Article

Trend and Momentum Technical Indicators for Investing in Market Indices

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ABSTRACT

The purpose of this study is to evaluate the effectiveness of technical analysis indicators in investment strategies.We conducted an empirical study using four trend indicators and four momentum indicators across seven market indices. Our methodology employs a parameter optimization process for each indicator and compares the results with classical parameters reported in the economics literature.Our findings indicate that no technical indicator consistently outperforms the buy-and-hold strategy in the long run. In addition, the optimization procedures did not yield significant improvements in the results.This study contributes to the ongoing debate on the effectiveness of technical analysis indicators in securities trading by adding to the literature on the subject.

Keywords: Technical Analysis; Active Investment; Passive Investment; Sharpe Ratio

JEL Classification: . E22, E44, E52

INTRODUCTION

Within the dynamic realm of financial markets, the pursuit of deciphering their intricacies and capitalizing on opportunities for profit has given rise to various methodologies. One such approach that has garnered substantial attention is technical analysis, a structured method for dissecting price and volume time series data, with the overarching objective of maximizing returns by identifying patterns and forecasting future market movements (Murphy, 1999; Chong and Ng, 2008; Pring, 2014). Grounded in three fundamental assumptions, technical analysis posits that (i) all

relevant market information is inherently embedded in price and volume data, (ii) prices evolve in discernible trends over time, and (iii) historical price patterns may cyclically reemerge, reflecting human behavior, especially during moments of extreme market turbulence.

Nevertheless, the efficacy of technical analysis remains a contentious and robustly debated topic in financial literature. Notably, Fama's seminal work challenges the foundational tenets of technical trading. In his groundbreaking study (Fama, 1965), he examined the empirical validity of the random walk model by scrutinizing the distribution of daily returns in the US stock market. His findings cast doubt on the predictive power of past prices, suggesting a close fit between the random walk model and the observed market data. Fama's subsequent exploration of the Efficient Market Hypothesis (Fama, 1970) further questioned the feasibility of forecasting future price movements based on historical price and volume data, asserting that all relevant information is instantaneously incorporated into current asset prices.

However, proponents of technical analysis present counterarguments that emphasize the ubiquitous nature of time-series prediction methodologies. They argue that technical analysis aligns with a broadly accepted framework for analyzing time-series data that is widely employed across various fields, including economics. Furthermore, proponents contend that the random walk model is ill-suited for explaining conspicuous and persistent trends witnessed in different market scenarios. They posit that, while price movements may exhibit noise, dismissing these fluctuations as entirely random appears unrealistic. Additionally, scholars such as Grimes (2012) contend that if markets are inefficient, profitable outcomes from active investment strategies would be implausible, rendering passive approaches, such as index fund

investments, as the sole recommendation. Nevertheless, they point out that market dynamics are not always driven by randomness; rather, they are influenced by human sentiments, particularly under extreme market conditions marked by fear and excitement.

Amidst this ongoing debate, several studies have undertaken systematic reviews of the published literature on technical analysis. Park and Irwin (2007) conducted a review of 95 studies spanning 1988 to 2004, highlighting that 56 studies yielded favorable results for technical analysis. Furthermore, they underscored that across various market types, including stocks, forex, and futures, the number of favorable studies was at least twice that of the unfavorable ones. Complementarily, Nazário et al. (2017) conducted a review of 85 papers published between 1959 and 2014, revealing that 79 of these papers reported positive technical analysis results. However, these reviews have raised pertinent questions such as the possibility of publication bias, where studies with negative outcomes face challenges in publication, and the issue of several studies not accounting for the level of risk associated with their strategies, potentially inflating their reported returns.

Given the profound implications of this discourse regarding the effectiveness of technical analysis and market efficiency, this study explores trends and momentum technical indicators within the realms of oil, market, and currency indices. Specifically, we address the pivotal research question: Is there empirical evidence supporting the notion that active investment strategies grounded in technical indicators can surpass a passive "buy-and-hold" approach in long-term investing? In conjunction with this primary question, we delve into a secondary inquiry: Can technical indicators enhance performance through parameter optimization, recognizing that market conditions may necessitate distinct parameter values?

In addition to this introductory section, this study unfolds as follows. The subsequent section, Methods, delineates the data sources, technical indicators, and experimental methodologies employed. The Results section presents the findings of the study, along with key insights gleaned from existing literature. Finally, we conclude with reflections and outline potential avenues for future research.

LITERATURE REVIEW

According to Murphy (1999), this approach is based on three key assumptions: (i) all relevant market information is reflected in price and volume, (ii) prices move in trends that change over time, and (iii) historical price movements may recur because they are an outcome of human behavior, especially in extreme market situations.

As highlighted by Chong and Ng (2008), the debate on the effectiveness of technical analysis in producing consistent profits has become an extensive and controversial topic. Eugene Fama published two papers, the conclusions of which opposed the main assumptions made by technical traders. In his first study, Fama (1965) tested the empirical validity of the random walk model based on the distribution of the daily returns of a set of stocks in the US market. As a main conclusion, the author provides strong evidence that the random walk model fits the data, and for that reason, the analysis of past prices would have no predictive power for future price movements. In his other work, Fama (1970) discussed the Efficient Market Hypothesis, which assumes that all available information related to a security is already incorporated into its current price. Therefore, predicting future price movements based on past prices and volumes would not be possible because such information would already be reflected in the market.

Alternatively, other authors presented counterarguments to the aforementioned studies. For example, Murphy (1999) argued that every time-series prediction method consists of projecting future behaviors based on past data. Therefore, technical analysis follows a widely accepted methodology for analyzing time-series data, including studies in the economic field. Furthermore, the author argues that the random walk model would not be able to explain the clear and persistent trend present in different market moments. In particular, he pointed out that although price movements are noisy, the assumption that such fluctuations are entirely random is unrealistic. In addition, Grimes (2012) states that, if markets are always efficient, it would not be possible to achieve profits with active investment strategies, and a passive approach that invests in index funds is recommended. However, the author points out that prices are determined by humans and at certain levels, normally extreme ones, and the behavior of market participants will not be random, as these situations involve feelings such as fear and excitement.

Considering the debate presented above, some papers have provided systematic reviews of published articles on technical analyses. Park and Irwin (2007) reviewed 95 studies that were published between 1988 and 2004. They emphasized that 56 studies presented favorable results for technical analysis. Additionally, they point out that for each type of market investigated (stocks, forex, and futures), the number of favorable studies was at least twice the number of unfavorable studies. Complementarily, Nazário et al. (2017) reviewed 85 papers published between 1959 and 2014 and observed that 79 papers reported positive results in technical analysis. However, the authors raised two relevant discussions: (i) there may be a strong publication bias since articles with negative results may be

difficult to publish and (ii) several studies that presented abnormal returns did not adjust for the level of risk taken by the strategies, meaning that such results may be a direct consequence of risk underestimation.

Given the relevance of the discussion on the effectiveness of technical analysis and market efficiency, this study investigated the trend and momentum of technical indicators for investing in oil, market, and currency indices. Specifically, we aimed to answer the following research question [Q1]: is there evidence that active investment strategies, based on technical indicators, can outperform a passive "buy-and-hold" [B&H] approach, which consists of buying a security at the beginning and selling it at the end of a period, in long-term investing?

In addition, to answer Q1, we must address a secondary research question [Q2]: Can technical indicators benefit from a parameter optimization procedure? This question is important because many technical indicators are typically used with classical parameterization, and as a result, their potential performance may be reduced. Furthermore, different market conditions require different parameter values.

METHODOLOGY

The remainder of this paper is organized as follows. First, we described the databases used in this study. We then introduce the eight technical indicators, their parameterizations, and rules for buying and selling stocks. Next, we describe the methodology through which our experiments were conducted. Finally, the measures used to evaluate the results are presented.

Data collection and preprocessing

The datasets consist of daily open, close, high, and low prices and trading volumes of the different market indices. Specifically, we collected the following time series.

- The three main US stock market indices are "Standard & Poor's 500" [S&P500], "Dow Jones Industrial Average" [DJIA] and "NASDAQ Composite" [NASDAQ].
- Two of the main stock market indices in Asia are the Shanghai Stock Exchange Composite Index" (SSE) and Hang Seng Index" (HSI).
- Euronext [EURO], the main stock market index from Europe.
- Ibovespa [IBOV], the Brazilian stock market index.
- Brent Crude Oil [BRENT] price.
- The US Dollar Index [DXY], which measures the US Dollar value versus six other currencies: Euro, Japanese Yen, British Pound Sterling, Canadian Dollar, Swedish Krona and the Swiss Franc.

All datasets were collected from "Yahoo Finance" [YF] using the Python programming language and the "yfinance" package. Occasionally, the data could contain missing values that were filled with the last valid value prior to the date of the missing value (Lo; Mamaysky; Wang, 2000). Table 1 presents the data collected from the YF.

Tabel 1.
Date intervals for the collected time series

Security	Start date	End date
S&P500	03/01/1928	30/12/2022
DJIA	02/01/1992	30/12/2022
NASDAQ	03/01/1972	30/12/2022
SSE	05/01/1998	30/12/2022
HSI	02/01/1987	30/12/2022
EURO	03/01/2000	30/12/2022
IBOV	03/01/1994	30/12/2022
BRENT	02/01/2008	30/12/2022
DXY	04/01/1971	30/12/2022

Source: Original Research Results

Technical indicators

We investigated eight technical indicators, four of which were based on moving averages and consisted of trend indicators, while the other four were used to identify momentum. The two categories and their indicators are as follows:

Trend indicators

Trend refers to the direction in which a time series moves over a time horizon (Murphy, 1999; Pring, 2014). Indicators belonging to this class aim to identify the trend of a price series and its profit. Many of these are based on moving averages, which can be considered dynamic support and resistance lines (Pring, 2014). The four trend technical indicators considered were as follows:

- A Simple Moving Average" [SMA] smoothens the original time series by calculating a simple average of its values over a predefined time window (Murphy, 1999; Pring, 2014). In other words, on the ith day, SMA is defined as

$$SMA_i(n) = \frac{1}{n} \sum_{j=i-n+1}^{i} C_j \qquad (1)$$

where C_j is the close price of security on the jth day and n is the length of the time window.

- "Weighted Moving Average" [WMA], which gives a larger weight for more recent prices when calculating the moving average. Consequently, compared with SMA, WMA is faster in changing its direction when the price trend changes (Pring, 2014). This is defined as follows:

$$WMA_i(n) = \frac{2}{n(n+1)} \sum_{j=1}^{n} jC_{i-n+j} \qquad (2)$$

- "Exponential Moving Average" [EMA], which is also an indicator that gives larger weights to more recent prices. However, while WMA weights follow a linear decay, EMA weights exhibit exponential decay (Murphy, 1999). The EMA indicator is formulated as follows:.

$$EMA_i(n) = \alpha C_i + (1-\alpha)EMA_{i-1}(n-1) \qquad (3)$$

$$\alpha = \frac{2}{n+1} \qquad (4)$$

- "Moving Average Convergence Divergence" [MACD], which is defined as the difference between a short and a long EMA (Pring, 2014):

$$MACD_i(n, m) = EMA_i(n) - EMA_i(m) \qquad (5)$$

where n < m. Subsequently, EMA(p) is calculated for the MACD series and the result is known as the MACD Signal (Murphy, 1999; Colby, 2003; Pring, 2014).

Moving average trading rules are usually defined by crosses between the original price series and moving average series. Because moving averages are lagged indicators of security prices, it is expected that in a rising market, the price series will be above the moving average series. However, in a falling market, the price series is located below the moving average series (Ellis; Parbery, 2005). Therefore, when running the SMA, WMA, and EMA experiments, we considered a buy signal whenever the price series crossed above the moving average series and a sell signal whenever a cross in the opposite direction occurred. For MACD, we employed a similar approach in which a buy signal is defined when the MACD series crosses above the MACD Signal, and a sell signal is defined when the MACD series crosses below the MACD Signal (Murphy, 1999; Colby, 2003).

Historically, a 200-day window has been a popular value when using moving averages (Colby, 2003), and we considered this as the default parameter value. For the optimization of SMA, WMA, and EMA, we considered the short- (10, 15, 20, 25, and 30 days) and mid-term (30, 50, 65, 80, 130, and 200 days) values listed in Table 11.2 from

Chapter 11 of Pring (2014). The default values of MACD are n = 12, m = 26, p = 9 (Pring, 2014) and. We used the short-term and mid-term values previously described for n and m, and p = 3, 6, 9, and 12.

Momentum indicators

Momentum indicators seek to anticipate price trend reversal and profits. In other words, they consider not only the trend itself but also the strength with which prices move in its direction. The main idea behind momentum indicators is that the trend starts slowing at its end, which is usually the point that anticipates its reversal (Pring, 2014). In this study, we investigated the following momentum indicators.

- "Relative Strength Index" [RSI], that measures the strength of the movement of a price time series. One of its main advantages is that it has a fixed range of values between 0 and 100, where 0 and 100 indicate the fall and rise in prices on all days of the time window considered, respectively. The RSI is defined as:

$$RSI_i(n)=100-\frac{100}{1+RS_i(n)} \qquad (6)$$

$$RS_i(n)=\frac{RS_{up}(n)}{RSI_{down}(n)} \qquad (7)$$

where RS_{up} and RS_{down} are calculated as the EMA of the percentage gains and losses during n days.

- "Stochastic Oscillator" [SO], which assumes that in a rising market the close prices tend to be close to the maximum prices in a time window, while in a falling market the close prices will be close to the minimum values in a time window (Murphy, 1999). Similar to the RSI, the SO is always contained in a fixed range [0, 100], where values close to 0 indicate oversold security and values close to 100 indicate

overbought security. For this, the SO relies on two lines, which are calculated as:

$$\%K_j(m)=100\left(\frac{C_j-L_m}{H_m-L_m}\right) \qquad (8)$$

$$\%D_i(n, m)=\frac{1}{n}\sum_{j=i-n+1}^{i}\%K_j(m) \qquad (9)$$

where n < m and L_m and H_m refer to the maximum and minimum prices of the past m days, respectively.

- "Stochastic Relative Strength Index" [SRSI], that is based on a similar idea as the SO to determine the location of RSI in the range of values that it assumed in n days (Chande; Kroll, 1994). It is defined as:

$$SRSI_i(n)=100\left(\frac{RSI_i(n)-\min\{RSI\}}{\max\{RSI\}-\min\{RSI\}}\right) \qquad (10)$$

where max{RSI} and min{RSI} are the maximum and minimum values of RSI in the time window, respectively.

- Williams %R [WR] measures the distance normalized in the range [-100, 0] between the ith close price and the maximum close price of a time window (Murphy, 1999):

$$WR=-100\left(\frac{H_n-C_i}{H_n-L_n}\right). \qquad (11)$$

Momentum trading rules are typically based on identifying oversold and overbought thresholds within the range of values of an indicator that anticipates trend reversals. For RSI, SRSI, and WR, a buy signal is defined whenever the security price crosses above the oversold threshold (which may indicate the reversion of a falling into a rising trend), whereas a sell signal is defined whenever the security price crosses below the overbought threshold (which may indicate the reversion of a rising into a falling trend). The SO employs a similar idea, where buy signals occur when the %K line

crosses the %D line in the oversold region and sell signals appear when the %K line crosses the %D line in the overbought region.

The momentum indicators introduced in this section are typically calculated considering a window length of 14 days (in the case of SO, the %K line is calculated using 14 days). For optimization, for all indicators, we also considered the alternative window values presented by Murphy (1999) (5, 7, 9, 14, 21, and 28 days) and Pring (2014) (9, 25, 30, and 45 days) for the RSI. In addition, we consider default overbought thresholds of 70 for RSI and SRSI, 80 for SO, and −20 for WR, and define default oversold thresholds of 30 for RSI and SRSI, 20 for SO, and −80 for WR (Murphy, 1999). During optimization, we considered upper values of 60, 65, 70, 75, and 80 (-40, -35, -30, -25 and −20 for WR) and lower values of 20, 25, 30, 35, and 40 (-80, -75, -70, -65 and −60 for WR). It should be noted that SO also has a window length parameter for the %D line. In the literature, %D is typically calculated based on three days. For the optimization procedure, we also considered lengths 6 and 9, increasing the span of the %D line time window and reducing the effect of noise.

Experimental methodology

We employed a time-series cross-validation methodology, in which an input time-series T was split into K equally sized subsets ordered by the time dimension. In the ith iteration, the ith subset is used to test a technical indicator, whereas subsets {1, …, i-1}, which contain past data, are used to optimize the parameters. It should be noted that, in this approach, the first few subsets do not have sufficient data for parameter optimization. Thus, these subsets were not used as the testing sets (Hyndman; Athanasopoulos, 2018). For the parameter optimization step, we employed a grid search procedure that considered all possible parameter value combinations (Bergstra; Bengio, 2012).

In this study, each cross-validation subset corresponds to a full year in a price time series. In addition, at each iteration, we consider the five most recent years with respect to the testing subset for parameter optimization, as older data may contain patterns that do not represent current market conditions (Coqueret; Guida, 2020). It is also important to note that each experiment was performed twice, considering a different performance measure when optimizing the parameters and evaluating the achieved results. The measures are described in the following subsections.

In all the experiments, we assume that a trading strategy starts with an initial amount of money, denoted by x_1. At the end of the experiment, the result of the strategy consists of time series X = {x_1, ..., x_N}, where x_i indicates the amount of money available on the ith day. In addition, whenever a buy or sell signal was identified on the j-th day of the testing set, we simulated the respective operation on the (j+1)-th day to avoid an optimistic scenario in which the closing price of the j-th day is used for both the calculation of the indicator and the operation in the market. Finally, we considered a trading fee of 0.2% for each buy-and-sell operation.

Evaluation of results

According to Nazário et al. (2017), most studies in which technical indicators achieved better results than the B&H strategy did not adjust returns based on the risk incurred. After identifying this limitation, the authors questioned whether these results could be a consequence of risk underestimation. Therefore, to optimize the parameters of the indicators and evaluate the results, we used two risk-adjusted return measures:

- The Sharpe Ratio" [SR] (Sharpe, 1966), defined as

$$SR = \frac{R_S - R_f}{\sigma_S} \qquad (12)$$

where R_S is the return generated by trading strategy S, σ_S measures the risk of S as the volatility (i.e., standard deviation) of its returns, and R_f is the return of a risk-free asset. In this study, we consider the United States "Treasury Bonds' [T-BOND] as a risk-free asset, as suggested by Assaf Neto (2017).

- "Calmar Ratio" [CR] (Young, 1991), which defines the risk of a strategy by its "Maximum Drawdown" [MD] during the investment period:

$$CR = \frac{R_S}{MD_S}. \qquad (13)$$

Finally, when calculating the result of each indicator for each dataset, we combined all of the resulting series from the test sets into a single time series that started in the first testing year and ended in the last testing year. Subsequently, the performance measures were calculated for such a series to generate a global and unique evaluation for each dataset.

RESULT AND DISCUSSION

Summary of Descriptive Statistics

The results are presented in the following section. First, the results of the default parameterizations for each indicator were compared with those obtained using the optimization procedure. The results of the indicators are then discussed in comparison to the passive investment approach (B&H). All codes developed for the experiments were made available on the GitHub platform (https://github.com/padilha/technical_analysis_study.

The discussion and conclusions derived from the results using the SR and CR measures were similar. Therefore, only the SR results are reported in this section. Tables with CR values are presented in the appendix at the end of this paper.

Parameter optimization results

The results of the default parameterizations for the SR measure are presented in Table 2, and those of the parameter optimization procedure are listed in Table 3. In Table 2, the results where the default parameters performed better than the optimization are shown in bold, whereas the cases where the optimization procedure achieved the best results are shown in bold in Table 3.

Tabel 2.
SR results for default parametrizations

Índice	SMA	WMA	EMA	MACD	RSI	SRSI	SO	WR
S&P500	**-0,29**	**-0,20**	-0,34	-0,51	**-0,16**	-0,32	**-0,24**	-0,17
DJIA	**-0,40**	**-0,49**	-0,47	-0,27	**0,16**	-0,34	-0,08	-0,20
NASDAQ	**0,01**	**0,14**	**0,19**	-0,26	-0,24	-0,22	-0,44	-0,20
EURO	**-0,32**	**-0,40**	**-0,56**	-0,36	-0,02	-0,27	-0,12	-0,19
HSI	**0,20**	**0,20**	**0,32**	-0,20	-0,14	-0,23	-0,21	<u>-0,19</u>
SSE	-0,19	-0,31	-0,36	**0,06**	-0,38	-0,20	**-0,20**	-0,28
IBOV	0,08	**0,15**	**0,23**	-0,14	-0,14	-0,25	**-0,18**	-0,15
BRENT	-0,08	-0,11	-0,11	**0,08**	**0,08**	-0,46	**-0,16**	-0,19
DXY	-1,28	-1,33	**-1,43**	**-1,60**	-1,49	-1,81	-1,69	-1,77

Source: Original Research Result

Tabel 3.
SR results for optimized parametrizations

Índice	SMA	WMA	EMA	MACD	RSI	SRSI	SO	WR
S&P500	-0,38	-0,28	**-0,32**	**-0,23**	-0,20	-0,17	-0,41	-0,08
DJIA	-0,51	-0,70	**-0,43**	**-0,19**	-0,10	-0,03	0,02	-0,09
NASDAQ	-0,07	-0,03	0,00	-0,32	**-0,08**	**-0,06**	-0,34	-0,03
EURO	-0,51	-0,50	-0,71	**-0,16**	**-0,01**	-0,11	-0,01	-0,17
HSI	0,15	0,07	0,09	-0,28	**-0,09**	**-0,08**	-0,19	<u>-0,19</u>
SSE	**0,19**	**0,17**	**0,12**	-0,32	-0,45	0,19	-0,47	-0,27
IBOV	**0,16**	0,14	0,11	-0,23	**-0,10**	-0,19	-0,26	-0,37
BRENT	**0,21**	**0,14**	**0,00**	-0,35	-0,23	-0,02	-0,21	-0,10
DXY	**-1,27**	-1,33	-1,47	-1,93	**-1,27**	-1,66	-1,45	-1,69

Source: Original Research Results

We evaluated 72 scenarios resulting from a combination of technical indicators and datasets. Among them, 39 cases (54.17%) exhibited better performance when using the parameter optimization procedure, whereas in the remaining scenarios, the default parameterizations achieved the best results. In general, the momentum indicators benefitted the most from the parameter optimization. However, these results were mostly negative. However, the trend indicators did not benefit from the optimization procedure.

As discussed by Park and Irwin (2007), some of the positive results reported in the technical analysis literature may be due to mere chance, as there are studies that present the data snooping problem in which the data for which the results are reported are the same as those used for parameter optimization. The results of our study corroborate this observation because for more than half of the experimental scenarios, a combination of optimized parameters was not able to improve the results for out-of-sample periods.

In summary, with respect to Q2, although the optimization procedure improved most of the results of the momentum indicators, it was not possible to make them positive. Furthermore, the four trend indicators (SMA, WMA, EMA, and MACD) show better performance when using their default parameterizations. Therefore, the optimization procedure employed in this study may not be the most appropriate for the selected technical indicators. Alternatively, other protocols may be more promising, such as random searches (Bergstra; Bengio, 2012) or metaheuristics (Feurer; Hutter, 2019), are widely used in machine learning studies.

Comparing the techincal indicators and the B&H strategy

The best results for each scenario in the last section were compared with the passive B&H benchmark. The final results are presented in Table 4, where the best performance for each dataset is highlighted in bold font.

Tabel 4.
Comparison of the technical indicators with the B&H strategy

Índice	B&H	SMA	WMA	EMA	MACD	RSI	SRSI	SO	WR
S&P500	0,19	-0,29	-0,20	-0,32	-0,23	-0,16	-0,17	-0,24	-0,08
DJIA	0,17	-0,40	-0,49	-0,43	-0,19	0,16	-0,03	0,02	-0,09
NASDAQ	0,30	0,01	0,14	0,19	-0,26	-0,08	-0,06	-0,34	-0,03
EURO	0,04	-0,32	-0,40	-0,56	-0,16	-0,01	-0,11	-0,01	-0,17
HSI	0,11	0,20	0,20	0,32	-0,20	-0,09	-0,08	-0,19	-0,19
SSE	0,15	0,19	0,17	0,12	0,06	-0,38	0,19	-0,20	-0,27
IBOV	0,27	0,16	0,15	0,23	-0,14	-0,10	-0,19	-0,18	-0,15
BRENT	0,13	0,21	0,14	0,00	0,08	0,08	-0,02	-0,16	-0,10
DXY	-0,78	-1,27	-1,33	-1,43	-1,60	-1,27	-1,66	-1,45	-1,69

Source: Original Research Results

The B&H strategy was better in six of the nine datasets, which demonstrates the difficulty in overcoming this benchmark using active investment strategies. One of the main difficulties arises from transaction costs, which excessively penalize a strategy that operates at a higher frequency. Particularly in consolidating markets, where there is no clear upward or downward trend, transaction costs are relevant because many false-positive signals may be generated by a technical indicator. Additionally, it must be noted that for most of the experiments, the technical indicators presented negative results, indicating that they were unable to overcome the T-BOND returns. Furthermore, in only two datasets (SSE and DXY), at least four indicators exhibited a positive performance.

Therefore, by considering the experiments that were carried out in this section with respect to Q1, we were not able to find any evidence for the superior and consistent performance of technical indicators when compared to the B&H in long-term investing.

CONCLUSION AND RECOMMENDATION
Conclusions

This paper presents a comparative study of eight technical indicators using nine datasets of oil, market, and currency indices. During the experiments, we compared the performances of classical parameterizations, parameter optimization procedures, and transaction costs. In the first stage, a significant improvement in the results justifies the computational cost of the optimization procedure. Subsequently, the best results were compared to those obtained using B&H. Second, there is no evidence that active technical investment strategies based solely on price time series achieve better risk-adjusted returns in the long run than a passive investment strategy. Notably, in our experiments, we assumed that a buy or sell operation would use all the available capital at that time. However, this approach is not optimal. Therefore, in future work, we will investigate the probabilistic criteria for buying or selling securities using fractions of available capital. Furthermore, one can investigate whether the combination of multiple technical indicators, aiming to complement each other, can reduce the influence of false-positive investment signals.

Appendix

This appendix presents the results obtained using the CR measure in the experiments. Tables 5 and 6 present the results of default parameterizations and optimization, respectively.

Table 7 compares the best results for these indicators with those of the B&H strategy.

With regard to parameter optimization, 31 cases (43.06%) showed an improvement. Similar to the results of the SR measures, the trend indicators did not benefit from optimization in most scenarios.

Tabel 5.
CR results for default parametrizations

Índice	SMA	WMA	EMA	MACD	RSI	SRSI	SO	WR
S&P500	0,08	0,07	0,06	-0,01	0,06	0,01	0,03	0,04
DJIA	0,01	-0,01	-0,01	0,02	0,15	-0,01	0,07	0,01
NASDAQ	0,15	0,19	0,29	0,04	0,05	0,03	0,00	0,04
EURO	0,00	-0,02	-0,05	-0,03	0,05	-0,02	0,03	-0,01
HSI	0,20	0,22	0,26	0,02	0,03	0,00	0,01	0,01
SSE	0,02	-0,02	-0,02	0,08	-0,05	-0,01	-0,01	-0,03
IBOV	0,11	0,14	0,16	0,02	0,02	-0,02	0,01	0,01
BRENT	-0,02	-0,04	-0,03	0,04	0,04	-0,14	-0,06	-0,07
DXY	0,01	-0,01	0,00	-0,03	-0,03	-0,05	-0,04	-0,04

Source: Original Research Results

Tabel 6.
CR results for optimized parametrizations

Índice	SMA	WMA	EMA	MACD	RSI	SRSI	SO	WR
S&P500	0,04	0,04	0,03	0,02	0,03	0,04	0,00	0,05
DJIA	-0,03	-0,05	0,00	0,02	0,07	0,00	0,03	0,04
NASDAQ	0,16	0,10	0,12	0,01	0,07	0,08	0,00	0,07
EURO	-0,05	-0,04	-0,06	-0,02	-0,01	0,02	-0,01	0,01
HSI	0,13	0,10	0,09	-0,02	0,05	0,10	0,01	0,02
SSE	0,11	0,14	0,05	-0,03	-0,06	0,18	-0,01	-0,03
IBOV	0,14	0,13	0,15	-0,02	0,06	0,03	0,00	-0,06
BRENT	0,03	0,09	0,01	-0,12	-0,07	0,00	-0,08	0,00
DXY	-0,01	-0,02	-0,03	-0,05	-0,01	-0,04	-0,03	-0,04

Source: Original Research Results

When comparing the best results of each indicator with those of B&H (Table 7), we can observe that B&H was superior in only three out of the nine datasets (S&P500, EURO, and IBOV). However, there was no clear pattern regarding which technical indicators performed best for the remaining datasets, which makes it difficult to recommend the use of one over another. Furthermore, the simplicity and low transaction costs of the B&H strategy make it an attractive choice that requires low effort to be executed when compared to the investigated technical indicators.

Tabel 7.

Comparison of the technical indicators with the B&H strategy

Índice	B&H	SMA	WMA	EMA	MACD	RSI	SRSI	SO	WR
S&P500	0,13	0,08	0,07	0,06	0,02	0,06	0,04	0,03	0,05
DJIA	0,13	0,01	-0,01	0,00	0,02	0,15	0,00	0,07	0,04
NASDAQ	0,16	0,16	0,19	0,29	0,04	0,07	0,08	0,00	0,07
EURO	0,06	0,00	-0,02	-0,05	-0,02	0,05	0,02	0,03	0,01
HSI	0,11	0,20	0,22	0,26	0,02	0,05	0,10	0,01	0,02
SSE	0,09	0,11	0,14	0,05	0,08	-0,05	0,18	-0,01	-0,03
IBOV	0,19	0,14	0,14	0,16	0,02	0,06	0,03	0,01	0,01
BRENT	0,07	0,03	0,09	0,01	0,04	0,04	0,00	-0,06	0,00
DXY	0,00	0,01	-0,01	0,00	-0,03	-0,01	-0,04	-0,03	-0,04

Fonte: Resultados originais da pesquis

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