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Technical trading rules' profitability and dynamic risk premiums of cryptocurrency exchange rates

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Abstract

Purpose – The study considers time-varying risk premium in investigating the capability of technical analysis (TA) to predict and outperform a buy–hold strategy in Bitcoin exchange rate returns.

Design/methodology/approach – The study tests the technical trading rule of fixed moving average (FMA) on daily actual and equilibrium returns of Bitcoin exchange rates. The equilibrium returns are computed using dynamic CAPM in conjunction with a VAR-MGARCH (1, 1) system. The empirical evaluation of the study uses a case study of four Bitcoin exchange rates (BTC/AUD, BTC/EUR, BTC/JPY and BTC/ZAR) for the period 19 June 2010 to 30 October 2020.

Findings – The findings are consistent with related studies in conventional foreign exchange markets that find TA to be profitable, especially in emerging markets. Nevertheless, the consideration of risk premium has the effect of reducing the abnormal returns. Also, further robust tests reveal that Bitcoin returns possess a momentum effect which prompts further study in efficient market hypothesis research.

Practical implications – The empirical findings of this study should benefit portfolio managers and active investors on the strength of TA to predict returns in a speculative market like the Bitcoin exchange rate market.

Originality/value – The study takes cognisance that cryptocurrency trading is speculative in nature which renders it a good candidate for TA methods. While there are studies that have explored the value of TA in Bitcoin exchange rates, these studies fail to incorporate the effects of time-varying risk premiums, the strength and focus of the current paper.

Keywords Bitcoin, Cryptocurrency, Efficient market hypothesis, Fixed moving averages, Profitability, Technical analysis

Paper type Research paper

1. Introduction

Over the years, academics and practitioners have demonstrated an overwhelming interest in the profitability of technical analysis (TA) on practically all financial systems and assets. Historical evidence indicates that technical trading strategies were profitable in foreign exchange markets and future markets (Smidt, 1965; Sweeney, 1986; Taylor, 1986), but not in stock markets (Fama and Blume, 1966; Van Horne and Parker, 1967). More recent empirical studies suggest that technical trading rules (TTRs) may generate positive profits in certain speculative markets, most notably in foreign exchange and futures markets (Nazário *et al.*, 2017). Various theoretical and empirical explanations have been proposed for TA-based profits. From the investment theory perspective, Neely *et al.* (2014) suggest that abnormal

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profits based on TA trading may arise because of market "frictions", such as noise in current equilibrium prices, traders' sentiments, herding behaviour, market power or chaos. Other possible explanations for the persistence of trading profits are the presence of central bank interventions (particularly in foreign exchange markets), order flow, temporary market inefficiencies, risk premiums, market microstructure deficiencies or data snooping (Park and Irwin, 2007). Regardless of the origin or description of profits, the current study only asks the question of whether TA trading is profitable, particularly in the Bitcoin case.

Cryptocurrencies may show connectedness to currency markets more than stock, and this means they may mimic some of the characteristics that make the foreign exchange market attractive to TA users. Extant literature shows that researchers have investigated the profitability of TTRs in a variety of markets for the purpose of either uncovering profitable trading rules or testing market efficiency, among other things. However, sufficient in-depth analysis of the cryptocurrency market is still lacking, so that the stylised facts of related TA benefits are yet to be understood. The current study contributes towards closing this knowledge gap. The objective of this paper is to investigate the profitability of TA on four Bitcoin exchange rates (BTC/AUD, BTC/EUR, BTC/JPY and BTC/ZAR) after accounting for time-varying risk premiums. Furthermore, the study evaluates the presence of a momentum effect in Bitcoin exchange rates. While most papers focus on Bitcoin as an individual currency (Urquhart, 2016; Bariviera, 2017; Khuntia and Pattanayak, 2018; Kristoufek and Vosvrda, 2018; Tiwari *et al.*, 2018; Sensoy, 2019), the current study investigates the TA profitability in four Bitcoin exchange rates for comparison and breadth. The current study extends and deepens the research on TA usage in foreign exchange markets (Kho, 1996) to cryptocurrency exchange rate. This study will test TA profitability in Bitcoin by employing 24 Fixed Moving Average (FMA) techniques.

The observed results were compared to a buy–hold strategy accordingly, and a significant difference was noted. The study's findings indicate that the chosen TTRs' strategies outperform the buy–hold strategy. A portion of the reported gains can be accounted for by time-varying risk premiums, as profits decline when risk is included. In view of the current and related studies, it is evident that Bitcoin may be an ideal laboratory for experimenting with TA since it lacks discernible fundamentals. The study advanced a novel stylised fact, indicating that the MA trading rule can forecast Bitcoin returns even when time-varying risk premiums are taken into consideration.

The remainder of this paper is structured as follows: Section 2 provides a literature review, Section 3 introduces the historical background of Bitcoin as a cryptocurrency, Section 4 describes Bitcoin's possible candidature of TA, Section 5 outlines the data and methodology utilised in the study, Section 6 presents the empirical results, Section 7 presents a discussion of results and Section 8 concludes the study.

2. Literature review

2.1 Related studies

According to the efficient market hypothesis (EMH), stock prices fully contain all relevant market information. This means that any new information should be reflected in the security prices as soon as it becomes available. To classify the type of information captured by stock prices, there are three classes of market efficiency: (1) strong form like private firm information, (2) semi-strong form such as published economic statistics and financial statements, as well as (3) weak form which is primarily historical security prices and trading volume. Gerritsen *et al.* (2021) discovered that Bitcoin price behaviour has intertemporal predictability, implying that investors may estimate future gains. Trading rules based on past data should not be successful according to weak-form market efficiency. TTRs such as filter rules (Alexander, 1961, 1964; Fama and Blume, 1966; Sweeney, 1988), relative strength rules (Levy, 1967; Jensen and Benington, 1970; Brush and Boles, 1983; Jacobs and Levy, 1988) and moving average trading rules (Van Horne and Parker, 1967; Dale and Workman, 1980) have been shown in earlier empirical studies to be unable to perform better than the traditional buy–hold strategy, and that any predictive variation in security returns is statistically and economically insignificant.

Recent research, on the other hand, has shown that simple trading strategies can be useful in predicting stock market returns. For example, an influential TA study by Brock *et al.* (1992) investigated two simple TTRs, namely, Moving Average (MA) rules as well as Trading Range Breakout (TRB) rules, and found that these two simple rules had considerable predictive power for the US equity index returns. These results were extended and confirmed by Bessembinder and Chan (1998) using US data, and Bessembinder and Chan (1995) using data from Asia–Pacific stock markets. The studies made an important observation that TA has less explanatory power in the more developed markets, but is more successful in emerging markets (Ito, 1999; Ratner and Leal, 1999; Miller *et al.*, 2019; Grobys *et al.*, 2020). Therefore, TA profitability (or its possibility) may be seen as one of the EMH anomalies arising from weak form efficiency.

Regarding the cryptocurrency market, the focus area of the current paper, there are several studies that have explored the implications of TA or its relevance in investment analysis. Miller *et al.* (2019) examined an identification technique in automated price patterns for Bitcoin cryptocurrency based on 1-min price data. The research examined several well-known TA patterns and developed trading procedures for and evaluated the effectiveness of selected trading strategies. The findings indicate that employing smoothing splines to deduce TA patterns has several advantageous and promising methodological properties. Additionally, the study discovers that methods based on certain TA patterns outperform the traditional buy-and-hold approach. A related study by Grobys *et al.* (2020) examined simple moving average trading strategies utilising daily price data from 2016 to 2018 for the 11 most-traded cryptocurrencies. Their findings indicated that the variable moving average technique is effective. When the average market return is considered, the TTR remains beneficial.

In a parallel study, Resta *et al.* (2020) used trend-following and mean-reverting techniques and found supportive results for the TA method when investigating the profitability of TTRs in the Bitcoin market. Using daily and five-minute interval data, their study period covered 1 January 2012 to 20 August 2019. Generally, the study concluded that daily trading data is more successful than trading intraday data. More meaningfully, the study revealed that simple Moving Averages techniques are superior when dealing with daily data. This study supports Gerritsen *et al.* (2020), who find TTRs to be more cost-effective than the buy–hold strategy when dealing with daily Bitcoin data. Other studies that reach favourable conclusions regarding the benefit of TA in cryptocurrency exchange rates include Tiwari *et al.* (2018), Miller *et al.* (2019), Gerritsen *et al.* (2020), and Detzel *et al.* (2021).

Given the increasing interest in cryptocurrency markets, including the spread into central bank digital currency, it is evident that the cryptocurrency market is enduring. The current study incorporates developments in the literature and expands knowledge on Bitcoin and TA profitability using more recent data, while applying the wisdom of tested techniques suggested by Brock *et al.* (1992) and Kho (1996).

2.2 Hypotheses

The current study examines three hypotheses to guide empirical investigation for TA profitability on four Bitcoin exchange rates (BTC/AUD, BTC/EUR, BTC/JPY and BTC/ZAR). The first hypothesis (hereafter coded, H1) states that when the mean returns derived from *TTR* are tested respectively on both equilibrium and actual returns, they are not different from the mean returns of normal trading days (buy–hold strategy). Simply put, this means that the buy (sell) returns of TTRs should not be different from the returns of normal trading days when there are no trading signals. The second hypothesis (H2) states that there is no difference in means between the buy and sell spread. This implies that if TTRs are not profitable, then the study should find no significant difference between the buy-and-sell returns. The next hypothesis is based on the momentum effect. Momentum is the rate of change of security prices or returns. If the rate of change of returns is high, momentum is regarded to be strong; if it is low, momentum is believed to be low (Jegadeesh and Titman, 1993; Gharaibeh *et al.*, 2021), and these patterned changes are exploitable for the predictability of security returns (Chan *et al.*, 2000). Therefore, the third hypothesis (H3) states that there is no relationship between price movements and return fluctuation (momentum effect). That is, the test enquires if further increases or decreases are associated with respective buy and sell signals.

3. Bitcoin's operational design

Bitcoin was birthed out of the concept of cryptocurrency which dates back to the 1980s when David Chaum wrote a seminal chapter on blind signature cryptographic primitives (Chaum, 1983). The author then proposed a useful cryptographic approach for application in safe digital currency transmissions. Cryptography, as defined by Harwick (2016), is a mechanism for creating virtual "money" and ensuring its secure ownership and transaction through the application of a cryptographic problem. Since its inception in 2009, Bitcoin as the first cryptocurrency has experienced both volatile and calm fluctuation over time.

Bitcoin is a decentralised digital currency system that is operated with blockchain technology. The production of Bitcoin is associated with a "mining" process (an equivalent of minting in fiat money), in which miners (or peers) use computers to create new Bitcoins by solving complex mathematical problems known as a *proof of work* or consensus method. Miners are rewarded with portions of Bitcoin for each Bitcoin created (Cheah and Fry, 2015). The Bitcoin structure is intended to remain unchanged from inception until the last Bitcoin is mined. The Bitcoin cash system is designed with a total capacity of 21 million (Shakya *et al.*, 2021). At the time of writing, there are 18,361,438 Bitcoins in circulation, leaving just 2,638,562 Bitcoins to be mined over the next approximately 119 years (Gandal and Halaburda, 2016). In view of the well-defined capacity and monetary system of Bitcoin, it is reasonable to conclude from the explained rules and empirical evidence (Gopane, 2019) that the worth of Bitcoin is remote from fundamental valuation. This creates a space for fundamental-free or speculative methods like TA to find direct opportunities for experimentation.

4. Bitcoin's speculative nature and technical analysis

The recurring characteristic of speculative assets, like Bitcoin, throughout history, has been due to their inability to be valued and/or unpredictable bubbles. Tulipmania, the South Sea Bubble, and others all signal speculation on one hand, and the difficulties of assigning an objective value to a speculative asset on the other (Garber, 1990). All speculative behaviours have been reflected in the exponential growth of the Bitcoin time series (Bariviera *et al.*, 2017). Bitcoin lacks savings accounts and, as a result, no lending interest rates. The implication is that economic knock-on effects and spillover shocks are severely constrained or inapplicable. Consequently, the trails of fundamental analysis valuation are disabled significantly. Empirical assessment by Ciaian *et al.* (2016) finds that there are no macroeconomic indicators influencing Bitcoin's price, but they do not rule out the possibility that investor speculation has a major impact on the price development. The attraction of Bitcoin as an investment opportunity is significant in financial markets (Dyhrberg, 2016; Bouri *et al.*, 2017) and this raises the need for appropriate price valuation methods that are empirically tested. In the instance of fundamental analysis irrelevance for Bitcoin, TA tools become a viable possibility. Therefore, the current study examines the profitability of technical trading methods and whether they are feasible alternatives as an analytical tool to evaluate Bitcoin exchange rate returns.

5. Data and methodology

The research method in this study is quantitative and utilises several econometric equations, but the primary models are dynamic CAPM and VAR-GARCH. The modelling approach is explained later. First, we describe data collection and pre-validation procedures. The secondary dataset was sourced from the IRESS (2017) database and Bitcoincharts (n.d.). The frequency of the time series is daily and covers the period between 19 July 2010 and 31 October 2019. For empirical modelling purposes, the price data is converted into logarithmic returns through Eqn (1):

$$R_t = \log(P_t) - \log(P_{t-1}), \tag{1}$$

where R_t represents daily Bitcoin exchange rates at time t, while P_t is the price of Bitcoin. This formula is applied sequentially on each of the Bitcoin (BTC) exchange rates of Australia (BTC/AUD), Europe (BTC/EUR), Japan (BTC/JPY) and South Africa (BTC/ZAR). Table 1 presents the descriptive summary statistics for each of these exchange rates along with the global stock market benchmark, namely, the Morgan Stanley Capital International (MSCI) index. The MSCI is widely used as benchmark in academic research and practice (Hsu *et al.*, 2010; Bena *et al.*, 2017; Sermpinis *et al.*, 2021). The composition of the MSCI includes securities from 29 nations, and it is rebalanced on a quarterly basis. Therefore, the MSCI is deemed a suitable benchmark in the current study.

Table 1 summarises the time series used in the study and preliminary data validation. Judged by the positive means and stable standard deviations, the variables are comparable which is a useful feature in econometric analysis. The observation on the Jarque–Bera test, kurtosis and skewness reveals a typical phenomenon of financial time series (Brooks, 2014) of being skewed (positively or negatively) and peaked around the mean (leptokurtic). Other pre-validation tests performed on the data include Augmented Dickey–Fuller (ADF), which confirms that all variables are stationary which is desirable in regression analysis.

5.1 The design of technical analysis trading rules

The study employs 24 FMAs. The Moving Averages (MAs) were chosen because they are the most popular TTRs. Two types of MAs are used to produce buy-and-sell signals: a short-period average and a long-period average. In its basic design, this system is described as a buy (b) when the short-term moving average rises above the long-term moving average, and a sell (s) when the short-term moving average falls below the long-term moving average. Days when there is no signal are defined as buy–hold or neutral days (n). While varieties of MA rules are utilised in the literature, four popular specifications are 1/20, 1/50, 1/150 and

	BTC/AUD	BTC/EUR	BTC/JPY	BTC/ZAR	MSCI (world stock index)
Mean	0.005	0.005	0.005	0.005	0.000
Median	0.003	0.003	0.003	0.004	0.001
Maximum	0.361	0.354	0.361	0.282	0.027
Minimum	−0.535	−0.529	−0.522	−0.274	−0.029
Std. Dev	0.057	0.057	0.057	0.051	0.007
Skewness	−0.206	−0.193	−0.186	0.098	−0.267
Kurtosis	14.172	14.221	14.067	8.196	4.716
Jarque–Bera	12,624	12,731	12,384	2730	326
Probability	0.000	0.000	0.000	0.000	0.000
Observations	2423	2423	2423	2423	2423

Source(s): Own computation

Table 1.
Descriptive summary statistics

1/200. The complete list of MA rules used in this study is found in Table A1 (in Appendix) with and without a 1% band. The 1% band is used to reduce the number of false signals and is introduced around the short-term moving average. Urquhart *et al.* (2015) define buy-and-sell signals as:

$$\left[\sum_{\lambda=1}^{s} R^{S}_{t-(\lambda-1)}\right] > \left[\sum_{\lambda=1}^{L} R^{L}_{t-(\lambda-1)}\right] + \delta = \text{ buy} \quad \delta \in \{0, 0.01,\}, \tag{2}$$

where R_t is the return at time t, while L and S are the number of days for the long- and short-term moving average, respectively. The symbol, λ, represents the daily time index. Sell signals are generated when the inequality sign is reversed.

$$\left[\sum_{\lambda=1}^{s} R^{S}_{t-(\lambda-1)}\right] < \left[\sum_{\lambda=1}^{L} R^{L}_{t-(\lambda-1)}\right] + \delta = \text{sell} \tag{3}$$

The study, however, uses FMAs and holds signals for ten days before closing and re-entering the market. The ten-day holding period separates the FMA from the variable moving average (VMA), where positions are taken every day as signals are generated. These trading rules are in line with usage in Kho (1996) and Brock *et al.* (1992). The procedure helps minimise the possibility of statistical bias. The TTRs based on FMA are modelled using econometric models to assess the profitability of TA.

5.2 Econometric models

The study applies TA rules to two sets of Bitcoin exchange rate returns, namely, actual returns and equilibrium returns. The latter are computed using dynamic CAPM. In this modelling, and to make beta dynamic, the study employs the multivariate generalised autoregressive conditionally heteroscedastic (MGARCH) system.

5.2.1 Modelling equilibrium returns using dynamic CAPM. In cryptocurrency and capital market studies (Bouri *et al.*, 2020; Nugroho, 2021) there is a continual realisation that dynamic asset pricing modelling have a greater benefit over static models. The constant risk premium, or the static CAPM such as used by Sweeney (1986), is not deemed a suitable benchmark model for testing the trading rules' profitability because the risk of TA on the original series cannot essentially be comparable to that of the equilibrium strategy, among other things. Therefore, dynamic CAPM is the preferred model specified in Eqn (4):

$$R_{it} - R_{ft} = \alpha + \beta_{i,t}(R_{mt} - R_{ft}) + u_{it}, \quad u_t \sim N\left(0, \sigma^2\right) \tag{4}$$

$$\beta_{i,t} = \frac{\sigma_{im,t}}{\sigma^2_{m,t}} \tag{5}$$

In Eqn (4), the subscript i indexes the four Bitcoin exchange rates (BTC/AUD, BTC/EUR, BTC/JPY and BTC/ZAR). The disturbance term (u_t) is assumed to be normally distributed. The variables, R_{it}, R_{ft} and R_{mt}, are the returns of a financial asset, risk-free rate and the MSCI global market benchmark, respectively. The risk-free rate is proxied with the US's 90 days treasury bill (TBill) sourced from Federal Reserve Bank of St. Louis (Fred Database, n.d). The parameter, α, is the intercept evaluated in the model, while $\beta_{i,t}$ is the time-varying beta estimated in Eqn (5), where $\sigma_{im,t}$ is the covariance between market returns and exchange returns and $\sigma^2_{m,t}$ is the market return's variance. These two moments (variance and covariance) are computed through the VAR-MGARCH in Eqn (6). The VAR-MGARCH system is estimated through the mean Eqn (6a) of vector-autoregressive, VAR(p), and the variance equation by Baba *et al.* (1989), BEKK-MGARCH (p, q) in Eqn (6b):

$$y_t = \Pi y_{t-1} \ + \varepsilon_t \tag{6a}$$

$$H_t = \ CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \tag{6b}$$

The parameters and standardised residuals are estimated using the maximum likelihood method. In the VAR(p) system (Eqn (6a)), y_t is a $k \times 1$ vector of exchange returns from Bitcoin exchange rates (BTC/AUD, BTC/EUR, BTC/JPY, BTC/ZAR), while Π is a $k \times k$ matrix of parameters to be estimated. In Eqn (6b), C is a $k \times k$ lower triangular matrix, while A and B are $k \times k$ coefficient matrices to be estimated. The disturbance term is assumed to be $\varepsilon_t \sim N(0, \Sigma_t)$, where Σ_t is the covariance matrix. The lag length for the equation is. $p = q = 1$.

To recapitulate, in tandem with Kho (1996) the dynamic CAPM (in Eqn (4)) is a mathematical formulation of log returns (Eqn (1)), and conditional beta (Eqn (5)) which is based on VAR-MGARCH system (Eqs (6a) and (6b)). Eqn (5) is a well-known relation of beta (see Brooks, 2014) and effectively captures covariation of Bitcoin exchange rates with the MSCI benchmark (introduced earlier). There are a few reasons why MSCI is deemed a viable proxy for global financial markets including cryptocurrency. First, virtual currencies are global in nature so the benchmark should have international positioning. Second, in the absence of a proved global index for cryptocurrency the literature (Neely *et al.*, 1997) shows that MSCI is a reasonable benchmark for foreign exchange market and by extension a close approximation or relevance for Bitcoin exchange rates in the current study. Other advantages of MSCI as a global benchmark is that it is widely applied in practice (Hsu *et al.*, 2010; Bena *et al.*, 2017) and academic research (Neely *et al.*, 2009; Bouri *et al.*, 2020), thus giving confidence for empirical usage. Another important feature of MSCI index is that it includes both large and small stocks thus mitigating the considerations of tradability and liquidity (Sermpinis *et al.*, 2021).

5.2.2 TA profitability: BLL's mean difference test. The Brock *et al.* (1992) (abbreviated, BBL) methodological approach is employed to study TA's individual (buy, sell and buy–hold strategy) mean returns. Brock *et al.* (1992) utilise the mean returns of trading rules and their respective *t*-statistic. The idea is to test the profitability of TA by comparing the difference between the conditional and unconditional mean returns from TA. The same technique is employed but with a robust approach instead of using the return on the buy–hold strategy. The return on days when no trading signal is emitted is represented by (n), which will be used to proxy the buy–hold strategy. The study does this by examining the difference in means for the normal buy–hold days and when either a buy (b) or sell (s) signal is emitted. This test helps answer hypothesis H1. Brock *et al.* (1992) examined the predictive ability of MA using the student *t*-statistic ratio test to inspect whether the mean returns generated by TA are zero. The *t*-statistic of the differences between the means of *daily* and *buy–hold* returns is denoted by:

$$t_x = \frac{\mu_x - u}{\sqrt{\sigma^2\left(\frac{1}{N} + \frac{1}{N_x}\right)}} \text{ where } x \in \{\text{buy}, \text{sell}\} \tag{7}$$

μ_x and N_x represent the mean return and number of signals. σ^2 is the estimated variance. The parameter, u, is the mean return for buy–hold days.

5.2.3 TA profitability: Kho's mean-spread test. The objective of Eqn (8) is to test hypothesis H2, whether the spread between buy and sell signals is equal to zero. This special regression equation was first utilised by Cumby and Modest (1987) in a market-timing study. This test equation was first applied by Kho (1996) in TA profitability investigation. For this reason, we label Eqn (8) as *Kho's mean-spread test* for identification and simplicity. This equation is similar to Eqn (7), but it has advantages of validating the regression analysis with robust standard errors (Newey and West, 1987). Empirically, if the spread equals zero, it will mean that the buy and sell signals are equal. This would be a case against TA profitability. Based on the framework of Eqn (8), then if the spread is zero, the coefficient, α_1 will be insignificant.

$$R_{it} = \alpha_0 + \alpha_1 X_{it-1} + \varepsilon_{it} \tag{8}$$

In Eqn (8), R_t is the Bitcoin exchange rate return and X_{t-1} is the trading signal observed at day $t-1$. The parameters, α_0 and α_1, are unknown coefficients to be estimated, while ϵ is the disturbance term which is assumed to follow normal distribution. The subscript, i, signifies Eqn (8) will be applied separately for each of the four Bitcoin exchange rate returns (BTC/AUD, BTC/EUR, BTC/JPY and BTC/ZAR). The regression equation is estimated separately for each type of signal. A signal is effectively a dummy, taking the value 1 if signal occurs and zero otherwise. Therefore, for buy signal, sell signal or both, the regressor, X_{t-1} takes the values X^b_{t-1}, $-X^s_{t-1}$ or $\{X^b_{t-1} - X^s_{t-1}\}$, respectively. By way of interpretation, a positive α_1 implies ". . . an average percentage increase in [daily] returns due to correct trading signals" (Kho, 1996, p. 258). Consequently, testing for the mean spread of buy–sell signals is equivalent to evaluating the null hypothesis, $\alpha_1 = 0$.

5.2.4 Time-varying risk premium and actual returns. The modelling objective of unconditional and conditional CAPM is to compare the equilibrium returns from both models based on the outcomes of buy and sell signals (TTRs). "If markets are efficient and the assumed model of asset pricing [CAPM] is correct, the technical rule returns in excess of the time-varying expected returns should have a zero conditional mean" (Kho, 1996, p. 279). This means that there should be no difference between expected returns under the two models. However, if the unconditional model outperforms the conditional model (or equal performance) it can be concluded that the abnormal profits derived from TTR are only reflecting time-varying risk premium. That is, investors who find TA profitable are merely compensated for their risk-bearing abilities. One way to determine the statistical significance of whether time-varying risk premium influences TTRs is to apply the standard t-test on the difference between the unconditional and conditional returns from TTR and examine if the spread is different from zero (Kho, 1996).

5.2.5 Consistency and robustness check. A robustness check in this study will examine the link between daily returns on Bitcoin and signals generated by the trading rules used (hypothesis H3). TA assumes that investors follow signals emitted at time $t-1$, and that trades are executed at time t. That is, the demand (supply) of any particular security will exceed supply (demand) at time t, which will cause the price to either increase, thereby activating buy signals, or decrease to trigger sell signals at time t. The momentum effect is backed by one of the basic beliefs in TA, where the market is said to discount all types of information like fundamentals, non-fundamentals and even rumours (Masry, 2018). Since the early 1990s, the only other paper that has attempted to study the relationship between returns and signals is that of Bessembinder and Chan (1995) which applied a similar framework as in Eqn (9):

$$\begin{aligned} R_{it} = \beta_0 &+ \beta_1 FMA_{1,i,0} + \beta_2 FMA_{1,i,1} + \beta_3 FMA_{2,i,0} + \beta_3 FMA_{2,i,1} \\ &+ \beta_4 FMA_{5,i,0} \beta_5 FMA_{5,i,1} + e_{it} \end{aligned} \tag{9}$$

where $i \in \{20MA, 50MA, 150MA, 200MA\}$

In Eqn (9), β_0 is the regression intercept, R_t is the daily Bitcoin exchange rate return at day t, while FMA_i is the long-term trading signal emitted by a particular FMA. The hypothesis tests the link between signals released by MA rules and price fluctuations in the Bitcoin environment using the Ordinary Least Squares (OLS) model. In view of the above, the study hypothesis [3] is rejected if Eqn (9) is upheld, based on coefficient significance and F-statistical test.

6. Empirical results

This section presents the results of the paper. That is, an evaluation of the study hypotheses, H1, H2 and H3, relating to the mean-difference test (Eqn (7)), spread test (Eqn (8)) and momentum test (Eqn (9)), respectively. In addition, the analysis of risk premium and its implication in the results are elaborated. Before explaining the study results, it is important to provide a comprehensive report on post-estimation validation of the models in light of relevant econometric theories.

The practical timeseries regressions are generally affected by heteroscedasticity and autocorrelation problems regarding the BBL Model (Eqn (8)) and Momentum Effect test (Eqn (9)). For this reason, the Newey and West (1987) robust standard errors are utilised to ensure the fitness of regression analysis. Further diagnostic procedures, including the ARCH-LM test, were applied to ensure that all the ARCH effects are fully modelled in the BEKK-MGARCH model (Eqn (6)).

6.1 TA profitability assessment based on dynamic CAPM

Based on a test of the 24 TTRs (listed in Table A1, in Appendix) using the dynamic CAPM model, the results of each exchange rate (BTC/AUD, BTC/EUR, BTC/JPY and BTC/ZAR) are reported separately in Tables 2–5, respectively.

6.1.1 BTC/AUD exchange rate. In what follows, we report on TA performance based on the returns of moving average rules applied on conditional CAPM for BTC/AUD exchange rate.

Based on BBL's mean difference test, the results in Table 2 compare TA generated trades to those of buy–hold strategy. The average number of buy and sell signals is 68 and 175, respectively. The findings on 24 trading rules tested show that all buy signals are significantly different from the buy–hold strategy at 1% level, while just under 80% of the sell signals are significant at conventional levels. This means that while buy signals yield better results than sell signals, they both outperform the buy–hold strategy. There are other noteworthy factors to observe in the results.

The trading rule that stands out is trading rule number 10, which is designed as (2,50,1) meaning 2 short days, long-moving average of 50 days and a premium band of 1% (hereafter and for convenience trading rules will be cited as *TTR* No. #, as sequenced in the result tables). *TTR* No. 10 produces 223 sell signals with average return of −0.12% compared to the 20 buy signals with the highest average daily returns of 1.5%. These returns are statistically significant at 1% level. Further, all the indicated 20 buy signals produce positive returns, while only 44% of the 223 sell signals achieve returns greater than zero (columns 8 and 9). Other trading rules that produce relatively high buy returns which are significantly different from the sell returns are TTR No. 5 (5,20,0) and TTR No. 20 (1,200,1). Thus, contrary to Brock *et al.* (1992) who note that profits derived from trading rules depend on the number of signals, even if there are fewer buy signals, it is discovered that the buy return is higher than the sell return.

On aggregate, the standard deviations of buy signals (column 5) and neutral or buy–hold strategy (column 6) are comparably higher than the sell signals (column 7). This implies that while the buy trades are riskier relative to sell signals, these buy signals are no riskier than the market. The average fraction of buy and sell returns (columns 8 and 9), which are above zero, are 87 and 35%, respectively. The daily mean returns for buy, buy–hold and sell are 0.9%, −0.01% and −0.2%, respectively (columns 10, 11 and 12). The buy returns are

Table 2. BTC/AUD results for BBL's mean difference test

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		16	
		Observations		Standard deviation			Return > 0		Mean returns								
No	*TTR*	*N*(buy)	*N*(sell)	Buy	Neutral	Sell	Buy > 0%	Sell > 0%	Buy	Neutral	Sell	S.E(buy)	S.E(sell)	*t* stat(buy)		*t* stat(sell)	
1	(1,20,0)	114	130	0.009	0.008	0.002	67	31	0.004	0.001	−0.004	0.001	0.001	−3.352	***	7.918	***
2	(1,20,1)	13	230	0.007	0.009	0.003	92	47	0.010	0.000	−0.001	0.002	0.001	−4.851	***	1.102	
3	(2,20,0)	112	131	0.009	0.008	0.002	65	35	0.004	0.000	−0.003	0.001	0.001	−4.188	***	5.832	***
4	(2,20,1)	12	232	0.011	0.009	0.003	92	48	0.013	0.000	0.000	0.003	0.001	−3.951	***	1.083	
5	(5,20,0)	110	133	0.009	0.009	0.002	67	35	0.005	0.000	−0.003	0.001	0.001	−4.617	***	4.261	***
6	(5,20,1)	8	234	0.008	0.009	0.003	100	49	0.011	−0.001	0.000	0.003	0.001	−4.099	***	−1.475	
7	(1,50,0)	110	134	0.008	0.008	0.002	73	28	0.005	0.000	−0.005	0.001	0.001	−5.280	***	8.594	***
8	(1,50,1)	22	221	0.006	0.009	0.002	100	48	0.013	0.001	−0.001	0.001	0.001	−9.377	***	2.098	**
9	(2,50,0)	110	134	0.008	0.008	0.002	75	30	0.005	−0.001	−0.004	0.001	0.001	−6.185	***	6.020	***
10	(2,50,1)	20	223	0.008	0.008	0.002	100	44	0.015	−0.001	−0.001	0.002	0.001	−8.061	***	0.497	
11	(5,50,0)	110	133	0.008	0.008	0.002	72	29	0.009	−0.001	0.005	0.001	0.001	−9.585	***	−8.539	***
12	(5,50,1)	19	224	0.006	0.008	0.003	100	44	0.013	0.000	0.007	0.002	0.001	−8.043	***	−11.227	***
13	(1,150,0)	114	129	0.007	0.009	0.002	83	21	0.007	0.000	−0.006	0.001	0.001	−7.091	***	8.501	***
14	(1,150,1)	28	215	0.006	0.010	0.002	100	45	0.014	−0.001	−0.001	0.001	0.001	−10.884	***	0.264	
15	(2,150,0)	114	129	0.007	0.009	0.002	78	24	0.006	0.000	−0.005	0.001	0.001	−6.794	***	7.654	***
16	(2,150,1)	28	215	0.007	0.009	0.002	100	41	0.013	0.000	−0.002	0.001	0.001	−8.926	***	2.772	***
17	(5,150,0)	113	130	0.007	0.009	0.002	80	22	0.006	−0.001	−0.005	0.001	0.001	−7.115	***	7.494	***
18	(5,150,1)	26	217	0.008	0.009	0.003	100	44	0.012	0.000	−0.001	0.002	0.001	−7.404	***	1.683	*
19	(1,200,0)	119	124	0.007	0.009	0.002	84	11	0.007	0.001	−0.006	0.001	0.001	−7.180	***	10.131	***
20	(1,200,1)	31	212	0.006	0.009	0.002	100	45	0.013	0.000	−0.002	0.001	0.001	−10.649	***	3.431	***
21	(2,200,0)	118	125	0.007	0.008	0.002	80	17	0.006	0.001	−0.005	0.001	0.001	−6.009	***	10.328	***
22	(2,200,1)	31	212	0.006	0.009	0.002	100	41	0.013	0.000	−0.002	0.001	0.001	−11.060	***	2.890	***
23	(5,200,0)	119	124	0.008	0.008	0.002	84	23	0.007	0.000	−0.005	0.001	0.001	−7.197	***	9.062	***
24	(5,200.1)	29	214	0.006	0.009	0.002	100	43	0.012	0.000	−0.002	0.001	0.001	−10.392	***	1.797	*
Average		68	175	0.007	0.009	0.002	87	35	0.009	0.000	−0.002	0.001	0.001				

Note(s): There are 16 columns in each Table. The 24 trading regulations are listed in column 1 from smallest to greatest. In fact, there are 12 trading rules, each of which is linked to another replication, which then introduces a band. The various trading regulations are listed in column 2. The number of signals created throughout the research period is shown in columns 3 and 4. The rolling standard deviation for buy, neutral and sell returns is shown in columns 5, 6 and 7. The percentage of buy and sell signals larger than zero is displayed in columns 8 and 9. The buy, neutral and sell mean returns are shown in columns 10, 11 and 12. The purchase and sell standard errors are shown in columns 13 and 14. Finally, columns 15 and 16 show the *t*-statistics as well as their significance levels

Statistical significance: *** 1%, ** 5%, *10

Source(s): Own computation

Table 3.
BTC/EUR results for BBL's mean difference test

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		16	
		Observations		Standard deviation			Return > 0		Mean returns			S.E	S.E				
No	*TTR*	*N*(buy)	*N*(sell)	Buy	Neutral	Sell	Buy > 0%	Sell > 0%	Buy	Neutral	Sell	(buy)	(sell)	*t*-stat(buy)		*t*-stat(sell)	
1	(1,20,0)	117	126	0.006	0.006	0.002	39	8	−0.001	−0.005	−0.009	0.001	0.001	−5.096	***	6.624	***
2	(1,20,1)	7	236	0.004	0.006	0.003	100	18	0.006	−0.005	−0.006	0.002	0.000	−6.792	***	0.858	
3	(2,20,0)	117	126	0.006	0.006	0.002	34	9	−0.002	−0.006	−0.008	0.001	0.000	−4.552	***	4.923	***
4	(2,20,1)	5	238	0.010	0.007	0.003	100	23	0.009	−0.005	−0.005	0.004	0.001	−3.369	***	−0.040	
5	(5,20,0)	116	127	0.006	0.007	0.002	34	12	−0.003	−0.005	−0.008	0.001	0.001	−3.726	***	5.026	***
3	(5,20,1)	240	0.008	0.007	0.003	100	22	0.008	−0.006	−0.005	0.005	0.000	−3.114	−1.416	***	6.026	***
7	(1,50,0)	114	129	0.006	0.006	0.002	42	2	−0.001	−0.005	−0.009	0.001	0.000	−5.957	***	7.941	***
8	(1,50,1)	13	231	0.008	0.007	0.003	85	19	0.006	−0.005	−0.006	0.002	0.001	−4.879	***	2.566	***
9	(2,50,0)	111	132	0.006	0.006	0.002	38	6	−0.002	−0.006	−0.008	0.001	0.000	−5.952	***	5.324	***
10	(2,50,1)	11	232	0.007	0.006	0.003	73	18	0.004	−0.006	−0.006	0.002	0.000	−4.697	***	0.451	
11	(5,50,0)	111	132	0.007	0.006	0.002	41	7	0.005	−0.006	0.002	0.001	0.000	−13.589	***	−14.967	***
12	(5,50,1)	8	235	0.006	0.006	0.003	88	20	0.006	−0.005	0.003	0.002	0.000	−4.572	***	−18.136	***
13	(1,150,0)	114	129	0.005	0.007	0.003	39	2	−0.001	−0.005	−0.010	0.001	0.001	−6.379	***	8.707	***
14	(1,150,1)	15	228	0.006	0.007	0.003	100	17	0.007	−0.006	−0.006	0.002	0.001	−8.008	***	−0.012	
15	(2,150,0)	115	128	0.005	0.007	0.002	41	2	−0.001	−0.006	−0.009	0.001	0.001	−6.981	***	7.113	***
16	(2,150,1)	15	228	0.005	0.007	0.003	100	19	0.006	−0.005	−0.006	0.001	0.001	−8.486	***	1.616	*
17	(5,150,0)	115	129	0.005	0.007	0.002	38	6	−0.001	−0.006	−0.009	0.001	0.001	−6.481	***	6.460	***
18	(5,150,1)	12	231	0.005	0.007	0.003	83	19	0.005	−0.005	−0.005	0.002	0.001	−6.568	***	0.436	
19	(1,200,0)	118	125	0.005	0.007	0.003	42	2	−0.001	−0.005	−0.010	0.001	0.001	−6.559	***	9.920	***
20	(1,200,1)	15	229	0.005	0.007	0.003	100	16	0.009	−0.005	−0.006	0.001	0.001	−9.645	***	1.581	*
21	(2,200,0)	118	125	0.006	0.006	0.002	42	3	−0.001	−0.005	−0.009	0.001	0.001	−6.500	***	8.849	***
22	(2,200,1)	13	230	0.005	0.007	0.003	92	16	0.007	−0.006	−0.006	0.001	0.000	−8.835	***	0.531	
23	(5,200,0)	119	124	0.005	0.006	0.003	47	2	−0.001	−0.005	−0.010	0.001	0.001	−6.809	***	8.831	***
24	(5,200.1)	8	235	0.056	0.007	0.015	88	20	0.005	−0.006	−0.006	0.020	0.001	−0.547		0.137	
Average		63	180	0.008	0.007	0.003	66	12	0.003	−0.005	−0.007	0.002	0.001				

Note(s): There are 16 columns in each Table. The 24 trading regulations are listed in column 1 from smallest to greatest. In fact, there are 12 trading rules, each of which is linked to another replication, which then introduces a band. The various trading regulations are listed in column 2. The number of signals created throughout the research period is shown in columns 3 and 4. The rolling standard deviation for buy, neutral, and sell returns is shown in columns 5, 6 and 7. The percentage of buy and sell signals larger than zero is displayed in columns 8 and 9. The buy, neutral and sell mean returns are shown in columns 10, 11 and 12. The purchase and sell standard errors are shown in columns 13 and 14. Finally, columns 15 and 16 show the *t*-statistics as well as their significance levels
Statistical significance: *** 1%, ** 5%, *10
Source(s): Own computation

Table 4. BTC/JPY results for BBL's mean difference test

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		16	
		Observations		Standard deviation			Return > 0		Mean returns			S.E	S.E				
No	*TTR*	*N*(buy)	*N*(sell)	Buy	Neutral	Sell	Buy > 0%	Sell > 0%	Buy	Neutral	Sell	(buy)	(sell)	*t* stat(buy)		*t* stat(sell)	
1	(1,20,0)	116	127	0.006	0.006	0.002	48	18	0.000	−0.003	−0.006	0.001	0.000	−3.092	***	7.088	***
2	(1,20,1)	8	235	0.011	0.007	0.002	88	31	0.007	−0.003	−0.004	0.004	0.000	−2.620	***	1.120	
3	(2,20,0)	115	128	0.007	0.006	0.002	51	20	0.000	−0.003	−0.006	0.001	0.000	−4.359	***	6.249	***
4	(2,20,1)	6	237	0.010	0.007	0.002	100	33	0.011	−0.003	−0.003	0.004	0.000	−3.390	***	0.419	
5	(5,20,0)	114	129	0.007	0.007	0.002	49	22	0.000	−0.003	−0.006	0.001	0.001	−3.302	***	5.813	***
6	(5,20,1)	3	240	0.012	0.007	0.002	100	31	0.015	−0.003	−0.003	0.007	0.000	−2.722	***	0.285	
7	(1,50,0)	114	129	0.006	0.006	0.002	58	10	0.001	−0.003	−0.007	0.001	0.000	−5.451	***	9.300	***
8	(1,50,1)	129	229	0.006	0.007	0.002	10	32	−0.007	−0.003	−0.004	0.001	0.001	6.452	***	1.690	*
9	(2,50,0)	112	131	0.006	0.006	0.002	56	12	0.001	−0.003	−0.007	0.001	0.000	−6.050	***	6.597	***
10	(2,50,1)	13	230	0.008	0.006	0.002	100	31	0.008	−0.004	−0.004	0.002	0.000	−5.312	***	0.137	
11	(5,50,0)	113	130	0.006	0.006	0.002	57	15	0.005	−0.003	0.003	0.001	0.000	−12.003	***	−13.336	***
12	(5,50,1)	10	233	0.007	0.007	0.002	100	31	0.010	−0.003	0.004	0.002	0.000	−5.597	***	−13.663	***
13	(1,150,0)	118	125	0.006	0.007	0.002	65	9	0.002	−0.003	−0.008	0.001	0.001	−7.318	***	8.626	***
14	(1,150,1)	15	228	0.006	0.007	0.002	100	29	0.010	−0.004	−0.004	0.002	0.001	−8.716	***	−1.257	
15	(2,150,0)	117	126	0.006	0.007	0.002	63	5	0.002	−0.003	−0.008	0.001	0.001	−7.612	***	8.226	***
16	(2,150,1)	15	228	0.008	0.007	0.002	93	31	0.010	−0.003	−0.004	0.002	0.001	−6.521	***	1.063	
17	(5,150,0)	117	126	0.005	0.007	0.002	63	13	0.002	−0.004	−0.007	0.001	0.001	−7.672	***	6.703	***
18	(5,150,1)	13	230	0.007	0.007	0.002	85	30	0.006	−0.003	−0.004	0.002	0.001	−4.124	***	1.377	
19	(1,200,0)	121	122	0.005	0.006	0.002	58	5	0.002	−0.003	−0.008	0.001	0.000	−7.311	***	10.225	***
20	(1,200,1)	17	227	0.005	0.007	0.002	100	28	0.009	−0.003	−0.004	0.001	0.001	−10.393	***	2.086	**
21	(2,200,0)	121	122	0.005	0.007	0.002	62	3	0.002	−0.002	−0.008	0.001	0.001	−6.164	***	11.990	***
22	(2,200,1)	15	228	0.007	0.007	0.002	100	29	0.010	−0.003	−0.004	0.002	0.001	−6.722	***	2.052	**
23	(5,200,0)	123	120	0.006	0.007	0.002	63	9	0.002	−0.003	−0.008	0.001	0.001	−7.325	***	8.798	***
24	(5,200.1)	12	232	0.055	0.007	0.013	92	31	0.007	−0.003	−0.004	0.016	0.001	−0.633		0.152	
Average		69	179	0.009	0.007	0.003	73	21	0.005	−0.003	−0.005	0.002	0.001				

Note(s): There are 16 columns in the Table. The 24 trading regulations are listed in column 1 from smallest to greatest. In fact, there are 12 trading rules, each of which is linked to another replication, which then introduces a band. The various trading regulations are listed in column 2. The number of signals created throughout the research period is shown in columns 3 and 4. The rolling standard deviation for buy, neutral, and sell returns is shown in columns 5, 6 and 7. The percentage of buy and sell signals larger than zero is displayed in columns 8 and 9. The buy, neutral and sell mean returns are shown in columns 10, 11 and 12. The purchase and sell standard errors are shown in columns 13 and 14. Finally, columns 15 and 16 show the *t*-statistics as well as their significance levels

Statistical significance: *** 1%, ** 5%, *10

Source(s): Own computation

Table 5.
BTC/ZAR results for BBL's mean difference test

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		16	
		Observations		Standard deviation			Return > 0		Mean returns			S.E	S.E				
No	*TTR*	*N*(buy)	*N*(sell)	Buy	Neutral	Sell	Buy > 0%	Sell > 0%	Buy	Neutral	Sell	(buy)	(sell)	*t*-stat(buy)		*t*-stat(sell)	
1	(1,20,0)	120	123	0.006	0.007	0.003	24	4	−0.004	−0.007	−0.010	0.001	0.001	−3.997	***	6.128	***
2	(1,20,1)	7	236	0.003	0.007	0.003	100	15	0.004	−0.007	−0.007	0.001	0.001	−9.034	***	0.170	
3	(2,20,0)	116	127	0.006	0.007	0.003	26	3	−0.004	−0.008	−0.010	0.001	0.001	−5.030	***	5.257	***
4	(2,20,1)	5	238	0.007	0.007	0.003	60	15	0.005	−0.007	−0.007	0.003	0.001	−3.795	***	0.173	
5	(5,20,0)	113	131	0.006	0.007	0.003	23	7	−0.004	−0.008	−0.010	0.001	0.001	−4.203	***	4.718	***
6	(5,20,1)	2	242	0.022	0.007	0.003	50	16	0.006	−0.008	−0.007	0.015	0.001	−0.871		−0.947	
7	(1,50,0)	115	128	0.006	0.006	0.003	30	2	−0.003	−0.007	−0.011	0.001	0.001	−5.349	***	7.260	***
8	(1,50,1)	10	233	0.006	0.007	0.003	80	14	0.005	−0.007	−0.008	0.002	0.001	−6.202	***	1.086	
9	(2,50,0)	112	131	0.006	0.006	0.003	32	3	−0.003	−0.008	−0.011	0.001	0.001	−6.215	***	6.459	***
10	(2,50,1)	7	236	0.004	0.007	0.003	43	14	−0.001	−0.008	−0.007	0.002	0.001	−4.077	***	−0.975	
11	(5,50,0)	110	134	0.006	0.006	0.003	25	4	0.004	−0.008	0.002	0.001	0.001	−16.896	***	−18.851	***
12	(5,50,1)	5	241	0.001	0.007	0.003	80	15	0.002	−0.007	0.004	0.001	0.001	−14.395	***	−22.039	***
13	(1,150,0)	119	124	0.005	0.007	0.003	27	1	−0.003	−0.007	−0.012	0.001	0.001	−6.423	***	8.352	***
14	(1,150,1)	14	229	0.005	0.008	0.003	71	8	0.004	−0.008	−0.008	0.001	0.001	−8.144	***	−1.126	
15	(2,150,0)	118	125	0.005	0.007	0.003	22	3	−0.003	−0.007	−0.011	0.001	0.001	−6.445	***	7.106	***
16	(2,150,1)	9	234	0.003	0.007	0.003	78	12	0.002	−0.007	−0.008	0.001	0.001	−8.562	***	0.706	
17	(5,150,0)	120	124	0.006	0.007	0.003	27	6	−0.003	−0.008	−0.011	0.001	0.001	−6.715	***	4.799	***
18	(5,150,1)	5	238	0.004	0.007	0.003	60	17	0.001	−0.007	−0.007	0.002	0.001	−4.312	***	−1.097	
19	(1,200,0)	123	120	0.005	0.007	0.003	28	3	−0.003	−0.007	−0.012	0.001	0.001	−6.835	***	7.794	***
20	(1,200,1)	11	232	0.002	0.007	0.003	100	11	0.004	−0.007	−0.008	0.001	0.001	−12.574	***	1.613	*
21	(2,200,0)	123	120	0.005	0.007	0.003	23	3	−0.003	−0.007	−0.012	0.001	0.001	−5.286	***	9.705	***
22	(2,200,1)	9	234	0.002	0.007	0.003	78	14	0.002	−0.007	−0.008	0.001	0.001	−10.178	***	0.159	
23	(5,200,0)	124	119	0.006	0.007	0.003	23	3	−0.004	−0.007	−0.011	0.001	0.001	−4.480	***	7.824	***
24	(5,200.1)	6	237	0.005	0.007	0.003	83	9	0.001	−0.008	−0.008	0.002	0.001	−4.045	***	0.226	
Average		63	181	0.006	0.007	0.003	50	8	0.000	−0.007	−0.008	0.002	0.001				

Note(s): There are 16 columns in the Table. The 24 trading regulations are listed in column 1 from smallest to greatest. In fact, there are 12 trading rules, each of which is linked to another replication, which then introduces a band. The various trading regulations are listed in column 2. The number of signals created throughout the research period is shown in columns 3 and 4. The rolling standard deviation for buy, neutral, and sell returns is shown in columns 5, 6, and 7. The percentage of buy and sell signals larger than zero is displayed in columns 8 and 9. The buy, neutral and sell mean returns are shown in columns 10, 11, and 12. The purchase and sell standard errors are shown in columns 13 and 14. Finally, columns 15 and 16 show the *t*-statistics as well as their significance levels
Statistical significance: *** 1%, ** 5%, *10
Source(s): Own computation

substantially different and higher than both the buy–hold and sell returns. To summarise, the above indicate that if the TA method were applied to BTC/AUD during the period under investigation, the TTR would have yielded returns' profitability better than that of a buy–hold strategy.

6.1.2 BTC/EUR exchange rate. The results of moving average rules based on conditional CAPM for the BTC/EUR exchange rate are reported in Table 3 and are discussed next.

An observation of the results in the context of the BBL's mean difference test shows that TA may be profitably used in the BTC/EUR exchange rate. The evidence for this finding is that out of the 24 tested trading rules, 96% (column 15) of the buy signals are strongly significant at 1% level. In addition, the sell signals are less impactful than buys, but 63% (column 16) of the executed experimental sell trades are significant. Furthermore, an overview of the rest of the table reveals other interesting insights. There are 180 sell signals compared to 63 buy signals, yet the buy trades outperform the sell (columns 3 and 4). For instance, a glance at columns 8 and 9 shows that there are significantly more returns that are greater than zero for the buy signals (averaging 66%) compared to the sell signals with an average of only 12%. Another example, TTR No. 6 (5,20,1) stands out in that it produces the greatest number of sell signals (of 240 trades) and it yields only three buy signals. The average daily mean returns for buy, buy–hold and sell trades are 0.3%, −0.5% and −0.7%, respectively (columns 10, 11 and 12). Again, it is noticed that the buy signals produce the highest return. Overall, the results show that the TA method is equally successful when applied to BTC/EUR. Nevertheless, it is also useful to observe that the results of BTC/EUR are less strong than BTC/AUD.

6.1.3 BTC/JPY exchange rate. The moving average rules results applied to conditional CAPM for the BTC/JPY exchange rate are shown in Table 4 and explained next.

The results of the BBL's mean difference test show that the TA method may be profitably applied to the BTC/JPY exchange rate. The evidence of this finding is based on the observation that out of the 24 tested trading rules, 23 buy signals are strongly significant at 1% level (column 15), while 67% of the experimented sell trades are significant at conventional levels (column 16). The background details also tell an informative story. In the total of 248 experimental trades from buy and sell signals, only 28% were generated by buy signals, yet the buy trades performed distinctly better with average returns of 73% compared to 21% of sell signals (see columns 8 and 9).

According to the above evidence, the average number of buy and sell signals for BTC/JPY is 69 and 179, respectively (columns 3 and 4). Again TTR No. 6 stands out as the TTR with the least buy signals but highest number of sell signals. Buy, sell and buy–hold have average standard deviations of 0.009, 0.003 and 0.007 (columns 5, 6 and 7) and daily mean returns of 0.5, −0.3 −0.5% respectively. Therefore, the buy signal is more profitable than the sell and buy–hold strategy, but at slightly higher risk. Overall, the results support the efficacy of the TA method.

6.1.4 BTC/ZAR exchange rate. The findings of moving average rules based on conditional CAPM for the BTC/ZAR exchange rate are displayed in Table 5 and are discussed next.

Unlike Bitcoin exchange rates discussed above, BBL's mean difference test shows that TTR signals are individually significant at conventional levels but cannot be called profitable. The last row of the table shows that in the total trades of 244 (63 + 181) from the 24 trading rules, the buy, buy–hold strategy and sell trades yield an average standard deviation of 0.006, 0.007 and 0.003, compared to mean returns of 0, −0.7 and −0.8%, respectively. This implies that while the risk measure is comparable to other Bitcoin exchange rates, the mean returns are eliminated.

From the findings above (in Tables 2–5), it can be observed that the efficacy of TA is emphasised more in economies that appear to be cryptocurrency-friendly or have positively explored the market with adoption possibilities into mainstream finance (BTC/AUD and BTC/JPY). Evidence of diminishing profits is found in BTC/EUR and BTC/ZAR. The results associated with BTC/EUR may be because of Bitcoin's becoming more efficient. The profits are entirely erased in the case of BTC/ZAR, where the official national position on cryptocurrency is rather unreceptive. Another reason why TA fails to yield profitable performance in the South African Bitcoin market (BTC/ZAR) is that the market itself is under-developed. Some believe that if there is influx of uninformed technical traders into a market, this may derail the technical strategy's power. The study's findings reveal that sell signals are more volatile than buy signals, which provide evidence that profits derived from *TTR* are not only compensation for risk.

6.2 Results of Kho's mean-spread test

The results of Kho's mean-spread test based on Eqn (8) are presented in Tables 6 and 7. These tables provide a report on the average spread between the conditional buy and sell signals along with their respective *t*-statistics. The tests in these tables are conducted under the null hypothesis that the spreads are not statistically different from zero. The *t*-statistics are computed using Newey and West's (1987) robust standard errors.

6.2.1 BTC/AUD and BTC/EUR exchange rate. Table 6 reports the results of Kho's buy–sell mean-spread test. The first two columns are tabulation and definition of rules. The first panel (columns 3 to 7) displays the results for BTC/AUD, while the second panel (columns 8 to 12) shows results for BTC/EUR.

The results of Kho's buy–sell mean-spread test provide enough evidence to reject the null hypothesis [H2] that the buy–sell spread is not different from zero, and we conclude that the buy signals differ from sell signals. Based on the 24 moving average trading rules that are tested, 54% of BTC/AUD are statistically significant at conventional levels, while all the *TTR*'s for BTC/EUR are strongly significant at 1% level. The rest of the table provides other supportive information. Eqn (8) is a special test equation (not conventional regression analysis) and as such the R^2's are deemed reasonable, and the model is validated with a strongly significant *F*-statistics test. The above explanation supports the conclusion that the application of the TA method on BTC/AUD is profitable.

6.2.2 BTC/JPY and BTC/ZAR exchange rate. Table 7 reports the results of Kho's buy–sell mean-spread test for BTC/JPY and BTC/ZAR. The first panel (columns 3 to 7) displays the results for BTC/AUD, while the second panel (columns 8 to 12) is for BTC/EUR.

The results of the test equation for BTC/JPY (column 6) and BTC/ZAR (column 11) provide convincing evidence to reject the null hypothesis (H2) that the buy–sell spread of MA signals are not different from zero and we conclude that they are different. This provides evidence to submit that TA methods may be employed profitably in BTC/JPY and BTC/ZAR. As in Table 6, the regression analysis was generated with robust standard errors and subjected to similar validation procedures.

So far, the study has examined the profitability of TTRs under a dynamic CAPM model that accounts for market risk using CAPM-based equilibrium returns. The results show that a time-varying risk premium can explain profits. When comparing the mean returns between the equilibrium model and actual series, the study finds that after accounting for risk, the previously discovered profits using the actual series diminish, implying that the Bitcoin market has elements of time-varying risk premium. After accounting for risk, TA has been found profitable in BTC/AUD and BTCJPY, but such profits diminish when studying BTC/EUR and are completely gone in BTC/ZAR.

6.3 Robust and completeness test

Tables 8 and 9 present the results on the momentum effect being tested for the third study hypothesis [H3]. The hypothesis examines whether price changes (or returns) have an association with TA signals of buy and sell trades as per Eqn (9).

Table 6. Kho's buy–sell mean-spread Test – BTC/AUD and BTC/AUD

		BTC/AUD						BTC/EUR					
1	2	3	4	5	6		7	8	9	10	11		12
No	*TTR*	Coeff	S.E	*F*-Stat	*t*-stat		R^2	Coeff	S.E	*F*-Stat	*t*-stat		R^2
1	(1,20,0)	−0.003	0.095	0.002	−0.026		0.000	0.191	0.058	13.937	3.293	***	0.006
2	(1,20,1)	0.816	0.063	168.093	12.964	***	0.065	0.581	0.038	136.616	15.262	***	0.053
3	(2,20,0)	−0.033	0.113	0.266	−0.291		0.000	0.174	0.057	11.538	3.074	***	0.005
4	(2,20,1)	0.692	0.120	124.588	5.740	***	0.049	0.526	0.070	102.876	7.477	***	0.041
5	(5, 20, 0)	−0.017	0.100	0.069	−0.167		0.000	0.221	0.057	19.434	3.900	***	0.008
6	(5, 20, 1)	0.893	0.064	217.271	13.868	***	0.082	0.603	0.043	145.939	14.134	***	0.057
7	(1, 50, 0)	−0.009	0.113	0.020	−0.081		0.000	0.269	0.048	28.269	5.556	***	0.012
8	(1, 50, 1)	0.516	0.104	63.091	4.983	***	0.025	0.472	0.065	86.335	7.260	***	0.034
9	(2, 50, 0)	−0.012	0.093	0.036	−0.134		0.000	0.228	0.051	19.231	4.438	***	0.008
10	(2, 50,1)	0.449	0.144	50.641	3.122	***	0.020	0.545	0.043	121.394	12.610	***	0.048
11	(5, 50,0)	−0.041	0.107	0.378	−0.380		0.000	0.203	0.066	17.200	3.097	***	0.007
12	(5,50,1)	0.627	0.101	102.019	6.194	***	0.040	0.549	0.049	110.672	11.286	***	0.044
13	(1,150,0)	−0.039	0.098	0.000	−0.392		0.000	0.359	0.040	52.013	8.933	***	0.021
14	(1, 150, 1)	0.342	0.115	28.206	2.982	***	0.012	0.449	0.064	78.726	7.024	***	0.032
15	(2,150,0)	−0.033	0.100	0.241	−0.328		0.000	0.300	0.047	34.524	6.374	***	0.014
16	(2,150,1)	0.381	0.137	35.254	2.782	***	0.014	0.515	0.044	105.595	11.710	***	0.042
17	(5,150,0)	0.034	0.094	0.278	0.363		0.000	0.342	0.045	45.839	7.654	***	0.019
18	(5,150,1)	0.504	0.108	69.646	4.672	***	0.028	0.534	0.049	103.748	10.803	***	0.041
19	(1,200,0)	−0.122	0.080	3.222	−1.530		0.001	0.350	0.040	49.736	8.842	***	0.020
20	(1,200,1)	0.325	0.116	25.094	2.815	***	0.010	0.419	0.064	68.482	6.542	***	0.028
21	(2,200,0)	−0.050	0.086	0.517	−0.578		0.000	0.258	0.063	24.724	4.075	***	0.010
22	(2,200,1)	0.357	0.114	30.879	3.131	***	0.013	0.447	0.044	70.776	10.062	***	0.028
23	(5,200,0)	−0.170	0.088	6.969	−1.919	*	0.003	0.327	0.045	42.097	7.339	***	0.017
24	(5,200.1)	0.345	0.098	25.905	3.538	***	0.011	0.577	0.050	132.239	11.500	***	0.052

Note(s): The first column is the tabulation of moving averages rules. Column 2 is the technical trading rule (*TTR*) structure. For reporting purpose, the table is divided into two panels. The first panel (columns 3 to 6) displays the results for BTC/AUD and the second panel (columns 8 to 12) gives results for BTC/EUR. Each row (1–24) presents a regression output for Eqn (8). Column 3 is the coefficient (α_1) of X_(t−1) where the intercept is set to zero. Other regression statistics are reported in the rest of the columns. All the *F*-stats are statistically significant at 1% level
Statistical significance: *** 1%, ** 5%, *10
Source(s): Own computation

Table 7.
Kho's buy–sell mean-spread Test–BTC/JPY and BTC/ZAR

		BTC/JPY						BTC/ZAR					
1	2	3	4	5	6		7	8	9	10	11		12
No	*TTR*	Coeff	S.E	*F* Stat	*t*-stat		R^2	Coeff	S.E	*F* Stat	*t*-stat		R^2
1	(1,20,0)	0.217	0.070	13.041	3.083	***	0.005	0.248	0.045	30.821	5.552	***	0.013
2	(1,20,1)	0.656	0.102	126.818	6.451	***	0.050	0.459	0.033	101.423	13.775	***	0.040
3	(2,20,0)	0.167	0.078	8.036	2.133	**	0.003	0.275	0.039	40.096	7.055	***	0.016
4	(2,20,1)	0.676	0.105	141.736	6.464	***	0.055	0.435	0.038	87.558	11.341	***	0.035
5	(5, 20, 0)	0.173	0.085	8.840	2.037	**	0.004	0.259	0.041	35.646	6.312	***	0.015
6	(5, 20, 1)	−0.719	0.096	171.759	−7.458	***	0.066	0.461	0.040	108.007	11.585	***	0.043
7	(1, 50, 0)	0.167	0.086	8.386	1.937	*	0.003	0.236	0.039	26.341	6.106	***	0.011
8	(1, 50, 1)	0.140	0.045	8.399	3.108	***	0.003	0.421	0.038	85.728	10.981	***	0.034
9	(2, 50, 0)	0.174	0.072	7.947	2.439	**	0.003	0.296	0.046	46.113	6.458	***	0.019
10	(2, 50,1)	0.609	0.104	113.815	5.841	***	0.045	0.496	0.035	126.376	14.235	***	0.050
11	(5, 50,0)	0.188	0.086	10.173	2.186	**	0.004	0.282	0.035	38.832	8.046	***	0.016
12	(5,50,1)	0.617	0.101	110.571	6.087	***	0.044	0.513	0.040	129.811	12.730	***	0.051
13	(1,150,0)	0.161	0.085	7.417	1.886	*	0.003	0.362	0.032	67.727	11.236	***	0.027
14	(1, 150, 1)	0.488	0.109	61.675	4.474	***	0.025	0.404	0.036	74.638	11.270	***	0.030
15	(2,150,0)	0.210	0.079	12.606	2.681	***	0.005	0.349	0.038	63.732	9.276	***	0.026
16	(2,150,1)	0.468	0.111	61.338	4.208	***	0.025	0.482	0.040	116.671	12.028	***	0.046
17	(5,150,0)	0.212	0.064	11.814	3.335	***	0.005	0.278	0.040	38.553	7.028	***	0.016
18	(5,150,1)	0.699	0.064	157.275	10.879	***	0.061	0.499	0.037	126.442	13.459	***	0.050
19	(1,200,0)	0.244	0.080	16.658	3.045	***	0.007	0.351	0.030	65.399	11.750	***	0.026
20	(1,200,1)	0.533	0.068	82.970	7.804	***	0.033	0.446	0.035	96.700	12.782	***	0.038
21	(2,200,0)	0.320	0.069	28.811	4.629	***	0.012	0.373	0.036	76.357	10.436	***	0.031
22	(2,200,1)	0.475	0.110	62.201	4.299	***	0.025	0.493	0.037	123.756	13.426	***	0.049
23	(5,200,0)	0.118	0.093	4.032	1.264		0.002	0.310	0.037	52.084	8.274	***	0.021
24	(5,200.1)	0.718	0.057	163.304	12.649	***	0.063	0.461	0.033	107.496	13.879	***	0.043

Note(s): The first column is the tabulation of moving averages rules. Column 2 is the technical trading rule (*TTR*) structure. For reporting purpose, the table is divided into two panels. The first panel (columns 3 to 6) displays the results for BTC/AUD and the second panel (columns 8 to 12). Gives results for BTC/EUR. Each row (1–24) presents a regression output for Eqn (8). Column 3 is the coefficient (α_1) of X_(t−1) where the intercept is set to zero. Other regression statistics are reported in the rest of the columns. All the *F*-stats are statistically significant at 1% level
Statistical significance: *** 1%, ** 5%, *10
Source(s): Own computation

Observation of the results for each of the regression outputs reported in Table 8 under both buy and sell signals provides strong evidence that there is an association between price changes of BTC/AUD and BTC/EUR, and the TA trade signals. This means that the null of H3 is rejected. The test serves to examine whether the properties of a trend apply to the study. In TA, the primary goal of price analysis (using a chart) is to detect the price trends and/or reversals in their early phases, which trigger trading.

The results of Table 9 provide an answer to H3 in respect of the relationship between price changes (or returns) and MA trade signals specifically for BTC/JPY and BTC/ZAR. The table shows that, like Table 8, there is convincing evidence that there is an association between the returns and trade signals. Overall, the study finds that concerning buy signals, the Bitcoin market possesses a momentum effect across the board as the results are strongly significant at conventional levels.

7. Discussion of results

To address the research question, 4 TA performance strategies were evaluated. To begin with, TTRs were applied to equilibrium returns calculated using the dynamic CAPM model. Second, the TA results were then replicated using the actual return series for comparison and robustness purposes. Thirdly, the study examined the extent to which time-varying risk premiums affect performance to determine the profitability of TA. Finally, the momentum effect in TA was investigated as a possible secondary mechanism to corroborate the results. The study's findings are similar to those of Gerritsen *et al.* (2020) and Grobys *et al.* (2020), who found that TTRs are more cost-effective than the buy–hold strategy when dealing with Bitcoin daily data. Their study investigates TA using trend-following tactics like the simple moving average. Further support is given by Tiwari *et al.* (2018) and Resta *et al.* (2020), who also emphasise the importance of TA and conclude that TA returns surpass those of a buy–hold strategy. Overall, the study finds that the performance of the chosen *TTR* strategies is superior to the buy–hold strategy. The study is different in that it accounts for time-varying risk premiums and finds that some of the registered profits diminish after the factoring of risk. Bitcoin may be seen as a natural laboratory for using TA because it has no apparent fundamentals to investigate. The study offers evidence that the MA trading rule can predict Bitcoin returns even after accounting for time-varying risk premiums. Similar to known literature (Ülkü and Prodan, 2013), the profits found in Bitcoin exchange rates are found to diminish after accounting for time-varying risk premiums. In the evaluation of the momentum effect, the study finds similar evidence to that of Borgards (2021), in that the Bitcoin market possesses a momentum effect. Emerging markets are known to be less liquid than industrialised markets and have more concentrated trade. As a result, it is only natural to assume that inefficiencies could be more easily exploited in these markets. Gerritsen *et al.* (2021), however, find that the informational efficiency of Bitcoin has improved.

8. Conclusion

The paper examines the profitability of 24 TTRs in each of four Bitcoin exchange rates (BTC/AUD, BTC/EUR, BTC/JPY and BTC/ZAR). The results show that the chosen FMA TTRs are all successful in generating profitable signals for Bitcoin returns. The buy signals generate positive returns and sell signals generate negative returns, which are, on average, significantly different from the returns earned by the buy–hold strategy. The study results are consistent with Grobys *et al.* (2020) and Borgards and Czudaj (2021) who found that the trading rules are successful in predicting Bitcoin price movements. The study also observes that the Bitcoin market may possess a momentum effect. Though these results suggest market inefficiency, we find that time-varying risk premiums can diminish

Table 8.
Momentum effect – BTC/AUD and BTC/EUR

	BTC/AUD						BTC/EUR					
	Buy			Sell			Buy			Sell		
1	2	3	4	5	6	7	8	9	10	11	12	13
TTR	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat
Long-term 20 MA												
(1,20,0)	0.010	0.003	3.252 ***	−0.005	0.001	−7.509 ***	0.029	0.004	7.673 ***	−0.027	0.003	−8.271 ***
(1,20,1)	0.004	0.001	5.408 ***	−0.001	0.000	−1.781 *	0.037	0.005	7.098 ***	−0.029	0.004	−7.050 ***
(2,20,0)	0.008	0.002	3.885 ***	−0.004	0.001	−6.213 ***	0.018	0.004	5.116 ***	−0.019	0.005	−4.180 ***
(2,20,1)	0.004	0.001	5.767 ***	−0.001	0.000	−2.064 **	0.032	0.006	5.350 ***	−0.016	0.003	−4.840 ***
(5,20,0)	0.010	0.002	5.147 ***	−0.003	0.001	−5.471 ***	0.030	0.008	3.580 ***	−0.012	0.005	−2.475 ***
(5,20,1)	0.004	0.001	6.094 ***	0.000	0.000	0.316	0.018	0.005	3.513 ***	−0.009	0.003	−3.062 ***
Intercept	−0.001	0.000	−1.074	0.001	0.001	1.766 *	−0.018	0.001	−13.967 ***	−0.006	0.002	−3.616 ***
Long-term 50 MA												
(1,50,0)	0.004	0.001	6.372 ***	−0.001	0.000	−3.559 ***	0.014	0.004	3.906 ***	−0.014	0.005	−2.930 ***
(1,50,1)	0.011	0.001	7.715 ***	−0.004	0.001	−7.248 ***	0.027	0.006	4.538 ***	−0.008	0.003	−2.268 **
(2,50,0)	0.004	0.001	5.882 ***	−0.001	0.000	−1.898 *	0.021	0.004	4.898 ***	−0.029	0.003	−9.431 ***
(2,50,1)	0.009	0.002	3.508 ***	−0.005	0.001	−8.909 ***	0.035	0.006	5.574 ***	−0.025	0.003	−8.701 ***
(5,50,0)	0.004	0.001	6.299 ***	−0.004	0.001	−6.448 ***	0.047	0.005	8.947 ***	−0.025	0.005	−4.857 ***
(5,50,1)	0.011	0.001	7.687 ***	−0.001	0.000	−2.574 ***	0.026	0.003	7.790 ***	−0.009	0.003	−3.375 ***
Intercept	−0.001	0.000	−1.400	0.001	0.001	2.242 **	−0.019	0.001	−14.373 ***	−0.006	0.002	−3.823 ***
Long-term 150 MA												
(1,150,0)	0.0105	0.002	6.299 ***	−0.001	0.000	−2.192 **	−0.024	0.003	−8.855 ***	0.033	0.005	6.832 ***
(1,150,1)	0.0062	0.001	9.533 ***	−0.006	0.001	−9.649 ***	0.044	0.005	8.777 ***	−0.029	0.004	−6.762 ***
(2,150,0)	0.0118	0.001	8.269 ***	−0.006	0.001	−9.158 ***	0.023	0.004	6.178 ***	−0.018	0.004	−4.341 ***
(2,150,1)	−0.0053	0.001	−9.426 ***	−0.002	0.000	−4.926 ***	0.034	0.005	6.557 ***	−0.015	0.003	−4.342 ***
(5,150,0)	0.0050	0.001	7.465 ***	0.006	0.001	9.756 ***	0.014	0.006	2.284 **	−0.015	0.005	−3.155 ***
(5,150,1)	0.0093	0.002	4.724 ***	−0.001	0.000	−2.860 ***	0.014	0.004	3.510 ***	−0.008	0.003	−2.284 **
Intercept	−0.0004	0.000	−0.922	0.001	0.001	1.595 *	−0.015	0.001	−11.873 ***	−0.008	0.002	−5.424 ***
Long-term 200 MA												
(1,200,0)	0.010	0.001	8.230 ***	−0.001	0.000	−2.765 ***	0.031	0.004	6.934 ***	−0.028	0.004	−7.625 ***
(1,200,1)	0.006	0.001	8.681 ***	−0.005	0.001	−8.609 ***	0.036	0.005	7.824 ***	−0.022	0.003	−7.489 ***

(*continued*)

Table 8.

	BTC/AUD						BTC/EUR					
	Buy			Sell			Buy			Sell		
1	2	3	4	5	6	7	8	9	10	11	12	13
TTR	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat
(2,200,0)	0.011	0.001	11.564 ***	−0.005	0.001	−9.055 ***	0.023	0.004	5.982 ***	−0.019	0.006	−3.220 ***
(2,200,1)	0.004	0.001	7.058 ***	−0.001	0.000	−2.042 **	0.034	0.005	6.630 ***	−0.018	0.003	−5.253 ***
(5,200,0)	0.012	0.001	11.076 ***	−0.001	0.000	−3.410 ***	0.009	0.004	2.203 **	−0.011	0.005	−2.222 **
(5,200,1)	0.006	0.001	9.769 ***	−0.006	0.001	−10.479 ***	0.031	0.007	4.493 ***	−0.007	0.004	−1.768 *
Intercept	−0.001	0.000	−2.113 **	0.001	0.001	2.464 ***	−0.018	0.001	−14.061 ***	−0.006	0.002	−3.755 ***

Note(s): The first column shows the list of regression outputs for each technical trading rule (*TTR*). Then the table is divided into two main panels. The first panel (2–7) reports results for BTC/AUD, while the second panel (8–13) displays results for BTC/EUR. The results for buy and sell signals are reported separately for each exchange rate (BTC/AUD, BTC/EUR). The regression outputs are reported under each long-term stretch for moving average rules, namely, 20, 50, 150 and 200

Statistical significance: ***1%, **5%, *10

Source(s): Own computation

Table 9.
Momentum effect: BTC/JPY and BTC/ZAR

	BTC/JPY								BTC/ZAR							
	Buy				Sell				Buy				Sell			
1	2	3	4		5	6	7		8	9	10		11	12	13	
TTR	Coefficient	S.E	*t*-stat		Coefficient	S.E	*t*-stat		Coefficient	S.E	*t*-stat		Coefficient	S.E	*t*-stat	
Long-term 20 MA																
(1,20,0)	0.002	0.001	4.797	***	−0.003	0.000	−6.378	***	0.003	0.000	6.436	***	−0.003	0.000	−6.297	***
(1,20,1)	0.007	0.003	2.419	**	−0.001	0.000	−2.053	**	0.011	0.001	8.180	***	0.000	0.000	−0.667	
(2,20,0)	0.003	0.001	5.184	***	−0.003	0.000	−5.760	***	0.012	0.003	4.234	***	−0.003	0.001	−6.050	***
(2,20,1)	0.013	0.005	2.805	***	0.000	0.000	0.346		0.003	0.000	6.689	***	0.000	0.000	0.812	
(5,20,0)	0.002	0.001	4.512	***	−0.003	0.000	−5.391	***	0.003	0.001	5.158	***	−0.003	0.001	−5.727	***
(5,20,1)	0.015	0.004	3.645	***	0.000	0.000	−1.343		0.013	0.011	1.243		0.000	0.000	0.012	
Intercept	−0.003	0.000	−8.973	***	−0.003	0.000	−6.282	***	−0.008	0.000	−21.503	***	−0.007	0.000	−18.256	***
Long-term 50 MA																
(1,50,0)	−0.004	0.000	−8.823	***	−0.004	0.000	−9.408	***	0.004	0.000	8.073	***	−0.003	0.000	−6.265	***
(1,50,1)	0.004	0.001	7.556	***	−0.001	0.000	−2.253	**	0.010	0.002	4.778	***	0.000	0.000	1.314	
(2,50,0)	0.003	0.001	6.959	***	−0.003	0.000	−7.872	***	0.004	0.001	7.768	***	0.000	0.000	−0.480	
(2,50,1)	0.010	0.002	5.648	***	−0.001	0.000	−1.987	**	0.002	0.003	0.915		−0.004	0.000	−7.524	***
(5,50,0)	0.004	0.001	6.711	***	−0.003	0.000	−6.728	***	0.004	0.001	6.978	***	0.000	0.000	−1.030	
(5,50,1)	0.012	0.002	7.573	***	−0.001	0.000	−2.164	**	0.008	0.001	7.494	***	−0.003	0.000	−7.727	***
Intercept	−0.003	0.000	−9.090	***	−0.002	0.000	−5.577	***	−0.008	0.000	−21.963	***	−0.007	0.000	−18.097	***
Long-term 150 MA																
(1,150,0)	−0.004	0.000	−9.753	***	0.005	0.000	10.385	***	−0.004	0.000	−8.964	***	0.001	0.000	1.945	*
(1,150,1)	0.012	0.002	6.256	***	0.000	0.000	−0.130		0.010	0.001	7.604	***	−0.003	0.001	−6.659	***
(2,150,0)	0.005	0.001	9.227	***	−0.005	0.000	−10.942	***	0.004	0.000	7.581	***	−0.004	0.001	−8.126	***
(2,150,1)	0.012	0.002	6.147	***	−0.001	0.000	−2.142	**	0.008	0.002	4.085	***	0.000	0.000	−1.010	
(5,150,0)	0.005	0.000	10.492	***	−0.004	0.000	−8.654	***	0.004	0.000	8.574	***	0.004	0.000	10.163	***
(5,150,1)	0.006	0.002	3.648	***	−0.001	0.000	−2.083	**	0.008	0.001	5.363	***	0.000	0.000	−0.951	
Intercept	−0.003	0.000	−9.229	***	−0.003	0.000	−6.638	***	−0.008	0.000	−20.989	***	−0.007	0.000	−19.044	***
Long-term 200 MA																
(1,200,0)	0.005	0.001	8.706	***	−0.005	0.000	−9.444	***	0.005	0.000	9.445	***	−0.005	0.001	−9.436	***
(1,200,1)	0.006	0.002	3.220	***	−0.001	0.000	−2.205	**	0.009	0.001	6.498	***	−0.001	0.000	−1.692	*

(*continued*)

Table 9.

	BTC/JPY						BTC/ZAR					
	Buy			Sell			Buy			Sell		
1	2	3	4	5	6	7	8	9	10	11	12	13
TTR	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat	Coefficient	S.E	*t*-stat
(2,200,0)	0.004	0.000	8.217 ***	−0.005	0.000	−11.439 ***	0.007	0.003	1.977 **	−0.005	0.000	−10.352 ***
(2,200,1)	0.011	0.002	4.911 ***	−0.001	0.000	−1.928 *	0.002	0.000	4.693 ***	0.000	0.000	−1.505
(5,200,0)	0.011	0.001	11.975 ***	−0.005	0.001	−9.495 ***	0.004	0.000	7.969 ***	−0.001	0.000	−2.148 **
(5,200,1)	0.004	0.000	8.053 ***	−0.001	0.000	−2.031 **	0.007	0.001	6.306 ***	−0.004	0.001	−7.400 ***
Intercept	−0.004	0.000	−10.072 ***	−0.002	0.000	−5.222 ***	−0.008	0.000	−21.735 ***	−0.006	0.000	−17.366 ***

Note(s): The first column shows the list of regression outputs for each technical trading rule (*TTR*). Then the table is divided into two main panels. The first panel (2–7) reports results for BTC/AUD, while the second panel (8–13) displays results for BTC/EUR. The results for buy and sell signals are reported separately for each exchange rate (BTC/AUD, BTC/EUR). The regression outputs are reported under each long-term stretch for moving average rules, namely, 20, 50, 150 and 200
Statistical significance: ***1%, **5%, *10
Source(s): Own computation

profits and thus moderate the potential of TA as an analytical tool in the cryptocurrency market.

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Appendix

No	Technical trading rules (short, long, band)
1	(1, 20, 0)
2	(1, 20, 1)
3	(2, 20, 0)
4	(2, 20, 1)
5	(5, 20, 0)
6	(5, 20, 1)
7	(1, 50, 0)
8	(1, 50, 1)
9	(2, 50, 0)
10	(2, 50, 1)
11	(5, 50, 0)
12	(5, 50, 1)
13	(1, 150, 0)
14	(1, 150, 1)
15	(2, 150, 0)
16	(2, 150, 1)
17	(5, 150, 0)
18	(5, 150, 1)
19	(1, 200, 0)
20	(1, 200, 1)
21	(2, 200, 0)
22	(2, 200, 1)
23	(5, 200, 0)
24	(5, 200, 1)

Source(s): Own

Table A1. Technical Trading Rules

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