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Technical Analysis in Cryptocurrency Markets: Do Transaction Costs and Bubbles Matter? *

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Abstract

The study of technical analysis in cryptocurrencies has largely ignored the implications of often high transaction costs and bubble periods on trade rule performance. We study the daily and 1-minute returns of 69 technical trade rules in the form of moving average and breakout strategies, with and without transaction costs, during price bubbles in the 2016-2021 period. For the most profitable trade rules, we find that bubble periods increase the likelihood that Ethereum, Ripple and Litecoin beat buy-and-hold, but not Bitcoin and Bitcoin Cash. Transaction costs decrease this likelihood for Ripple and Litecoin, but increase it for Bitcoin and Ethereum.

JEL Classification : G14, G20, G30, G32

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1 Introduction

Cryptocurrencies are a very risky new asset class, and investors spend time to understand their price trends in order to profit as a reward for that risk. To make money, investors aim to create trend trading rules or strategies based on technical analysis to respond quickly to price changes, either between days or within a day. A new strand of the cryptocurrency literature has explored the profitability of technical trading rules, finding positive returns with Bitcoin (Miller et al., 2019; Corbet et al., 2019; Gerritsen et al., 2020) and other major cryptocurrencies (Grobys et al., 2020; Ahmed et al., 2020). Their results might be evidence of inefficiency in crytocurrency markets, and challenge the weak form of the efficient market hypothesis (EMH). However, most of the previous literature has not adjusted their profits by transaction costs, and has not studied the impact of bubble periods on the profitability of technical trading rules. We aim to close this gap in the literature.

This paper studies the impact of transaction costs and bubble periods on the returns of technical trading rules in cryptocurrency markets. To that end, we first extend and complement the most recent literature on technical trading analysis in cryptocurrency markets by applying 69 parameterized trading rules from Corbet et al. (2019), Gerritsen et al. (2020), and Grobys et al. (2020) to Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), and Bitcoin Cash (BCH), from 2016 to 2021. In particular, we calculate 69 trading returns, with and without transaction costs, in the form of moving average and breakout strategies in the 1-minute and 1-day frequency. The idea behind this approach is to assess whether there is a significant decrease in the number of trading rules producing positive profits after adjusting by transaction costs (details in the next section).

According to the EMH, investors cannot make profits above the buy-and-hold (BH) strategy using any technical trading rule that depends on past asset price patterns, because current prices already reflect all information. On this matter, we study the probability that a trading strategy produces higher returns than the buy-and-hold rule by employing a logistic regression model. That is, we examine whether the chances of having an *excess return* – the return of a particular trade strategy minus the buy-and-hold return – can be explained by transaction costs and bubble periods. We identify bubble periods by applying the Phillips et al. (2015) (PSY) method. Moreover, we examine whether the impact of transaction costs on the the odds ratio is stronger during bubble periods (interaction terms). It is worth mentioning that, while we study trading rules that produce positive profits adjusted by transaction costs and the chances of having an excess return, we do not aim to prove the existence of market inefficiency. However, market inefficiency and excess return by applying trading rules might be related[1].

This paper contributes to the growing literature on trading rules in cryptocurrency markets in several ways. First, previous literature has used either daily (Ahmed et al., 2020; Gerritsen et al., 2020; Grobys et al., 2020) or intraday (Miller et al., 2019; Corbet et al., 2019) data without transaction costs. We close this gap in the literature by calculating trading returns with transaction costs in both the 1-minute and 1-day price frequency. Second, although cryptocurrency markets have experienced bubbles (Cheah and Fry, 2015; Corbet et al., 2018; Geuder et al., 2019; Cagli,

[1]For further details on cryptocurrency market inefficiency, readers are referred to Zhang et al. (2018) and Al-Yahyaee et al. (2018), and to the references therein.

2019; Bouri et al., 2019), their effects on trading profits have not been studied yet. By formally examining the bubbles' effects on the probability of getting excess return, we also complement the literature of both bubble periods and technical analysis in cryptocurrency markets. Third, contrary to studies that only analyze Bitcoin (Miller et al., 2019; Corbet et al., 2019; Gerritsen et al., 2020), we study the performance of trade rules for the most traded cryptocurrencies. In this regard, we complement the few studies examining trading strategies employing daily price data on the most traded cryptocurrencies (Grobys et al., 2020; Ahmed et al., 2020). Fourth, in considering the less frequently studied 1-minute time frequency, we contribute to understanding the relevance of the time frequency of the trading strategies since Dempster and Jones (2001) find that price frequency can dramatically vary technical trading profits in the Forex market.

This paper offers some important insights into the understanding of *adjusted returns*, i.e., trading returns including transaction costs. Our results show that the number of profitable trading rules decrease after adjusting by transaction costs. However, we provide evidence that some rules can still produce positive adjusted returns in both the 1-minute and 1-day time frequency. With respect to excess returns with transaction costs, there are more trade rules producing positive excess returns in the 1-day time frequency compared to the 1-minute frequency. To the best of our knowledge, there is no other cryptocurrency research comparing adjusted returns and excess returns in the 1-minute and 1-day frequency. With reference to positive profits beyond buy-and-hold without transaction costs, our intraday and daily results are in line with previous studies (Miller et al., 2019; Corbet et al., 2019; Gerritsen et al., 2020; Grobys et al., 2020; Ahmed et al., 2020).

On the question of the probability of having excess returns, we demonstrate with a subset of the five most profitable strategies for each cryptocurrency[2] that transaction costs and bubble periods matter. In particular, transaction costs increase the odds ratio of excess return for Bitcoin and Ethereum, but decrease it for Ripple and Litecoin. Regarding bubble periods, we find that this variable increases the odds ratio of excess return for Ethereum, Ripple, and Litecoin, but it does not have any effect on the odds ratio for Bitcoin. Surprisingly, neither transaction costs nor bubbles have any influence on the chances of having excess returns for Bitcoin Cash.

The rest of the paper is organized as follows. Section 2 describes the methodology we use, section 3 presents the data and discusses the results, and section 4 concludes.

2 Methodology

2.1 Detecting Bubbles

Identifying bubble periods in each cryptocurrency price series is a key ingredient in the analysis of the performance of trading rules. Since cryptocurrencies lack intrinsic value (Cheah and Fry, 2015; Cheung et al., 2015; Klein et al., 2018; Huang et al., 2019), the dating algorithm of Phillips et al. (2015) (PSY) is used to overcome the asset bubble definition based on fundamental value. PSY propose a Generalized Supremum Augmented Dickey–Fuller (GSADF) test which is based on

[2] We select these top-5 rules via a process described below.

a rolling-window ADF-style regression:

$$x_t = \alpha_{rw}^0 + \alpha_{rw}^1 x_{t-1} + \sum_{i=1}^{p} \phi_{rw}^i \Delta x_{t-i} + \varepsilon_t, \tag{1}$$

where x_t is the cryptocurrency price; α_{rw}^0, α_{rw}^1, and ϕ_{rw}^i are parameters estimated using OLS; p is the number of lags; ε_t is the innovation; and $rw = r_2 - r_1$ is a rolling window that starts and ends respectively with a fraction r_1 and a fraction r_2. The null hypothesis states that the time series x_t has a unit-root ($H_0 : \alpha_{rw}^1 = 1$), while the alternative hypothesis states that x_t is an explosive process ($H_a : \alpha_{rw}^1 > 1$). The GSADF test statistic is $GSADF(r_0) = \sup_{r_2 \in (r_0,1)} SADF_{r_2}(r_0)$, where $SADF_{r_2}(r_0) = \sup_{r_2 \in (r_0,1)} ADF_0^{r_2}$, and the asymptotic critical values are obtained from Monte Carlo simulation with 2000 replications.

After the GSADF test detects explosive price behavior, the following date-stamping strategy is used. For instance, the first observation on which the backward GSADF statistic is greater than the critical value is the start date of a bubble. Likewise, the first observation after that start date on which the GSADF statistic goes below the critical value is the end date of a bubble. Subsequent bubbles can be identified similarly.

2.2 Technical Analysis Methodology

Corbet et al. (2019), Gerritsen et al. (2020), and Grobys et al. (2020) apply common technical trading rules to cryptocurrency markets, generally focusing on Bitcoin, the first cryptocurrency in the market. Following the Neftci (1991) insight that the most fundamental kind of technical trading rules are those that consider averages and extrema, we apply the *Moving Average* (MA) and *Breakout* (BO) trade rules, to five cryptocurrencies in both the 1-minute and 1-day time frequency. These rules are among the most well-studied in technical analysis, and we use common parameterizations, several of which are studied in all three papers cited. Tables 1 and 2 specify the trading rules and labels each with the paper(s) from which we cite it.

The first, and perhaps single most well-studied technical analysis trade rule type is the Moving Average (MA). Generally, there is a short-run MA (MA_S), a long-run MA (MA_L), and some band length ($band$) where $band = band_{param} \times MA_L$. Following the parameterizations in the studies cited above, we use a $band_{param}$ of either 0 or 0.01 here. When $MA_S > MA_L \pm band$, the trade rule provides a "buy" signal, and a "sell" signal otherwise. Our notation closely follows the Corbet et al. (2019) approach:

$$MA_S = \sum_{n=1}^{S} P_{t-(n-1)}/S > MA_L = \sum_{n=1}^{L} P_{t-(n-1)}/L + band \Rightarrow \text{buy signal at time t}, \tag{2}$$

$$MA_S = \sum_{n=1}^{S} P_{t-(n-1)}/S < MA_L = \sum_{n=1}^{L} P_{t-(n-1)}/L - band \Rightarrow \text{sell signal at time t}, \tag{3}$$

The MA rule is fully defined by its MA_S, MA_L and $band$ lengths. The parameterizations of each rule used is fully defined in Table 1.

The second trading rule we use is of the Breakout (BO) rule type. The BO rule is defined in the following manner:

$$P_t > max(P_{t-1}, ..., P_{t-n}) + band \Rightarrow \text{buy at time } t, \tag{4}$$

$$P_t < min(P_{t-1}, ..., P_{t-n}) - band \Rightarrow \text{sell at time } t, \tag{5}$$

where the $band$ is different for the buying and selling signals. Here, in the buying signal, $band = max(P_{t-1}, ..., P_{t-n}) \times band_{param}$, while for the selling signal, $band = min(P_{t-1}, ..., P_{t-n}) \times band_{param}$. Similarly to the MA rules, we follow the parameterizations in the studies cited above, and use a $band_{param}$ of either 0 or 0.01.

For the purposes of this study, the BO trading rule is fully defined by the length of time n over which an extreme value is compared to price in time t and the size of its $band_{param}$. The parameterizations of each rule used is fully defined in Table 2.

We use 69 total parameterized trade rules of the MA and BO type for this study. These are constructed by pooling all the rules of MA and BO type that are tested in Corbet et al. (2019), Gerritsen et al. (2020), and Grobys et al. (2020), with the exception of two BO rules with $BO_L = 1440$. This BO_L is not included because it would require close to 4 years of price data before trading in the daily time frequency, nearly the size of some of our full data sets. To maintain consistency, we do not test the $BO_L = 1440$ rules in the 1-minute time frequency either.

2.3 The role of bubble periods and transaction costs

Having identified bubble periods by the PSY method and defined each trade rule, we follow Bouri et al. (2019) to study the role of bubble periods in the excess return time series (the percentage trading period return of a particular trade strategy minus the percentage trading period return of buy-and-hold). To that end, we employ the logistic regression model:

$$log\left(\frac{p(Y=1|X)}{1-p(Y=1|X)}\right) = \beta_0 + \beta_1 D, \tag{6}$$

where the dependent variable Y is a dummy variable that takes the value of one when a trade rule return is greater than the buy-and-hold return and zero otherwise, β_0 is the intercept, and D is a dummy variable that equals 1 for a bubble period and 0 otherwise.

One central aspect of the multiple logistic models is the estimation of the coefficients and testing for their significance. If bubble periods increase the likelihood that a trading strategy produces higher returns than the buy-and-hold rule, then β_1 would be statistically significant and positive.

Similarly, we study the impact of both transaction costs (X_1) and bubble periods (D) on the odds ratio, and investigate if transaction costs have a strong effect on the odds ratio during bubble periods (i.e. *the interaction term* β_2):

$$log\left(\frac{p(Y=1|X)}{1-p(Y=1|X)}\right) = \beta_0 + \phi D + \beta_1 X_1 + \beta_2 X_1 \times D. \tag{7}$$

If there is no difference in the impact of transaction costs during the bubble periods, we expect that β_2 is close to zero or is statistically insignificant.

Finally, we control for volume of transactions (X_2) in the multivariate logistic regression model:

$$log\left(\frac{p(Y=1|X)}{1-p(Y=1|X)}\right) = \beta_0 + \phi D + \beta_1 X_1 + \beta_2 X_1 \times D + \beta_3 X_2 + \beta_4 X_2 \times D. \tag{8}$$

As in the previous cases, if volume of transactions increases the probability that a trading strategy produces higher returns than the buy-and-hold rule, then β_3 would be statistically significant and positive. In addition, we are interested in the interaction terms between transaction costs and bubble periods (β_2), and between volume of transactions and bubble periods (β_4). That is, we examine whether the effect of transaction costs (volume of transactions) is different among bubble and non-bubble periods.

We run all three logistic models with all rules studied in each cryptocurrency. A summary of all results, with more details for the five best performing trade rules is described below.

3 Results

3.1 Data and trading rules

Our dataset consists of 1-minute and daily cryptocurrency prices of Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), and Litecoin (LTC) measured in U.S. dollars, for the period January 1, 2016 – November 10, 2021 (or the earliest available), sourced from CryptoDataDownload.com. We work with these cryptocurrencies due to the time length of data availability, in part because a wider time span allows us to test for bubbles. As of writing, they account for about two-thirds of cryptocurrency market capitalization. Additionally, they are among the most liquid digital monies – a necessary condition for technical trading strategies to work. Transaction cost data is sourced from coinmetrics.io. Transaction costs here refer to the sum of all fees paid to miners, transaction validators, stakers and/or block producers divided by the number of transactions during a particular interval of time. Future research might break transaction cost down on a more granular basis, using individual transactions on the blockchain, but we believe this data is at least sufficient for initial transaction cost consideration. For the purpose of this research, we calculate trading strategy profits by their continuously compounded rate of return. Let $P_{i,t}$ be the price of cryptocurrency i at time t, and $r_{i,t} = lnP_{i,t} - lnP_{i,t-1}$ be the logarithmic return.

Table 3 presents a comparison of all 69 trade rules in the 1-minute price frequency with the buy-and-hold return (holding the cryptocurrency from the first period to the last), where the number of trading rules greater than the buy-and-hold return each year are reported. Each column corresponds to a specific cryptocurrency, where the superscript u refers to *unadjusted* or the trading returns that do not include transaction costs, and the superscript a refers to *adjusted* or the trading returns that include transaction costs. To understand this table it is better to present an example. The number 52 in the first column means 52 out of 69 trading strategies for Bitcoin, not including transaction costs, produce better returns than the buy-and-hold rule. Likewise, the number 29 in the second column refers to 29 out of 69 trading strategies for Bitcoin, including transaction costs, that produce better returns than the buy-and-hold rule.

Table 3 shows, as expected, that there are more unadjusted trading strategies than adjusted trading strategies that outperform the buy-and-hold rule in the 1-minute period. Notably, for Bitcoin in 2016 and 2018, profitable rules decrease from 52 to 29 and 59 to 32, respectively. The finding that some intraday Bitcoin trading strategies, without including transaction costs, produce positive profits broadly supports the work of other studies in this area (Miller et al., 2019; Corbet et al., 2019).

In Ethereum, a more pronounced (by proportion) decrease happened in 2019 because 20 profitable rules become 5, after the inclusion of transaction costs. In the majority of cases, besides Litecoin, the inclusion of transaction costs eliminates several instances of profitability. However, as time passes, in particular, in 2020 and 2021, this difference is not as substantial. The most interesting aspect of this table is that there are some trading strategies including transaction costs that produce profits beyond the buy-and-hold rule.

The results of the trading rules at the daily time frequency are shown in Table 4. Similar to the 1-minute results, there are more unadjusted trading strategies than adjusted trading strategies that outperforms the buy-and-hold rule. Nevertheless, compared to the 1-minute results, the difference is smaller. What stands out in the table is that the trading rules at the daily time frequency perform substantially better than on the 1-minute time frequency. In the majority of cases, the 1-minute time frequency has less profitable rules than the daily time frequency. The decrease in profitable rules when transaction costs are not included, to when they are, is substantially more in the 1-minute time frequency. In other words, in the 1-day time frequency, the inclusion of transaction costs sometimes does not decrease the number of trade rules producing profits beyond the buy-and-hold strategy at all, and most frequently by only one. The number of trade rules outperforming the buy-and-hold rule, with and without transaction costs, did not change in 2020 and 2021 for Bitcoin, Ethereum, and Bitcoin Cash. The single greatest decrease by number is from 45 rules to 40 in 2016 in Litecoin.

Taken together, the results shown in Tables 3 and 4 are quite revealing in several ways. First, in terms of returns with transaction costs, the superiority of the daily trade rules over the 1-minute trade rules could be explained by the fact that the 1-minute strategies have substantially more time periods during which to trade, and would tend to produce more trading as a result. Second, also interesting to note is the year 2018, in the daily time frequency, when every rule, both with and without transaction costs, returned greater than buy-and-hold. This is a period that was characterized by a large decrease in prices, suggesting these trade rules can help investors avoid such periods. Third, the number of daily trading rules including transaction costs that produce profits greater than the buy-and-hold strategy for each cryptocurrency decrease after 2018. Fourth, it is worth noting that, in terms of daily trading rules without adjusting by transaction costs, our Bitcoin results are in line with those of Gerritsen et al. (2020).

To the best of our knowledge, there is no other research showing that a particular trading strategy can produce profits beyond transaction costs in cryptocurrencies. We provide evidence, however, in Ethereum, Ripple, and Bitcoin Cash, three of five cryptocurrencies, of a general decline in relative profitability from year 2019 to 2021. The implication of this interesting finding is in line with recent literature suggesting that Bitcoin (Khuntia and Pattanayak, 2018; Vidal-Tomás and Ibañez, 2018; Sensoy, 2019) and other cryptocurrency markets (Tran and Leirvik, 2020) are becoming more efficient over time.

There is a question as to whether 1-minute trading frequency is even possible in several cryptocurrencies. When trades are undertaken through the blockchain, without the intermediary of an exchange, transactions often take several minutes, at minimum, to complete. Also, most data besides prices are available on a daily as opposed to 1-minute frequency. In part for these reasons, our risk-return and regression analysis focus on the daily results.

It is conceivable that these excess returns are a reward for investors bearing extra risk on a return to risk basis. To explore this argument, we report Sharpe ratios using daily data. Table 5 reports the number of trade-rule Sharpe ratios greater than the buy-and-hold Sharpe ratio in each cryptocurrency, with and without transaction costs. For example, in Bitcoin without transactions, 49 trade rules have a higher Sharpe ratio than buy-and-hold. The latter supports evidence in Gerritsen et al. (2020) that found relatively high Sharpe ratios among technical analysis trade rules in Bitcoin. We find this is the case in several other important cryptocurrencies as well. These ranks remain relatively stable even with the inclusion of transaction costs. In Bitcoin and Bitcoin Cash, the number of superior Sharpe ratios does not change, while in Ethereum, it decreases by 3, in Ripple by 4 and in Litecoin by 10. All in all, there is a substantial number of trade rules – more than 50% of trade rules for Bitcoin, Ethereum, and Bitcoin Cash – that generate a superior Sharpe ratio. A natural implication is that technical trade rules with relatively better reward to risk ratios than buy-and-hold exist, with stronger evidence in three of the five cryptocurrencies studied.

3.2 Trade rule returns and bubble periods

3.2.1 The big picture: 69 trading strategies

Table A.1 in the appendix provides a general overview of the Equation (6) results, indicating positive and negative coefficients, where the dependent variable is the logit of the odds ratios of excess return (beyond buy-and-hold). The independent variable is a dummy variable indicating the presence of a bubble as identified by the PSY process detailed above. The immediately proceeding columns indicate the number of trade rules with a positive or negative coefficient, and the number of rules with statistical significance at the 10%, 5% and 1% level, respectively. The results presented are for excess returns with transaction costs. The bubble coefficient (β_1) directions and statistical significance levels are identical for excess return with and without transaction costs in all five cryptocurrencies.

At the 1% level of statistical significance, there are no coefficients that are negative. The Ethereum logit regressions indicate a statistically significant positive relationship between excess return and bubbles in a little over a third of rules. In the Bitcoin case, we find similar results, with over half the rules having a statistically significant relationship between excess return and the presence of bubbles. In the Ripple case, the logit regressions show slightly less than a third of bubble coefficients that are positive and statistically significant. In the Litecoin case, about two-thirds of the rules exhibit a positive and statistically significant bubble coefficient. In the Bitcoin Cash logit regression case, about one-quarter of trade rules have a statistically significant and positive coefficient.

Table A.2 summarizes the coefficients directions of Equation (7): the bubble coefficient, the transaction cost coefficient and the interaction term coefficient. After performing 345 total regressions (one Equation (7) for each cryptocurreny and trade rule), at the 1% level of statistical significance, we find that there are only 5 total regressions with a negative bubble coefficient, versus 116 total regressions with a bubble coefficient that is positive. While there are a few exceptions, the evidence still strongly suggests that bubbles matter for trade rule profits, and most often in a positive direction, with four of five cryptocurrencies having at least 18 positive and statistically significant at the 1% level bubble coefficient trade rule regressions. Transaction cost coefficients are split almost evenly between positive and negative coefficients with statistical significance at the 10% level in Ripple, Litecoin and Bitcoin, but positive and statistically significant at the 10% level the majority of the time in Ethereum and Bitcoin Cash. Some Bubble-TC interaction coefficients are positive, the most notable of which is Litecoin with 24 that are statistically significant at the 1% level.

Equation (8), which includes volume of transactions and a volume-bubble interaction term, is qualitatively similar with respect to bubble and transaction cost coefficients, with similar direction and levels of statistical significance to those reported in Table A.2. The results indicate that neither volume nor volume-bubble interaction terms appear to be relevant. Tables summarizing the direction and statistical significance of coefficients for Equation (8) are available upon request.

Due to space constraints and in order to focus more closely in on important top performing trade rule parameterizations, we describe a process below to limit more detailed reporting to five trade rules. This process helps us determine whether the statistical significance of bubbles and transaction costs coefficients are indeed coming from the most profitable trade rules, and shed some light on the salient direction of transaction cost coefficients given the conflicting pooled results.

3.2.2 The best strategies: top-5

In this section, we select five high performing rules in each cryptocurrency to describe in further detail[3]. The selection criteria is as follows: first, for each cryptocurrency, we order total return of each trading strategy from the highest to the lowest, both adjusted and unadjusted by transaction costs. Then, to make the analysis comparable between adjusted and unadjusted strategies, we select the 10 highest of each of them. Finally, we select the 5 highest return strategies that are repeated in both rankings. We do not assume that a technical analyst could know these highest returning rules before the time period begins. Overall results summarized above indicate statistical significance with bubbles in an often significant portion of technical trade rules.

[3]More detailed summaries of all rules are available upon request.

To illustrate the interaction between bubbles and excess return, we plot the returns of the top returning trade strategy, the buy-and-hold return and the bubble periods (shaded area) in Figure 1. As Figure 1 shows, most cryptocurrencies experience higher profits in their top trade rule during bubble periods. It is worth noting that most cryptocurrencies experience bubble periods between October 2017 - January 2018 and October 2020 - March 2021. In Table 6, descriptive statistics of the top five trade rules as defined above are reported. As previously stated, Table 4 shows the relatively few differences in excess returns with and without transaction costs. The sample means here in Table 6 confirm this, with average daily returns staying fairly steady with and without transaction costs in the top-5 rules for each cryptocurrency.

Table 7 presents the Sharpe ratios by year for each cryptocurrency's top-5 rules, as compared to buy-and-hold returns. The rightmost two columns labeled "Full Sample" combine returns over the full period. Noteworthy is that in every rule, and in every cryptocurrency, the top-5 trade rules have a higher full sample Sharpe ratio than the buy-and-hold return. It is implied then that, in most years and in most cryptocurrencies, the annual Sharpe ratio of a top-5 trade rule is higher than that of the buy-and-hold strategy[4]. Noteworthy exceptions include rule 57 in 2016 Bitcoin, and nearly all rules in 2016 Litecoin.

Table 8 shows the top-5 rule results of the logit estimates of Equation (6) on the bubble coefficient. It can be seen that bubble periods do not change the odds ratio of a trade strategy generating higher return than the buy-and-hold return for Bitcoin, and all but one trade rule in Bitcoin Cash. For the other cryptocurrencies, bubble periods have a strong effect on the odds ratio, with 1% statistical significance in every trade rule except rule 55 for Litecoin.

Table 9 shows the results of the logit estimates of Equation (7). The bubble coefficient results support those reported in Table 8. All bubble coefficients are positive and statistically significant at the 5% level for Ethereum, Ripple, and Litecoin (except for the trade rule 55), but not for Bitcoin and Bitcoin Cash. Interestingly, for Ethereum, the interaction coefficient (β_2) of trade rule 6 is positive and statistically significant at the 1% level. This suggests that for this rule transaction costs matter very much during bubble periods. Regarding the interaction coefficient (β_2) of Bitcoin Cash in trade rule 4, a note of caution is due here since this coefficient is extremely high, even though it is statistically significant at the 1% level. A potential explanation is that Bitcoin Cash had the lowest transaction costs of all five cryptocurrencies, thus even a small change could increase the odds ratio[5].

All cryptocurrencies, except Bitcoin Cash, have a transaction cost coefficient with some statistical significance. Interestingly, the coefficient directions are not consistent at the 5% level of statistical significance. For Ethereum, the positive coefficient indicates that transaction costs increase the chances to beat the buy-and-hold strategy. On the other hand, for Ripple and Litecoin (except rule 41), the negative coefficient implies that transaction costs lower the chance to produce profits beyond the buy-and-hold strategy. In the Bitcoin case, the top-2 rules' results suggest that an increase in transaction cost increases the likelihood that a particular trading rule produces higher return than the buy-and-hold return.

[4]It is interesting to note that top returning trade rules do not always have the highest Sharpe ratio, although the ordering of returns and Sharpe ratios by rule are typically quite close. We leave a more detailed look at this phenomenon to future research.

[5]Typically, the Bitcoin Cash transaction cost is lower by an order of magnitude or more in each period.

The evidence presented in Table 9 implies that transaction costs play a role in both increasing and decreasing the likelihood that a particular trading rule produces higher return than the buy-and-hold return, depending on the cryptocurrency. It is possible that traders bid slightly higher trading fees in Bitcoin and Ethereum at times when common technical indicators indicate profitability. Also, Table 9 reveals that the coefficient of the interaction between transaction costs and bubble periods is not statistically significant at the 1% level, except in two cases. That is, typically, the effect of transaction costs is not different among bubble and non-bubble periods.

To verify that transaction costs could be a relevant factor that explains the likelihood that a particular trading rule generates a higher return than the buy-and-hold return, we control for volume of transactions. The results of Equation (8) are available upon request. The volume of transaction coefficient is not statistically significant for most of the regression equations, or has a value of zero in the few cases that it is statistically significant. The coefficient of the interaction between bubble periods and volume of transactions is not statistically different from zero. These two results together imply that Equation (8) is not relevant.

4 Closing remarks

Earlier studies of technical analysis in cryptocurrencies did not include transaction costs. We have shown that they change profitability dramatically in the 1-minute time frequency, but not substantially in the daily time frequency. We have shown also that bubbles can increase the probability that a trade rule including transaction costs produces profits beyond the buy-and-hold strategy. To our knowledge, this is the first study which provides evidence that bubbles and transaction costs play a major role in the profitability of moving average and breakout strategies.

We have also studied a set of the top-5 trade rules in each cryptocurrency. Clearly, bubbles matter to technical analysis profit in Ethereum, Ripple and Litecoin. Our additional regressions demonstrate that transaction costs are relevant as well. Transaction costs increase the probability of having excess returns in the two most profitable trade rules in Bitcoin and five most in Ethereum. However, it decreases the chances of having excess returns in Litecoin and Ripple. In addition, this subset of strategies allowed us to demonstrate that there is at least one trading strategy including transaction costs – for each year and for the entire sample – that produces a higher Sharpe ratio (risk-adjusted return) than the buy-and-hold strategy. Here, we contribute to the Gerritsen et al. (2020) evidence, who found high Sharpe ratios in the technical trading of Bitcoin.

Further studies might look at other methods of determining bubbles, other less commonly studied trade rules, transaction costs that vary based on a per transaction basis, and differing methods of risk-return measurement. The returns we demonstrate above buy-and-hold, even with transaction costs, may be evidence for some inefficiency in cryptocurrency markets. Formal efficiency testing methods are needed to further study this matter. We provide evidence for a positive relationship between transaction costs and the probability of having excess returns in top rules of Bitcoin and Ethereum. It is possible that higher transaction costs are the result of higher transaction demand from traders using these trade rules. Further work is needed to fully understand this phenomena. We believe that traders can learn from our results, particularly in times with substantial price decline. For example, in 2018, a year when our cryptocurrencies declined substantially for much of the year, all trading rules performed better than the buy-and-hold strategy. In cases where regulators find that excessive technical trading in cryptocurrencies contributes to a loss of welfare, our evidence suggests that transaction costs alone may not be sufficient to prevent these from occurring. A supply-and-demand responsive Tobin-style tax may help prevent welfare-reducing technical trades further. Our results suggest that regulators ought to be particularly wary of excess return rules in bubble periods.

References

Ahmed, S., Grobys, K., and Sapkota, N. (2020). Profitability of technical trading rules among cryptocurrencies with privacy function. *Finance Research Letters*, 35:101495.

Al-Yahyaee, K. H., Mensi, W., and 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 Research Letters*, 27:228–234.

Bouri, E., Shahzad, S. J. H., and Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters*, 29:178–183.

Cagli, E. C. (2019). Explosive behavior in the prices of bitcoin and altcoins. *Finance Research Letters*, 29:398–403.

Cheah, E.-T. and Fry, J. (2015). Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. *Economics Letters*, 130:32–36.

Cheung, A., Roca, E., and Su, J.-J. (2015). Crypto-currency bubbles: an application of the phillips–shi–yu (2013) methodology on mt. gox bitcoin prices. *Applied Economics*, 47(23):2348–2358.

Corbet, S., Eraslan, V., Lucey, B., and Sensoy, A. (2019). The effectiveness of technical trading rules in cryptocurrency markets. *Finance Research Letters*, 31:32–37.

Corbet, S., Lucey, B., and Yarovaya, L. (2018). Datestamping the bitcoin and ethereum bubbles. *Finance Research Letters*, 26:81–88.

Dempster, M. A. H. and Jones, C. M. (2001). A real-time adaptive trading system using genetic programming. *Quantitative Finance*, 1:397–413.

Gerritsen, D. F., Bouri, E., Ramezanifar, E., and Roubaud, D. (2020). The profitability of technical trading rules in the bitcoin market. *Finance Research Letters*, 34:101263.

Geuder, J., Kinateder, H., and Wagner, N. F. (2019). Cryptocurrencies as financial bubbles: The case of bitcoin. *Finance Research Letters*, 31.

Grobys, K., Ahmed, S., and Sapkota, N. (2020). Technical trading rules in the cryptocurrency market. *Finance Research Letters*, 32:101396.

Huang, J.-Z., Huang, W., and Ni, J. (2019). Predicting bitcoin returns using high-dimensional technical indicators. *The Journal of Finance and Data Science*, 5(3):140–155.

Khuntia, S. and Pattanayak, J. (2018). Adaptive market hypothesis and evolving predictability of bitcoin. *Economics Letters*, 167:26–28.

Klein, T., Thu, H. P., and Walther, T. (2018). Bitcoin is not the new gold–a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, 59:105–116.

Miller, N., Yang, Y., Sun, B., and Zhang, G. (2019). Identification of technical analysis patterns with smoothing splines for bitcoin prices. *Journal of Applied Statistics*.

Neftci, S. N. (1991). Naive trading rules in financial markets and wiener-kolmogorov prediction theory: A study of" technical analysis". *Journal of Business*, pages 549–571.

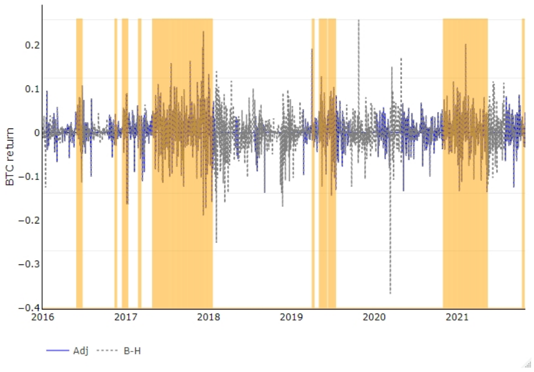
Phillips, P. C., Shi, S., and Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the s&p 500. *International Economic Review*, 56(4):1043–1078.

Sensoy, A. (2019). The inefficiency of bitcoin revisited: A high-frequency analysis with alternative currencies. *Finance Research Letters*, 28:68–73.

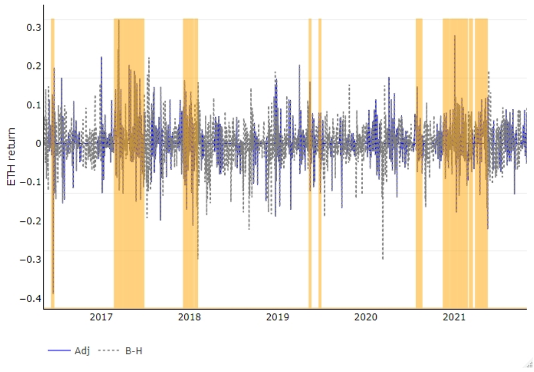
Tran, V. L. and Leirvik, T. (2020). Efficiency in the markets of crypto-currencies. *Finance Research Letters*, 35:101382.

Vidal-Tomás, D. and Ibañez, A. (2018). Semi-strong efficiency of bitcoin. *Finance Research Letters*, 27:259–265.

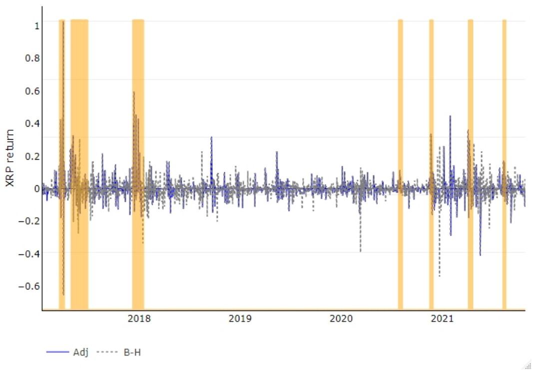
Zhang, W., Wang, P., Li, X., and Shen, D. (2018). The inefficiency of cryptocurrency and its cross-correlation with dow jones industrial average. *Physica A: Statistical Mechanics and its Applications*, 510:658–670.



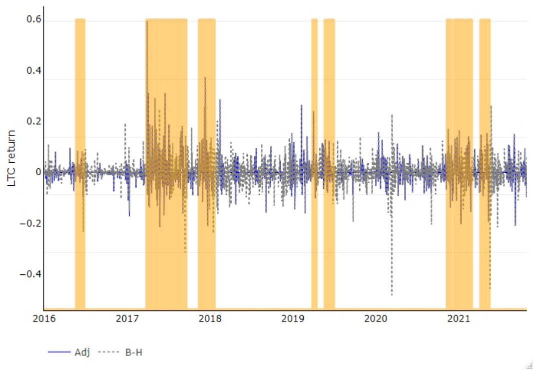
(a) *Bitcoin returns*



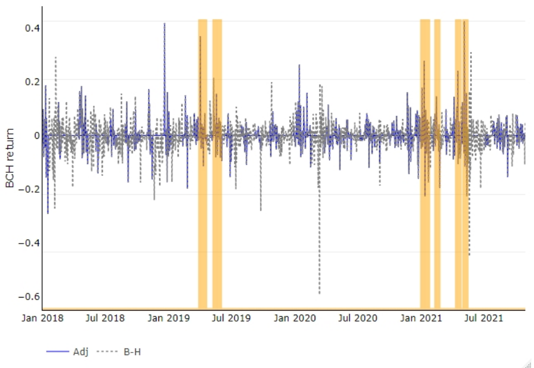
(b) *Ethereum returns*



(c) *Ripple returns*



(d) *Litecoin returns*



(e) *Bitcoin Cash returns*

Figure 1. *Cryptocurrency returns and bubble periods. Trading strategies: Strategies including transaction costs (solid blue line), and buy-and-hold (dashed black line). Bubble periods are represented by shaded areas.*

Table 1. *Technical Trade Rules: Moving Average.*

MA_S	MA_L	$band_{param}$	Paper	MA_S	MA_L	$band_{param}$	Paper
1	5	0	A	2	150	0	A
1	5	0.01	A	2	150	0.01	A
1	10	0	A	2	200	0	A and B
1	10	0.01	A	2	200	0.01	A
1	20	0	A and C	5	20	0	A
1	20	0.01	A	5	20	0.01	A
1	50	0	A, B, and C	5	50	0	A
1	50	0.01	A	5	50	0.01	A
1	100	0	A and C	5	100	0	A
1	100	0.01	A	5	100	0.01	A
1	150	0	A, B, and C	5	150	0	A and B
1	150	0.01	A	5	150	0.01	A
1	200	0	A, B, and C	5	200	0	A
1	200	0.01	A	5	200	0.01	A
2	5	0	A	10	20	0	A
2	5	0.01	A	10	20	0.01	A
2	10	0	A	10	50	0	A
2	10	0.01	A	10	50	0.01	A
2	20	0	A	10	100	0	A
2	20	0.01	A	10	100	0.01	A
2	50	0	A	10	150	0	A
2	50	0.01	A	10	150	0.01	A
2	100	0	A	10	200	0	A
2	100	0.01	A	10	200	0.01	A

Notes: This table defines all trade rules used of the Moving Average (MA) rule type. The short-hand for MA rules are as follows: MA(MA_S, MA_L, $band_{param}$).

Table 2. *Technical Trade Rules: Breakout.*

BO_L	*Band*	Paper	BO_L	*Band*	Paper
10	0	A	120	0	A
10	0.01	A	120	0.01	A
20	0	A	150	0	B
20	0.01	A	180	0	A
30	0	A	180	0.01	A
30	0.01	A	200	0	B
50	0	B	360	0	A
60	0	A	360	0.01	A
60	0.01	A	720	0	A
90	0	A	720	0.01	A
90	0.01	A			

Notes: This table defines all trade rules used of the Breakout (BO) rule type. The short-hand for these BO rules are as follows: BO(1, BO_L, $band_{param}$), where 1 represents that P_t is equivalent to a one-period average. "A" denotes the paper of Corbet et al. (2019), and "B" denotes the paper of Gerritsen et al. (2020).

Table 3. *Trading strategies greater than buy-and-hold, 1-minute time frequency.*

Year	BTC^u	BTC^a	ETH^u	ETH^a	XRP^u	XRP^a	LTC^u	LTC^a	BCH^u	BCH^a
2016	52	29	22	5	0	0	0	0	0	0
2017	11	5	6	5	4	4	0	0	6	6
2018	59	32	35	12	29	13	0	0	31	30
2019	20	9	20	5	18	6	2	2	7	6
2020	17	6	6	5	9	4	2	2	5	5
2021	19	7	6	5	5	4	2	2	5	5

Notes: Number of 1-minute trading strategies that performs better than the buy-and-hold rule. The superscript u denotes a return of a trading strategy that does not include transaction cost, the superscript a denotes a return of a trading strategy that includes transaction cost, and 0 means that there is no data for a particular cryptocurrency.

Table 4. *Trading strategies greater than buy-and-hold, 1-day time frequency.*

Year	BTC^u	BTC^a	ETH^u	ETH^a	XRP^u	XRP^a	LTC^u	LTC^a	BCH^u	BCH^a
2016	27	27	53	53	0	0	45	40	0	0
2017	6	6	5	5	5	4	6	6	35	35
2018	69	69	69	69	69	69	69	69	69	69
2019	32	32	50	47	60	59	42	38	25	25
2020	16	16	16	16	42	38	17	17	18	18
2021	28	28	16	16	17	17	41	37	18	18

Notes: Number of 1-day trading strategies that performs better than the buy-and-hold rule. The superscript a denotes the *adjusted* trading return (with transaction costs), the superscript u denotes the *unadjusted* trading return (without transaction costs), and 0 means that there is no data for a particular cryptocurrency.

Table 5. *Number of trade rules with a Sharpe ratio greater than that of buy-and-hold, 1-day frequency.*

Cryptocurrency	No TC Rank	TC Rank
BTC	49	49
ETH	62	59
XRP	30	26
LTC	41	31
BCH	47	47

Notes: Daily Sharpe ratios for each rule's return and buy-and-hold return were calculated and ranked. The number recorded indicates the number of trade rules with a Sharpe ratio greater than that of buy-and-hold. TC here is an acronym for transaction costs.

Table 6. *Descriptive Statistics of the top-5 trade rules and buy-and-hold (B-H) strategy.*

		Adjusted							Unadjusted						
	Index	Mean	Median	Std.	Skew.	Kurt.	Min	Max	Mean	Median	Std.	Skew.	Kurt.	Min	Max
	34	0.26	0.00	3.28	-0.05	7.46	-18.88	23.15	0.26	0.00	3.28	-0.05	7.46	-18.88	23.15
	33	0.25	0.00	3.28	-0.06	7.52	-18.88	23.15	0.25	0.00	3.28	-0.06	7.52	-18.88	23.15
BTC	12	0.25	0.00	3.31	-0.11	7.41	-18.88	23.15	0.25	0.00	3.31	-0.11	7.41	-18.88	23.15
	11	0.25	0.00	3.31	-0.11	7.44	-18.88	23.15	0.25	0.00	3.31	-0.11	7.44	-18.88	23.15
	57	0.25	0.00	3.36	-0.13	6.89	-18.88	23.15	0.25	0.00	3.36	-0.13	6.89	-18.88	23.15
	B-H	0.23	0.24	4.17	-0.47	6.88	-36.76	25.75							
	40	0.39	0.00	4.43	0.21	9.92	-38.78	31.94	0.40	0.00	4.43	0.22	9.91	-38.78	31.94
	20	0.37	0.00	4.32	0.27	10.84	-38.78	31.94	0.39	0.00	4.31	0.28	10.85	-38.78	31.94
ETH	19	0.37	0.00	4.30	0.34	10.76	-38.78	31.94	0.39	0.00	4.29	0.35	10.81	-38.78	31.94
	51	0.36	0.00	4.39	0.15	10.17	-38.78	31.94	0.37	0.00	4.37	0.18	10.15	-38.78	31.94
	6	0.35	0.00	4.34	0.23	10.85	-38.92	31.94	0.37	0.00	4.32	0.27	10.86	-38.78	31.94
	B-H	0.31	0.23	5.76	-0.17	3.98	-38.78	31.94							
	17	0.43	0.00	6.40	3.82	58.83	-65.30	102.80	0.47	0.00	6.38	3.86	59.39	-65.30	102.80
	4	0.41	0.00	6.39	3.82	59.23	-65.30	102.80	0.44	0.00	6.37	3.87	59.92	-65.30	102.80
XRP	18	0.40	0.00	6.21	3.83	64.12	-65.30	102.80	0.42	0.00	6.20	3.87	64.53	-65.30	102.80
	3	0.40	0.00	6.39	3.82	59.18	-65.30	102.80	0.44	0.00	6.36	3.89	60.25	-65.30	102.80
	5	0.38	0.00	6.37	3.75	59.93	-65.30	102.80	0.40	0.00	6.36	3.80	60.45	-65.30	102.80
	B-H	0.29	-0.05	7.80	1.85	28.11	-65.30	102.80							
	6	0.25	0.00	4.40	2.51	26.69	-21.43	59.15	0.27	0.00	4.39	2.55	27.00	-21.07	59.15
	30	0.25	0.00	4.37	2.37	27.11	-23.42	59.15	0.26	0.00	4.36	2.38	27.24	-23.42	59.15
LTC	41	0.24	0.00	4.81	1.20	23.57	-45.59	59.15	0.24	0.00	4.81	1.20	23.60	-45.59	59.15
	55	0.23	0.00	4.85	1.17	22.71	-45.63	59.15	0.24	0.00	4.85	1.18	22.76	-45.59	59.15
	5	0.23	0.00	4.42	2.49	26.38	-21.43	59.15	0.26	0.00	4.40	2.54	26.84	-21.07	59.15
	B-H	0.19	0.00	5.85	0.47	12.81	-48.21	59.15							
	5	0.17	0.00	4.58	1.67	20.04	-29.21	42.54	0.17	0.00	4.57	1.67	20.04	-29.20	42.54
	6	0.15	0.00	4.61	1.61	19.62	-29.21	42.54	0.15	0.00	4.61	1.61	19.62	-29.20	42.54
BCH	19	0.14	0.00	4.59	1.61	19.80	-29.21	42.54	0.14	0.00	4.59	1.61	19.80	-29.20	42.54
	4	0.13	0.00	4.44	2.06	21.18	-22.64	42.54	0.13	0.00	4.44	2.06	21.18	-22.64	42.54
	49	0.11	0.00	4.57	1.68	20.18	-29.21	42.54	0.11	0.00	4.57	1.68	20.19	-29.20	42.54
	B-H	-0.10	-0.09	6.55	-0.24	11.46	-59.38	42.54							

Notes: This table shows the descriptive statistics of the top-5 trade rules and the buy-and-hold (B-H) strategy for each cryptocurrency, using daily data. Index denotes the *Trade Rule Index*.

Table 7. *Sharpe ratio of the top-5 trade rules and buy-and-hold (B-H) strategy.*

		2016		2017		2018		2019		2020		2021		Full Sample	
	Index	A	U	A	U	A	U	A	U	A	U	A	U	A	U
BTC	34	1.75	1.75	2.59	2.59	-1.57	-1.57	1.40	1.40	2.31	2.31	1.30	1.30	8.90	8.91
	33	1.62	1.62	2.60	2.60	-1.53	-1.52	1.39	1.39	2.10	2.10	1.19	1.19	8.57	8.58
	12	2.17	2.17	2.69	2.69	-1.42	-1.42	1.19	1.19	2.04	2.04	0.98	0.98	8.41	8.42
	11	2.29	2.29	2.69	2.69	-1.57	-1.56	1.21	1.21	2.04	2.04	0.89	0.89	8.33	8.34
	57	1.41	1.41	2.69	2.69	-1.59	-1.59	1.15	1.15	2.07	2.07	1.31	1.31	8.16	8.16
	B-H	1.70	1.70	2.69	2.69	-1.42	-1.42	0.87	0.87	1.94	1.94	0.89	0.89	6.21	6.21
ETH	40	-0.21	-0.20	3.96	3.97	0.05	0.07	0.38	0.40	3.13	3.16	1.03	1.13	9.28	9.48
	20	-0.36	-0.34	3.82	3.83	-0.23	-0.20	0.39	0.41	2.55	2.69	1.71	1.87	9.05	9.41
	19	-0.37	-0.35	3.75	3.77	-0.08	-0.03	0.50	0.53	2.08	2.30	1.89	2.06	9.04	9.51
	51	-0.61	-0.59	3.59	3.60	0.18	0.19	0.06	0.08	2.45	2.55	1.55	1.63	8.55	8.76
	6	-0.17	-0.15	3.82	3.84	-0.58	-0.53	0.42	0.44	2.21	2.42	1.64	1.86	8.55	9.05
	B-H	-0.09	-0.09	3.39	3.39	-1.44	-1.44	-0.03	-0.03	1.96	1.96	1.60	1.60	5.58	5.58
XRP	17			2.81	2.96	0.34	0.49	-1.02	-0.89	1.10	1.13	1.02	1.08	6.89	7.43
	4			2.81	2.89	0.01	0.17	-1.12	-1.02	1.06	1.09	1.05	1.12	6.60	7.03
	18			2.67	2.76	0.06	0.19	-0.69	-0.59	0.93	0.95	1.13	1.18	6.57	6.95
	3			2.63	2.82	-0.02	0.19	-1.15	-1.00	1.46	1.51	0.93	1.01	6.38	7.08
	5			2.32	2.42	0.30	0.42	-0.67	-0.56	1.55	1.58	0.61	0.67	6.01	6.43
	B-H			2.53	2.53	-1.37	-1.37	-0.83	-0.83	0.11	0.11	0.99	0.99	3.38	3.38
LTC	6	-0.13	0.46	1.81	1.93	-0.03	0.00	1.72	1.74	1.31	1.33	0.71	0.72	6.35	6.84
	30	-0.26	0.06	2.38	2.44	-1.10	-1.07	1.06	1.08	1.75	1.76	0.57	0.58	6.27	6.57
	41	-0.05	0.19	2.33	2.35	-1.70	-1.68	1.24	1.24	1.45	1.45	0.17	0.18	5.46	5.61
	55	-0.35	-0.23	2.50	2.50	-1.62	-1.61	1.23	1.23	0.80	0.81	0.32	0.32	5.34	5.42
	5	-0.54	0.39	2.00	2.13	-0.29	-0.24	1.15	1.18	1.26	1.27	0.87	0.87	5.85	6.63
	B-H	0.42	0.42	2.50	2.50	-1.86	-1.86	0.29	0.29	1.04	1.04	0.34	0.34	3.58	3.58
BCH	5					-0.15	-0.14	1.12	1.12	0.73	0.73	1.01	1.01	2.70	2.70
	6					-0.35	-0.35	0.98	0.98	0.80	0.80	0.92	0.92	2.29	2.30
	19					-0.35	-0.35	1.01	1.01	0.78	0.78	0.86	0.87	2.24	2.24
	4					0.17	0.17	-0.03	-0.03	-0.08	-0.08	1.64	1.64	2.09	2.09
	49					-0.11	-0.11	0.93	0.93	-0.29	-0.29	1.10	1.10	1.81	1.82
	B-H					-1.96	-1.96	0.28	0.28	0.46	0.46	0.37	0.37	-1.14	-1.14

Notes: This table reports the Sharpe ratio for the top-5 trade rules and the buy-and-hold (B-H) strategy for each cryptocurrency, using daily data. Index denotes the *Trade Rule Index*, A denotes the *Adjusted* trading return (with transaction costs), and U denotes the *Unadjusted* trading return (without transaction costs).

Table 8. *Equation (6) - Logit Regression Results of the top-5 trade rules.*

	Trade Rule Index	Trade Rule	Bubble (ϕ)
BTC			
	11	MA(1,150,0)	33.606
	12	MA(1,150,.01)	33.33
	33	MA(5,100,0)	33.104
	34	MA(5,100,.01)	32.809
	57	BO(1,60,.01)	33.792
ETH			
	6	MA(1,20,.01)	3.926***
	19	MA(2,20,0)	3.911***
	20	MA(2,20,.01)	3.514***
	40	MA(10,20,.01)	2.6***
	51	BO(1,20,0)	4.583***
XRP			
	3	MA(1,10,0)	2.251***
	4	MA(1,10,.01)	2.305***
	5	MA(1,20,0)	3.756***
	17	MA(2,10,0)	2.036***
	18	MA(2,10,.01)	2.084***
LTC			
	5	MA(1,20,0)	1.626***
	6	MA(1,20,.01)	1.679***
	30	MA(5,20,.01)	1.456***
	41	MA(10,50,0)	4.251***
	55	BO(1,50,0)	32.791
BCH			
	4	MA(1,10,.01)	2.36***
	5	MA(1,20,0)	32.206
	6	MA(1,20,.01)	33.532
	19	MA(2,20,0)	30.769
	49	BO(1,10,0)	31.348

Notes: This table reports the coefficient results of Equation (6) for the top-5 trade rules for each cryptocurrency, using daily data. (*), (**), and (***) represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. *Equation (7) - Logit Regression Results of the top-5 trade rules.*

	Trade Rule Index	Trade Rule	Bubble (ϕ) .	TC (β_1)	Bubble $\times$TC (β_2)
BTC					
	11	MA(1,150,0)	32.379	0.052**	-0.049
	12	MA(1,150,.01)	32.36	0.053**	-0.049
	33	MA(5,100,0)	33.169	0.032	-0.028
	34	MA(5,100,.01)	33.326	0.034	-0.029
	57	BO(1,60,.01)	31.894	-0.01	0.009
ETH					
	6	MA(1,20,.01)	1.685**	0.021**	23.942***
	19	MA(2,20,0)	3.36***	0.017*	0.264
	20	MA(2,20,.01)	3.039***	0.022**	0.187
	40	MA(10,20,.01)	2.627***	0.037***	-0.029
	51	BO(1,20,0)	5.122***	0.036***	-0.082
XRP					
	3	MA(1,10,0)	3.47***	-30.274**	-116.406*
	4	MA(1,10,.01)	3.526***	-29.087**	-117.593*
	5	MA(1,20,0)	2.725***	-24.038**	550.498
	17	MA(2,10,0)	2.834***	-31.127**	-81.266
	18	MA(2,10,.01)	2.886***	-28.7**	-83.693
LTC					
	5	MA(1,20,0)	1.842***	-2.898***	0.933
	6	MA(1,20,.01)	1.839***	-3.002***	1.28
	30	MA(5,20,.01)	1.634***	-2.772***	0.991
	41	MA(10,50,0)	4.315***	-1.216	0.46
	55	BO(1,50,0)	32.954	-1.577**	1.547
BCH					
	4	MA(1,10,.01)	-9.795***	0.268	3121.724***
	5	MA(1,20,0)	32.691	-0.012	0.011
	6	MA(1,20,.01)	34.98	-0.034	0.028
	19	MA(2,20,0)	32.725	-0.109	0.094
	49	BO(1,10,0)	32.319	-0.282	0.256

Notes: This table reports the coefficient results of Equation (7) for the top-5 trade rules for each cryptocurrency, using daily data. (*), (**), and (***) represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix: Regression - All Strategy Summary

Table A.1. *Equation (6) - Logit Regression Results' Summary.*

	Coeff. Value	Times	p-value<.1	p-value < .05	p-value < .01
Bitcoin					
ϕ	(positive)	69	37	37	37
	(negative)	0	0	0	0
Ethereum					
ϕ	(positive)	69	26	26	26
	(negative)	0	0	0	0
Ripple					
ϕ	(positive)	69	22	22	20
	(negative)	0	0	0	0
Litecoin					
ϕ	(positive)	69	52	52	52
	(negative)	0	0	0	0
Bitcoincash					
ϕ	(positive)	67	16	16	16
	(negative)	0	0	0	0

Notes: This table reports the number of trade rules, including transaction costs, with statistically significant bubble coefficient (ϕ) in the Equation (6). The column "Coeff. Value" indicates whether ϕ is positive or negative. The column "Times" indicates the number of times that ϕ is either positive or negative.

Table A.2. *Equation (7) - Logit Regression Results' Summary.*

	Coeff. Value	Times	p-value<.1	p-value < .05	p-value < .01
Bitcoin					
ϕ	(positive)	67	37	37	33
	(negative)	2	0	0	0
β_1	(positive)	36	29	28	20
	(negative)	33	24	16	1
β_2	(positive)	10	1	0	0
	(negative)	59	8	6	4
Ethereum					
ϕ	(positive)	69	40	40	36
	(negative)	0	0	0	0
β_1	(positive)	69	61	57	55
	(negative)	0	0	0	0
β_2	(positive)	25	14	14	13
	(negative)	44	8	6	4
Ripple					
ϕ	(positive)	62	22	18	18
	(negative)	7	5	4	2
β_1	(positive)	27	18	15	10
	(negative)	42	19	12	0
β_2	(positive)	45	8	8	8
	(negative)	24	6	4	0
Litecoin					
ϕ	(positive)	47	28	28	28
	(negative)	22	4	2	0
β_1	(positive)	38	30	30	30
	(negative)	31	24	19	15
β_2	(positive)	49	24	24	24
	(negative)	20	0	0	0
Bitcoincash					
ϕ	(positive)	63	4	4	1
	(negative)	4	3	3	3
β_1	(positive)	54	37	37	37
	(negative)	13	0	0	0
β_2	(positive)	24	3	3	3
	(negative)	43	0	0	0

Notes: This table reports the number of trade rules, including transaction costs, with statistically significant bubble coefficient (ϕ) in the Equation (7). The column "Coeff. Value" indicates whether ϕ (β_1 or β_2) is positive or negative. The column "Times" indicates the number of times that ϕ (β_1 or β_2) is either positive or negative.