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# ANALYSIS OF THE ACCURACY OF SELECTED TECHNICAL INDICATORS ON THE EXAMPLE OF INVESTMENTS IN AMERICAN SECTORAL ETF FUNDS IN THE YEARS 1998-2025 FOR THE DAILY INTERVAL

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**Purpose**: This study evaluates the effectiveness of technical analysis indicators compared to a buy-and-hold strategy for US sector ETFs from 1998 to 2025 using a daily timeframe. It also investigates the relationship between trade frequency and achieved returns.
**Design/methodology/approach**: The research examines five technical indicators—Relative Strength Index (RSI), Commodity Channel Index (CCI), Williams Percent Range (W%R), DeMarker (DM), and Stochastic Oscillator—applied to 11 ETFs tracking major US industry indices. Two hypotheses were tested: H1, that technical strategies yield higher average annual returns than buy-and-hold, and H2, that trade frequency strongly correlates with returns. Daily closing prices were analyzed, with statistical significance assessed via one-way ANOVA and normality tested using the Shapiro-Wilk test with Lilliefors correction. Spearman's rank correlation coefficient was used to evaluate trade frequency and returns.
**Findings**: The Stochastic Oscillator outperformed buy-and-hold in 45.45% of cases, achieving a 6.29% average annual return compared to 6.01% for buy-and-hold. RSI yielded the lowest returns at 2.46%. A moderate correlation (Spearman's coefficient 0.42) was found between trade frequency and returns, rejecting H2.
**Research limitations/implications**: Limitations include shorter data periods for XLC and XLRE funds and limited high-frequency data availability. Future research could explore lower timeframes or alternative indicators.
**Practical implications**: Stochastic Oscillator-based strategies may enhance returns in specific sectors, offering actionable insights for investors.
**Originality/value**: This study addresses a research gap by combining multiple technical indicators for sector-specific ETF trading, challenging efficient market theory assumptions.
**Keywords**: ETFs, technical analysis, Stochastic Oscillator, buy-and-hold, sector investing.
**Category of the paper**: Research paper.

## 1. Introduction

In recent years, passive ETFs (Exchange-Traded Funds) have gained popularity, mainly due to their high level of diversification and the ability to directly invest in instruments that track the performance of a stock market index (Madhavan, 2017). Compared to actively managed funds, ETFs, in addition to their broad diversification capabilities, are also characterized by low operating costs, which translates into lower fees for investors than in the case of traditional funds, and higher liquidity, because, unlike actively managed funds, they are not valued only once a day (Mitrenga, 2013). The above-mentioned features confirm that ETFs are generally considered instruments worth investing in for the long term (Mazumder, 2014). Therefore, determining the best timing to start and end an investment seems important from the perspective of both researchers and investors.

Technical analysis indicators are tools commonly used in many markets to determine investment entry and exit points. The purpose of these indicators is to predict price movements based on historical patterns and trends (Sokolov Germanov, 2023). Previous research indicates that these indicators are also applicable to the ETF market. For example, strategies based on the RSI indicator achieved accuracy exceeding 80% and enabled annual returns close to 24%, while strategies combining various indicators and machine learning methods achieved accuracy of 75-83.6% (Özbayoğlu, Umur Erkut, 2010). In contrast, simple strategies based on moving averages generated accuracy of approximately 54% (Bollapragada, Savin, Kerbache, 2013). Research also indicates that moving averages and the MACD, along with momentum used as a volatility filter, can generate returns as much as 79% higher than the buy-and-hold strategy (Cohen, 2020). These results suggest that strategies based on technical analysis can also provide profitable trading signals in the ETF market (Metghalchi, Cloninger, Niroomand 2023). It is worth noting, however, that most of existing research focuses on ETFs that represent broad markets, not individual industries, and technical indicators have been most often used individually. Therefore, there is a lack of clear evidence demonstrating the validity of strategies based on a combination of technical indicators, especially in relation to individual industries. This represents a significant research gap, which, if filled, could expand knowledge about the practical application of technical analysis in ETF investments.

The aim of the study is to determine whether selected technical analysis indicators yield higher rates of return than a buy-and-hold strategy, and whether the number of trades executed by investors is related to the resulting rates of return. The study was conducted using ETFs that track the performance of major US industry indices based on the daily timeframe, commonly used in long-term investments. Therefore, the following research hypotheses were tested:

- **$H_1$**: The use of investment strategies based on technical analysis indicators allows for obtaining higher average annual rates of return than the use of the "buy and hold" strategy in the case of sector ETFs on the US market for the daily timeframe.

– **$H_2$**: There is a strong relationship between the number of trades and the returns obtained from investing in US sector ETFs using technical indicator strategies in the daily time frame.

The proposed research problem is situated within the context of three important economic theories:

– efficient markets theory – by analyzing whether technical strategies can outperform the passive approach postulated by this concept (Fama, 1970),
– portfolio theory – through the subject of research, which is highly diversified ETF funds, and in the context of searching for strategies that can improve portfolio efficiency (Markowitz, 1952),
– the theory of adaptive markets – which assumes that market efficiency changes over time depending on conditions and the adaptation of participants – by examining whether technical strategies can be more effective in specific market conditions, e.g., for a specific sector (Lo, 2004).

The article consists of six parts. The introduction outlines the context of the study, identifies the research gap, and defines the objective and hypothesis. The second part provides a literature review on the accuracy of technical oscillators as a basis for investment decision-making. The third part describes the research methodology and assumptions. The fourth part presents the results obtained in the study. The fifth part contains conclusions, a discussion of the results of other studies, a description of the research limitations, and suggestions for future research directions. The final part provides information on the funding sources for the article.

## 2. Review on the accuracy of technical oscillators as a basis for making investment decisions.

A review of the literature concerning the accuracy or effectiveness of technical oscillators indicates significant variability in results, which depends both on the type of instruments analyzed and on the adopted research methodology. The studies can be divided into groups encompassing strategies integrating oscillators with machine learning models, classical oscillators applied to indices and ETFs of developed markets, analyses of domestic indices, as well as simplified binary systems and low-frequency investment strategies. Such a division allows for comparison of results, identification of conditions for the effectiveness of particular tools, and presentation of the conclusions formulated so far regarding the use of oscillators in different market contexts.

Deep, A., Shirvani, A., Monico, C., Rachev, S., and Fabozzi, F.J. (2025) conducted research on the use of machine learning in price forecasting in financial markets. The authors focused on the integration of classical technical indicators with Random Forest Regression (RFR) models in the context of high-frequency trading. The subject of analysis was minute-level data for the SPY ETF, a highly liquid instrument reflecting the performance of the S&P 500 index. The aim of the study was to assess whether the addition of technical indicators, such as the RSI oscillator, Bollinger Bands, EMA moving averages, or Fibonacci retracements, could increase the effectiveness of price forecasts and improve the risk–return trade-off under conditions of elevated market volatility. Methodologically, the study relied on comparative analysis of RFR model results with different sets of input variables. The authors performed a feature importance analysis, juxtaposing basic price data (opening, high, low, closing prices) with technical indicators. In addition, advanced measures of investment strategy performance evaluation were introduced, such as the Rachev ratio or the profit–loss ratio, which allowed for a more comprehensive assessment of model quality than using returns alone. The key benchmark was a buy-and-hold strategy. The results indicated that classical technical indicators had limited predictive value, and that raw price data played the most important role in forecasts. Although models enhanced with indicators achieved better risk-adjusted performance measures (with Rachev ratios ranging from 0.919 to 0.961), they consistently underperformed compared to the simple buy-and-hold strategy, generating returns in the range of -2.4% to -3.9%. The authors emphasized that the findings are consistent with the weak form of the efficient market hypothesis, since the applied models were not able to consistently generate abnormal returns.

Similar research was conducted by Macchiarulo, A. (2018), who attempted to compare the effectiveness of methods based on machine learning and technical analysis in the context of predicting stock market movements and generating excess returns. The analysis was based on historical data covering the period from January 1995 to December 2005, which were used to train machine learning models such as neural networks and support vector machines (SVM). These forecasts were then applied in investment strategies from January 2006 to December 2016, during which their effectiveness was tested in real market conditions. The analysis was referenced against the performance of the SPDR S&P 500 ETF, which served as a benchmark. The study made extensive use of various statistical tools, including paired-sample t-tests, which were used to assess whether the results obtained with machine learning methods differed significantly from those achieved with traditional technical analysis indicators, such as moving averages or oscillators. Particular attention was paid to market conditions, as the study covered both bull and bear markets, allowing for assessment of the resilience and adaptability of the applied methods in different phases of the business cycle. The results indicate that, in the analyzed period, the machine learning model achieved a higher average monthly return (1.19%) compared to the average return of the S&P 500 index (0.48%). Particularly noteworthy is the observation that among technical indicators, oscillators played a key role. For example, indicators such as the parabolic SAR or the Rate of Change (ROC) showed high effectiveness in predicting trend reversals and generating trading signals. These findings suggest that integrating oscillators with machine learning models can significantly enhance the effectiveness of predictive systems and trading strategies, supporting investors in achieving better returns at an acceptable level of risk.

Other studies focusing exclusively on classical oscillators analyzed their effectiveness compared to a buy-and-hold strategy in international markets. Cohen, G. and Cabiri, E. (2015) compared the performance of a buy-and-hold strategy with results obtained from applying selected, popular oscillators of technical analysis to various indices representing key global markets—DJI, FTSE100, Nikkei 225, and TA100—over the period 2007-2012. The aim of the analysis was to determine whether technical analysis tools are able to systematically generate higher returns than a buy-and-hold strategy under different market conditions. The results indicate that among the analyzed oscillators, the Relative Strength Index (RSI) achieved the best results, outperforming returns from the DJIA, FTSE100, and Nikkei 225 indices in five out of six years studied. The only exception was the Israeli TA100 index, which proved to be more effective than all analyzed oscillators, including RSI. The second-best performer was the MACD (Moving Average Convergence/Divergence) oscillator, which outperformed the buy-and-hold strategy for the Nikkei 225 index and ranked second relative to TA100. The analysis also showed that in bear market conditions, the RSI and MACD oscillators generally performed better than passive strategies, whereas in bull markets their effectiveness was lower compared to buy-and-hold.

In a subsequent study, Cohen, G. (2020) conducted a detailed analysis of the effectiveness of popular technical oscillators in ETF trading, covering the period 1999-2018. The author examined whether standard settings of these tools, as well as their modifications and combinations, could outperform the buy-and-hold strategy. To this end, daily data were used for six of the most popular U.S. ETFs, including SPY, QQQ, IWM, XLF, XLK, and XLI. The methodology relied on programmatic implementation of oscillators such as RSI, Stochastics, MACD, CCI, CMF, and Bollinger Bands. After initially applying the settings recommended by their creators, the author modified and optimized them to maximize the profit ratio—the ratio of gross profit to gross loss. In addition, the study tested combinations of various oscillators to determine whether their combination could improve results. The results showed that the most effective tools were the CCI and Bollinger Bands, with CCI performing better on more volatile ETFs (XLF and XLK), while Bollinger Bands were more effective on less volatile funds such as IWM and XLI. A particularly favorable outcome was obtained for the strategy combining RSI and Chaikin Money Flow, which generated positive returns in all analyzed ETFs and significantly outperformed the buy-and-hold strategy by as much as 79% in the case of ETF XLF. Importantly, none of the tested tools outperformed the buy-and-hold strategy in the case of ETF QQQ. The study confirms that certain technical solutions can improve results in ETF trading, although their effectiveness varies depending on the characteristics of the instrument and market conditions. As the author emphasized, the findings may have significant implications for traders using algorithmic strategies based on technical oscillators, highlighting the necessity of adjusting settings and tools to the specificity of a given ETF and market.

At the same time, research by Trembiński, M. and Stawska, J. (2021) showed that in European conditions, oscillators and indicator-based trading systems can also outperform passive strategies, provided that parameters are properly selected. The authors conducted a study aimed at evaluating the effectiveness of trading systems based on technical analysis tools on the German DAX index in the years 2015-2020. The analysis included six different strategies based on indicators and oscillators such as moving averages, ADX, MACD, Parabolic SAR, RSI, Bollinger Bands, Ichimoku Kinko Hyo, Donchian Channel, CCI, and Keltner Channel. All trades were executed on the Meta Trader 4 platform, and the strategy was evaluated using portfolio performance measures such as the Sharpe ratio and the Managed Account Ratio (MAR). The study compared the effectiveness of the selected trading systems with a passive buy-and-hold strategy, i.e., long-term passive investing. The results showed that most of the analyzed systems achieved positive returns, and their effectiveness largely depended on the appropriate selection of indicator and oscillator parameters. It turned out that four out of six tested strategies were more effective than the passive strategy already by the end of 2019, and by the end of the first quarter of 2020 all strategies had shown an advantage. Furthermore, the study confirmed that technical analysis tools can be useful in investment practice, enabling not only profit generation but also loss limitation during unfavorable market periods. The findings suggest that although the effectiveness of systems based on technical analysis depends on proper parameter selection and strategy choice, their use can significantly improve investment results compared to passive investing. At the same time, the authors emphasized that further optimization and development of indicator parameters can further increase the effectiveness of these systems.

Naved, M. and Srivastava, P. (2015), in turn, conducted a study aimed at evaluating the effectiveness of three of the most popular oscillators used in technical analysis on the financial market, namely: the Stochastic Oscillator, RSI (Relative Strength Index), and Commodity Channel Index (CCI). The analysis covered the period from 2004 to 2014 and focused on the S&P CNX Nifty 50 index, representing the Indian stock market. The study applied various methods of testing trading strategies based on signals generated by the selected oscillators. The results indicate that among the considered oscillators, the CCI demonstrated the highest profitability in the analyzed period. The CCI-based strategy generated 7012 profit points, which was 9.52% higher than the buy-and-hold strategy in the same period. The strategy produced a total of 182 trades, of which 88 were profitable and 94 unprofitable, resulting in an accuracy rate of 48.35%. Importantly, the study analyzed time horizons ranging from 7 to 21 days, enabling a detailed assessment of indicator performance in different time configurations. For CCI, the 21-day period proved to be the most beneficial, with higher profits than other oscillators. The study therefore shows that the appropriate selection of technical indicator parameters—in this case, the CCI period length—can significantly affect the effectiveness of investment strategies.

The work of Jiménez-Preciado, A.L., Cruz-Aké, S., and Santillán-Salgado, R.J. (2021) shows that even simple binary systems using selected oscillators can provide an advantage over passive strategies under different market conditions. The authors developed a binary trading system intended for algorithmic trading in a low-frequency environment. To identify buy and sell signals, two popular technical analysis indicators were applied: Bollinger Bands and Williams Percent Range. The constructed model was then empirically verified, and its results were compared with a buy-and-hold strategy serving as the benchmark. The aim of the study was to demonstrate that the developed system can generate profits even in conditions of a downward trend and high volatility, as well as after accounting for brokerage commissions. The study was conducted for three ETFs: SPY (SPDR S&P500), DUST (Direxion Daily Gold Miners Index Bear 2x Shares), and EDZ (Emerging Markets Direxion Daily MSCI Emerging Markets Bear 3X Shares). The idea of using ETFs was to reflect stock market results of different economic sectors (including indices, metals, and emerging markets in this case). The data covered the period from January 2018 to March 2020, including two training years and the first quarter of 2020, when high market volatility was observed due to the COVID-19 pandemic and falling oil prices. The results indicate that this system made it possible to achieve positive returns, even under conditions of sharp market declines. Importantly, after accounting for brokerage commissions (on average 0.25%), the system still showed higher returns than holding ETF units. The study confirms that the use of Bollinger Bands and Williams Percent Range in a binary system can improve investment performance, reducing potential losses and generating profits under various market conditions. As the authors emphasized, these results are relevant for investors and traders seeking effective methods of analysis and automation of investment decisions in stock and ETF markets.

Attention should also be paid to the study by Paik, C.K., Choi, J., and Vaquero, I.U. (2024). This study aimed to examine whether it is possible to achieve above-average investment results without the need for complex analytical tools, dynamic portfolio rebalancing, or advanced technological infrastructure required by high-frequency trading strategies. Within the framework of the study, the DeepSignal algorithm was developed, based on two technical oscillators - the stochastic oscillator and the Williams Percent Range - and applied to tests on two ETFs: SPY, reflecting the S&P 500 index (a developed market), and EWY, tracking the MSCI Korea index (an emerging market). The authors did not apply portfolio rebalancing, limiting the number of trades to an average of one per month, which allowed for significant reduction of operating costs. The simulation results showed that even with such a simplified approach, the strategy delivered stable and clearly better performance than the buy-and-hold strategy, with a very low maximum drawdown (–1.0%) and a high signal accuracy rate. The authors argue that this approach not only allows effective responses to market volatility but also constitutes a real alternative for investors seeking simple, low-cost, and effective investment solutions. The study also makes an important methodological contribution to the literature, highlighting the potential of simple technical signals in long-term asset allocation in the ETF market.

The literature analysis indicates that the effectiveness of technical oscillators compared to the buy-and-hold strategy is varied and largely dependent on the characteristics of the instrument, market volatility, the adopted time horizon, and indicator parameters. Despite the lack of conclusive empirical evidence confirming the systematic superiority of technical oscillators over passive strategies, they remain an important component of technical analysis, supporting the investment decision-making process.

## 3. Research methodology and assumptions

The research was conducted based on data from December 23, 1998, to June 30, 2025, except for the XLC and XLRE funds, which were established later. For the XLC fund, the beginning of the research period was June 20, 2018, and for the XLRE fund, October 9, 2015. The beginning of the research period was determined by the beginning of each fund's market listing. The research period ended at the end of the last full month preceding the commencement of the analysis. Daily closing prices were used for the study, as they are most commonly used in long-term investments and have the greatest informative value. The study included eleven ETFs representing major industries. Each fund reflects the performance of companies from a specific sector within the S&P 500 index, enabling the analysis of diverse sector conditions. Most of the selected funds have been listed since the late 1990s, allowing for a long-term analysis. The parameters of each fund are presented in Table 1.

**Table 1.**
*Parameters of ETF funds selected for the study*

| ETF fund name | ETF ticker | Industry | Beginning of the research period | End of the research period |
|---|---|---|---|---|
| Materials Select Sector SPDR Fund | XLB | Raw materials and supplies | 1998-12-23 | 2025-06-30 |
| Communication Services Select Sector SPDR Fund | XLC | Telecommunication | 2018-06-20 | 2025-06-30 |
| Energy Select Sector SPDR Fund | XLE | Power engineering | 1998-12-23 | 2025-06-30 |
| Financial Select Sector SPDR Fund | XLF | Finances | 1998-12-23 | 2025-06-30 |
| Industrial Select Sector SPDR Fund | XLI | Industry | 1998-12-23 | 2025-06-30 |
| Technology Select Sector SPDR Fund | XLK | Information technologies | 1998-12-23 | 2025-06-30 |
| Consumer Staples Select Sector SPDR Fund | XLP | Basic consumer products | 1998-12-23 | 2025-06-30 |
| Real Estate Select Sector SPDR Fund | XLRE | Real estate | 2015-10-09 | 2025-06-30 |
| Utilities Select Sector SPDR Fund | XLU | Utility supply | 1998-12-23 | 2025-06-30 |
| Health Care Select Sector SPDR Fund | XLV | Health care | 1998-12-23 | 2025-06-30 |
| Consumer Discretionary Select Sector SPDR Fund | XLY | Discretionary consumer products | 1998-12-23 | 2025-06-30 |

Source: own study.

The analysis used oscillators frequently used by investors, i.e., indicators allowing the identification of oversold and overbought levels (Brown, 1999), such as: Relative Strength Index (RSI), Commodity Channel Index (CCI), Williams Percent Range (W%R), DE Marker (DM) and Stochastic Oscillator (ST).

The Relative Strength Index is an indicator developed by Welles Wilder that compares the upward and downward movements of closing prices over a given period (Wilder, 1978) – see formula 1.

$$RSI = 100 - \frac{100}{1+RS} \text{Where} RS = \left(\frac{a}{b}\right) \quad (1)$$

where:
a – average value of the closing price increase for the analyzed period,
b – average value of the closing price decline in the analyzed period.

The indicator ranges from 0 to 100. Values above 70 (and above 80 in the conservative variant) indicate an overbought market and are a signal to open a short position or close a long position. Values below 30 (below 20 in the conservative variant) indicate an oversold market and are a signal to open a long position or close a short position (Panerai, Vachhani, Chaudhury, 2021).

The Commodity Channel Index is an indicator developed by Donald Lambert that measures the difference between the current and average prices for a given period (Lambert, 1983) – see formula 2.

$$CCI = \frac{1}{0{,}015} * \frac{CT - SMA(CT)}{\sigma(CT)} \text{Where} CT = \frac{C_{max} + C_{min} + C_z}{3} \quad (2)$$

where:
CT – typical rate,
$C_{max}$ – maximum rate,
$C_{min}$ – minimum rate,
$C_z$ – closing price,
SMA – simple moving average,
σ – mean standard deviation.

The CCI does not have a strict range. Values below -100 indicate oversold conditions and are a signal to take a long position or close short, while values above 100 suggest overbought conditions, which are a signal to take a short position or close long (Maitah et al., 2016).

The Williams Percent Range (W%R) is an indicator developed by Larry Williams. The W%R is derived by dividing the current closing price by the high over n periods by the low over n periods. This result is then multiplied by 100 (Williams, 1979). The W%R is calculated using Formula 3.

$$\%R = \frac{C_z - C_{max}}{C_{max} - C_{min}} * 100 \quad (3)$$

where:
$C_z$ – current closing rate,
$C_{max}$ – maximum rate from n periods,
$C_{min}$ – minimum rate from n periods.

The Williams Percent Range oscillator ranges from -100 to 0. Values close to -100 indicate an oversold zone, while values close to 0 indicate an overbought zone. A buy signal is generated when the oscillator reaches values below -80, while a sell signal is generated when they are above -20 (Williams, 1979).

DeMarker (DM), an indicator developed by Tom DeMark, compares periods in which maximum prices are reached with a selected period (DeMark, 1994) – see formula 4.

$$DeM = \frac{SMA\ (DeMax, O)}{SMA\ (DeMax, O) + SMA\ (DeMin, O)}; \text{ where}$$
$$DeMax = H\ (i) - H\ (i-1) \text{if } H\ (i) > H\ (i-1) \text{or}$$
$$DeMax = 0; \text{if } H\ (i) =< H\ (i-1) \quad (14)$$
$$\text{DeMin} = \text{L}\ (\text{i}-1) - \text{L}\ (\text{i}) \textbf{if} \text{L}\ (\text{i}) < \text{L}\ (\text{i}-1),$$
$$\text{DeMin} = 0 \textbf{if} \text{L}\ (\text{i}) >= \text{L}\ (\text{i}-1)$$

where:
H(i) – maximum rate of the current period,
L(i) – minimum rate of the current period,
H(i – 1) – maximum rate of the previous period,
L(i – 1) – minimum rate of the previous period,
SMA – simple moving average,
O – number of periods for which the indicator value was calculated.

The oscillator ranges from 0 to 1. Values above 0.7 indicate an overbought market and signal a short or close a long position. Values below 0.3 indicate an oversold market and signal a long or close a short position (Lane, 1984).

The Stochastic Oscillator, developed by George Lane, consists of two lines: %K and %D. The %K line is the main oscillator line, and the %D line is a three-period moving average of the %K line (Lane, 1984). The method for calculating the %K line of the stochastic oscillator is presented in Formula 5.

$$ST = \frac{C_z - C_{min}}{C_{max} - C_{min}} * 100 \quad (5)$$

where:
$C_z$ – current closing rate,
$C_{max}$ – maximum rate from n periods,
$C_{min}$ – minimum rate from n periods.

Both the %K and %D lines take values from 0 to 100. Values of the %K lines above 0.9 indicate an overbought market and are a signal to open a short position or close a long position. Values below 0.1 indicate an oversold market and are a signal to open a long position or close a short position (Damayanti, 2020).

The study was conducted using the time series analysis method, and the statistical significance of the obtained results was confirmed using one-way ANOVA analysis, and the normality of the distributions of return rates and the annual number of transactions was checked using the Shapiro-Wilk test with Lilliefors correction, which is designed for time series with small sample sizes (Öztuna et al., 2006). The research procedure consisted of the following stages:

1. Obtaining daily closing prices for individual ETF funds from www.investing.com (Investing, 24.07.2025) and processing them in the indicated research periods.
2. Calculation of the values of individual oscillators for each fund in the adopted research periods.
3. Determining overbought and oversold zones in accordance with the methodology for calculating individual indicators and determining transaction signals.
4. Simulations of buy and sell transactions in ETF shares were conducted based on signals generated by individual indicators. If a buy signal was not followed by a sell signal by the end of the research period, the transaction was closed on the last trading day.
5. Calculation of rates of return for the "buy and hold" strategy and for a strategy that includes the purchase and sale of shares in individual funds, and a cross-sectional analysis of the results obtained.
6. To examine the relationship between the average annual number of transactions using individual oscillators and the average annual rates of return for each fund, the Spearman rank correlation coefficient was chosen for the analysis, as the hypothesis of normality in the distribution of the average annual number of transactions was rejected.
7. Conducting statistical tests using one-way ANOVA analysis to confirm which of the obtained results are statistically significant.

Overall, the study analyzed daily closing prices of 11 sector ETFs from 1998 to 2025 (with shorter periods for XLC and XLRE). Popular oscillators (RSI, CCI, W%R, DM, ST) were used to generate buy and sell signals, and results were compared with a buy-and-hold strategy. Simulated trades, rate of returns, and the relationship between trading frequency and performance (Spearman correlation) were examined. Statistical significance was assessed with one-way ANOVA, and normality was tested using the Shapiro–Wilk test with Lilliefors correction.

## 4. Research results

The rates of return obtained using the classic “buy and hold” strategy and strategies using technical indicators are presented in Table 2.

**Table 2.**
*Comparison of rates of return achieved using buy-and-hold strategies and strategies using technical indicators*

| ETF ticker | Buy and hold | RSI (20/80) | CCI (-100/100) | W%R (-100/0) | DM (0.3/0.7) | ST (10/90) |
|---|---|---|---|---|---|---|
| XLB | 5.53% | 2.76% | 5.37% | 6.64% | 4.46% | 8.88% |
| XLC | 10.21% | -2.33% | 7.60% | 5.90% | 3.98% | 6.44% |
| XLE | 5.03% | 6.41% | 4.61% | 4.61% | 4.77% | 6.83% |
| XLF | 3.85% | 0.39% | 7.27% | 3.02% | 2.36% | 5.13% |
| XLI | 7.14% | 1.78% | 6.17% | 5.64% | 4.42% | 6.17% |
| XLK | 8.01% | 0.91% | 4.94% | 2.64% | 2.29% | 4.74% |
| XLP | 4.21% | 3.91% | 2.91% | 4.29% | 3.67% | 4.27% |
| XLRE | 3.32% | 2.57% | 4.85% | 2.22% | 5.04% | 5.72% |
| XLU | 3.89% | 5.24% | 3.53% | 2.92% | 1.51% | 4.89% |
| XLV | 6.49% | 3.88% | 5.80% | 5.07% | 1.34% | 7.53% |
| XLY | 8.40% | 1.51% | 5.96% | 3.34% | 5.25% | 8.56% |
| **Mean** | **6.01%** | **2.46%** | **5.36%** | **4.21%** | **3.55%** | **6.29%** |

| | the lowest rate of return for the examined fund | | the highest rate of return for the examined fund |
|---|---|---|---|

Source: own study.

The "buy and hold" strategy produced the highest rates of return for three of the eleven ETFs examined (27.27% of the total). The strategy based on the stochastic oscillator as a signal indicator demonstrated the highest accuracy, generating the highest rates of return in five of the eleven cases (45.45%). The strategy using the stochastic oscillator also generated the highest average rate of return (6.29%), which exceeded the rate achieved by the "buy and hold" strategy by 0.29 percentage points. The strategy using signals generated by the RSI indicator achieved the worst returns. In over half of the cases (54.54%), this strategy generated the lowest rates of return, with the average annual rate of return being just 2.46% (a whopping 3.55 percentage points lower) than the "buy and hold" strategy. In the case of the XLC fund, it even generated a negative result (-2.33%), which may indicate the limited usefulness of this indicator in the analyzed period or its inadequacy to the specific nature of the given sector. The results indicate that for most indicators, the rates of return were lower than for a "buy and hold" strategy. Using the example of a strategy based on the stochastic oscillator, it is worth noting that properly constructed technical strategies can outperform traditional passive approaches in terms of generated returns.

To provide a more comprehensive comparison of rate of returns, we calculated average rates of return obtained by using technical indicators as a signal source, highlighting the differences between the two approaches. A comparison of rates of return obtained by using the "buy and hold" strategy and average rates of return for technical strategies is presented in Table 3.

**Table 3.**
*Comparison of Buy-and-Hold Returns and Average Returns for Technical Strategies*

| ETF ticker | Buy and hold | Technical indicators | Difference [in pp] | Higher rate of return |
|---|---|---|---|---|
| XLB | 5.53% | 8.88% | 3.35 pp | Technical indicators |
| XLC | 10.21% | 4.65% | 5.55 pp | Buy and hold |
| XLE | 5.03% | 5.56% | 0.53 pp | Technical indicators |
| XLF | 3.85% | 4.32% | 0.47 pp | Technical indicators |
| XLI | 7.14% | 5.13% | 2.01 pp | Buy and hold |
| XLK | 8.01% | 3.39% | 4.62 pp | Buy and hold |
| XLP | 4.21% | 3.84% | 0.37 pp | Buy and hold |
| XLRE | 3.32% | 4.16% | 0.85 pp | Technical indicators |
| XLU | 3.89% | 3.84% | 0.05 pp | Buy and hold |
| XLV | 6.49% | 5.20% | 1.29 pp | Buy and hold |
| XLY | 8.40% | 5.60% | 2.80 pp | Buy and hold |
| **Mean** | **6.01%** | **4.96%** | **1.05 pp** | **Buy and hold** |
| (green) lower rate of return for the examined fund | | (orange) higher rate of return for the examined fund | | |

Source: own study.

According to the above table, the "buy and hold" strategy generated higher rates of return than technical strategies in seven cases (63.63% of the total). The average rate of return for the passive strategy was 6.01%, while the average for technical strategies reached 4.96%, representing a 1.05 percentage point advantage in favor of the "buy and hold" approach. In particular, the rates of return for the XLC, XLK, XLI, and XLY funds proved significantly higher for this strategy, with differences ranging from 2.01 percentage points to 5.55 percentage points. Funds representing the information technology (XLK), communications (XLC), and consumer goods (XLY) sectors demonstrated a clear advantage for the passive strategy, which may indicate greater stability and long-term growth potential for these sectors. Funds representing the raw materials and real estate sectors (XLB, XLRE) responded better to technical signals. The higher accuracy of the buy-and-hold strategy in most cases may be due to its ability to capitalize on long-term uptrends, while technical strategies may be more susceptible to false signals in conditions of increased volatility – see Figure 1.


**Figure 1.** Comparison of the volatility of XLB and XLK funds.

Source: own study.

Two funds were selected for comparison, where the passive approach was most dominant (XLK – a 4.62 percentage point surplus) and technical strategies (XLB – a 3.35 percentage point higher rate of return). The XLC fund was excluded from the comparison because it was only listed in 2018.

Given the varying accuracy of technical strategies, it is also reasonable to examine whether the number of transactions may be a factor in determining rates of return. Table 4 presents the number of open and closed transactions executed within each technical strategy.

**Table 4.**
*Number of transactions executed within individual technical strategies*

| ETF ticker | RSI (20/80) | CCI (-100/100) | W%R (-100/0) | DM (0.3/0.7) | ST (10/90) |
|---|---|---|---|---|---|
| XLB | 27 | 182 | 190 | 93 | 102 |
| XLC | 6 | 44 | 42 | 21 | 29 |
| XLE | 28 | 179 | 177 | 87 | 96 |
| XLF | 23 | 179 | 183 | 86 | 89 |
| XLI | 27 | 177 | 180 | 81 | 104 |
| XLK | 22 | 174 | 165 | 77 | 97 |
| XLP | 23 | 165 | 179 | 80 | 91 |
| XLRE | 10 | 68 | 68 | 35 | 32 |
| XLU | 29 | 179 | 170 | 78 | 79 |
| XLV | 26 | 176 | 177 | 82 | 93 |
| XLY | 20 | 184 | 171 | 77 | 104 |
| **Mean** | **21.91** | **155.18** | **154.73** | **72.45** | **83.27** |

Source: own study.

The number of transactions for individual technical strategies varies, but it's worth noting that the lowest values for the XLC and XLRE funds result from their shorter research period. To maintain data comparability, the average annual number of transactions was calculated for each of the indicators studied – see Table 5.

**Table 5.**
*Average annual number of transactions executed within individual technical strategies*

| ETF fund | RSI (20/80) | CCI (-100/100) | W%R (-100/0) | DM (0.3/0.7) | ST (10/90) |
|---|---|---|---|---|---|
| XLB | 1.02 | 6.86 | 7.16 | 3.51 | 3.85 |
| XLC | 0.85 | 6.26 | 5.97 | 2.99 | 4.12 |
| XLE | 1.06 | 6.75 | 6.67 | 3.28 | 3.62 |
| XLF | 0.87 | 6.75 | 6.90 | 3.24 | 3.36 |
| XLI | 1.02 | 6.67 | 6.79 | 3.05 | 3.92 |
| XLK | 0.83 | 6.56 | 6.22 | 2.90 | 3.66 |
| XLP | 0.87 | 6.22 | 6.75 | 3.02 | 3.43 |
| XLRE | 1.03 | 6.99 | 6.99 | 3.60 | 3.29 |
| XLU | 1.09 | 6.75 | 6.41 | 2.94 | 2.98 |
| XLV | 0.98 | 6.64 | 6.67 | 3.09 | 3.51 |
| XLY | 0.75 | 6.94 | 6.45 | 2.90 | 3.92 |
| **Mean** | **0.94** | **6.67** | **6.64** | **3.14** | **3.60** |

Source: own study.

Of the five technical indicators analyzed, three groups can be distinguished: those with a high number of signals (CCI – 6.67 and W%R – 6.64), moderate ones (ST – 3.60 and DM 3.14), and the RSI indicator, for which the number of transactions was the lowest (only 0.94). It is also worth noting the relative stability of results between the analyzed funds. The values of the average annual number of transactions for individual funds are relatively consistent, suggesting that the characteristics of the technical indicators dominate the specificity of the analyzed sectors in terms of signal frequency. Next, based on data on the average annual number of transactions executed within individual strategies and the corresponding rates of return, after checking the distributions using Shapiro-Wilk tests with the Lillefors correction and finding that the distribution of the number of transactions was not close to normal, the Spearman rank correlation coefficient was calculated. The obtained coefficient value was 0.42, which indicates a moderate level of dependence between the variables examined (Evans, 1996) – the rates of return are moderately dependent on the number of transactions made within individual strategies.

## 5. Conclusions and Discussion

Based on the analysis, we rejected hypothesis H1, which states that the use of investment strategies based on technical analysis indicators allows for higher average annual rates of return than the use of a "buy-and-hold" strategy for sector ETFs on the US market for the daily timeframe. However, the results of the study indicate that there are individual indicators that allow for higher rates of return than the "buy-and-hold" strategy.

Hypothesis H2 which states that there is a strong relationship between the number of transactions and the rates of return obtained from investing in US sector ETFs using strategies based on technical indicators, should also be rejected in the case of the daily timeframe, as the discussed relationship is at a moderate level (the Spearman rank correlation coefficient was 0.42).

The research conducted allowed us to draw the following conclusions:

- C1: Of all the oscillators examined, the highest average annual rates of return were recorded for the Stochastic Oscillator.
- C2: The index and technical analysis yielded higher average rates of return for industries such as raw materials, energy, finance, and real estate. Except for the raw materials industry, the difference in rates of return did not exceed 1 percentage point.
- C3: The average annual number of transactions made using individual oscillators varies. The Commodity Channel Index recorded the most, with 6.67 pairs of buy and sell signals. The Relative Strength Index recorded the fewest, with less than one pair (0.94).
- C4: The level of correlation between the average annual number of transactions executed on the basis of signals generated by oscillators and the average annual rate of return measured by the Spearman rank correlation coefficient is 0.42, which indicates a weak level of correlation between the variables examined.

The results of the conducted study indicate that, overall, investment strategies based on technical oscillators do not outperform the “buy-and-hold” strategy for sector ETFs on the U.S. market in the daily timeframe, which is consistent with the findings presented in the literature. The research by Deep et al. (2025) and Cohen (2015, 2020) demonstrated that classical technical indicators have limited predictive value and, in many cases, yield results lower than the passive strategy. At the same time, the literature emphasizes that some oscillators can outperform buy-and-hold under certain conditions, which is reflected in our study – the Stochastic Oscillator achieved the highest average annual returns among the examined indicators. Further results of the study confirm the dependence of oscillator effectiveness on the characteristics of the instrument and the market. In our research, higher returns were achieved in the materials, energy, financial, and real estate sectors, which aligns with the observations of Cohen (2020) and Trembiński & Stawska (2021), highlighting the necessity of adjusting indicator parameters to the characteristics of the instrument. The observed differences in the effectiveness of strategies across sectors, as well as their dependence on market volatility and the number of transactions, can be interpreted in light of the Adaptive Market Hypothesis – the results indicate that the effectiveness of investment strategies varies according to market conditions and sector characteristics, reflecting the adaptive behavior of market participants. The analysis of the number of trades revealed a moderate correlation (0.42) between the number of signals and the rate of return, which is also supported by the literature – more frequent signals generated by oscillators, such as the CCI, do not necessarily translate into higher investment performance (Naved, Srivastava, 2015; Cohen, 2020). In conclusion, the study results confirm the observations from the literature: technical oscillators can support the investment decision-making process and, in certain situations, improve investment outcomes; however, their effectiveness is variable, depending on the instrument, the market, the indicator parameters, and market conditions, and systematic outperformance of the passive strategy is not consistently achievable.

The main limitation of the conducted study was the length of the research period (XLC and XLRE funds were established in later years), determined by the period of existence of individual ETF funds and the availability of data - especially high frequency. Considering potential future research directions, it seems worthwhile to repeat the study, considering different, primarily lower, time frames. The study could also be repeated using other, lesser-known oscillators, a different group of indicators, such as trend or volume indicators, or a different method of interpreting the signals generated by the indicators. Another interesting concept seems to repeat the study in the coming years while maintaining the same parameters and incorporating a larger dataset. It would also be worthwhile to explore combining multiple indicators, applying machine learning techniques, or testing the strategies in non-US markets.

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