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Research Article

Can Technical Analysis Generate Superior Returns in the Cryptocurrency Ecosystem? Evidence from the Bitcoin Market

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Abstract

This study examines the profitability of nine novel technical trading rules in the Bitcoin market over the period 2010 to 2021. The technical rules that will be explored are variations of moving averages, Parabolic SAR, Directional Movement, RSI, Stochastic MACD and Williams. I compare technical trading strategies employing traditional standard tests and bootstrap methodology under GARCH (1,1) model. The results indicate that the examined rules have indeed a predictive power in the Bitcoin market. Overall, trading strategies based on technical indicators significantly outperform the buy-and-hold benchmark. My findings contradict the Efficient Market Hypothesis as traders and investors can gain abnormal returns using various trading strategies on the cryptocurrency ecosystem.

Keywords: Technical analysis; Cryptocurrencies; Bitcoin; Bootstrap; GARCH (1,1)

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Introduction

Cryptocurrencies have attracted significant attention from investors, regulators and the media. Bitcoin is the first decentralised digital currency and remains the cryptocurrency market's leader. At the same time, it is the most accepted cryptocurrency in the world, which makes it attractive for investors and traders. Amid its rapidly increasing usage and immense public interest Bitcoin has raised profound economic issues. However, the challenge in predicting the prices of Bitcoin is its high volatility and therefore, the prediction of its behavior is of great importance to financial markets [1].

Unlike the vast majority of other financial assets available, Bitcoin has no association with any higher authority and has no physical representation. Also, unlike traditional financial assets, the value of Bitcoin and other cryptocurrencies is not based on any tangible asset, any countries' economy or any firm, but is instead based on the security of an algorithm which is able to trace all transactions. The growth of the use of Bitcoin and other cryptocurrencies can be linked to their low transaction costs and peer-to-peer system [2].

Bitcoin price prediction has attracted the interest of researchers and investors. Some studies have used traditional statistical and econometric methods to understand the economic determinants of Bitcoin, while few have considered the development of predictive models using these determinants for technical analysis. Several studies have been published in the last 55 years exploring technical analysis [3]. However, there is a lack of research that consolidates the available knowledge concerning technical analysis in cryptocurrencies such as Bitcoin. Technical analysis has been understood as a set of tools that allows the prediction of future returns in financial assets by studying past market data, mainly stock prices and volume [4-6]. Technical analysis is popular among both institutional and individual investors alike. Recent studies have combined traditional technical analysis trading rules with statistical models as well, including [7-17].

The efficient market hypothesis states that when new information comes into the market, it is immediately reflected in stock prices and thus neither technical nor fundamental analysis can generate excess returns. However, many studies have discovered that some events in the financial market are inexplicable with EMH Is there a similar pattern in cryptocurrency ecosystem (Bitcoin) [15,16,5].

This study explores the profitability of nine technical rules in cryptocurrencies and in particular for Bitcoin prices from 2010 to 2021. Bitcoin is the most traded and largest by market capitalization of the cryptocurrencies available. The technical trading rules that I use to evaluate the profitability of technical analysis against the buy-and-hold strategy (benchmark) are variations of the moving average rule, the Parabolic SAR rule, the Directional Movement rule, the RSI rule, the Stochastic rule, the MACD rule and the Williams rule.

Technical analysis is a method used by investors to determine when to buy and sell stocks. Although the majority of the professional traders and investors use technical analysis, most academics, until recently, had not recognized the validity of these methods. Technical anomalies are observed in most developed and developing markets [18-28], leading traders and investors to earn significantly abnormal returns. This study investigates these anomalies which appear to be in contrast with the efficient market hypothesis (EMH). A financial market may be considered efficient if prices fully reflect all available information and no profit opportunities are left unexploited [29-31].

The methodology employed for the analysis of the data is the traditional t-test, which has been used in many previous studies for the investigation of technical anomalies [8,15,32-34]. Additionally, I compare the t-test results with those obtained by the bootstrap methodology. Bootstrapping, introduced by [35], is a method for estimating the properties of an estimator by measuring those properties when sampling from an approximating distribution. One standard choice for an approximating distribution is the empirical distribution of the observed data. In the case where a set of observations can be assumed to be from an independent and identically distributed population, this can be implemented by constructing a number of resamples of the observed dataset (and of equal size to the observed dataset), each of which is obtained by random sampling with a replacement from the original dataset. Following the bootstrap methodology, I use the returns generated from the pseudo-Bitcoin series and I apply the examined trading rules to the series. Therefore, comparisons are then made between returns from these simulated series and the original Bitcoin series.

My contribution can be substantiated in three ways. First of all, to the best of my knowledge, this is the first study to investigate technical profitability using novel technical systems and rules such as the Parabolic SAR and the Directional Movement. So, I test Parabolic SAR, Directional Movement, Moving Averages, RSI, Stochastic, MACD, Williams together, effectively evaluating which of the them is better suited for predicting bitcoin prices. In addition, I extend and complement previous studies on technical trading analysis in cryptocurrency markets [36-38] by applying two more parameterized trading rules (Parabolic SAR and Directional Movement). The parabolic SAR attempts to give traders an edge by highlighting the direction an asset (bitcoin) is moving. This technical indicator uses a sophisticated technical approach which is trailing stop and reverse method called "SAR," to identify suitable exit and entry points. The directional movement indicator is a valuable tool for assessing price direction and strength. This indicator is excellent at quantifying trend strength and is very useful for day trading but also for swing trading and accumulation periods. Secondly, by extending previous literature on Technical Analysis by investigating the performance of nine technical rules on Bitcoin prices. Finally, I analyze and document the performance of various technical trading rules by using a new methodology approach via standard tests and bootstrap methodology. This study which compare nine technical trading strategies is crucial for investors and portfolio managers in their effort to make better investment decisions and benefit from encompassing assets like Bitcoin in their portfolios that do not have the trend to move simultaneously to the same direction.

This paper is organized as follows: Section 2 summarizes the literature review. Section 3 outlines the technical trading rules used to test market efficiency and the methodology used. The empirical results are presented in section 4. Section 5 concludes the paper.

Literature review

[39] examine whether Bitcoin returns are predictable by a large set of Bitcoin price-based technical indicators. Their finding indicates that using big data and technical analysis can help predict Bitcoin returns that are hardly driven by fundamentals. [37] study the profitability of technical trading rules in the Bitcoin market. They use seven trend-following indicators on daily data from July 2010 to January 2019. They found that technical analysis contains a significant forecasting power in the Bitcoin Market.

[40] predict the Bitcoin price direction and forecast the Bitcoin exchange rates considering daily data. The proposed algorithm obtained the best results to forecast the Bitcoin exchange rates. [41] find that technical analysis of Bitcoin prices combined with non-linear forecasting models becomes significantly more dominant statistically in relation to the random walk model on a daily horizon. [42] examine the causal relation between Bitcoin's return/volatility and its traded volume. Their result highlights the importance of modelling nonlinearity and accounting for the tail behaviour when analysing causal relationships between Bitcoin returns and its trading volume. They show that volume can predict returns, but not volatility, at some quantiles.

[43] investigate the persistence in the level and volatility of the Bitcoin price. They find strong evidence in favour of a permanency of the shocks and lack of mean reversion in the level series. Practical implications are discussed on the inefficiency of the Bitcoin market and its importance for Bitcoin users and investors. [44] focuses on the role of the trading volume in predicting the returns and volatility in the cryptocurrency market. Their results show that trading volume carries useful information for predicting extreme negative and positive returns of all cryptocurrencies. However, volume can predict volatility for only three cryptocurrencies (Litecoin, NEM, and Dash), when the volatility is low.

[45] undertake the economic and econometric modelling of Bitcoin prices. They find that Bitcoin's prices contain a considerable speculative component and that Bitcoin markets are susceptible to bubbles. [46] develop a two-stage approach for exploring whether the information hidden in economic and technology determinants can accurately predict the Bitcoin exchange rate. Their results show that by using the economic and technology determinants, the LSTM could achieve a better predictive performance than the autoregressive integrated moving average, the support vector regression, the adaptive network fuzzy inference system, and the LSTM methods, which all use the previous exchange rate. Thus, the information obtained from economic and technology determinants is more important for predicting the Bitcoin exchange rate than the previous exchange rate.

[36] analyse various technical trading rules in the form of the moving average-oscillator and the trading range break-out strategies. They test resistance and support levels as well as their trading performance by using high-frequency Bitcoin returns. Their results provide significant support for the moving average strategies. [47] with the use of eleven of the largest cryptocurrencies and the CRIX index, confirms the general evidence in favour of bubbles, which are however much less pronounced than under constant volatility.

[48] measure the interaction between media sentiment and the Bitcoin price. They conclude that the interaction between media sentiment and the Bitcoin price exists, and that there is a tendency for investors to overreact on news in a short period of time. [49] investigate some well-known technical analysis patterns and construct an algorithmic trading strategy to evaluate the effectiveness of the patterns in Bitcoin prices. They find that the method of smoothing splines for identifying the technical analysis patterns and that the strategies based on certain technical analysis patterns yield returns that significantly exceed the results of unconditional trading strategies. [50] explore Bitcoin intraday technical trading based on artificial neural networks for the return prediction. ANN models with technical indicator inputs are applied for return prediction. Numerical experiments show that technical analysis outperforms a buy-and-hold strategy.

[51] analyse the high-frequency data of the cryptocurrency market in regards to intraday trading patterns related to algorithmic trading and its impact on the European cryptocurrency market. Their results highlight technical analysis profitability in Bitcoin prices.

Data, methodology and examined technical trategies

Data

In this study, I use daily closing prices of the Bitcoin Prices from 7/16/2010 to 9/31/2021. The database used is composed of 4,107 observations. Bitcoin is the most accepted cryptocurrency in the world, which makes it attractive for investors and traders. Therefore, the prediction of its behavior is of great importance for financial markets. I evaluate the performance of the nine technical strategies. In particular, I evaluate the moving average rules (1,5), (1,45), (1,120), the Parabolic SAR rule, the Directional Movement rule, the RSI rule, the Stochastic rule, the MACD rule and the Williams rule against the buy-and-hold strategy. The first number in each pair indicates the days in the short period and the second number shows the days in the long period.

Methodology

In order to evaluate the performance of the examined technical rules (variations of moving averages, Parabolic SAR, Directional Movement, RSI, Stochastic, MACD and Williams), I compare the returns given by the buy signals of the technical rule examined with the returns of the buy-and-hold strategy. Then I calculate the returns after deducting transaction costs. All transactions assume commission as entry and exit fees (0.02 percent of the investing capital).

First, I examine whether of the examined technical rules (variations of moving averages, Parabolic SAR, Directional Movement, RSI, Stochastic, MACD and Williams), produce better results than the buy-and-hold strategy using the standard t-test. I use the t-test in order to assess if the means of two data groups are statistically different from each other in order to compare these returns. I calculate the t statistic using the following formulas:

where σ2 is the square root of the standard deviation of the returns, μ is the return for the buys, the sells and the buy-and-hold position, and N is the number of signals for the buys, the sells, and the observations.

$$\frac{\mu_{buys(sells)} - \mu_{buys(sells)}}{\sqrt{\frac{\sigma^2}{N_{obser}} + \frac{\sigma^2}{N_{buys(sells)}}}} \qquad (1)$$

$$\frac{\mu_{buys(sells)} - \mu_{sells}}{\sqrt{\frac{\sigma^2}{N_{buys}} + \frac{\sigma^2}{N_{sells}}}} \qquad (2)$$

Using t-tests, I compare the returns of the unconditional buy methodology with the returns of the buy signals given by the examined technical rules and the returns of the unconditional buy methodology with the returns of the buy signals minus the returns of the sell signals given by the examined technical rules. The results provided by the t-test will help to either accept the null hypothesis (i.e. there is no actual difference between returns) or reject it (i.e. there is an actual difference between the returns). Therefore, the two hypotheses for the above test are the following:

$$\text{Accept Null Hypothesis: } H_1 : \bar{R}_1\ \bar{R}_2 = 0$$

$$\text{Reject Null Hypothesis: } H_2 : \bar{R}_1\ \bar{R}_2 \neq 0 \qquad (3)$$

It is known that the results obtained by t-test assume independent, stationary, and asymptotically normal distributions. However, it is quite common that financial time series exhibit non-normality based on excessive skewness, kurtosis, and heteroscedasticity. Following [32] and [8] I overcome these statistical problems by adopting the bootstrap methodology.

Bootstrap is a computer-based resampling procedure introduced by [35], which has been discussed in the statistics and econometrics literature over the past 20 years [52,53,55]. This method requires no analytical calculations and the procedure uses only the original data for resampling to access the unobservable sampling distribution and to provide a measure of sampling variability, bias, and confidence intervals. [56] propose that the use of the bootstrap enlarges the type of statistical problems that can be analyzed, reduces the assumptions required to validate the analyses, and eliminates the tedious theoretical calculations associated with the assessment of accuracy.

The idea behind the bootstrap methodology is to use resampling to estimate an empirical distribution for the statistic. In order to use the bootstrap method, a data generating process for market prices or returns must be specified a priori. The bootstrap method can be used to generate many different return series by sampling with replacement from the original return series. The bootstrap samples created are pseudo return-series that retain all the distributional properties of the original series, but are purged of any serial dependence. Financial time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes, and small changes tend to follow small changes. In either case, the changes from one period to the next are typically of unpredictable sign. To account for the phenomenon of volatility clustering, which is very common in financial time series, the model I use is the generalized autoregressive conditional heteroscedasticity, or GARCH (1,1), model, proposed initially by [57] and further developed by [58]. The specification of the GARCH (1,1) model is the following:

$$r_t = \delta + \rho r_{t-1} + e_t$$

$$h_t = w + a e^2_{t-1} + b h_{t-1}$$

$$e^t = h^{1/2}_t z_t,\ z_t \sim N(0, 1) \qquad (4)$$

where e_t is an independent, identically distributed normal random variable, r_t is the conditional variance, the standardized residuals are independent and identically distributed N(0,1). The variance equation is a function of three terms: the mean w, news about volatility from the previous period, measured as the lag of the squared residual from the mean ε^2_{t-1} equation (a is the ARCH term), and last period's forecast variance ε^2_{t-1}(b is the GARCH term).

In order to use the bootstrap method under GARCH (1,1), I first estimate the GARCH (1,1) by using maximum likelihood and apply the bootstrap method on the standardized residuals. Then I produce the GARCH series by using the estimated parameters and the crumbled residuals. Each of the simulation is based on 500 replications of the null model which should provide a good approximation of the return distribution under the null model.

To test the significance of the trading rule excess returns, the following hypothesis can be stated:

$$\text{Accept Null Hypothesis: } H_1 : \bar{R}_1 - \bar{R}_2 = 0$$

$$\text{Reject Null Hypothesis: } H_2 : \bar{R}_1 - \bar{R}_2 \neq 0 \qquad (5)$$

Under the null hypothesis (H1), the trading rule excess return (XR) calculated from the original series is less than or equal to the examined trading rule return for the pseudo data samples (XR*). The p values from the bootstrap procedure are then used to determine whether the examined trading rule excess returns are significantly greater than the examined trading rule return given that the true data-generating process is GARCH (1,1).

Examined Technical Rules

Parabolic SAR: The Parabolic SAR is an indicator favored by technical traders that captures reversal signals. The Parabolic SAR (Stop and Reverse) was developed by J. Wells Wilder [59] and is mainly used by traders to determine the future short-term momentum of a given asset. The basic formula is:

Rising SAR = Prior SAR + Prior AF (Prior HP – Prior SAR)
Falling SAR = Prior SAR – Prior AF (Prior SAR – Prior LP (6)

where AF stands for the acceleration factor, which has a default of 0.02 and increases by 0.02 each time a new high price is achieved in the current trend. This has a maximum of 0.20. HP stands for high point, which is the highest high in a current uptrend. Similarly, LP stands for low point, which is the lowest low in a current downtrend.

Relative Strength Index (RSI): The Relative Strength Index (RSI), developed by J. Welles Wilder, is a momentum oscillator that measures the speed and change of price [60,61]. The RSI oscillates between zero and 100. The basic formula is:

RSI=100–[100/(1+(Average of Upward Price Change/Average of Downward Price Change))] (7)

Stochastic oscillator: The stochastic oscillator is a momentum indicator that uses support and resistance levels which has been developed by George Lane [62,63]. The term stochastic refers to the point of a current price in relation to its price range over a period of time. This method attempts to predict price turning points by comparing the closing price of a security to its price range. The basic formula is:

%K = 100(C - L14) / (H14 - L14) (8)

where: C = the instrument's most recent closing price, L14 = the instrument's lowest price of the 14-day period, H14 = the instrument's highest price of the 14-day period.

Moving Average Convergence Divergence (MACD): MACD Indicator is a momentum oscillator, which measures both the speed as well as the rise or fall of price movements of a stock in terms of complete stock trading [60,64]. The MACD is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA. MACD is calculated by subtracting th[60, e long-term EMA (26 periods) from the short-term EMA (12 periods). An exponential moving average (EMA) is a type of moving average (MA) that places a greater weight and significance on the most recent data points. The basic formula is:

MACD=12 -Period EMA − 26-Period EMA (9)

Williams %R: Williams %R is a type of momentum indicator that moves between 0 and -100 and measures overbought and oversold levels which has been developed by Larry Williams. Williams %R reflects the level of the close relative to the highest high for the look-back period [63]. The basic formula is:

$$Williams\ \%R = \frac{Highest\ High - Close}{Highest\ High - LowestLow} \qquad (10)$$

where Highest High = Highest price in the look back period, typically 14 days, Close = Most recent closing price, Lowest Low = Lowest price in the look back period, typically 14 days.

Directional movement index: The directional movement index is an indicator developed by J. Welles Wilder that identifies in which direction the price of an asset is moving. The indicator does this by comparing prior highs and lows and drawing two lines: a positive directional movement line (+DI) and a negative directional movement line (-DI). The basic formula is:

$$+DI = (\frac{Smoothed + DM}{ATR})x100 - DI = (\frac{Smoothed - DM}{ATR})x100 DX$$
$$= (\frac{|(+DI) - (-DI)|}{|(+DI) + (-DI)|})x100 \qquad (11)$$

where: +DM (Directional Movement) = Current High−PH, PH = Previous high, -DM = Previous Low−Current Low, CDM = Current DM, ATR = Average True Range

Empirical results

Standard statistical results

Table I reports some summary descriptive statistics for the daily returns of the Bitcoin prices. I calculate the returns as log differences of the Bitcoin prices. I observe that the returns exhibit excessive (lepto) kurtosis and non-normality [65].

Table 2 presents the results using the examined trading strategies. Nine rules are examined (different moving average strategies, Parabolic SAR, Directional Movement, RSI indicator, Stochastic indicator, MACD indicator, and Williams indicator). The entire sample is divided into either buy or sells periods when using the above-mentioned technical rules/indicators. An investor or trader goes buyer (long position) when the short-term moving average crosses the long-term from below and goes seller (short position) when the short-term crosses the long-term from above. When an investor has a buy (long) position, he or she believes that the price will rise in the future, and vice versa for a sell (short) position. The moving average rules differ by the length of the short and long period. For example, (1,5) indicates that the short period is one day and the long period is five days. I report the "number of buy trades" and "number of sell trades" generated during the period in columns 3 and 4. The "average win" in terms of amount of money is reported in column 6, while columns 7 and 8 lists the total amount of money in the examined rules and the "buy-and-hold strategy" respectively. Finally, column 9 presents the percent change of the examined rule gain above (or below) the buy and sell strategy. These tests are computed using the method (Figure 1) [34, 8].

As I observe in column 7 that the buy/sell differences in terms of amount of money are significantly positive for all rules. This leads to the rejection of the null hypothesis (equality with zero). The mean buy/sell returns are all positive with an average return of average 10,10 percent. 8 from 9 technical strategies are profitable. The most profitable technical rule appears to be moving average (1,45) with 23,20% gains. Only one technical rule (Directional Movement) has negative returns. The most profitable technical rules appear to be moving average (1,45) with 23,20% gains.

Table 1: Descriptive statistics.

Num	Max	Min	Mean	Median	Skewness	Kurtosis	Jarque-Bera	Std. Dev.
4,107	0.0878088	-0.0950469	0.0005764	0.000112	0.0724332	6.655639	0.0017931	0.017146063

Note: The table above provides descriptive statistics for the daily returns of bitcoin for the period 7/16/2010 to 9/31/2021.

Table 2: Results of the examined technical strategies.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Period	**Technical Strategy**	**Number of buy trades**	**Number of Sell trades**	**Sum**	**Average Win**	**Examined Rule**	**Buy and Hold Strategy**	**%Profits over buy-hold strategy**
1/1/2010	Moving Average (1,5)	192	276	468	150.64	70498.92	57390.5	22.84%
to					(4.446)	(4.242)		
9/31/2021	Moving Average (1,45)	39	57	96	736.51	70704.72	57390.5	23.20%
					(4.322)	(4.216)		
	Moving Average (1,120)	17	23	40	1721.39	68855.66	57390.5	19.98%
					(4.196)	(4.017)		
	Parabolic SAR	129	0	129	459.94	59332.7	57390.5	3.38%
					(3.994)	(3.818)		
	Directional Movement (14)	27	0	27	1844.05	49789.45	57390.5	-13.24%
					(3.883)	(3.712)		
	RSI (14)	170	0	170	382.85	65085.12	57390.5	13.41%
					(3.719)	(3.598)		
	Stochastic	226	0	226	276.59	62510.34	57390.5	8.92%
					(3.618)	(3.456)		
	MACD	145	0	145	409.85	59427.69	57390.5	3.55%
					(3.395)	(3.341)		
	Williams	226	0	226	276.55	62500.31	57390.5	8.90%
					(3.219)	(3.193)		

Note: The table above provides the results of the examined technical strategies [Moving Average (1,45), Moving Average (1,120), Parabolic SAR, Directional Movement (14), RSI (14), Stochastic, MACD, Williams] for Bitcoin for the period 7/16/2010 to 9/31/2021. Numbers marked in parenthesis are significant at the 5% levels for two-tailed test.

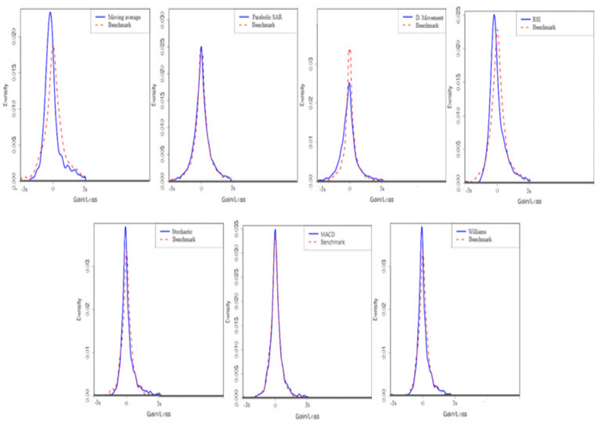

Figure 1: Gain/loss distributions of long position technical strategies applied to Bitcoin data. The Figure above depicts the gain/loss distributions of the seven strategies (blue line) against the benchmark strategies (red line).

This leads to 10% average abnormal gains over the buy & gold strategy. In this study, I provide evidence that the examined technical strategies used win the buy-and-hold strategy (Bitcoin prices).

Bootstrap Results

Following [34,8] methodology, I create 500 bootstrap samples, each consisting of 4,107 observations by resampling with replacement of the standardized residuals of the GARCH (1,1) model. Then, I generate GARCH price-series by using the estimated parameters and the crumbled residuals. After that, I apply the moving averages to each of the 500 pseudo price series. Then, I determine the p-value by calculating the number of times the statistic from the artificial series exceeds the statistic from the original price series (Bitcoin prices).

Table 3 presents the estimates of the GARCH (1,1) model. Based on the Akaike Information Criterion, the Schwarz Criterion, and Dickey- Fuller and Phillips-Perron unit root tests, I find that the GARCH (1,1) model is well specified.

Table 3: Parameter estimates for model GARCH (1,1).

δ	ρ	ω	a	b
0.00046	0.19781	3.65E-06	0.13071	0.88679
-1.9091	-9.5287	-5.3898	-14.595	-117.33

Note: The table above provides the parameter estimates for model GARCH (1,1). The GARCH (1,1) is estimated using OLS and maximum likehood. The numbers in the parenthesis are t-ratios.

Table 4 displays the results of GARCH (1,1) simulations using the examined trading strategies via bootstrapping. I present results for the nine trading strategies that I examine. All the numbers presented in columns 4 and 5 are the fractions of the simulated result which are larger than the results for the original Bitcoin prices. The results presented in columns 4 and 5 are p values. The p values from the bootstrap procedure are then used to determine whether the examined trading rule excess returns are significantly greater than the trading rule return given from the original series. The numbers in the parentheses in columns 4 and 5 show how many series from 500 replications are greater than the original returns. From Table 4 (columns 4 and 5), I observe that most of the simulated GARCH (1,1) series are greater than those from the original Bitcoin prices. All the results are highly significant, resulting in the acceptance of the null hypothesis. This means that the trading rule excess return (XR) calculated from the original series is less than or equal to the examined trading rule return for the pseudo data samples (XR*). Finally, my results are consistent with [34,8] and in line with the existing evidence on the profitability of technical trading strategies in cryptocurrencies.

Table 4: Simulations for GARCH (1,1) tests for 500 replications.

Period	Test	Results	Buy	Buy-Sell
7/16/2010	Moving Average (1,5)	Fraction >Bitcoin Prices	0.83	0.614
to			-415	-307
9/31/2021	Moving Average (1,45)	Fraction > Bitcoin Prices	0.84	0.542
			-420	-312
	Moving Average (1,120)	Fraction > Bitcoin Prices	0.852	0.632
			-426	-316
	Parabolic SAR	Fraction >Bitcoin Prices	0.834	0.618
			-417	-309
	Directional Movement (14)	Fraction >Bitcoin Prices	0.828	0.604
			-414	-302
	RSI (14)	Fraction >Bitcoin Prices	0.844	0.652
			-422	-326
	Stochastic	Fraction >Bitcoin Prices	0.854	0.666
			-427	-333
	MACD	Fraction >Bitcoin Prices	0.842	0,642
			-421	-321
	Williams	Fraction >Bitcoin Prices	0.824	0.602
			-412	-301
	Average		0.839	0.619

Note: Table above provides the simulations of GARCH (1,1) simulations for 500 replications using examined trading strategies (9) via bootstrapping. All the numbers presented in 4,5 columns are the fractions of the simulated result (p-values) which are larger than the results for the original Bitcoin prices. The numbers in parenthesis in 4,5,6 columns show how many series from 500 replications are greater than from original returns.

Conclusions

Technical analysis can be understood as a set of rules that tends to anticipate future price shifts based on the study of certain information such as price and volume. This study investigates the profitability of novel technical trading rules in the cryptocurrency ecosystem such as the Bitcoin prices. In particular, I use variations of simple moving averages and six novel technical strategies (Parabolic SAR, Directional Movement, RSI, Stochastic, MACD and Williams) for Bitcoin prices, using daily data for the period 2010 to 2021. Following the [34,8] methodology, I evaluate the performance of the aforementioned technical rules against the buy and hold strategy, using both standard tests and bootstrap methodology. The null model tested is the GARCH (1,1).

All the t-tests are highly significant rejecting the null hypothesis. Overall, my results indicate that making trading decisions based on the examined technical rules lead to significantly higher returns than the buy and hold strategy, even after deduction of transaction costs. In addition, the results show that technical rules produce useful signals and can help to predict Bitcoin movements. More specific, the profitability of the proposed technical strategies is better than the profitability I get by simply following the Bitcoin market (buy and hold). So the results validate the predictive and profitability power of the examined technical indicators in the Bitcoin market. So this study uses nine different trading strategies to test for the ability to translate the predictive ability of trading rules to profits in terms of Bitcoin.

My findings contradict the efficient market hypothesis as traders and investors can gain abnormal returns using various trading strategies on the cryptocurrency ecosystem. So, the results documenting the predictive power and profitability of trading rules are evidence of weak-form inefficiency in Bitcoin Prices. In this study I demonstrate the three most (technical) profitable strategies for Bitcoin prices which are Moving Averages, RSI and Stochastic.

My results (after deduction of transactions costs) are in line with the existing literature on the performance of technical trading rules [39,37,40,41,43,46,66,36,48,50,51]. However, the findings can be seen as new evidence against the market efficiency of Bitcoin extending the aforementioned studies that consider the predictability of Bitcoin prices based on attention, trading volume and uncertainty. Consequently, there is strong evidence that investors pay attention to technical trading rules and implement them as part of their investment strategies. I provide a comprehensive study on the benefit of employing a wide-range of technical trading rules in Bitcoin market. Furthermore, recording the results of the examined technical rules is crucial for investors and portfolio managers in their effort to make better investment decisions and benefit from encompassing assets like Bitcoin in their portfolios that do not have the trend to move simultaneously to the same direction.

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