

Do technical trading rules outperform the simple buy-and-hold strategy in the cryptocurrency market?

Technical
trading of
cryptocurrency

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JunHyeong Jin, JiHoon Jung and Kyojik Song
Department of Fintech, Sungkyunkwan University, Seoul, South Korea

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Abstract

The authors test the weak-form efficiency in cryptocurrency markets using the most recent and comprehensive data as of 2021. The authors apply various technical indicators to take a long or short position on 99 cryptocurrencies and compare the 10-day returns based on the technical trading strategies to the simple buy-and-hold returns. The authors find that the trading strategies based on single indicators or the combination of two indicators do not generate higher returns than buy-and-hold returns among cryptos. These findings suggest that cryptocurrency markets are weak-form efficient in general.

Keywords Market efficiency, Cryptocurrency, Technical analysis, Bitcoin, Trading indicator

Paper type Research paper

1. Introduction

Since Bitcoin was created as a cryptocurrency in 2009, numerous cryptocurrencies have been introduced into the market. Even though cryptocurrency markets have geometrically grown in value over the last decade, the price of each cryptocurrency is extremely fluctuating. Despite the extreme variability of the cryptocurrency, many investors have still tried to earn excess returns in the markets. The efficient market theory states that the price of an asset reflects all available information, leaving no room to make excess returns by investing based on some trading strategies. In theory, neither technical nor fundamental analysis can produce excess returns consistently if markets are efficient. Whether the cryptocurrency market is efficient or not has attracted academicians' and practitioners' interests as the size of the market has grown.

Because investors are not able to use fundamental analysis in the cryptocurrency market, they tend to resort to technical trading rules to earn higher returns. The technical analysis

JEL Classification — G01, G21, G30, G32

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examines the historical price patterns, trading volume or any other trends that predict future price movements. The technical trading rules tend to be more heavily used in the cryptocurrency market, compared to other markets in which traditional financial assets like stocks and bonds are traded. It is well known that investors cannot earn excess returns easily based on technical trading rules in relatively efficient equity or bond markets. Whether the technical analysis is effective in cryptocurrency markets is an empirical question.

The literature provides controversial evidence about whether cryptocurrency markets are weak-form inefficient [1]. Earlier papers have investigated the weak-form efficiency of Bitcoin returns. For instance, [Al-Yahyaee et al. \(2018\)](#) compares the Bitcoin market to gold, stock and currency markets, and find that the bitcoin (BTC) market is more inefficient than other markets. [Krstoufek \(2018\)](#) also finds that Bitcoin returns in US (American) and Chinese markets are inefficient over the period of 2010–2017. [Corbet et al. \(2019\)](#) use Bitcoin close-price data at one-minute intervals and find that the trading strategy based on moving average shows predictive power in the Bitcoin returns. Some studies include more cryptocurrencies to test the weak-form efficiency of cryptocurrency markets. For instance, [Grobys et al. \(2020\)](#) examine 11 cryptocurrencies with high market capitalizations over the sample period of 2016–2018 and find that a variable moving average strategy generates significantly positive excess returns.

In contrast, other papers show the evidence of efficient cryptocurrency markets. Specifically, the Bitcoin returns have become informationally efficient in the later sample periods (for instance, [Urquhart, 2016](#); [Khuntia and Pattanayak, 2018](#)). Moreover, [Grobys and Sapkota \(2019\)](#) find that momentum trading strategies do not generate positive abnormal returns among many cryptocurrencies over the period of 2014–2018.

Earlier literature focuses on Bitcoin returns to test the efficiency of cryptocurrency markets because the cryptocurrency market has started with the trading of Bitcoin. As cryptocurrency markets have exponentially grown since 2017, Bitcoin accounts for only about 20% of total crypto trading volume as of 2021. It is necessary to revisit the issue on the efficiency of cryptocurrency markets using more comprehensive and recent data. Extending the previous literature, we test the weak-form efficiency in cryptocurrency markets using the more completed data. For our analyses, we collect data from Binance with largest trading volume among crypto exchanges and include 99 cryptocurrencies with a trading history of at least 1 year as of 2021 into our sample. We then use the most popular technical trading indicators, parabolic stop and reverse (SAR), moving average convergence-divergence (MACD), money flow index (MFI), commodity channel index (CCI) and relative strength index (RSI), to test the efficient market hypothesis (EMH).

We assume to take a long or short position on each cryptocurrency according to the signal of each trading indicator and calculate returns over the next 10-day period, and compare the returns to the simple buy-and-hold returns. First of all, we find that the returns based on single technical indicators are not statistically different from the buy-and-hold returns among the sample cryptocurrencies, regardless of long or short strategies. Secondly, we take a long or short position according to the combination of two technical indicators and test whether the trading strategies generate higher returns, comparing to buy-and-hold returns. We document that the trading strategies with the combination of two technical indicators do not generate abnormal returns among the sample cryptocurrencies. Limiting our tests to five cryptocurrencies with largest market capitalization, we still do not find any different results. These findings imply that the prices of cryptocurrencies are not predictable by past trading history.

Our research contributes to the literature related to the weak-form efficiency of cryptocurrency markets. Previous literature provides conflicting evidence about whether cryptocurrency markets are weak-form efficient or not. [Corbet et al. \(2019\)](#) suggest that future research considers a wide set of cryptocurrencies and applies more complicated technical

trading rules such as pairs trading. Following them, we revisit the issue of the weak-form efficiency in cryptocurrency markets. Cryptocurrency markets have experienced exponential growth in 2017 and a large bubble burst in early 2018 [2]. Then, cryptocurrencies have dramatically increased in value during the pandemic period of 2020–2021. There is some evidence that the cryptocurrency market has moved toward becoming an efficient market with the growth of the market (for instance, see [Urquhart, 2016](#)). Therefore, we need to use the most comprehensive and up-to-dated data, including the pandemic period, to test the market efficiency of cryptocurrency markets. In this research, we find the main evidence that trading strategies using various technical indicators do not generate higher returns than the simple buy-and-hold strategy, which supports that cryptocurrency markets are weak-form efficient in general.

This research also has practical implications beyond the contribution to extant literature. In cryptocurrency markets, programmatic trading based on technical indicators has received increasing attention and many automated trading systems are developed. However, our results cast doubt on the profitability of the programmatic trading.

The rest of the paper is organized as follows. [Section 2](#) reviews the relevant literature, [Section 3](#) describes technical indicators and [Section 4](#) elaborates on our empirical analyses. [Section 5](#) concludes this study.

2. Related literature

The EMH proposed by [Fama \(1970\)](#) has been an important research topic in the field of finance. A weak-form efficiency means that the stock price cannot be predicted, using the information of the past stock price or trading volume. In this research, we apply technical trading strategies developed in traditional financial markets into cryptocurrency markets to test the weak-form efficiency. Previous literature has used technical indicators to test the weak-form efficiency in stock markets or bond markets. For instance, [Brock *et al.* \(1992\)](#) investigate whether simple technical trading rules can generate higher returns than null models using the Dow Jones indices. They use two of the simplest and most popular trading rules, moving average and trading range break and compare with four popular null models: the random walk, the autoregressive model (AR), the generalized autoregressive conditional heteroskedasticity in the mean (GARCH-M) model and the Exponential GARCH model. Also, [Chong and Ng \(2008\)](#) test the trading indicators of MACD and RSI using the data on 60-year London Stock Exchange FT30 indices, and find that trading strategies using the technical indicators can yield higher returns than buy-and-hold strategies. Furthermore, [Chong *et al.* \(2014\)](#) apply the trading strategies based on MACD and RSI in the stock markets of five Organization for Economic Cooperation and Development (OECD) countries (US, Japan, Canada, German, Italy). They argue that their results strongly support for the technical trading strategies. These studies indicate that the trading strategies based on technical indicators provide the validity of technical indicators to some degree in the traditional financial markets.

As cryptocurrency markets have remarkably grown over the last decade, the use of technical indicators has also increased in cryptocurrency trading. Accordingly, there has been a debate whether trading strategies using technical indicators can generate meaningful returns in the cryptocurrency markets. Earlier studies apply trading indicators into Bitcoin markets to test the efficiency of crypto markets. [Al-Yahyaee *et al.* \(2018\)](#) compares the Bitcoin market to gold, stock and currency markets, and find that the long-memory feature and multifractality of the Bitcoin market is stronger and the Bitcoin market is more inefficient than other markets. [Kristoufek \(2018\)](#) utilizes the Efficiency Index which can cover different types of (in) efficiency measures, and he finds that Bitcoin returns in US and Chinese markets are inefficient over the period of 2010–2017. [Corbet *et al.* \(2019\)](#) also apply trading strategies

using moving average-oscillator and trading range break-out strategies into high-frequency data, and find that the trading strategy based on moving average shows predictive power in the Bitcoin returns. [Huang et al. \(2019\)](#) construct a classification tree-based model for return prediction using 124 technical indicators and provide evidence that the proposed model has strong out-of-sample predictive power for narrow ranges of daily returns on Bitcoin. [Kim \(2021\)](#) also utilizes technical trading rules for Bitcoin futures and finds that the trend-following rules show higher investment performance than the simple buy-and-hold strategy. These studies suggest that the cryptocurrency markets are weak-form inefficient to some degree.

In contrast, other papers provide the evidence of efficient cryptocurrency markets. [Urquhart \(2016\)](#) divide the sample by period and find that Bitcoin is moving toward becoming an efficient market. [Khuntia and Pattanayak's \(2018\)](#) also find that Bitcoin returns exhibiting market efficiency over time, supporting the adaptive market hypothesis. These studies suggest that the Bitcoin returns have become informationally efficient in the later sample periods. Moreover, [Grobys and Sapkota \(2019\)](#) find that momentum trading strategies do not generate positive abnormal returns among many cryptocurrencies over the period of 2014–2018.

Recent studies include more cryptocurrencies beyond Bitcoin to test the weak-form efficiency of cryptocurrency markets. For instance, [Zhang et al. \(2018\)](#) investigate nine cryptocurrencies and find that all these cryptocurrencies are inefficient markets and that a value-weighted cryptocurrency composite index and Dow Jones industrial average are persistently cross-correlated. [Grobys et al. \(2020\)](#) find that a variable moving average strategy generates significantly positive excess returns, using daily price data for the 11 most traded cryptocurrencies over the period of 2016–2018.

The literature does not provide consistent evidence about whether cryptocurrency markets are weak-form efficient or not. In addition, some papers have examined only Bitcoin returns even though the market share of Bitcoin has gradually decreased over the time. Extending the literature, we try to test the validity of trading strategies using various technical indicators based on most comprehensive and up-to-dated data.

3. Technical indicators

We use the following five technical indicators for our analyses: Parabolic SAR, MACD, MFI, CCI and RSI. They are explained in detail in the subsections below.

3.1 Parabolic stop and reverse (SAR)

[Wilder \(1978\)](#) developed the parabolic SAR indicator to improve the fact that many technical indicators' trading signals are based on lagging. The indicator is normally used by traders to determine trend direction and potential reversals in price, and it uses a trailing "SAR" method to detect suitable exits and entry points. That is, it assumes that traders are trading a trend, and, thus, expects price to change over time.

The SAR uses a trailing stop level that follows prices as they move up or down. The stop level increases speed based on α (acceleration variable). Following [Wilder \(1978\)](#), we assume that α starts with 0.02, increasing by 0.02 whenever the new or high new low price is updated, with 0.2 being the maximum. Extreme Point (EP) is a local maximum or minimum price. The SAR is calculated as follows.

$$SAR_{n+1} = SAR_n + \alpha(EP - SAR_n)$$

When the price and the stop level are plotted on the chart, they resemble a parabolic curve. Basically, a trading signal occurs when the price and the SAR value intersect. When the SAR value is greater than the price, it is a sell signal, and when the SAR value is less than the price,

it is a buy signal. In the buy signal section, it is the new high price of the section and in the sell signal section, it is the new low price of the section.

3.2 Moving average convergence-divergence (MACD)

The moving average is the simplest and most widely used technical indicator. A line drawn by arithmetic average of stock prices over a certain period is used as a trigger. When the stock price is above the moving average line, it signals a buy, and when it is below the moving average line, it is recognized as a sell time. It is common to use multiple moving averages at the same time. When the short-term moving average crosses above the long-term moving average, it is interpreted as a buy timing, and when the short-term moving average crosses below the long-term moving average, it is interpreted as a sell timing. However, it has a disadvantage that it cannot quickly reflect market conditions because it is used within a certain period on average.

Appel (1979) develops MACD which is designed to detect changes in the strength, direction, momentum and duration of a trend in securities' prices. It is characterized by compensating for the lag, which is a weakness of moving averages. The MACD indicator generally uses MACD line and signal line. The MACD line represents the 12-day exponential moving average (EMA) of prices minus the 26-day EMA. And the signal line is the EMA of the MACD values over 9 days.

When the MACD line breaks above the signal line, it is called a golden cross, and when the MACD line crosses the signal line, it is called a dead cross. A golden cross is considered a buy signal and a dead cross is a sell signal. However, there is a disadvantage in that reliability is lowered because the frequency of crosses increases in the sideways section.

3.3 Commodity channel index (CCI)

The CCI indicator was originally developed in commodities markets in 1980, but it can be used in any market. It indicates the direction and trend of the stock price by quantifying how far the current stock price is from the moving average. CCI is calculated as follows (typical price is a simple average of high, low and close price):

$$CCI = (\text{Typical Price} - \text{Simple Moving Average}) / (0.015 \times \text{Mean Deviation})$$

Traders can detect buy or sell signals by assuming trading with multiple timeframes. We detect trading signals based on zero line and use 14 days as a timeframe. When the CCI indicator crosses above 0, it is considered a buy signal, and when the CCI index crosses below 0, it is considered as a sell signal. Alternatively, if the CCI indicator crosses above 100, it is considered overbought, and if it crosses below -100, it is considered oversold. In general, the CCI indicator has the disadvantage of being weak in sideways direction.

3.4 Relative strength index (RSI)

Wilder (1978) also developed the RSI indicator that evaluates the strength of a trend as a percentage by quantifying the width when a price rises or falls. The indicator tracks market momentum through the speed and change in price movements. The RSI can be calculated as follows with a typical timeframe of 14 days.

$$\begin{cases} U = \text{close}_{\text{now}} - \text{close}_{\text{prev}} & (\text{if, } \text{close}_{\text{now}} > \text{close}_{\text{prev}}) \\ D = 0 \end{cases}$$

$$\begin{cases} D = \text{close}_{\text{prev}} - \text{close}_{\text{now}} & (\text{if, } \text{close}_{\text{now}} < \text{close}_{\text{prev}}) \\ U = 0 \end{cases}$$

$$RS = \frac{SMA(U)}{SMA(D)} \quad (SMA : \text{Simple Moving Average})$$

$$RSI = 100 - \frac{100}{1 + RS}$$

In the calculation above, *relative strength (RS)* is the ratio of average gain (simple moving average of U) to average loss (simple moving average of D). We count periods with price decreases as zero in the calculations of average gain and periods with price increases as zero in the calculations of average loss. Generally, the RSI of 0–30 (70–100) is considered oversold (overbought), so it is interpreted as the direction of the trend will change soon. In general, the indicator has a disadvantage that it is difficult to take advantage of a strong trend that lasts for a long time.

3.5 Money flow index (MFI)

The MFI indicator represents the volume-weighted adaptation of the RSI indicator. Compared to the RSI, the MFI reflects buying and selling pressure based on trading volume fluctuations when it detects trading signals. In general, traders use the data with a 14-day timeframe to calculate the MFI as follows:

$$\text{Typical Price}(TP) = \frac{\text{High} + \text{Low} + \text{Close}}{3}$$

$$\text{Money Flow}(MF) = TP \times \text{Volume}$$

$$\text{Money Flow Ratio (MFR)} = \frac{14\text{Period Positive Money Flow}}{14\text{Period Negative Money Flow}}$$

$$MFI = 100 - \frac{100}{1 + MFR}$$

In the calculation above, *Money Flow (MF)* is positive when the price increases from one period to the next, and it is added to *positive MF*. When the price decreases from one period to the next, *MF* is negative and it is added to *negative MF*.

Similar to the RSI, the MFI of 0–30 (70–100) is considered oversold (overbought). Since the MFI indicator is a value calculated based on trading volume, a timelier indicator can be obtained. However, like the RSI indicator, it is a relatively meaningful indicator in sideways trade, but has the disadvantage that it is not useful in a strong trend market.

4. Empirical findings

We collect the data on 99 cryptocurrencies from the largest cryptocurrency exchange, Binance. Among all cryptocurrencies traded on the Binance, we select 99 cryptocurrencies which have a transaction record of at least one year from the time of trading on the exchange to the end of September, 2021. For our analyses, we collect trading date, closing price, and trading volume on a 24-hour basis per day on each cryptocurrency. It should be noted that the trading period used for each coin is different. For instance, the data on Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB) range from July, 2017 to September, 2021 because the exchange was opened in July, 2017. The data on Ripple (XRP) and Cardano (ADA) are collected from November, 2017 when the two cryptocurrencies were listed on the exchange.

We develop on the work of Brock *et al.* (1992) and investigate whether five of the most popular technical trading rules explained in the previous section generate higher returns than

the simple buy and hold strategies in order to test the weak-form efficiency of cryptocurrency markets. After the trade signal of a technical indicator on a cryptocurrency is issued, we calculate the return over next 10 days. When the trade signal is once issued, other signals on the currency for the 10-day period are ignored. We can take a long or short position on each cryptocurrency based on the trade signal. To calculate the average buy-and-hold return, we divide entire sample period into 10-day periods and then calculate the buy-and-hold returns of 99 cryptocurrencies over the each 10-day period. Finally, we calculate the average buy-and-hold return for the entire sample. To test a weak-form market efficiency of cryptocurrency markets, we first calculate the returns of trading strategies using only one technical indicator. We also calculate the returns of trading strategies using two technical indicators.

4.1 The returns of trading strategies based on one technical indicator

Table 1 presents the average return of 99 cryptocurrencies when trading strategies are implemented using only one technical indicator over 10-day period. It also shows that the simple average buy-and-hold return of the sample cryptos is 0.0265 over the sample period. When trading using only one technical indicator, the average return of long positions on 99 cryptocurrencies is lower than the average return on buy and hold trading strategies in general. When the trade signal of MACD is used, the average return is 0.0589, which is higher than the average buy and hold return of 0.0265. When MACD is used, the returns on 65 cryptocurrencies are higher than the average buy and hold return, but those on only three coins are statistically significant at 5% confidence level. Short selling of cryptocurrencies using only one technical indicator shows much worse results than buy and hold strategies. The findings indicate that trading strategies based on one technical indicator, regardless of long or short position, do not generate higher returns than the simple buy and hold strategy [3].

Table 2 presents the average returns of trading strategies when only one technical indicator was used for five cryptocurrencies with the largest market capitalization; Bitcoin (BTC), Ethereum (ETH), BNB, Ripple (XRP) and Cardano (ADA). The *t*-statistics in the parentheses of the fourth and last columns indicate the statistical test results about whether the average returns of long or short positions based on the five trading indicators are higher

Average buy and hold return	Technical indicator	Average return on long position (number of cryptos with statistical significance)	Number of cryptos with higher returns than buy and hold return when being longed	Average return on short position (number of cryptos with statistical significance)	Number of cryptos with higher returns than buy and hold return when being shorted
0.0265	SAR	0.0206 (0)	41	-0.0153 (0)	34
	MACD	0.0589 (3)	65	-0.0018 (1)	38
	MFI	-0.0038 (0)	30	-0.0149 (0)	25
	CCI	0.0071 (0)	32	-0.0256 (0)	20
	RSI	0.0216 (0)	44	-0.0312 (0)	17

Note(s): This table presents the average returns of 99 crypto currencies when trading strategies are implemented over 10 trading days based on each technical indicator, and the simple buy and hold return over the same period. The technical indicators include SAR (parabolic stop and reverse), MACD (moving average convergence divergence), MFI (money flow index), CCI (commodity channel index) and RSI (relative strength index). The value in parentheses is the number of cryptos with the returns that are statistically higher than the average buy and hold return

Source(s): Table by authors

Table 1.
Trading results using
one technical indicator

	Crypto	B&H_ return	Long_return (<i>t</i> -stat)	The portion of positive returns	Short_return (<i>t</i> -stat)	The portion of positive returns
SAR	BTC	0.0160	0.0064 (−0.37)	0.62	−0.0161 (−0.00)	0.36
	ETH	0.0150	0.0039 (−0.32)	0.49	0.0043 (0.58)	0.41
	BNB	0.0380	−0.0270 (−1.50)	0.60	−0.0236 (0.38)	0.44
	XRP	0.0015	−0.0106 (−0.26)	0.41	0.0153 (0.38)	0.42
	ADA	0.0164	−0.0362 (−1.32)	0.45	−0.0265 (−0.26)	0.48
MACD	BTC	0.0160	0.0168 (0.02)	0.65	0.0500 (1.69)	0.77
	ETH	0.0150	0.0675 (0.95)	0.75	−0.0109 (0.07)	0.31
	BNB	0.0380	0.0360 (−0.03)	0.67	−0.0047 (0.52)	0.62
	XRP	0.0015	−0.0087 (−0.18)	0.39	0.0549 (0.98)	0.63
	ADA	0.0164	0.0373 (0.35)	0.50	0.0420 (1.00)	0.67
MFI	BTC	0.0160	−0.0036 (−0.78)	0.46	0.0019 (0.69)	0.52
	ETH	0.0150	0.0141 (−0.02)	0.50	−0.0119 (0.09)	0.46
	BNB	0.0380	−0.0133 (−1.03)	0.45	−0.0500 (−0.29)	0.38
	XRP	0.0015	0.0530 (1.17)	0.63	0.0040 (0.11)	0.52
	ADA	0.0164	−0.0686 (−2.04)	0.40	−0.0117 (0.11)	0.48
CCI	BTC	0.0160	−0.0145 (−1.24)	0.47	−0.0043 (0.48)	0.50
	ETH	0.0150	−0.0273 (−1.17)	0.45	−0.0192 (−0.13)	0.45
	BNB	0.0380	−0.0048 (−0.99)	0.63	−0.0534 (−0.39)	0.35
	XRP	0.0015	0.0072 (0.13)	0.53	0.0146 (0.37)	0.47
	ADA	0.0164	−0.0035 (−0.52)	0.48	0.0036 (0.48)	0.56
RSI	BTC	0.0160	0.0163 (0.01)	0.50	0.0076 (0.79)	0.50
	ETH	0.0150	0.0187 (0.09)	0.57	0.0032 (0.49)	0.40
	BNB	0.0380	−0.0266 (−1.39)	0.38	−0.0332 (0.10)	0.37
	XRP	0.0015	0.0490 (0.93)	0.62	0.0148 (0.33)	0.58
	ADA	0.0164	0.0138 (−0.05)	0.53	−0.0150 (0.03)	0.52

Note(s): This table presents the average returns of trading strategies when only one technical indicator was used for five cryptocurrencies with the largest market capitalization. Five cryptocurrencies are Bitcoin (BTC), ethereum (ETH), binance coin (BNB), ripple (XRP) and cardano (ADA). The *t*-statistics in the parentheses of the fourth and last columns indicate the statistical test results about whether the average returns of long or short positions based on the five trading indicators are higher than the relevant buy-and-hold return. The technical indicators include SAR (parabolic stop and reverse), MACD (moving average convergence divergence), MFI (money flow index), CCI (commodity channel index) and RSI (relative strength index)

Source(s): Table by authors

Table 2.
Top 5 cryptocurrencies
by market cap and 1
technical indicator

than the relevant buy-and-hold return. The results imply that the trading strategies using each technical indicator do not generate abnormal returns in top five cryptocurrencies [4].

4.2 The returns of trading strategies based on two technical indicators

When we implement trading strategies using two technical indicators, we select a main indicator and then a sub-indicator out of the other four indicators. Therefore, we implement 40 trading strategies for the test. For implement the trading strategies, we assume to basically follow the trading signal of the main indicator, and begin trading by looking at the value of the sub-indicator. For example, when MFI, a main indicator, generates a buy signal (when it changes from a value below 50 to over 50) and then when the value of a subindicator, MACD, also generates a buy signal (a value greater than 0), it is assumed to buy a cryptocurrency. Conversely, if the MACD value is not in the buying range, no trading is made.

Table 3 shows the average returns when trading strategies using two technical indicators are implemented. We present the average returns of 40 trading strategies (long and short positions, respectively) by the combination of main and subindicators. The value in parentheses is the number of cryptocurrencies of which the returns are statistically

	SUB Main	SAR Average return	MACD Average return	MFI Average return	CCI Average return	RSI Average return
Long	SAR	–	0.0762 (5)	0.0446 (1)	0.0185 (0)	0.0572 (2)
	MACD	0.0609 (4)	–	0.0696 (2)	0.0288 (0)	0.0617 (3)
	MFI	0.0197 (1)	0.0675 (5)	–	–0.0014 (1)	0.0528 (3)
	CCI	0.0264 (1)	0.0572 (3)	0.0424 (0)	–	0.0487 (1)
	RSI	0.0311 (0)	0.0386 (1)	0.0158 (1)	0.0149 (1)	–
Short	SAR	–	0.0402 (2)	0.0381 (5)	–0.0226 (0)	0.0257 (3)
	MACD	–0.0074 (0)	–	–0.0166 (0)	0.0295 (3)	–0.0021 (0)
	MFI	–0.0118 (1)	0.0211 (1)	–	0.0054 (0)	0.0076 (1)
	CCI	–0.0156 (0)	0.0342 (2)	0.0264 (4)	–	0.0180 (3)
	RSI	–0.0239 (0)	0 (1)	–0.0179 (0)	–0.0188 (0)	–

Note(s): This table present the average returns when trading strategies using two technical indicators are implemented and present the average returns of 40 trading strategies (long and short positions, respectively) by the combination of main and sub indicators. The value in parentheses is the number of cryptocurrencies of which the returns are statistically significant at 5 percent confidence level. The technical indicators include SAR (parabolic stop and reverse), MACD (moving average convergence divergence), MFI (money flow index), CCI (commodity channel index) and RSI (relative strength index)

Source(s): Table by authors

Table 3.
Trading results using two technical indicators

significant at 5% confidence level. In general, when two technical indicators are used, the average returns are slightly higher, compared to those when one technical indicator is used. When MACD and RSI are used as subindicators, a slightly higher return are obtained than when other technical indicators are used as sub-indicators. However, the number of cryptocurrencies that generate the returns with statistical significance are small. The findings suggest that the trading strategies using even two technical indicators do not generate excess returns.

We present the results of applying two technical indicators to the five cryptocurrencies by with largest market capitalization in Table 4 as we do in Table 2. Table 4 presents the average return of a long position, *t*-statistics in parentheses, and the portion of positive returns. The *t*-statistics indicate that the returns are not statistically significant in general.

Table 5 presents the results of short positions using two technical indicators. The results are qualitatively similar to those presented in Table 4. The findings in Tables 4 and 5 indicate that technical trading does not outperform the simple buy-and-hold strategy even when two technical indicators are applied to large cryptocurrencies.

5. Conclusion

In this study, we apply trading strategies using various technical indicators into cryptocurrency market to test a weak-form efficiency. We utilize one technical indicator or the combination of two technical indicators to construct the trading strategies and take long or short positions based on the signal for those strategies. Using the most comprehensive and recent data of 99 cryptocurrencies, we generate returns from the trading strategies and compare them to those from simple buy and hold trading strategies. We find that the returns based on single technical indicators or the combination of two indicators is not statistically different from the buy-and-hold returns in general, regardless of long or short positions.

Our findings support that cryptocurrency market are weak-form efficient in general. The results are contrary to the evidence of inefficient cryptocurrency markets documented in the previous literature. Considering the rapid growth of cryptocurrency markets and the recent bubbles and bursts in the market, we suspect that the evidence of inefficient markets might be

Table 4.
Top 5 cryptocurrencies
by market cap and 2
technical indicators
(long position)

Main	SUB	BTC	ETH	BNB	XRP	ADA	The portion of positive returns
		Return (<i>t</i> -stat)	Return (<i>t</i> -stat)	Return (<i>t</i> -stat)	Return (<i>t</i> -stat)	Return (<i>t</i> -stat)	
SAR	MACD	0.0044 (−0.39)	0.0190 (0.10)	0.0725 (0.76)	−0.0111 (−0.19)	0.0594 (0.86)	0.47
	MFI	0.0128 (−0.10)	0.0320 (0.39)	0.0370 (−0.02)	0.0032 (0.02)	0.0472 (0.64)	0.58
	CCI	0.0603 (1.05)	−0.0540 (−1.25)	0.0464 (0.14)	0.0174 (0.25)	−0.0095 (−0.42)	0.45
	RSI	0.0352 (0.65)	0.0549 (0.97)	0.0668 (0.65)	0.0492 (0.83)	0.0135 (−0.06)	0.43
MACD	SAR	0.0168 (0.02)	0.1040 (1.55)	0.0360 (−0.03)	−0.0099 (−0.20)	0.0516 (0.57)	0.55
	MFI	−0.0180 (−0.87)	0.0675 (0.95)	0.0494 (0.15)	−0.0229 (−0.45)	0.0434 (0.44)	0.55
	CCI	0.0588 (0.69)	−0.0156 (−0.28)	0.0136 (−0.24)	0.0162 (0.16)	0.1677 (1.71)	1.00
	RSI	0.0168 (0.02)	0.0675 (0.95)	0.0360 (−0.03)	−0.0022 (−0.05)	0.0373 (0.35)	0.50
MFI	SAR	0.0214 (0.19)	0.0108 (−0.12)	0.0456 (0.15)	0.1033 (2.08)	−0.0628 (−1.77)	0.41
	MACD	0.0351 (0.63)	0.0209 (0.14)	0.1219 (1.54)	0.0200 (0.33)	0.0515 (0.70)	0.59
	CCI	−0.0178 (−0.92)	−0.0269 (−1.00)	0.0429 (0.09)	−0.0308 (−0.53)	−0.1115 (−2.42)	0.33
	RSI	0.0206 (0.15)	0.0206 (0.14)	0.0863 (1.02)	0.0537 (1.00)	0.0080 (−0.16)	0.56
CCI	SAR	0.0160 (0.00)	0.0558 (1.01)	−0.0131 (−1.10)	0.0518 (1.00)	0.0199 (0.08)	0.52
	MACD	0.0562 (1.38)	0.0302 (0.40)	0.0693 (0.73)	−0.1045 (−1.99)	0.0793 (1.29)	0.44
	MFI	0.0320 (0.54)	0.0506 (0.81)	−0.0185 (−1.43)	−0.0118 (−0.27)	0.0577 (0.90)	0.52
	RSI	0.0490 (1.30)	−0.0013 (−0.43)	0.0282 (−0.24)	−0.0505 (−1.02)	0.0520 (0.84)	0.48
RSI	SAR	0.0159 (−0.00)	0.0323 (0.40)	0.0067 (−0.62)	0.0499 (0.93)	0.0529 (0.74)	0.61
	MACD	0.0319 (0.43)	−0.0124 (−0.62)	0.0736 (0.66)	−0.0717 (−1.31)	0.0554 (0.78)	0.53
	MFI	−0.0107 (−0.91)	0.0281 (0.29)	0.0105 (−0.62)	0.0156 (0.29)	0.0394 (0.48)	0.58
	CCI	0.0123 (−0.10)	0.0003 (−0.16)	−0.0369 (−1.44)	0.0740 (0.73)	0.0335 (0.32)	0.47

Note(s): This table presents the results of applying two technical indicators to the five cryptocurrencies by with largest market capitalization as in Table 2, and presents the average return of a long position, *t*-statistics in parentheses and the portion of positive returns. Five cryptocurrencies are bitcoin (BTC), ethereum (ETH), binance coin (BNB), ripple (XRP) and cardano (ADA). The technical indicators include SAR (parabolic stop and reverse), MACD (moving average convergence divergence), MFI (money flow index), CCI (commodity channel index) and RSI (relative strength index)

Source(s): Table by authors

Main	SUB	BTC		ETH		BNB		XRP		ADA	
		Return (<i>t</i> -stat)	The portion of positive returns	Return (<i>t</i> -stat)	The portion of positive returns	Return (<i>t</i> -stat)	The portion of positive returns	Return (<i>t</i> -stat)	The portion of positive returns	Return (<i>t</i> -stat)	The portion of positive returns
SAR	MACD	-0.0305 (-0.42)	0.24	0.0657 (1.52)	0.54	0.0494 (1.38)	0.54	-0.0316 (-0.46)	0.33	0.0515 (1.32)	0.50
	MFI	0.0368 (1.57)	0.50	0.0837 (1.92)	0.57	0.0075 (0.60)	0.56	0.0392 (0.71)	0.44	0.0270 (0.71)	0.55
	CCI	0.0213 (1.18)	0.48	0.0165 (0.67)	0.47	-0.0301 (0.15)	0.45	-0.0056 (-0.06)	0.38	0.0243 (0.74)	0.43
MACD	RSI	0.0129 (0.99)	0.44	0.0232 (0.81)	0.47	0.0210 (1.02)	0.44	0.0262 (0.52)	0.47	0.0206 (0.75)	0.56
	SAR	0.0500 (1.69)	0.77	0.0168 (0.59)	0.31	-0.0047 (0.52)	0.62	0.0544 (0.97)	0.63	0.0321 (0.86)	0.62
	MFI	0.0517 (1.54)	0.70	-0.0109 (0.07)	0.31	-0.0058 (0.49)	0.58	0.0716 (0.98)	0.78	0.0429 (0.84)	0.63
MFI	CCI	0.0313 (0.77)	0.80	-0.0076 (0.05)	0.50	-0.0289 (0.09)	0.60	0.0413 (0.51)	0.57	0.0347 (0.45)	0.67
	RSI	0.0500 (1.69)	0.77	-0.0109 (0.07)	0.31	-0.0129 (0.38)	0.58	0.0395 (0.71)	0.56	0.0420 (1.00)	0.67
	SAR	0.0255 (1.62)	0.58	0.0293 (1.09)	0.52	-0.0085 (0.69)	0.41	0.0271 (0.62)	0.59	-0.025 (-0.21)	0.42
CCI	MACD	0.0149 (1.11)	0.48	0.0542 (1.61)	0.60	0.0108 (0.98)	0.50	0.0018 (0.06)	0.50	0.0116 (0.61)	0.45
	RSI	-0.0131 (0.10)	0.44	-0.0008 (0.31)	0.53	0.0091 (0.84)	0.47	0.0282 (0.54)	0.67	0.0181 (0.70)	0.50
	SAR	-0.0112 (0.18)	0.50	0.0477 (1.58)	0.58	0.0392 (1.55)	0.50	0.0013 (0.06)	0.48	0.0119 (0.70)	0.52
RSI	MACD	0.0006 (0.57)	0.40	0.0093 (0.55)	0.30	0.0120 (0.96)	0.50	-0.0261 (-0.50)	0.39	0.0445 (1.18)	0.53
	MFI	0.0089 (0.88)	0.48	-0.0002 (0.35)	0.41	-0.0673 (-0.43)	0.36	0.0165 (0.33)	0.33	0.0203 (0.57)	0.56
	SAR	0.0318 (1.80)	0.52	-0.0095 (0.14)	0.31	-0.0399 (-0.03)	0.38	-0.0129 (-0.26)	0.42	0.0143 (0.64)	0.56
MACD	RSI	0.0350 (1.78)	0.62	0.0126 (0.73)	0.39	-0.0204 (0.36)	0.38	0.0195 (0.42)	0.61	0.0064 (0.52)	0.61
	MFI	0.0095 (0.75)	0.56	0.0049 (0.40)	0.53	0.0379 (1.39)	0.56	0.0129 (0.19)	0.44	0.0313 (0.78)	0.64
	CCI	0.0239 (1.12)	0.69	0.0356 (1.20)	0.45	-0.0441 (-0.09)	0.31	0.0259 (0.42)	0.58	0.0169 (0.66)	0.59
		0.0195 (1.10)	0.55	-0.0005 (0.17)	0.47	-0.1060 (-1.11)	0.14	0.0380 (0.72)	0.50	-0.0399 (-0.38)	0.36

Note(s): This table present the results of applying two technical indicators to the five cryptocurrencies by with largest market capitalization as in Table 2, and presents the average return of a short position, *t*-statistics in parentheses, and the portion of positive returns. Five cryptocurrencies are bitcoin (BTC), Ethereum (ETH), binance coin (BNB), ripple (XRP) and cardano (ADA). The technical indicators include SAR (parabolic stop and reverse), MACD (moving average convergence divergence), MFI (money flow index), CCI (commodity channel index) and RSI (relative strength index)

Source(s): Table by authors

Table 5.
Top 5 cryptocurrencies
by market cap and 2
technical indicators
(short position)

sample-specific. In the efficient market, it is very difficult for investors to earn better returns using the information of the past price movement or trading volume, compared to the simple buy and hold strategy. Our results also cast doubt on the profitability of programmatic trading systems built on technical indicators.

Notes

1. Refer to [Fang et al. \(2022\)](#) for the survey of the research on cryptocurrency trading.
2. Refer to [Fang et al. \(2022\)](#) for the growth of cryptocurrency markets.
3. We do not consider transaction costs to implement the technical trading strategies used in this research. The inclusion of transaction costs would make the returns of the trading strategies even worse, which will corroborate our argument on the weak-form efficiency of cryptocurrency markets.
4. The results presented in [Table 2](#) are comparable to [Groby's et al.'s \(2020\)](#) findings even though the sample period and trading strategies are different. [Groby's et al. \(2020\)](#) investigate the data on 11 largest cryptocurrencies over the period of 2016–2018 while our data from Binance covers the period of 2017–2021. The variable moving average strategy used in their paper is different from the MACD indicator used in this research. They document that the trading rules generate excess returns. However, our results in [Table 2](#) show that the return from long positions on ETH based on MACD indicator and the return from short positions on XRP are higher than those from the simple buy and hold strategies, but they are not statistically significant.

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About the authors

JunHyeong Jin is a MS student in Dept. of Fintech, Sungkyunkwan University in Seoul, Korea. He has been doing active research in fintech area after he admitted to the MS program in 2021, and will graduate in February, 2023 with a MS degree in Fintech.

JiHoon Jung is a MS student in Dept. of Fintech, Sungkyunkwan University in Seoul, Korea. He has been doing active research in fintech area after he admitted to the MS program in 2021, and will graduate in February, 2023 with a MS degree in Fintech.

Kyojik Song is a professor of finance at Sungkyunkwan University (SKKU) in Seoul, Korea. He received Ph.D. in finance from Louisiana State University (LSU) in 2003, and he has been an active researcher in the field of corporate finance and closed-end funds. His research focus has been on the payout policy of closed-end funds, equity offering, corporate cash holdings, fintech, etc. For last several years, he has published papers in leading journals in finance, such as *Journal of Financial Economics*, *Journal of Financial and Quantitative Analysis*, *Financial Management* and *Journal of Banking and Finance*. Kyojik Song is the corresponding author and can be contacted at: roysong@skku.edu

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