard fork, thus accept all the hacked transactions, and being a separate community from Ethereum. See Leising (2017) for more details.

Table 3

Summary Statistics of daily *log returns* for the 5 crypto-currencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). The sample is from 29 April 2013 to 28th February 2019. *n* is the number of observations, *mean* is the sample average of the returns, *sd* is the sample standard deviation of the returns, *min* and *max* are the minimum and maximum daily returns, respectively. *skew* is the skewness of returns, *kurtosis* measures the thickness of the tails of the return distributions, and *se* is the standard error of the mean.

Crypto	<i>n</i>	mean	sd	median	min	max	skew	kurtosis	se
BTC	2132	0.16%	4.35%	0.18%	-26.62%	35.75%	-0.19	7.88	0.00
EOS	607	0.21%	9.54%	-0.20%	-38.50%	98.70%	2.18	20.11	0.00
ETH	1301	0.30%	7.70%	-0.09%	-130.21%	41.23%	-3.38	65.28	0.00
LTC	2132	0.11%	6.68%	0.00%	-51.39%	82.90%	1.74	25.18	0.00
XRP	2034	0.20%	7.66%	-0.29%	-61.63%	102.74%	2.01	27.55	0.00

Table 4

Summary Statistics of AMIM for 5 crypto-currencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). The AMIM is computed daily with one year overlapping data using *log return*. The sample is from 29 April 2013 to 28th February 2019. *n* is the number of observations, $\overline{\text{AMIM}}$ is the sample average of AMIM, *sd* is the sample standard deviation of AMIM, *min* and *max* are the minimum and maximum AMIM, respectively. *skew* is the skewness of AMIM, *kurtosis* measures the thickness of the tails of the AMIM distributions, and *se* is the standard error of the mean.

Crypto	<i>n</i>	$\overline{\text{AMIM}}$	sd	median	min	max	skew	kurtosis	se
BTC	1933	0.081	0.128	0.000	-0.364	0.376	0.515	-0.412	0.003
EOS	408	0.039	0.071	0.048	-0.167	0.174	-0.479	-0.382	0.004
ETH	1102	0.043	0.071	0.000	-0.311	0.253	0.712	0.695	0.002
LTC	1933	0.039	0.108	0.000	-0.364	0.415	0.123	0.851	0.002
XRP	1835	0.234	0.152	0.253	-0.367	0.545	-0.517	0.737	0.004

2018 but return to the efficient level at the end of 2018. These results corroborates the main idea of the Adaptive Market Hypothesis of Lo (2004), where market efficiency is changing over time, and reacting to events in the market.

We also redo the above exercises with AMIM using log-return. The results are given in the appendix (see Tables 3, 4 and Fig. 3). The estimated AMIM using log-returns is qualitatively the same as the AMIM results using simple returns. However, we should be aware that the log-return series will be mechanically smoother than the simple return series in the positive return region. For example, a simple return of 5% will have a log-returns of about $\log(1.05) = 4.88\%$, and a simple return of 10% will be about $\log(1.1) = 9.53\%$ in log return. For negative simple returns, the corresponding log-return will be larger in absolute terms. For large negative deviations, log-returns might in fact be less than -100%. For example, a price moving from 50 to 10, yielding a simple return

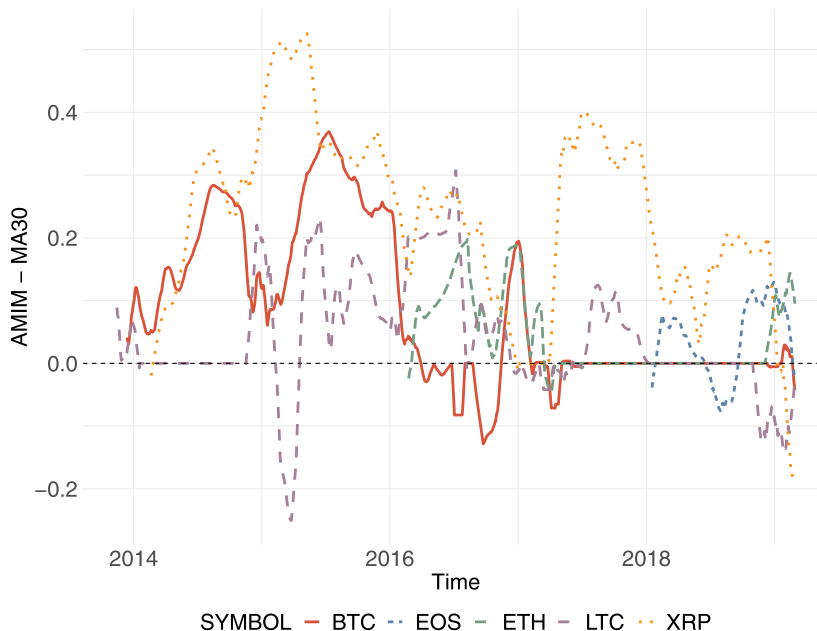


Fig. 3. The time series plot of Moving-Average 30 days (MA30) of AMIM for 5 crypto-currencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), EOS (EOS). The AMIM is computed daily with 1 year overlapping data using *log return*.

of -80%, will give a log-return of about -160%, which is not economically sound. Therefore, we need to be more cautious on the interpretation of any result from log-returns with highly volatile financial assets.

5. Conclusion

In this paper we investigate the inefficiency of the prices of five different cryptocurrencies. Using a rolling window, we find that the prices has been significantly inefficient during our sample. However, there are signs that the efficiency of all cryptocurrencies are improving, with all having significant drop in *AMIM* in the last 6 quarters. These results are consistent with recent research on the topic. The markets for cryptocurrencies are improving at an exceptional pace, with volume improving and becoming less volatile. This invites more research in the near future, both on the topic of efficiency of these markets, but also other aspects, such as for example price-return volatility, liquidity, and the relationship to other assets.

CRedit authorship contribution statement

Vu Le Tran: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Thomas Leirvik:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Validation.

Appendix

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