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A Technical Analysis of Indonesia Stock Market (IDX) Composite Index

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Abstract

Does technical analysis outperform a buy-and-hold strategy? This study compares the returns of technical analysis based on four indicators (moving average, relative strength index, and moving average convergence divergence) to the returns of a buy-and-hold from January 2008 to September 2021 for the Indonesian Stock Exchange Composite Index (IDX). This study collects daily closing price data, then generates buy and sell signals for each indicator. Daily returns are sorted into buy-day returns and sell-day returns, then compared to overall buy-and-hold returns. For each indicator, four t-tests are applied to see if there is a statistically significant difference between (1) buy-day returns and buy-and-hold returns, (2) sell-day returns and buy-and-hold returns, (3) buy-day returns and sell-day returns, and (4) technical analysis returns and buy-and-hold returns. This study finds that for all the t-tests, technical analysis does not statistically significantly outperform a buy and hold strategy. This finding is consistent with the IDX being weak-form market efficient.

Keywords
Indonesia stock market (IDX); technical analysis; composite index

I. Introduction

The number of Indonesian retail investors has increased by 95% in the year 2021 (Kenneth & Husodo, 2021), especially in millennials and younger (Budiarso & Pristy, 2021). This has been linked to Covid-19 pushing people to spend more time at home. Many of these people decide to start investing in the stock market. The presence of Covid-19 as a pandemic certainly has an economic, social and psychological impact on society (Saleh and Mujahiddin, 2020).

However, their rate of investment literacy is relatively low. According to a survey by the Financial Services Authority, the Indonesian financial literacy index is 38.08% in 2019, up from 29.7% in 2016 (Prasidya, 2020). This number is worryingly low. With an increase in the numbers of unsophisticated retail investors and a dizzying array of potential strategies, there needs to be educational materials that are relatively easy for retail investors to understand.

This study compares two investment strategies that are relatively easy for retail investors to understand and execute. The first strategy is to passively buy and hold the Indonesian composite stock index. The second strategy is to use simple technical analysis to make buy and sell decisions based on market data that is free and easy to find.

The research question being asked is: As applied to the Indonesian Stock Composite Index (IHSG) during the time period 1 January 2008 to 30 September 2021, do investment strategies based on technical analysis provide higher returns than buying and holding?

This research question indirectly tests the weak-form efficient market hypothesis, which states that stock market prices fully reflect all past information related to the trading of said stock (Fama, 1970). If such a hypothesis is true, then investors cannot consistently

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achieve excess returns using technical analysis. The correctness of the efficient market hypothesis is still an active field of study, with studies in various countries using various methodologies giving inconsistent results (Han et al., 2011; Leković, 2018).

Leković (2018) states that there are two general groups of tests for weak-form market efficiency: the first is an autocorrelation test (also known as a random walk test) to see if future price movements are correlated with past price movements. The second group of tests use technical analysis on past data to search for opportunities to earn excess returns.

Studies using autocorrelation tests on Indonesian stocks have been inconclusive on weak-form efficiency. Various autocorrelation studies have found that Indonesian stocks are weak-form efficient (Andrianto & Mirza, 2016; Chye, 1992; Erdaş, 2020; Malhotra et al., 2015; Worthington & Higgs, 2006). Other autocorrelation studies find that Indonesian stocks are not weak-form efficient (Kiky, 2018; Mubarok & Fadhli, 2020; Munir et al., 2012; Utomo & Fuad, 2008).

Studies using technical analysis tend to show that the Indonesian stock market is weak-form efficient. Only one old study (Ito, 1999) found that technical analysis provides excess returns. Other studies find that technical analysis doesn't offer excess returns after accounting for transaction costs (Chen et al., 2009; Heng & Niblock, 2014; Tharavanij et al., 2015). Recent studies tend to show that investors can't use technical analysis alone to gain excess returns in the Indonesian market.

This study uses the technical analysis methodology to search for opportunities to earn excess returns in the Indonesian stock market.

II. Review of Literature

2.1 Technical Analysis and the Efficient Market Hypothesis

Technical analysis finds its roots in Dow Theory, which states that price movements in a market are somewhat predictable, and analogous to rising or falling tides (Schannep, 2008). There are primary movements, secondary movements, and noise. An investor who can correctly predict when primary or secondary movements form or reverse will be able to make profitable trades. Technical analysis has become broader, and can be defined as the study of past market information to predict future price movements.

The Efficient Market Hypothesis (EMH), originally formulated by Fama (1970), states that prices in an efficient market already reflect all available information. There are three tests of efficiency: weak form efficiency where prices reflect historic market information, semi-strong efficiency where prices reflect publicly available information, and strong efficiency where prices reflect private information. Fama acknowledges that his hypothesis requires assumptions (no transaction cost, no information cost, agreement on how to interpret information) that are not true. Therefore, studies have generally focused on whether the efficient market hypothesis is good enough as a model.

Malkiel (2003) defines an efficient market as one where an investor cannot achieve excess returns without taking on excess risk. Leković (2018) and O'Sullivan (2018) have identified a few known theoretical and empirical weaknesses in the EMH. First, if the EMH was proven true and became widely accepted, then nobody would study prices and prices would become inefficient as a result. Second, EMH proponents tend to tautologically dismiss failures of EMH as market anomalies. Empirical weaknesses have been found, most famously Jegadees & Titman's (1993) momentum effect. Malkiel (2003) counters that "whatever patterns or irrationalities in the pricing of individual stocks … have been discovered … are unlikely to persist". In the example of momentum trading, transaction costs are too high and economic significance too low to earn a reliable profit.

2.2 Technical Analysis Indicators

Technical analysis indicators are tools that use past market data to predict future price movements. These indicators should help investors to identify primary or secondary trends in a market. This study selects four indicators based on previous work done by Metghalchi et al. (2019). The chosen indicators are moving average (MA), relative strength index (RSI), moving average convergence divergence (MACD), and rate of change (ROC). These indicators were chosen for simplicity of use and for the useful property of always emitting a buy or sell signal.

2.3 Transaction Costs

Transaction costs are those costs incurred while conducting a transaction. This study includes exchange fees, typical broker fees, and a bid-ask spread to estimate a round-trip transaction cost of 1.238%. Not included are costs related to large-volume transactions.

III. Research Method

3.1 Data

This study simulates trading from 1 January 2008 to 31 September 2021. This study uses IDX Composite closing prices from 1 January 2007 to 31 September 2021, where the data from 2007 is used for trading signals in early 2008. IDX closing price data was sourced from Google Finance. Interest rate data for 1 January 2008 to 31 September 2021 was sourced from the Indonesian Central Bank, using JIBOR and IndONIA rates as available.

For robustness, the study splits this period into two periods. Subperiod 1 is from 1 January 2008 until 31 December 2014, where the market is bullish. Subperiod 2 is from January 2015 until 31 September 2021, where the market has a sideways trend with multiple failures to break 6,600.

Transaction costs was calculated for a single date, 1 October 2021, and assumed to apply to the whole period. Exchange fees were sourced from the Indonesian Stock Exchange, and broker fees were sourced from BNI, which offers brokerage services. Bid-ask spread was calculated using bid price, ask price, and market capitalization data from S&P Capital IQ, which sourced its data from ICE Data Services.

3.2 Technical Indicators

Following (Metghalchi et al., 2019), this study uses four technical indicators, which are the simple moving average (SMA), the relative strength index (RSI), moving average convergence divergence (MACD), and rate of change (ROC). These indicators are chosen for being relatively simple as well as always emitting an unambiguous buy or sell signal.

The simple moving average is a lagging indicator calculated by taking the mean of the last 30-, 50-, 100-, 150-, or 200-days' closing prices. A buy (sell) signal is emitted when the SMA is higher (lower) than the last closing price.

The relative strength index is a leading momentum indicator (Lavanya, 2019) that looks at price movements. It is calculated using the original formula (Wilder, 1978):

$$RSI_{t=14} = 100 - \frac{100}{1 + RS} \quad (1)$$

Where

$$RS = \frac{average\ of\ positive\ returns_{t=14}}{|average\ of\ negative\ returns_{t=14}|} \quad (2)$$

Where the average positive or negative returns are calculated using a simple 14-day average for the initial value and calculated using a 14-day exponential moving average for future values. Following (Metghalchi et al., 2019), this study uses Wilder's (1978) suggestion of a 14-day calculation period. Following (Metghalchi et al., 2019), the RSI emits a buy signal when its value is above 50, and emits a sell signal when its value is at or below 50 such that there is always a buy or sell signal.

The moving average convergence divergence is leading indicator taking a short-period exponential moving average and subtracting it by a long-period moving average. A signal line is taken using an exponential moving average of the MACD. This study uses the original suggestion (Appel, 1974) of 12 days for the short period, 26 days for the long period, and 9 days for the signal line. There is a buy signal whenever the MACD is above the signal, and a sell signal otherwise.

The rate of change is a lagging momentum indicator that measures the speed of price movements as a proportion of the price. This study follows (Metghalchi et al., 2019) in using time periods of 10, 20, and 30 days. A buy (sell) signal is emitted whenever the ROC is positive (not positive).

3.3 Calculations of Returns

The index returns are calculated daily and converted to a daily logarithmic return. The money market interest rate is likewise converted into a daily logarithmic return.

$$R_t = \log(P_t/P_{t-1}) \tag{3}$$

Where R_t is the logarithmic return for day *t*, P_t is the closing price on day *t*, and P_{t-1} is the closing price on day *t-1*.

Following (Metghalchi et al., 2015, 2019), this study assumes a one-day lag between the emission of a signal and the trader's ability to move in and out of the market based on that signal. This study assumes that, some time before trading closes on day t-1, the trader can calculate the price at which a buy or sell signal is emitted. The trader waits until a few minutes before closing and places a conditional order based on the signal price, and trades at closing price. The trader is in or out of the market at the end of day t-1, based on the closing price at the end of day t-1. Since returns are calculated as $R_t = P_t/P_{t-1}$, the trader gets a return on day t based on the outcome of the limit order placed at the end of day t-1.

Buy days (sell) days are defined as days in which the trader has a buy (sell) position. This position lags one day behind the signal. Index returns on buy (sell) days are equal to the index returns whenever the trader has a buy (sell) position, and are not calculated otherwise. The average returns of buy days is calculated using the arithmetic mean of logarithmic returns. The average returns for sell days and for buy-and-hold days is calculated analogously.

The returns on buy days and sell days for each indicator, as well as returns on a buy-and-hold strategy will be compared with each other. If the returns on buy or sell days based on technical indicators are not meaningfully different than buy and hold returns, then the technical indicators chosen will not provide excess returns. The test hypotheses are listed below:

Table 1. Test Hypotheses 1-3

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**
Null	$\mu_B - \mu_H = 0$	$\mu_S - \mu_H = 0$	$\mu_B - \mu_S = 0$
Alternative	$\mu_B - \mu_H \neq 0$	$\mu_S - \mu_H \neq 0$	$\mu_B - \mu_S \neq 0$

These hypotheses will be tested using Welch's unequal variances t-test. Using a t-test on non-normal data provides valid results as long as there are enough observations, since the Central Limit Theorem will lead to a normal distribution of the mean (Lumley et al., 2002). Estimates on how many observations differ depending on how much the sample deviates from normality, but 80 observations is a conservative estimate (Lumley et al., 2002; Ratcliffe, 1968; Sawilowsky & Hillman, 1992). The test statistic for Hypothesis 1 is defined below:

$$t = \frac{X_B - X_H}{\sqrt{\left(\frac{VAR_B}{N_B}\right) + \left(\frac{VAR_H}{N_H}\right)}} \tag{4}$$

Where X_B and X_H are the sample mean returns of buy days and buy-and-hold days, VAR_B and VAR_H are the sample variance of buy day and buy-and-hold day returns, and N_B and N_H are the number of buy days and buy-and-hold days. The test statistics for hypotheses 2 and 3 substitute the relevant variables in this formula. The critical t-value will be t=1.96, which corresponds to a two-tailed test at p=0.05.

3.4 Trading Strategies

It would be more economically useful to simulate trading based on technical analysis. What kind of position should be held on buy days, and what kind of position on sell days? Following (Metghalchi et al., 2019), there are two possible positions on buy days: taking a long position on the index, and leveraging a long position on the index while borrowing at the money market rate. For sell day positions, this study uses only the money market rate, since short-selling is often banned in the Indonesian stock market. The total returns for each trading strategy are listed below:

Table 2. Returns on Various Trading Strategies

Trading Strategy	Returns on Buy Days	Returns on Sell Days
Without Leverage	$TR_t = R_t$	$TR_t = M_t$
With Leverage	$TR_t = 2R_t - M_t$	$TR_t = M_t$
Buy-and-Hold (for comparison)	$TR_t = R_t$	$TR_t = R_t$

Source: Adapted from (Metghalchi et al., 2019)

The daily difference of returns is the difference between the total returns of a trading strategy, and the returns on a buy and hold strategy:

$$ddif_t = TR_t - R_t \tag{5}$$

Where TR_t is the logarithmic total return on day t, and R_t is the logarithmic index return on day t.

Hypothesis 4 tests whether or not the daily difference of returns (ddif) for each combination of trading strategy and indicator is different from zero. The null hypothesis is that $ddif = 0$, and the alternative is that $ddif \neq 0$. The test statistic uses a one-variable t-test, shown below:

$$t = \frac{X(ddif)}{\sqrt{Var(ddif)/N}} \tag{6}$$

Where $X(ddif)$ is the mean of the ddif, $Var(ddif)$ is the variance of the ddif, and N is the number of trading days. Using a two-tailed test at p=0.05, the critical t-value is 1.96.

3.5 Calculating for Transaction Costs

Whether or not a trader can realistically use technical analysis to gain excess returns also depends on transaction costs. For each indicator and trading strategy, this study calculates the one-way break-even cost (BEC), which is the transaction cost at which a trading strategy provides zero excess returns. BEC is calculated using the following formula:

$$BEC(logarithmic) = (\sum ddif)/N \tag{7}$$

BEC is initially calculated in a logarithmic form, as the sum of the daily difference in returns (ddif) divided by the number of one-way transactions (N). It is then transformed into a more intuitive percentage form using the following formula:

$$BEC = 100\% - 10^{-BEC\ (logarithmic)} \tag{8}$$

The BEC will then be compared to the actual transaction cost, which is estimated at 0.626% for a one-way transaction. This number is estimated by adding broker fees, exchange fees, and the bid-ask spread for a round-trip transaction, divided by two. This transaction cost was calculated for 31 September 2021 and might not be accurate for previous years. Impact costs are not calculated.
For each trading rule and strategy, the Sharpe ratio will also be calculated to see whether any excess returns can be had without taking excess risks.

Lastly, an annual excess return will be calculated. This starts with calculating the gross annual excess return, which is the sum of ddif over a trading period divided by the number of years in that trading period, expressed in a percentage form. The net annual excess return is calculated by taking the gross annual excess return and reducing it by the average transaction cost for a year.

IV. Results and Discussion

Table 3 summarizes the descriptive statistics for the IDX Composite Index, written in logarithmic returns. The most striking result is that the first subperiod has a mean return of 0.000170, which is about 3.7 times the mean return of the second subperiod at 0.000046. These numbers confirm that subperiod 1 reflects a bullish market, while subperiod 2 reflects a sideways market. The kurtosis and skewness show that the data deviates somewhat from a normal curve. Fortunately, these deviations are low enough, and the number of observations high enough, that using t-tests will result in valid results (Lumley et al., 2002).

Table 3. Descriptive Statistics for Logarithmic Returns

Time Period	Mean	Median	SD	Kurt.	Skew	Min	Max	n
1 Jan 2008 – 31 Sept 2021	0.000108	0.000403	0.005674	8.7605	-0.5623	-0.04757	0.04214	3304

1 Jan 2008 – 31 Dec 2014	0.000170	0.000555	0.006622	7.1416	-0.6725	-0.04757	0.03311	1670
1 Jan 2015 – 31 Sept 2021	0.000046	0.000259	0.004504	8.6655	-0.1389	-0.02955	0.04214	1634

Mean is the arithmetic mean, Median is the median, SD is the standard deviation, Kurt. is kurtosis, Skew is the skewness, Min is the minimum value, Max is the maximum value, and n is the number of trading days in the period.

Table 4. Returns on IDX Composite using Various Indicators, Full Period

Indicator	Buy	Sell	Buy/Sell	SD buy	SD sell	N_B	N_S	Trades
SMA 30	0.000231 (0.89)	-0.000101 (-0.9)	0.000333 (1.44)	0.00443	0.00733	2088	1216	316
SMA 50	0.000203 (0.7)	-0.000063 (-0.71)	0.000266 (1.12)	0.00435	0.00750	2131	1173	222
SMA 100	0.000228 (0.86)	-0.000096 (-0.89)	0.000324 (1.41)	0.00452	0.00724	2090	1214	140
SMA 150	0.000152 (0.31)	0.000027 (-0.34)	0.000125 (0.52)	0.00450	0.00743	2174	1130	128
SMA 200	0.000163 (0.4)	-0.000007 (-0.46)	0.000170 (0.68)	0.00458	0.00750	2255	1049	86
RSI	0.000219 (0.8)	-0.000098 (-0.85)	0.000316 (1.31)	0.00441	0.00750	2159	1145	348
MACD	0.000098 (-0.07)	0.000120 (0.06)	-0.000022 (-0.11)	0.00498	0.00631	1666	1638	279
ROC 10	0.000155 (0.32)	0.000043 (-0.32)	0.000112 (0.53)	0.00484	0.00668	1937	1367	479
ROC 20	0.000237 (0.92)	-0.000089 (-0.89)	0.000327 (1.47)	0.00442	0.00719	2005	1299	330
ROC 30	0.000220 (0.79)	-0.000067 (-0.79)	0.000288 (1.29)	0.00454	0.00711	2023	1281	272

Source: Author's calculations

Calculations for the full period, beginning 02/01/2008 and ending 30/09/2021. For each indicator: buy is the logarithmic IDX returns on buy position days, sell is the logarithmic IDX returns on sell position days, buy/sell is the average return on by days minus the average return on sell days. SD buy and SD sell refer to the standard deviation of returns for buy and sell position days respectively. N_B and N_S refer to the number of days in the buy position and sell position respectively. Trades refer to the number of one-way trades. Numbers in parentheses are the t-statistics of hypotheses 1, 2, and 3. Numbers that are given an asterisk show statistical significance at p=0.05 for a two-tailed test ($t_{crit.0.05} = 1.96$).

Table 4 summarizes the returns of the IDX composite on buy position and sell position days using various indicators, as well as the results for hypotheses 1-3. None of the tested indicators display a statistically significant ability to predict price movements. While the indicators by themselves generally result in profitable trades without taking transaction costs into account, the relative returns are low enough and the standard deviations high enough that the study fails to reject the null hypotheses for hypotheses 1 through 3 for all indicators. These results also hold true for both subperiods (results not shown). These results are consistent with previous studies that demonstrate weak-form efficiency in Indonesian stock markets.

Table 5. Returns using Simulated Trading Strategies, Full Period

	Without Leverage		With Leverage	
Indicator	M	X(ddif)	M	X(ddif)
	0.000183	0.000074	0.00027	0.000161
SMA 30	[0.00352]	(1.21)	[0.00704]	(1.31)
	0.000167	0.000059	0.000238	0.000129
SMA 50	[0.00350]	(0.96)	[0.00699]	(1.06)
	0.000182	0.000073	0.000267	0.000158
SMA 100	[0.00359]	(1.17)	[0.00718]	(1.27)
	0.000136	0.000027	0.000175	0.000066
SMA 150	[0.00365]	(0.43)	[0.0073]	(0.52)
	0.000146	0.000037	0.000194	0.000086
SMA 200	[0.00378]	(0.56)	[0.00757]	(0.65)
	0.000178	0.000069	0.000259	0.000150
RSI	[0.00356]	(1.11)	[0.00713]	(1.21)
	0.000096	-0.000013	0.000096	-0.000013
MACD	[0.00353]	(-0.2)	[0.00707]	(-0.11)
	0.000131	0.000022	0.000165	0.000057
ROC 10	[0.00371]	(0.35)	[0.00741]	(0.44)
	0.000183	0.000074	0.00027	0.000161
ROC 20	[0.00344]	(1.24)	[0.00689]	(1.34)
	0.000174	0.000065	0.000251	0.000143
ROC 30	[0.00355]	(1.06)	[0.0071]	(1.15)

Source: Author's calculations

Calculations for the full period, beginning 02/01/2008 and ending 30/09/2021. For each indicator: M is the mean logarithmic return, with the standard deviation in square brackets. X(ddif) is the mean daily difference of returns when using a combination of trading strategy and indicator compared to a buy and hold strategy. The parentheses refer to the t-statistic for hypothesis 4. Numbers that are given an asterisk show statistical significance at p=0.05 for a two-tailed test ($t_{crit.0.05} = 1.96$).

Table 5 shows the average daily logarithmic returns of each indicator using two simulated trading strategies. The performance of each indicator and strategy is compared to the buy and hold strategy, highlighted in the mean daily difference of returns (ddif). While the mean daily difference of returns are mostly positive, the standard deviation is high enough that the results are not statistically significant at p=0.05. This study fails to reject the null hypothesis for hypothesis 4, such that these indicators don't provide a statistically significant return in simulated trading for the IDX Composite Index. This test is repeated for subperiods 1 and 2 (not shown) and show similar results.

Even if the indicators and trading strategies don't provide a statistically significant return, perhaps those a trader using those strategies can still gain an economically significant return. The next step of this study is to apply transaction costs to the simulated strategies. In table 6, we find that for the full period, there are two strategies that have greater returns than the buy and hold strategy. Both of these strategies use leverage to increase returns, while using long-period averages and lower numbers of trades to minimize transaction costs. Keeping in mind the Sharpe Ratio of 0.019 for the full period, all of the strategies are riskier than buying and holding.

Table 6. Break Even Costs and Sharpe Ratios for the Full Period

	Without Leverage		With Leverage	
Indicator	BEC%	Sharpe	BEC%	Sharpe
SMA 30	0.179%	0.052	0.386%	0.038
SMA 50	0.200%	0.048	0.441%	0.034
SMA 100	0.396%	0.051	**0.856%**	0.037
SMA 150	0.160%	0.037	0.392%	0.024
SMA 200	0.324%	0.038	**0.754%**	0.026
RSI	0.151%	0.050	0.328%	0.036
MACD	-0.034%	0.027	-0.035%	0.014
ROC 10	0.035%	0.035	0.090%	0.022
ROC 20	0.171%	0.053	0.370%	0.039
ROC 30	0.182%	0.049	0.398%	0.035

Source: Author's calculations

Calculations for the full period, beginning 02/01/2008 and ending 30/09/2021. BEC% is the breakeven cost of transaction in percent. Sharpe ratio is the daily return divided by the standard deviation. Numbers in **bold** refer to a BEC that is higher that the transaction cost of 0.619%.

Table 7. Annual Excess Returns for the Full Period

	Without Leverage				With Leverage			
Indicator	AER (gross)	TC (annual)	AER (net)	Risk%	AER (gross)	TC (annual)	AER (net)	Risk%
SMA 30	4.20%	15.34%	-11.14%	0.35%	9.30%	15.34%	-6.04%	0.70%
SMA 50	3.29%	10.54%	-7.26%	0.35%	7.40%	10.54%	-3.14%	0.70%
SMA 100	4.13%	6.53%	-2.40%	0.36%	9.15%	6.53%	**2.62%**	0.72%
SMA 150	1.51%	5.95%	-4.44%	0.37%	3.73%	5.95%	-2.22%	0.73%
SMA 200	2.05%	3.96%	-1.91%	0.38%	4.84%	3.96%	**0.88%**	0.76%
RSI	3.89%	17.02%	-13.13%	0.36%	8.66%	17.02%	-8.36%	0.71%
MACD	-0.69%	13.43%	-14.12%	0.35%	-0.71%	13.43%	-14.14%	0.71%
ROC 10	1.24%	24.15%	-22.91%	0.37%	3.18%	24.15%	-20.97%	0.74%
ROC 20	4.20%	16.07%	-11.87%	0.34%	9.31%	16.07%	-6.76%	0.69%
ROC 30	3.67%	13.07%	-9.39%	0.36%	8.21%	13.07%	-4.86%	0.71%

Source: Author's calculations

Calculations for the full period, beginning 02/01/2008 and ending 30/09/2021. Gross annualized excess returns (gross AER) minus annualized transaction costs (annual TC) gives the net annual excess return (net AER). The risk is the standard deviation of daily returns. Numbers in **bold** indicate positive excess returns.

Table 7 provides the calculations for excess annual returns after taking transaction costs into account. While most strategies provide gross annual excess returns in the single digit range, these gains do not exceed the high transaction costs. Only two strategies (SMA 100 and SMA 200 with leverage) provide an annual excess return after transaction costs. The leverage allows the investor to accept greater risk for greater rewards, while the indicators chosen result in infrequent trades.

Table 8. Annual Excess Returns for Subperiod 1

	With Leverage				Without Leverage			
Indicator	AER (gross)	TC (annual)	AER (net)	Risk%	AER (gross)	TC (annual)	AER (net)	Risk%
SMA 30	5.14%	13.83%	-8.69%	0.41%	14.07%	13.83%	**0.24%**	0.83%
SMA 50	4.52%	9.08%	-4.56%	0.40%	12.73%	9.08%	**3.64%**	0.81%
SMA 100	6.37%	5.65%	**0.72%**	0.43%	16.76%	5.65%	**11.11%**	0.85%
SMA 150	2.05%	4.91%	-2.85%	0.44%	7.47%	4.91%	**2.56%**	0.88%
SMA 200	1.33%	3.98%	-2.65%	0.46%	5.95%	3.98%	**1.97%**	0.93%
RSI	5.44%	15.04%	-9.60%	0.42%	14.73%	15.04%	-0.32%	0.84%
MACD	-1.67%	12.32%	-13.99%	0.42%	-0.23%	12.32%	-12.55%	0.83%
ROC 10	1.00%	23.61%	-22.62%	0.44%	5.26%	23.61%	-18.35%	0.88%
ROC 20	8.80%	13.42%	-4.62%	0.39%	22.15%	13.42%	**8.72%**	0.78%
ROC 30	4.25%	11.23%	-6.98%	0.42%	12.15%	11.23%	**0.92%**	0.83%

Source: Author's calculations

Calculations for subperiod 1, beginning 02/01/2008 and ending 30/12/2014. Gross annualized excess returns (gross AER) minus annualized transaction costs (annual TC) gives the net annual excess return (net AER). The risk is the standard deviation of daily returns. Numbers in **bold** indicate positive excess returns.

Table 9. Annual Excess Returns for Subperiod 2

	With Leverage				Without Leverage			
Indicator	AER (gross)	TC (annual)	AER (net)	Risk%	AER (gross)	TC (annual)	AER (net)	Risk%
SMA 30	3.23%	16.93%	-13.70%	0.28%	4.57%	16.93%	-12.36%	0.55%
SMA 50	2.03%	12.08%	-10.05%	0.28%	2.15%	12.08%	-9.93%	0.57%
SMA 100	1.85%	7.44%	-5.59%	0.28%	1.78%	7.44%	-5.65%	0.55%
SMA 150	0.94%	7.04%	-6.10%	0.27%	-0.02%	7.04%	-7.06%	0.54%
SMA 200	2.81%	3.94%	-1.13%	0.26%	3.71%	3.94%	-0.23%	0.53%
RSI	2.31%	19.10%	-16.79%	0.28%	2.71%	19.10%	-16.39%	0.56%
MACD	0.34%	14.58%	-14.25%	0.28%	-1.21%	14.58%	-15.79%	0.55%
ROC 10	1.49%	24.70%	-23.22%	0.28%	1.07%	24.70%	-23.64%	0.56%
ROC 20	-0.36%	18.88%	-19.24%	0.29%	-2.58%	18.88%	-21.46%	0.58%
ROC 30	3.08%	15.01%	-11.93%	0.28%	4.26%	15.01%	-10.75%	0.56%

Source: Author's calculations

Calculations for subperiod 2, beginning 02/01/2015 and ending 30/9/2021. Gross annualized excess returns (gross AER) minus annualized transaction costs (annual TC) gives the net annual excess return (net AER). The risk is the standard deviation of daily returns. Numbers in **bold** indicate positive excess returns.

Robustness calculations, as shown in Tables 8 and 9, show that simulated trading based on technical analysis are much more profitable in the first subperiod, with eight of twenty combinations of indicator and trading strategy providing excess returns after transaction costs. Compare that to the second period, where there are no strategies that provide excess returns after transaction costs.

There are various possible reasons for this discrepancy. Perhaps the real transaction costs during the first period were much higher than what they currently are, such that calculating past returns based on current transaction costs erroneously show a possibility of getting excess returns. Perhaps the Indonesian stock market has become more efficient in the past decade, making it more difficult to gain excess returns. Lastly, perhaps the success of the technical indicators are dependent on market conditions, as the first subperiod was more volatile and more bullish than the second.

V. Conclusion

Technical analysis-based investment strategies using variations of the MA, RSI, MACD, and ROC indicators don't provide statistically significantly better returns than a buy and hold strategy as tested for the IDX Composite Index for the time period 1 January 2008 to 30 September 2021. The gross excess returns, while not statistically significant, are positive. After accounting for transaction costs, these net annual excess returns are mostly negative. Robustness analysis shows that technical analysis provides much better returns during the first subperiod (1 Jan 2008 – 30 Dec 2014) than during the second subperiod (1 Jan 2015 – 30 Sep 2021).

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