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Technical trading rules in the cryptocurrency market

Klaus Grobys[1,*], Shaker Ahmed[1], Niranjan Sapkota[1]

School of Accounting and Finance, University of Vaasa, P.O. Box 700, FI-65101 Vaasa, Finland

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ABSTRACT

This paper studies simple moving average trading strategies employing daily price data on the eleven most-traded cryptocurrencies in the 2016–2018 period. Our results indicate a variable moving average strategy is successful when using the 20 days moving average trading strategy. Specifically, excluding Bitcoin the technical trading rule generates an excess return of 8.76% p.a. after controlling for the average market return. Our results suggest that cryptocurrency markets are inefficient.

1. Introduction

Cryptocurrencies are a growing asset class, with a total market capitalization of USD 228 billion as of Novemmber 2019, where Bitcoin with a market capitalization of USD 151 billion is the dominant cryptocurrency.[2] As pointed out in Fry and Cheah (2016, p.350) "from an economic perspective the sums of money involved are substantial." Bitcoin, the first cryptocurrency, was created in 2009 to use a decentralized peer-to-peer payment system based on blockchain technology as proposed by Nakamoto (2008). Nowadays Bitcoin is traded twenty-four hours a day on several exchanges worldwide, and is one of more than 3000 cryptocurrencies.

Cryptocurrency markets have been subject to several investigations concerning market efficiency. A recent strand of literature takes the view that cryptocurrency markets are inefficient. In this regard, Al-Yahyaee et al. (2018), who study the market efficiency of the Bitcoin market compared to gold, stock, and currency markets, find that Bitcoin is more inefficient than those markets. Kristoufek (2018) studies the USD and Chinese Yuan Bitcoin market return between 2010 and 2017 and finds Bitcoin returns in both markets to be inefficient in the sample period. Moreover, Zhang et al. (2018), who analyze the efficiency of nine different cryptocurrency markets, support the findings of Al-Yahyaee et al. (2018) and Kristoufek (2018) and conclude that all those cryptocurrencies are inefficient markets. Urquhart (2016) also tests the market efficiency of Bitcoin using daily data for the 2010- 2016 period and reports findings in line with those of Al-Yahyaee et al. (2018), Zhang et al. (2018), and Kristoufek (2018) indicating that Bitcoin returns are inefficient over the full sample period.

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* Corresponding author.

E-mail addresses: kgrobys@uva.fi, klaus.grobys@uwasa.fi (K. Grobys), shaker.ahmed@uva.fi (S. Ahmed), nsapkota@uva.fi (N. Sapkota).

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[2] There is a strand of literature that takes the perspective of cryptocurrencies being an asset market, see Urquhart (2016), Dyhrberg (2016a), Klein et al (2018), for instance. The data were retrieved from coinmarketcap.com on November 19, 2019.

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Interestingly, Urquhart (2016) performs a sample-split test that shows Bitcoin returns are efficient in the later subsample indicating that Bitcoin is moving toward becoming an efficient market. Khuntia and Pattanayak's (2018) findings support Urquhart's (2016) result for the later subsample in providing evidence of Bitcoin returns exhibiting market efficiency over time, in other words, the evidence is in favor of the adaptive market hypothesis. Other studies show that the Bitcoin market has become more informationally efficient since 2014 (Bariviera, 2017) and 2016 (Sensoy, 2019). Similarly, Tiwari et al. (2018) find that the Bitcoin market exhibits informational efficiency using computationally efficient long-range dependence estimators. Moreover, Grobys and Sapkota (2019), who study momentum trading strategies implemented among 143 cryptocurrencies over the 2014– 2018 period, do not find any evidence for significant momentum payoffs. As a consequence, their results confirm the literature suggesting that cryptocurrency markets are efficient. In summary, the different views found in the literature illustrate that there is currently no consensus on the efficiency of cryptocurrency markets.

Our paper contributes first to the small but rapidly expanding finance literature on Bitcoin and cryptocurrencies. Specifically, our paper extends the literature testing the efficiency of cryptocurrencies in several important ways. While most papers focus on Bitcoin (Urquhart, 2016; Khuntia and Pattanayak, 2018; Tiwari et al., 2018; Bariviera, 2017; Sensoy, 2019; Kristoufek, 2018), we investigate eleven cryptocurrencies that exhibit high market capitalizations. Specifically, we extend Gerritsen et al. (2019), Corbet et al. (2019), and Miller et al. (2019), who explore the profitability of technical trading rules in the Bitcoin market, by employing a multivariate approach which enables us to make market-wide conclusions. The recent paper from Grobys and Sapkota (2019) is perhaps the most relevant for our current research, as it examines implementing different momentum strategies on the whole cross section of 143 available cryptocurrencies. Our paper makes use of the simplest and most widely used technical trading rule referred to as the Variable Moving Average oscillator that generates trading signals employing a short-period and a long-period moving average of the corresponding index's level. To make proper statistical inference, we employ a multivariate test for testing jointly our cryptocurrency markets. Importantly, we hypothesize that if cryptocurrency markets were efficient, it would not be possible to generate profits using past price information.

In contrast to that study, however, this paper explores the profitability of both long-memory processes and short-memory processes. Our approach is very different from momentum trading strategies that, simply speaking, follow six- to twelve-month trends in asset prices. From a broader perspective, our paper also contributes to the literature on exploring the profitability of technical trading rules implemented among different asset classes. In an early paper, Brock et al. (1992) investigate simple moving average-oscillators for U.S. equity data. Other studies explore technical trading rules applied to U.K. equity data (Hudson et al., 1996), emerging market equity data (Ratner and Leal, 1999; Conover et al., 2017), and traditional foreign exchange market data (Levich and Thomas, 1993; Neely et al., 1997; Qi and Wu, 2006; Schulmeister, 2008; Coakley et al., 2016). Surprisingly, there is no paper available that explores simple technical trading rules implemented among the new digital currency markets despite the topic receiving considerable attention in the recent academic literature. Our paper closes this gap in the literature by extending earlier research to new digital financial markets.

2. Data and methodology

2.1. Data

We collected daily price data on eleven cryptocurrencies for the period January 1, 2016– December 31, 2018.[3] Our sample of cryptocurrencies consists of cryptocurrencies that exhibited the highest market capitalization as of as of January 3, 2016.[4] To avoid our results being affected by Bitcoin that has dominated the cryptocurrency markets for many years, we excluded Bitcoin from the primary sample. The sample thus comprises the following cryptocurrencies: Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar Lumen (XLM), Nxt (NXT), MaidSafeCoin (MAID), Namecoin (NMC). The corresponding market capitalizations are reported in Table A1 in the appendix, whereas Table A2 in the same appendix reports the descriptive statistics for all individual cryptocurrencies over our sample period. Using a simple buy-and-hold strategy of an equally weighted portfolio, our sample of cryptocurrencies produced an average return of 36.87% p.a. return over the sample period.[5]

2.2. Trading rule and methodology

In this paper, we implement the simplest and most widely used technical trading rule- referred to as Variable Moving Average oscillator (VMA) that generates trading signals employing a short-period and a long-period moving average of the level of the index. We calculate the long and short period moving average as follows:

$$Long\ MA_n = \frac{1}{n}\sum_{t=0}^{t=(n-1)} \log(P_t)$$

[3] We retrieved cryptocurrency data from coinmarketcap.com.

[4] In order to keep our sample homogenous, we only account for non-privacy cryptocurrencies. As Dash is not completely non-private like those cryptocurrencies investigated in our sample, we exclude it from the analysis. For instance, Dash offers the function 'Optional privacy' (PrivateSend).

[5] The annualized average return including Bitcoin is 36.50%.

$$Short\ MA_t = \log(P_t)$$

where, $Long\ MA_n$ ($Short\ MA_t$) is the long (short) period moving average, P_t is the price of a given cryptocurrency on day t and n is the number of days used to calculate the long-term moving average. Different n indicates difference strategies implemented under the VMA trading rule. We use $n = 20, 50, 100, 150, 200$. As in the cryptocurrency market, it is not possible to take a short position or use cryptocurrency related financial instruments to mimic the payoffs of the short position (at the time of writing this paper), we only focus on the payoffs from buy positions. Using the long and short moving averages, we take the investment decision in two steps. First, we generate buy signals when a short-period moving average rises above a long-period moving average. The idea behind computing moving average is to identify the trend in the price movement, and whenever the short-period moving average crosses over the long-period moving average, a new trend is considered initiated (Brock et al., 1992).

$$Buy\ signal_t = \begin{cases} 1, & if\ Short\ MA_t - Long\ MA_t > 0 \\ 0, & otherwise \end{cases}$$

Second, a long position is taken on the underlying cryptocurrency when a buy signal is initiated and hold the position until a sell signal is generated.

Finally, we employ a multivariate test because we are interested in drawing market-wide conclusions. To do so, we test the payoffs of our strategies implemented in the cross-section of all cryptocurrency markets and thus account for contemporaneous correlation. This seems to be necessary because cryptocurrency returns are highly correlated with each other, as pointed out in Borri (2019). Let's denote cryptocurrency return i at time t as $crypto_{i,t}$ and let's assume we consider a set of N assets. Then we can stack the returns into a Nx1 vector such as

$$\begin{bmatrix} crypto_{1,t} \\ crypto_{2,t} \\ \vdots \\ crypto_{N,t} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{N,t} \end{bmatrix},$$

where $\alpha_1, \alpha_2, \ldots, \alpha_N$ are the sample averages and $u_{1,t}, u_{2,t}, \ldots, u_{N,t}$ are white-noise processes. If $cov(crypto_{i,t}, crypto_{j,t}) \neq 0$ for some $i \neq j$, then the sample averages are, in turn, correlated also. Seemingly-Unrelated-Regression (SUR) technique addresses this correlation problem as the corresponding test statistic for testing the joint hypothesis

H_0: $\alpha_i = 0$ for at least one i with $i = \{1, \ldots, N\}$ versus

H_1: $\alpha_i \neq 0$ for at least one i where $i = \{1, \ldots, N\}$, is based on a Wald-test, where the asymptotically valid test statistic λ^{Asy} is given by

$$\lambda^{Asy} = (\boldsymbol{R}\beta - \boldsymbol{r})'\left(\boldsymbol{R}\left(\widetilde{\boldsymbol{X}'}\left(\hat{\Sigma}^{-1} \otimes \boldsymbol{I}_T\right)\tilde{\boldsymbol{X}}\right)\boldsymbol{R}'\right)^{-1}(\boldsymbol{R}\beta - \boldsymbol{r}), \text{with}$$

$$\boldsymbol{\beta} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} = \boldsymbol{R} = \begin{bmatrix} 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \ldots & 0 & 1 \end{bmatrix}, \boldsymbol{r} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tilde{\boldsymbol{X}} = \begin{bmatrix} \boldsymbol{X} & \boldsymbol{0} & \boldsymbol{0} & \ldots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{X} & \boldsymbol{0} & \ldots & \vdots \\ \vdots & \boldsymbol{0} & \boldsymbol{X} & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \ldots & \boldsymbol{X} \end{bmatrix}, \boldsymbol{X} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}, \boldsymbol{0} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \text{and}$$

$$\hat{\Sigma} = \begin{bmatrix} cov(u_{1,t}, u_{1,t}) & cov(u_{1,t}, u_{2,t}) & \ldots & cov(u_{1,t}, u_{N,t}) \\ cov(u_{2,t}, u_{1,t}) & cov(u_{2,t}, u_{2,t}) & \ldots & cov(u_{2,t}, u_{N,t}) \\ \vdots & \vdots & \vdots & \vdots \\ cov(u_{N,t}, u_{1,t}) & cov(u_{N,t}, u_{2,t}) & \ldots & cov(u_{N,t}, u_{N,t}) \end{bmatrix}$$

In our notation, the matrix dimensions are $\boldsymbol{R}, \hat{\Sigma} \in \boldsymbol{M}_{\boldsymbol{N},\boldsymbol{N}}$, $\boldsymbol{\beta}, \boldsymbol{r} \in \boldsymbol{M}_{\boldsymbol{N},1}$, $\boldsymbol{X}, \boldsymbol{0} \in \boldsymbol{M}_{\boldsymbol{T},1}$, and $\tilde{\boldsymbol{X}} \in \boldsymbol{M}_{\boldsymbol{TN},\boldsymbol{N}}$. The contemporaneous correlations between $\alpha_1, \alpha_2, \ldots, \alpha_N$ are accounted for by the covariance matrix $\hat{\Sigma}$ in the term $(\boldsymbol{R}(\widetilde{\boldsymbol{X}'}(\hat{\Sigma}^{-1} \otimes \boldsymbol{I}_T)\tilde{\boldsymbol{X}})\boldsymbol{R}')^{-1}$. Since we use daily data and more than 1000 observations, we can easily make use of the law of large numbers implying that the test statistic has feasible asymptotical distributional properties and is under the null hypothesis distributed as $\chi^2(N)$.

3. Results and discussion

Table 1 presents the payoffs and the corresponding t-statistics of variable moving average (MA) strategies. Individual strategies are defined as *(short-period MA, long-period MA)*, where the *short-period* and *long-period* represent the number of days used to calculate the MA for the short-term MA and long-term MA. The joint test for statistical significances of ten coins exclude Bitcoin from the sample. Then, we also report a joint test accounting for Bitcoin that means we test 11 coins jointly in our sample. From the joint test for ten cryptocurrencies, as reported in Table 1, we observe that returns are jointly significant for only the (1, 20), (1, 50), and (1, 100) trading strategies. Specifically, implementing the (1, 20) strategy, five of the ten cryptocurrencies generated payoffs that were statistically significant on at least a 5% level. However, implementing the (1, 50) strategy, only three of the ten cryptocurrencies generated payoffs that were statistically significant on a 5% level, whereas the implementation of the (1, 100) strategy generated profits only for Ethereum. Applying longer time horizons did not generate profits in any of the cryptocurrencies. On an average (1, 20) buy moving average strategy produces 45.63% p.a. average return for the ten cryptocurrencies compared to their buy and hold average return of 36.87% p.a. That means this technical trading rule generates

Table 1
Moving average (MA) trading strategy payoffs using logarithmic daily prices of sample cryptocurrencies.

Strategy	Tests on individual coin's MA returns											Joint Test of MA returns	
	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID	NMC	10 coins	11 coins
(1, 20)	0.0012***	0.0022**	0.0012*	0.0026***	0.0019**	−0.0002	0.0021**	0.0016	0.0021***	0.001	−0.002*		
t-statistic	3.25	2.44	1.95	3.84	2.46	−0.21	2.46	1.62	2.61	1.46	−1.93	33.10***	37.7***
(1,50)	0.0009**	0.0019**	0.0008	0.0017***	0.0013*	0.0004	0.0017*	0.0019*	0.0018**	0.0006	−0.001		
t-statistic	2.12	2.01	1.16	2.70	1.73	0.54	1.95	1.88	2.15	0.86	−0.96	18.27*	19.97**
(1, 100)	0.0011**	0.0013	0.0011	0.0015**	0.0009	−0.0001	0.0012	0.0014	0.0018*	−0.0004	−0.002*		
t-statistic	2.24	1.28	1.46	2.16	1.12	−0.15	1.34	1.27	1.93	−0.50	−1.82	18.66**	25.38***
(1, 150)	0.0011**	0.0014	0.0013	0.0015**	0.0007	−0.0001	0.0013	0.0009	0.0014	0.0001	−0.0014		
t-statistic	2.08	1.27	1.64	2.14	0.77	−0.09	1.25	0.76	1.40	0.07	−1.23	12.94	15.35
(1, 200)	0.0011**	0.0017	0.0012	0.0019**	0.0005	0	0.0013	0.0013	0.0007	0.0004	−0.0011		
t-statistic	2.08	1.50	1.42	2.53	0.55	0.04	1.18	1.04	0.72	0.49	−0.93	12.66	15.65

Note: This table presents the average buy moving average strategy implemented on daily cryptocurrency returns (first row) and the statistical significance (second row). Employing the Seemingly Unrelated Regression (SUR) technique, we test the sample averages for each strategy jointly. The joint test equally weighs the payoff series. We use the following 11 cryptocurrencies: BTC (Bitcoin), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar Lumen (XLM), Nxt (NXT), MaidSafeCoin (MAID), Namecoin (NMC). The sample of 10 cryptocurrencies excludes BTC. Individual strategies are defined as *(short-period, long-period),* where the *short-period* and *long-period* represent the number of days used to calculate the moving average (MA) for the short-term MA and long-term MA. The joint tests of *10 coins* exclude Bitcoin from the sample and *11 coins* includes all 11 cryptocurrencies in our sample.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

8.76% p.a. average excess return over the sample period.[6] The excess average return drops to 3.65% p.a. for the (1,50) trading strategy while the rest of the strategies cannot produce higher returns than the simple buy and hold trading strategy. The results indicate that economically it is justifiable to calculate the *long-period* moving average using up to the 50 past trading days.

As a robustness check, we report the results of joint significance tests for 11 cryptocurrencies including Bitcoin (BTC). In line with our earlier results, the returns are jointly significant for the (1, 20), (1, 50), and (1, 100) trading strategies. On an individual level, Bitcoin shows statistically significant positive returns for all trading strategies. However, statistical significance is at its highest for the trading strategy (1, 20) and the significance of predictability drops both economically and statistically as we employ a longer period to calculate the long moving average. Overall, six of the 11 cryptocurrencies show statistically significant payoffs at a 5% level and six of them even show statistically significant payoffs at a 10% level. On an average (1, 20) buy moving average strategy produces 45.46% p.a. for our set of cryptocurrencies compared to their buy and hold average return of 36.5% p.a. that produces around an 8.96% p.a. excess return for our technical trading rule. Perhaps the higher volatility in the cryptocurrency markets makes it hard to generate significant returns from comparatively longer trading strategies. Interestingly, our findings indicate that Bitcoin and Ethereum generate profits for all trading strategies investigated. Joint tests reveal, however, that only the (1, 20) moving average trading strategy generates statistically significant profits across all samples which suggests that cryptocurrencies are rather short-memory processes. The latter finding might explain why Grobys and Sapkota's (2019) study does not find any significant momentum payoffs in cryptocurrency markets; a finding contrary to those of Asness et al. (2013) who argue that momentum is persistent across different asset markets.

One could argue that Dash is transparent by default and thus could correspond to other non-privacy crypto-assets included in the sample. As an additional robustness check and in addressing this concern, we implement our (1, 20), (1, 50), (1, 100), (1, 150), and (1, 200) trading strategies for Dash. The corresponding returns of these strategies are estimated between 25.6% p.a. and 29.2% p.a. with *t*-statistics ranging between 2.28 for the (1, 200) trading strategy and 2.79 for the (1, 20) trading strategy, indicting statistical significance on a common 5% level. This result strongly supports our previous findings.

4. Concluding remarks

Investigating the profitability of simple technical trading rules implemented among different cryptocurrency markets suggests that the (1, 20) moving average trading strategy generates profits in cryptocurrency markets, irrespective of whether Bitcoin is accounted for. This time horizon is shorter than the popular moving average strategy applied in the stock market: (1, 50), (1, 150), (5, 150), (1, 200) and (2, 200) (Brock et al., 1992). In summary, our findings suggest that cryptocurrency markets do not exhibit market efficiency in its weak form. Furthermore, our study does not include any fully articulated dynamic general equilibrium asset-pricing models to determine whether the observed payoffs are merely the equilibrium rents that accrue to investors willing to bear the risks associated with such strategies (Lo et al., 2000). Therefore, further studies are required to discern the economic sources of returns in cryptocurrency markets.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2019.101396.

Appendix

Tables A1 and A2, A3

Table A1
Market capitalization of cryptocurrencies.

Panel A. Top 11 Cryptocurrencies (Including Bitcoin)			
No	Cryptocurrency	Symbol	Capitalization ($)
1	Bitcoin	BTC	6,467,437,080
2	Ripple	XRP	201,799,631
3	Litecoin	LTC	152,873,521
4	Ethereum	ETH	73,843,278
5	Dogecoin	DOGE	14,940,681
6	Peercoin	PPC	9,756,959
7	BitShares	BTS	8,591,688
8	Stellar	XLM	8,436,465
9	Nxt	NXT	6,863,998
10	MaidSafeCoin	MAID	6,789,470
11	NameCoin	NMC	6,073,338

Note. This table reports the top 11 cryptocurrencies (including Bitcoin) based on their market capitalization as of January 3, 2016. Data were retrieved from coinmarketcap.com.

[6] See Table A3 for the returns of Table 1 and Table A2 in annualized percentage rate.

Table A2
Descriptive statistics.

Currency	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt	Obs.
BTC	0.0009	0.0011	0.0978	−0.0901	0.0177	−0.1647	7.3762	1095
XRP	0.0016	−0.0015	0.4462	−0.2676	0.0343	2.9585	39.8046	1095
LTC	0.0009	0.0000	0.2216	−0.1716	0.0258	1.2806	15.3050	1095
ETH	0.0020	0.0000	0.1315	−0.1370	0.0279	0.2936	7.0092	1095
DOGE	0.0011	0.0000	0.2251	−0.2140	0.0312	0.9158	13.7879	1095
PPC	0.0002	−0.0005	0.1437	−0.2897	0.0311	−0.5530	13.2555	1095
BTS	0.0010	−0.0008	0.2258	−0.1701	0.0357	0.7644	9.5155	1095
XLM	0.0017	−0.0016	0.3140	−0.1591	0.0380	1.9892	17.3391	1095
NXT	0.0006	−0.0029	0.2046	−0.1643	0.0349	0.8603	7.9614	1095
MAID	0.0009	0.0001	0.1490	−0.1463	0.0299	0.1049	5.8144	1095
NMC	0.0001	−0.0010	0.3064	−0.5029	0.0428	−1.1249	26.9347	1095

Note: This table presents the description statistics (i.e. Mean, Median, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis and number of observations) using daily logarithmic return of cryptocurrencies: Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar Lumen (XLM), Nxt (NXT), MaidSafeCoin (MAID), Namecoin (NMC) over the period 2016–2018. Data were retrieved from coinmarketcap.com.

Table A3
Average returns in annualized percentage rates (APR).

Panel A: APR of sample cryptocurrencies for Table A2

Strategy	APR for individual coins											Average APR	
	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID	NMC	10 coins	11 coins
Buy and Hold	32.85	58.4	32.85	73	40.15	7.3	36.5	62.05	21.9	32.85	3.65	36.87	36.50

Panel B: APR of Moving average (MA) trading strategies using log of daily prices of sample cryptocurrencies for Table 1

Strategy	APR for individual coins											Average APR	
	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID	NMC	10 coins	11 coins
(1,20)	43.80	80.30	43.80	94.90	69.35	−7.30	76.65	58.40	76.65	36.50	−73.00	45.63	45.46
(1,50)	32.85	69.35	29.20	62.05	47.45	14.60	62.05	69.35	65.70	21.90	−36.50	40.52	39.82
(1, 100)	40.15	47.45	40.15	54.75	32.85	−3.65	43.80	51.10	65.70	−14.60	−73.00	24.46	25.88
(1. 150)	40.15	51.10	47.45	54.75	25.55	−3.65	47.45	32.85	51.10	3.65	−51.10	25.92	27.21
(1, 200)	40.15	62.05	43.80	69.35	18.25	0.00	47.45	47.45	25.55	14.60	−40.15	28.84	29.86

Note: This table presents the average returns in the annualized percentage rate (APR) for Tables 1 and A2 using the convention of 365 days in a year as cryptocurrency market operates every day during a year. The sample of 11 cryptocurrencies are: BTC (Bitcoin), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar Lumen (XLM), Nxt (NXT), MaidSafeCoin (MAID), Namecoin (NMC). The average return for 10 coins exclude Bitcoin from the sample. Data were retrieved from coinmarketcap.com.

References

Al-Yahyaee, K.H., Mensi, W., Yoon, S.M., 2018. Efficiency, multifractality, and the long-memory property of the Bitcoin market: a comparative analysis with stock, currency, and gold markets. Finance Res. Lett. 27, 228–234.
Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. J. Finance 68 (3), 929–985.
Bariviera, A.F., 2017. The inefficiency of Bitcoin revisited: a dynamic approach. Econ. Lett. 161, 1–4.
Borri, N., 2019. Conditional tail-risk in cryptocurrency markets. J. Empir. Finance 50, 1–19.
Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple technical trading rules and the stochastic properties of stock returns. J. Finance 47 (5), 1731–1764.
Coakley, J., Marzano, M., Nankervis, J., 2016. How profitable are FX technical trading rules? Int. Rev. Financ. Anal. 45, 273–282.
Conover, C.M., Jensen, G.R., Johnson, R.R., Szakmary, A.C., 2017. Emerging markets: is the trend still your friend? Glob. Finance J. 32, 128–148.
Corbet, S., Eraslan, V., Lucey, B., Sensoy, A., 2019. The effectiveness of technical trading rules in cryptocurrency markets. Finance Res. Lett. 31, 32–37.
Dyhrberg, A.H., 2016a. Bitcoin, gold and the dollar–a Garch volatility analysis. Finance Res. Lett. 16, 85–92.
Fry, J., Cheah, E.T., 2016. Negative bubbles and shocks in cryptocurrency markets. International Review of Financial Analysis 47, 343–352.
Gerritsen, D.F., Bouri, E., Ramezanifar, E., Roubaud, D., 2019. The profitability of technical trading rules in the Bitcoin market. Finance Res. Lett In press.
Grobys, K., Sapkota, N., 2019. Cryptocurrencies and Momentum. Econ. Lett. 180, 6–10.
Hudson, R., Dempsey, M., Keasey, K., 1996. A note on the weak form efficiency of capital markets: the application of simple technical trading rules to UK stock prices – 1935 to 1964. J. Bank. Finance 20, 1121–1132.
Khuntia, S., Pattanayak, J.K., 2018. Adaptive market hypothesis and evolving predictability of bitcoin. Econ. Lett. 167, 26–28.
Klein, T., Thu, H.P., Walther, T., 2018. Bitcoin is not the new gold–a comparison of volatility, correlation, and portfolio performance. Int. Re. Financ. Anal. 59, 105–116.
Kristoufek, L., 2018. On Bitcoin markets (in) efficiency and its evolution. Physica A. 503, 257–262.
Levich, R.M., Thomas III, L.R., 1993. The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach. J. Int. Money Finance 12 (5), 451–474.
Lo, A.W., Mamaysky, H., Wang, J., 2000. Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. J. Financ. 55 (4), 1705–1765.
Miller, N., Yang, Y., Sun, B., Zhang, G., 2019. Identification of technical analysis patterns with smoothing splines for bitcoin prices. J. Appl. Stat. 46, 2289–2297.

Nakamoto, S., 2008. Bitcoin: a peer-to-peer electronic cash system.
Neely, C., Weller, P., Dittmar, R., 1997. Is technical analysis in the foreign exchange market profitable? A genetic programming approach. J.Financ.Quant. Anal. 32 (4), 405–426.
Qi, M., Wu, Y., 2006. Technical trading-rule profitability, data snooping, and reality check: evidence from the foreign exchange market. J. Money, Credit . Bank. 2135–2158.
Ratner, M., Leal, R.P., 1999. Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. J. Bank Finance 23 (12), 1887–1905.
Schulmeister, S., 2008. Components of the profitability of technical currency trading. Appl. Financ. Econ. 18 (11), 917–930.
Sensoy, A., 2019. The inefficiency of Bitcoin revisited: a high-frequency analysis with alternative currencies. Finance Res. Lett. 28, 68–73.
Tiwari, A.K., Jana, R.K., Das, D., Roubaud, D., 2018. Informational efficiency of Bitcoin—an extension. Econ. Lett. 163, 106–109.
Urquhart, A., 2016. The inefficiency of Bitcoin. Econ. Lett. 148, 80–82.
Zhang, W., Wang, P., Li, X., Shen, D., 2018. The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average. Physica. A 510, 658–670.