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Profitability of technical trading rules among cryptocurrencies with privacy function

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ABSTRACT

This paper studies simple moving average trading strategies employing daily price data on the ten most-traded cryptocurrencies that exhibit the 'privacy function'. Investigating the 2016–2018 period, our results indicate a variable moving average strategy is successful only

when applied to Dash generating returns of 14.6% − 18.25% p.a. in excess of the simple buy-and-hold benchmark strategy. However, when applying our technical trading rules to the entire set of ten privacy coins shows that, on an aggregate level, simple technical trading rules do not generate positive returns in excess of a buy-and-hold strategy.

1. Introduction

Cryptocurrency markets have attracted a great deal of attention in the most recent academic literature. In this regard, Gerritsen et al. (2019), Corbet et al. (2019), and Miller et al. (2019) explore the profitability of technical trading rules in the Bitcoin market. Gerritsen et al.'s (2019) findings suggest that the profitability of specific technical trading rules, such as the trading range breakout rule, can consistently exceed that of a buy-and-hold strategy. Corbet et al. (2019) analyse various popular trading rules in form of the moving average and trading range break strategies and their performance when applied to high-frequency Bitcoin returns. Their results support Gerritsen et al. (2019) in finding evidence for the profitability of technical trading rules. Moreover, Miller et al. (2019) proposed employing smoothing splines to identify technical analysis patterns in the Bitcoin market. Their findings indicate that method of smoothing splines for identifying the technical analysis patterns and that strategies based on certain technical analysis patterns generate returns that significantly exceed the returns of unconditional trading strategies. While Gerritsen et al. (2019), Corbet et al. (2019), and Miller et al. (2019) exclusively study a single cryptocurrency (i.e., Bitcoin), Grobys et al. (2020) investigate the profitability of simple technical trading rules implemented amongst eleven most liquid cryptocurrency markets. Their results show that– excluding Bitcoin from the sample– a simple 20 days moving average trading strategy generates a return of 8.76% p.a. in excess of the average market return.

Extending the most recent literature on technical trading rules in cryptocurrency markets, our study investigates the profitability of simple technical trading rules implemented amongst cryptocurrencies that exhibit the so-called 'privacy function'. The privacy function allows users to maintain a certain degree of anonymity on either the user level, the transaction level, the account balance

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level, or having full privacy on all levels. For example, Dash allows users to have the 'anonymous send' option if they want to anonymize their user level information. Foley et al. (2019) estimate that around $76 billion of illegal activity per year appears to be associated with Bitcoin which corresponds to 46% of all Bitcoin transactions. As Bitcoin is considered a non-privacy coin, the only option how traders might achieve (full) anonymity is via the dark web. However, the usage of the dark web is per se a criminal offence. Therefore, traders might prefer choosing privacy coins for their transcations instead of non-privacy coins. This enables users making transactions in cryptocurrencies (e.g., privacy coins) in the legal world-wide-web domain while still meeting their demands for legal transfers of digital currency, security, and confidentiality through anonymous transactions. Moreover, such security features may be of considerable importance for traders from countries where economic and political freedom is limited.

Sapkota and Grobys (2019) argue that privacy coins are different from non-privacy coins not only on the cryptographic level, but probably also on the user level. Using cointegration analysis, their study shows that privacy coins and non-privacy coins generate two distinct cointegration equilibria. Following Grobys et al. (2020) and Grobys and Sapkota (2019), we focus on several cryptocurrency markets jointly so that we are able to draw market-wide conclusions. Using daily data over the January 1, 2016–December 31, 2018 period, we follow Grobys et al. (2020) in analysing a total of five common trading rules for each sample of cryptocurrencies accounting for past information between 20 and 200 trading days. We also hypothesize that if cryptocurrency markets were efficient, it would not be possible to generate profits using past price information.

First our study contributes to the literature on technical trading rules in cryptocurrency markets (Gerritsen et al., 2019; Corbet et al., 2019; Miller et al., 2019; Grobys et al., 2020). While earlier studies focused on non-privacy coins, our study takes a different perspective and focuses exclusively on privacy coins as a submarket of the overall cryptocurrency universe. Second, our study contributes to the literature on testing the market efficiency of cryptocurrency markets. While most papers focus on Bitcoin as a single cryptocurrency (Urquhart, 2016; Khuntia and Pattanayak, 2018; Tiwari et al., 2018; Bariviera, 2017; Sensoy, 2019; Kristoufek, 2018), we follow Grobys et al. (2020) and Grobys and Sapkota (2019) in taking a market-wide perspective and analyse several privacy coins jointly enabling us to draw market-wide conclusions.

Our results show that a variable moving average strategy is successful only when applied to Dash generating returns of 14.6%–18.25% p.a. in excess of the simple buy-and-hold benchmark strategy supporting Gerritsen et al. (2019), Corbet et al. (2019), and Miller et al. (2019) on the single cryptocurrency level. In contrast, taking a market-wide perspective our results are very different: Applying our technical trading rules to the entire set of ten privacy coins shows that, on an aggregate level, simple technical trading rules do not generate positive returns in excess of a buy-and-hold strategy that invests in an equally-weighted portfolio of privacy coins. While this result is contrary to Grobys et al. (2020) – because it suggests that the market for privacy coins, as a submarket of the entire cryptocurrency universe, is efficient – our results confirm Grobys and Sapkota (2019) who concluded that the cryptocurrency markets are more efficient than earlier believed.

2. Data and methodology

2.1. Data

Our sample of privacy coins consists of the ten largest cryptocurrencies in terms of market capitalizations as of January 2, 2016.[1] The sample comprises the following cryptocurrencies: Dash (DASH), Bytecoin (BCN), DigitalNote (XDN), Monero (XMR), CloakCoin (CLOAK), Aeon (AEON), Stealth (XST), Prime-XI (PXI), NavCoin (NAV), Verge (XVG). We collected the daily price data of sample coins from the website coinmarketcap.com for the period January 1, 2016– December 31, 2018. The market capitalizations and the descriptive statistics for our sample of privacy coins is reported in appendix tables A.1 and A.2. Table A.2 indicates that a simple buy-and-hold strategy of an equally weighted portfolio of privacy coins produces an average return of 45.63% p.a. over the sample period.[2] Interestingly, the average return is higher than the average buy-and-hold payoff of 36.5% p.a. for a portfolio of eleven non-privacy coins covering the same period (Grobys et al., 2020).

2.2. Trading rule and methodology

Following Grobys et al. (2020), we implement different trading strategies using the Variable Moving Average (VMA) oscillator technical trading rule. VMA uses a short-period and a long-period moving average to generate trading signals and compound the long and short period moving average as follows:

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

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

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

[1] In order to provide an out-of-sample analysis, we use the market capitalization at the begining of the sample period to select our sample of privacy coins.

[2] Grobys et al. (2020) find that the top eleven non-privacy cryptocurrencies – Bitcoin, Ripple, Litecoin, Ethereum, Dogecoin, Peercoin, BitShares, Stellar Lumen, Nxt, MaidSafeCoin, and Namecoin – exhibit an average return of 36.5% p.a for the buy-and-hold strategy.

number of days used to calculate the long-term moving average. Moreover, we employ $n = 20, 50, 100, 150, 200$ to calculate the payoffs from our buy positions.[3] In VMA technical analysis, crossings of short-period moving averages over long-period moving averages signify the initiation of a new trend (Brock et al., 1992). Specifically, in our analysis, a buy signal is generated when a short-period moving average rises above a long-period moving average, that is,

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

Following a buy signal, we take a long position on the underlying cryptocurrency and hold the position until a sell signal is generated. Finally, to make market-wide conclusions concerning the profitability of VMA rules for our universe of privacy coins, we follow Grobys et al. (2020) and employ a multidimensional econometric test accounting for contemporaneous correlations amongst cryptocurrency returns, as pointed out in Borri (2019). Let's denote the return of privacy coin i at time t as $crypto_{i,t}^{private}$ and let's assume we consider a set of N assets. Stacking the returns into a Nx1 vector gives

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

where $\alpha_1, \alpha_2, \ldots, \alpha_N$ are the sample averages and $u_{1,t}, u_{2,t}, \ldots, u_{N,t}$ are standard white-noise processes. If $cov(crypto_{i,t}^{private}, crypto_{j,t}^{private}) \neq 0$ for some $i \neq j$, then the sample averages are correlated too. A joint test 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

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

with

$$\boldsymbol{\beta} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix}, \boldsymbol{R} = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}, \boldsymbol{r} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \widetilde{\boldsymbol{X}} = \begin{bmatrix} \boldsymbol{X} & 0 & 0 & \cdots & 0 \\ 0 & \boldsymbol{X} & 0 & \cdots & \vdots \\ \vdots & 0 & \boldsymbol{X} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \cdots & \boldsymbol{X} \end{bmatrix}, \boldsymbol{X} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}, \boldsymbol{0} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

and

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

where the matrix dimensions are $\boldsymbol{R}, \wedge\Sigma \in \boldsymbol{M}_{N,N}$, $\boldsymbol{\beta}$, $\boldsymbol{r} \in \boldsymbol{M}_{N,1}$, $\boldsymbol{X}$, $\boldsymbol{0} \in \boldsymbol{M}_{T,1}$, and $\widetilde{\boldsymbol{X}} \in \boldsymbol{M}_{TN,N}$. Using daily data and more than 1000 observations, justifies the application of the law of large numbers implying that the test statistic has feasible asymptotical distributional properties and is under the null hypothesis distributed as $\chi^2(N)$ (Grobys et al., 2020).

3. Results and discussion

Table 1 presents the average returns and the corresponding t-statistics of different VMA trading strategies. We define each strategy as *(short-period MA, long-period MA)*, where the *short-period* and *long-period* represent the number of days used to calculate the short and long-term moving averages, respectively.[4] From table 1 in association with table A.2 we observe, for instance, that the (1, 20) trading strategy implemented for Dash generates an average excess return of 18.25% p.a.[5] Furthermore, the joint test of ten

[3] As argued in Grobys et al. (2020), we do not consider the payoffs from sell trading strategies because so far it is not possible to take a short position on cryptocurrencies or mimic the payoffs of the short positions using cryptocurrency related financial instruments.

[4] For cryptocurrencies, the majority of trading activities occurs on cryptocurrency exchanges where orders (buy/sell) are directly placed by the cryptocurrency users into the order book. Therefore, the majority of exchanges do not monetize from bid-ask spreads but charge trading fees instead. Note that there are a few exchanges like Binance, Bitfinex, Kraken, Coinbase, etc. that take the spread on Dash (see coinliquidity.com/currency/DASH). For our analysis, however, we employed data from coinmarketcap.com which aggregates the whole available market data. For instance, at coinmarketcap.com, there are 5127 cryptocurrencies available that are traded at 20747 markets around the world as of February 17, 2020.

[5] $(0.0018 - 0.0013) \cdot 365 = 0.1825$

Table 1
Payoffs of MA trading strategies using the log of price data.

Strategy	Tests on individual coin's MA returns										Joint Test		
	DASH	BCN	XDN	XMR	CLOAK	AEON	XST	PXI	NAV	XVG	*3 coins*	*7 coins*	*10 coins*
(1, 20)	0.0018***	0.0006	0.0015	0.0022***	0.0002	0	−0.0004	−0.0042**	0.0007	−0.0016			
	2.79	0.4	1.24	2.76	0.13	−0.03	−0.28	−2.15	0.45	−0.94	11.61***	13.15*	22.43**
(1,50)	0.0017***	0.0004	0.0011	0.0017**	0.0002	0.001	0.0005	−0.003	0.001	−0.0016			
	2.59	0.29	0.94	2.08	0.13	0.79	0.36	−1.52	0.59	−0.98	8.20**	8.52	15.12
(1, 100)	0.0018**	0.0005	0.0009	0.0017*	0	0.0016	0.0005	−0.0028	0.0006	−0.002			
	2.49	0.32	0.74	1.92	0.02	1.18	0.36	−1.41	0.34	−1.18	7.22*	7.76	14.95
(1, 150)	0.0017**	0.0007	0.0014	0.0025***	0.0006	0.002	0.0007	−0.0013	0.0022	−0.0012			
	2.29	0.42	1	2.63	0.37	1.38	0.44	−0.63	1.17	−0.66	8.57**	9.12	13.30
(1, 200)	0.0018**	0.0007	0.0014	0.0021**	0.0017	0.0023	0.0008	−0.0021	0.002	0.0002			
	2.28	0.4	0.94	2.17	0.95	1.53	0.49	−0.97	1.46	0.12	6.89*	7.70	10.89

Note: This table presents the average returns of buy moving average trading strategies and their associated statistical significance using Seemingly Unrelated Regression (SUR) for individual coins along with joint significance test across three, seven and ten coins. The sample denoted as *10 coins* comprises ten privacy cryptocurrencies including Dash (DASH), Bytecoin (BCN), DigitalNote (XDN), Monero (XMR), CloakCoin (CLOAK), Aeon (AEON), Stealth (XST), Prime-XI (PXI), NavCoin (NAV), Verge (XVG). The sample denoted as *3 coins* contains the privacy cryptocurrencies with the largest market capitalization which are Dash, Bytecoin and Monero (see, table A.1). The sample denoted as *7 coins* excludes the three privacy cryptocurrencies that exhibited the lowest market capitalizations which are Stealth, Prime-XI and Verge. 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 sample period is from January 2016 until December 2018.

*** $p < 0.01$,.

** $p < 0.05$,.

* $p < 0.10$.

Table A.1
Top-ten privacy coins.

No	Privacy coin	Symbol	Capitalization ($)
1	Dash	DASH	19,794,713
2	Bytecoin	BCN	5,582,979
3	Monero	XMR	5,295,952
4	DigitalNote	XDN	447,057
5	CloakCoin	CLOAK	201,995
6	Aeon	AEON	137,088
7	NavCoin	NAV	121,805
8	Verge	XVG	109,968
9	Stealth	XST	8,352
10	Prime-XI	PXI	8,889

Note. This table reports the top ten privacy coins based on their market capitalization as of January 2, 2016.

cryptocurrencies in table 1 shows that average returns are jointly significant only for the (1, 20) trading strategy at a 5% level (see column *10 coins* in table 1). However, from panel B of table A.4, we find that the raw average portfolio return, which is the equally-weighted average across all cryptocurrency markets, is a mere 2.92% p.a. for this trading strategy. Despite of the significance of the raw average return, the buy-and-hold strategy generates 45.63% p.a. implying that the VMA trading strategy is not generating positive returns in excess of the buy-and-hold strategy. Thus, on an aggregate level, VMA trading strategies are not profitable when implemented amongst privacy coins. This result is contrary to Grobys et al. (2020) who document that the (1, 20) moving average trading strategy generates statistically significant profits over buy-and-hold returns across their sample of non-privacy coins.

Further, unlike the results of Grobys et al. (2020), we find that applying longer time horizons beyond 20 days to calculate long-period MA improves the average returns of our implemented strategies. However, the joint tests for testing the significance of the returns remain statistically insignificant: None of them outperforms the average returns from the simple buy-and-hold strategies (see column *10 coins* in table 1). Closer inspection of the average returns of the individual coins indicates that two privacy coins generated extraordinary losses. Specifically, Prime-XI and Verge produce extremely high negative returns that unduly reduce the average return for the portfolio of ten privacy coins which might explain the surprising underperformance of technical trading strategies in this

Table A.2
Descriptive statistics.

Currency	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt	Obs.
DASH	0.0013	−0.0005	0.1901	−0.1056	0.0272	0.8476	8.7271	1095
BCN	0.0012	0.0000	0.6939	−0.3953	0.0561	3.5782	46.3122	1095
XDN	0.0012	−0.0012	0.4394	−0.2229	0.0483	2.1572	18.3847	1095
XMR	0.0018	−0.0001	0.2539	−0.1273	0.0317	1.0620	10.1287	1095
CLOAK	0.0013	−0.0006	0.5724	−0.4470	0.0617	1.5343	21.6904	1095
AEON	0.0012	−0.0018	0.4453	−0.2178	0.0517	1.1308	10.9023	1095
XST	0.0012	−0.0014	0.5194	−0.4077	0.0588	1.0123	15.6361	1095
PXI	−0.0009	−0.0025	0.7282	−0.5947	0.0840	0.9249	17.2251	1095
NAV	0.0018	−0.0018	0.8914	−0.6569	0.0585	2.6581	69.0285	1095
XVG	0.0024	0.0000	0.4227	−0.3010	0.0701	0.7374	8.6747	1095

Note: This table presents the descriptive statistics (i.e., Mean, Median, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis and number of observations) using daily logarithmic returns of the following cryptocurrencies: Dash (DASH), Bytecoin (BCN), DigitalNote (XDN), Monero (XMR), CloakCoin (CLOAK), Aeon (AEON), Stealth (XST), Prime-XI (PXI), NavCoin (NAV), Verge (XVG). The sample period is from 2016–2018.

submarket.

Notably, from table 1 we also observe that only two coins–Dash and Monero–produce statistically significant returns for all implemented VMA trading strategies. Interestingly, for Dash the returns remain within 62.05% − 65.7% p.a. for all trading strategies corresponding to 14.6% − 18.25% p.a. average returns in excess of the simple buy-and-hold strategy for this specific cryptocurrency. Unlike Dash, other privacy coins, such as Monero, generate significant returns that are also economically profitable over the benchmark trading strategy for some trading strategies only. As mentioned in Grobys et al. (2020), a possible explanation could be that Dash differs from other privacy coins considered here as it is not *completely non-private*: For instance, Dash offers the function 'Optional privacy' (PrivateSend). Overall, caution is recommend when implementing technical trading rules amongst privacy coins.

In our main analysis we use the log of daily prices to calculate the short and long-term moving average. By construction, the moving average calculated in that way corresponds to the log of the geometric average. One could wonder if our results would change if we used the simple price series. Hence, as a robustness check, we re-estimated table 1 using the simple price series and, as a

Table A.3
Payoffs of MA trading strategies using price data.

Strategy	Tests on individual coin's MA returns										Joint Test of MA returns		
	DASH	BCN	XDN	XMR	CLOAK	AEON	XST	PXI	NAV	XVG	*3 coins*	*7 coins*	*10 coins*
(1, 20)	0.0018***	0.0005	0.0015	0.0022***	0.0001	−0.0003	−0.0004	−0.0042**	0.0007	−0.0019			
	2.75	0.35	1.25	2.7	0.08	−0.21	−0.27	−2.14	0.46	−1.16	11.22**	13.15*	23.37***
(1,50)	0.0016**	0.0006	0.0012	0.0018**	0.0002	0.001	0.0005	−0.0031	0.0009	−0.0014			
	2.46	0.39	1	2.13	0.16	0.76	0.32	−1.56	0.58	−0.85	7.83**	8.17	14.44
(1, 100)	0.0018***	0.0001	0.0012	0.0015*	−0.0001	0.0015	0.0002	−0.0035*	0.0006	−0.0019			
	2.63	0.05	0.93	1.77	−0.04	1.17	0.13	−1.79	0.35	−1.15	7.46*	8.25	16.87*
(1, 150)	0.0018**	0.0007	0.0013	0.0024**	0.0007	0.0017	0.0009	−0.0014	0.002	−0.0014			
	2.47	0.39	0.98	2.53	0.44	1.16	0.6	−0.69	1.12	−0.79	8.8**	9.21	14.18
(1, 200)	0.0018**	0.0008	0.0008	0.0022**	0.0016	0.0024	0.0007	−0.002	0.0022	0.0004			
**	2.28	0.43	0.56	2.25	0.91	1.59	0.45	−0.92	1.63	0.22	7.19*	8.41	11.02

Note: This table presents the average returns of buy moving average trading strategies and their associated statistical significance using Seemingly Unrelated Regression (SUR) for individual coins along with joint significance test across three, seven and ten coins. The sample denoted as *10 coins* comprises ten privacy cryptocurrencies including Dash (DASH), Bytecoin (BCN), DigitalNote (XDN), Monero (XMR), CloakCoin (CLOAK), Aeon (AEON), Stealth (XST), Prime-XI (PXI), NavCoin (NAV), Verge (XVG). The sample denoted as *3 coins* contains the privacy cryptocurrencies with the largest market capitalization which are Dash, Bytecoin and Monero (see, table A.1). The sample denoted as *7 coins* excludes the three privacy cryptocurrencies that exhibited the lowest market capitalizations which are Stealth, Prime-XI and Verge. 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 sample period is from January 2016 until December 2018.

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

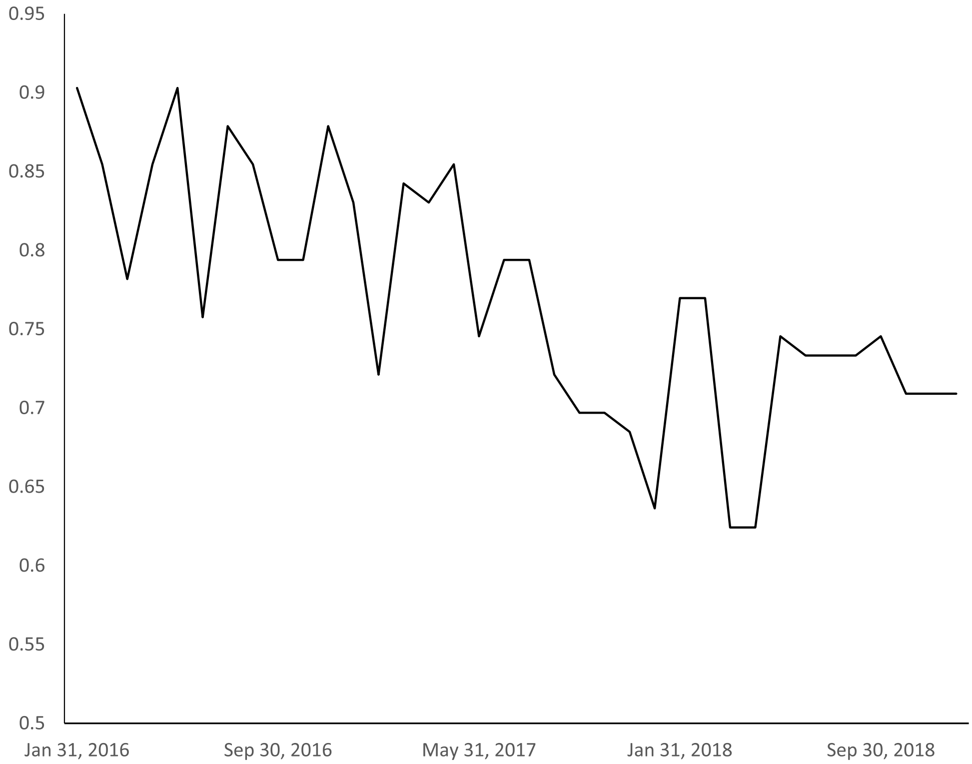

Fig. A.1. Rank correlations of the selected privacy coins' market capitalizations between the beginning of the sample and the end of each month.

consequence, the arithmetic average. The results are reported in table A.3. Our results remain virtually the same and our conclusion remain unchanged.

One could argue that the rank of market capitalizations of our set of selected privacy coins could be too volatile during the sample period which could cast doubt on the reliability of our results. To address this concern, we analyse the time-variation of the rank correlations between the privacy coins' market capitalizations at the beginning of the sample and the end of´each month. Specifically, on the last trading day of each month we sort all privacy cryptocurrencies in an increasing order with respect to their market capitalizations. Then we estimate the correlation between the corresponding rank at the beginning of our sample (e.g., January 2, 2016) and at the end of each consecutive month. We plot the time-varying correlations in Fig. A.1 in the appendix. The average correlation is estimated at 0.77 with a *t*-statistic of 60.68 indicating statistical significance on any level. As a result, we infer that even though there is some variation in market capitalizations across time, the rank amongst the coins is fairly stable confirming the reliability of our results.

Next, to test if the market capitalization has any effect on the profitability of our trading rules, we extend our empirical analysis by incorporating two additional joint profitability tests accounting for three and seven coins, respectively. The sample denoted as *3 coins* includes the three privacy cryptocurrencies with highest market capitalizations (Dash, Bytecoin and Monero), whereas the sample denoted as *7 coins* excludes the three privacy cryptocurrencies from the initial sample of ten coins that exhibit the lowest market capitalizations (Stealth, Prime-XI and Verge). Table 1 shows that the join tests for the three largest coins are statistically significant for the (1, 20) and (1, 200) trading strategies at a 1% and 10% level with an excess return of about 3.65% p.a. over the benchmark buy-and-hold trading strategy (see table A.4). However, considering this small profit margin in term of excess payoffs (and the lack of consistency in producing higher excess returns across different trading strategies), we recommend caution in implementing these two trading strategies. Further, other trading rules for these subsamples are either not statistically significant or economically relevant. Hence, our main conclusion remains unchanged.

In our empirical analysis, we do not explicitly consider the effect of market frictions‒ such as transaction cost‒ on the profitability of our trading strategies. For example, an increase in the number of trading signals would lead to increased transaction costs. In table A.5 we provide the total number of trading days under the buy signal (denoted as *Days*) and the number of executed trading positions for each coin (denoted as *POS)*, given each strategy along with the length of sample days for each trading strategy. Note that the implementation of our trading strategies divides the sample of trading days into either buy- or sell-signal days. Moreover, the difference in sample sizes (e.g., from 896 – 1076 observations) reflects the number of days it takes to generate the first signal for different trading strategies. The results indicate that *Days* generally increases as the long-term MA increases (e.g., from 20 to 200 days), whereas *POS* decreases resulting, in turn, in longer average holding periods (e.g., *Days/POS*). Interestingly, considering the individual levels, only Dash and Monero show significant payoffs, as reported in table A.4. However, the profitability of the (1, 20) trading strategy would be more susceptible to market frictions than (1, 200) trading strategy.

Table A.4
Average return in annualized percentage rate.

Strategy	DASH	BCN	XDN	XMR	CLOAK	AEON	XST	PXI	NAV	XVG	*3 Coins*	*7 Coins*	*10 coins*
Buy and Hold	47.45	43.80	43.80	65.70	47.45	43.80	43.80	−32.85	65.70	87.60	52.32	51.10	45.63
Panel B: Log of price													
Strategy	**DASH**	**BCN**	**XDN**	**XMR**	**CLOAK**	**AEON**	**XST**	**PXI**	**NAV**	**XVG**	***3 Coins***	***7 Coins***	***10 coins***
(1, 20)	65.70	21.90	54.75	80.30	7.30	0.00	−14.60	−153.30	25.55	−58.40	55.97	36.50	2.92
(1,50)	62.05	14.60	40.15	62.05	7.30	36.50	18.25	−109.50	36.50	−58.40	46.23	37.02	10.95
(1, 100)	65.70	18.25	32.85	62.05	0.00	58.40	18.25	−102.20	21.90	−73.00	48.67	37.02	10.22
(1, 150)	62.05	25.55	51.10	91.25	21.90	73.00	25.55	−47.45	80.30	−43.80	59.62	57.88	33.95
(1, 200)	65.70	25.55	51.10	76.65	62.05	83.95	29.20	−76.65	73.00	7.30	55.97	62.57	39.79
Panel C: Price													
Strategy	**DASH**	**BCN**	**XDN**	**XMR**	**CLOAK**	**AEON**	**XST**	**PXI**	**NAV**	**XVG**	***3 Coins***	***7 Coins***	***10 coins***
(1, 20)	65.70	18.25	54.75	80.30	3.65	−10.95	−14.60	−153.30	25.55	−69.35	54.75	33.89	0.00
(1,50)	58.40	21.90	43.80	65.70	7.30	36.50	18.25	−113.15	32.85	−51.10	48.67	38.06	12.05
(1, 100)	65.70	3.65	43.80	54.75	−3.65	54.75	7.30	−127.75	21.90	−69.35	41.37	34.41	5.11
(1, 150)	65.70	25.55	47.45	87.60	25.55	62.05	32.85	−51.10	73.00	−51.10	59.62	55.27	31.76
(1, 200)	65.70	29.20	29.20	80.30	58.40	87.60	25.55	−73.00	80.30	14.60	58.40	61.53	39.79

Note: This table reports the average returns in the annualized percentage rate (APR) using the convention of 365 days in a year as the cryptocurrency market operates every day during a year. The sample denoted as *10 coins* comprises ten privacy cryptocurrencies including Dash (DASH), Bytecoin (BCN), DigitalNote (XDN), Monero (XMR), CloakCoin (CLOAK), Aeon (AEON), Stealth (XST), Prime-XI (PXI), NavCoin (NAV), Verge (XVG). The sample denoted as *3 coins* contains the privacy cryptocurrencies with the largest market capitalization which are Dash, Bytecoin and Monero (see, table A.1). The sample denoted as *7 coins* excludes the three privacy cryptocurrencies that exhibited the lowest market capitalizations which are Stealth, Prime-XI and Verge. The sample period is from January 2016 until December 2018.

Table A.5
Number of trading days under each moving average trading strategy.

Panel A: Number of VMA buy signals using the Log of price																					
Strategy	Obs.	DASH		BCN		XDN		XMR		CLOAK		AEON		XST		PXI		NAV		XVG	
		Days	*POS*	*Days*	*POS*	*Days*	*POS*	*Days*	*POS*	*Days*	*POS*	*Days*	*POS*	*Days*	*POS*	*Days*	*POS*	*Days*	*POS*	*Days*	*POS*
(1, 20)	1076	576	45	480	95	498	72	576	52	508	68	543	81	537	71	438	91	558	80	442	99
(1,50)	1046	588	27	431	67	486	56	616	36	528	30	537	36	552	36	445	55	554	49	454	77
(1, 100)	996	578	14	448	64	476	53	656	24	549	21	522	14	529	33	475	45	596	31	454	56
(1, 150)	946	575	6	494	57	493	40	655	6	531	26	599	5	501	14	465	18	605	16	454	46
(1, 200)	896	559	9	515	47	543	28	637	4	536	10	602	1	491	12	453	24	588	14	449	29
Panel B: Number of VMA buy signals using the price																					
Strategy	**Obs.**	**DASH**		**BCN**		**XDN**		**XMR**		**CLOAK**		**AEON**		**XST**		**PXI**		**NAV**		**XVG**	
		Days	***POS***	***Days***	***POS***	***Days***	***POS***	***Days***	***POS***	***Days***	***POS***	***Days***	***POS***	***Days***	***POS***	***Days***	***POS***	***Days***	***POS***	***Days***	***POS***
(1, 20)	1076	574	47	475	95	490	69	572	53	501	67	535	81	524	73	431	90	548	82	432	98
(1,50)	1046	564	44	468	94	487	70	566	50	497	66	531	79	514	69	434	89	543	78	428	97
(1, 100)	996	571	13	428	67	454	48	636	28	537	22	516	14	508	35	437	51	579	32	427	55
(1, 150)	946	564	7	481	55	467	41	653	7	514	25	591	11	486	16	457	21	588	19	431	46
(1, 200)	896	552	10	502	50	503	34	633	4	525	14	599	1	464	14	435	21	580	9	443	29

Note: This table reports the number of trading days under the buy signals. *Days* represents the total number of trading days under each moving average trading strategy. *POS* denotes the number of executed trading positions for each coin. The sample of ten non-privacy cryptocurrencies are Dash (DASH), Bytecoin (BCN), DigitalNote (XDN), Monero (XMR), CloakCoin (CLOAK), Aeon (AEON), Stealth (XST), Prime-XI (PXI), NavCoin (NAV), Verge (XVG). The sample period is from January 2016 until December 2018.

4. Concluding remarks

This paper studies the profitability of variable technical trading rules implemented amongst a set of privacy coins using the popular moving average strategy as applied to stock markets: (1, 20), (1, 50), (1, 100), (1, 150) and (1, 200) (Brock et al., 1992). Our results indicate that VMA trading strategies are successful only for Dash (on the single cryptocurrency level) and generate excess returns of 14.6% − 18.25% p.a. in excess of the simple buy-and-hold trading strategy for this coin. However, averaging the average returns across the entire set of ten privacy coins, we do not find any significant positive average portfolio returns in excess of the equally-weighted average buy-and-hold portfolio. From a market-wide perspective, our results are contrary to the literature suggesting that technical trading rules are profitable for cryptocurrency markets (Grobys et al., 2020; Gerritsen et al., 2019; Corbet et al., 2019; Miller et al., 2019). Our study thus indicates that, on a portfolio level, privacy and non-privacy coins can be fundamentally different in their payoff profiles and investors should take this issue into account when applying different technical trading rules to cryptocurrency markets. Finally, our study does not include any fully elaborated dynamic general equilibrium asset-pricing model to assess whether the observed payoffs are merely the equilibrium rents that accrue to investors willing to carry the risks associated with such strategies (Lo et al., 2000). Future studies are encouraged to discern the economic sources of return differentials amongst cryptocurrency submarkets.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101495.

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