Investigating Profitability of Technical Trading Rules Around COVID Pandemic: Evidence from PSX

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ABSTRACT

This paper investigates the role of technical analysis in predicting the stock prices of listed companies on the Pakistan Stock Exchange (PSX). Technical indicators such as Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI), Bollinger Bands (BB), and Money Flow Index (MFI) are evaluated to explore their significance for stock gains in the Pakistan Stock Exchange. For this purpose, daily price data from 29 companies listed on the PSX was collected during the period from 2018 to 2022. This sample period provides a unique opportunity to analyze the impact of Covid-19 on the accuracy of technical trading signals. MACD, RSI, BB, and MFI are calculated, and the accuracy of the results is then assessed. Evidence from the PSX highlights that these indicators perform differently across various sectors. The t-test outcomes indicate significant differences in results before and after Covid-19, emphasizing the impact of the pandemic on stock movements. Based on these results an index has been developed and proposed to aid future decision-making processes.

Keywords: *Technical indicators, Covid 19, PSX, MACD, RSI, BB, MFI*

INTRODUCTION

Investors, whether individual or institutional, face challenges in selecting stocks with similar projected returns, given the complexity of accurately forecasting stock price movements in today's dynamic industrial landscape. Investors require various techniques to aid them in identifying investment opportunities. Stockbrokers provide crucial guidance to investors, offering insights based on their knowledge. Through the use of technical trading rules and forecasting stock prices with technical indicators, investors aim to make informed decisions for potential profitability. However, projecting the performance of the stock market is a challenging task, and the ultimate goal of predicting stock prices is to secure substantial returns.

Technical analysis examines market price movements using price, volume, and open interest, guided by the belief that market action reflects all relevant information, trends persist until reversal, and history repeats itself. It focuses on short-term signals, assessing a security's strength based on past trading activities, and utilizes tools to evaluate market conditions influenced by political, economic, and psychological factors to reveal price trends. In spite of the availability of different technical analysis techniques and methods, analysts now become more interested in using indicators that use mathematical functions to generate a buy or sell call (Clement, 2010). Incorporating technical indicators like moving averages, RSI, MACD, and MFI in stock prediction is beneficial for objective and quantitative insights based on historical price and volume patterns. These indicators aid in identifying buy or sell signals and

offer valuable information about market trends. Technical indicators are valuable tools in stock prediction, offering specific and quantifiable signals based on mathematical calculations. These indicators utilize historical price and volume data to provide insights into market trends and potential trading opportunities. Moving averages, oscillators like RSI, and indicators like MACD are commonly used, offering information on trend direction, overbought or oversold conditions, and changes in momentum. Traders leverage these indicators for more effective timing of trades, gaining objective signals to make informed decisions and manage risk efficiently.

Technical Indicators

Numerous scholarly works, written by well-known researchers such as Bulkowski (2005) and Kaufman (2011) have extensively explored technical indicators. A multitude of technical indicators has been developed for predicting securities' future price movements, focusing on aspects such as identifying trends and assessing their strength. These indicators vary in their approaches, some rooted in price-based analyses, others in trading volumes, and some combining both. Moving averages, breadth indicators, and momentum indicators like MACD and RSI play crucial roles in trend analysis and quantifying the pace of price fluctuations. This study strategically employs a diverse set of technical indicators, including MACD, RSI, MFI, and BB, each offering a unique perspective in financial analysis and forecasting.

Moving Average Convergence and Divergence

MACD is a key momentum indicator for trading, created by Gerald Appel. It employs exponential moving averages (EMAs) to analyze stock price trends, indicating the direction, strength, and duration of trends. It consists of two lines: the MACD line (red) and the signal line (green). Buy signals occur when the MACD crosses above zero, indicating an uptrend, while sell signals happen when it drops below zero, signaling a downtrend. Rising MACD above the signal line indicates bullish momentum, whereas falling MACD below it suggests bearish momentum.

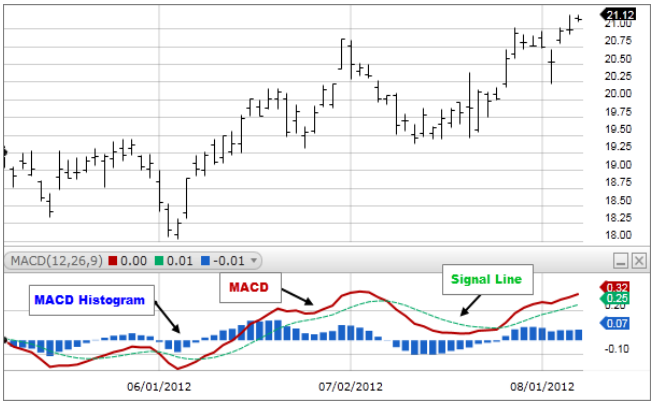

Figure 1: Source: Fidelity.com

Relative Strength Index

RSI is a momentum oscillator, measuring a security's price strength on a scale from zero to one hundred with 50 indicating a neutral market. It identifies overbought (RSI > 70) and oversold (RSI < 30) conditions, suggesting buys when RSI is above 50 for strengthening momentum and sells when below 50 for weakening strength, calculated over typically 14 days.

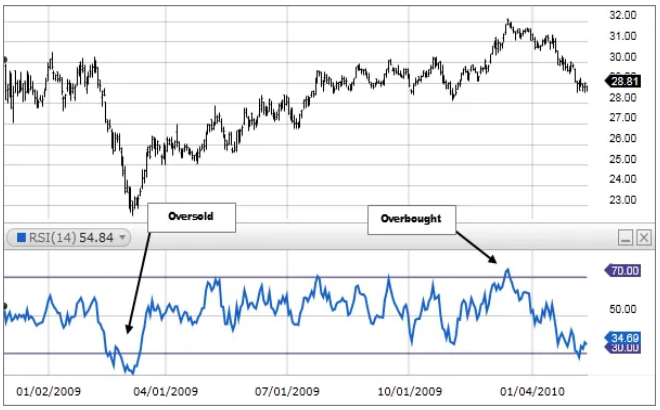

Figure 2: Source: Fidelity.com

Money Flow Index

MFI is a technical oscillator analyzing capital flow in a security using both price and volume data. Unlike the RSI, which considers only price, MFI assesses overbought and oversold signals within a timeframe by combining price and trading volume. Ranging from 0 to 100, MFI provides a comprehensive view of money dynamics in a security, offering insights into market sentiment and potential trend shifts.

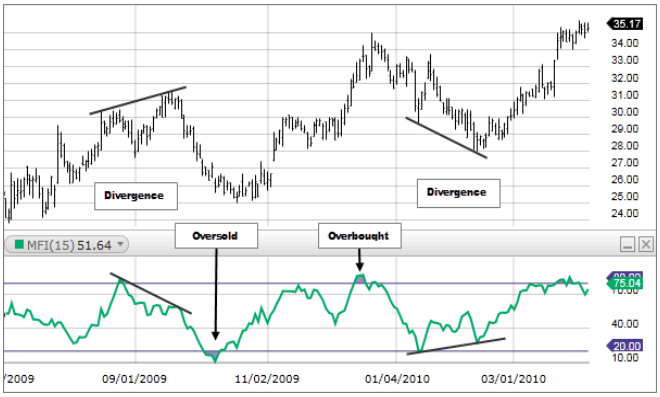

Figure 3: Source: Fidelity.com

Bollinger Bands

Bollinger Bands (BB) by John Bollinger assist investors in pinpointing entry points and recognizing overbought/oversold conditions using a 20-day SMA and standard deviations. The upper band indicates potential overbought, lower band suggests oversold, aiding in identifying support/resistance levels for informed investment decisions.

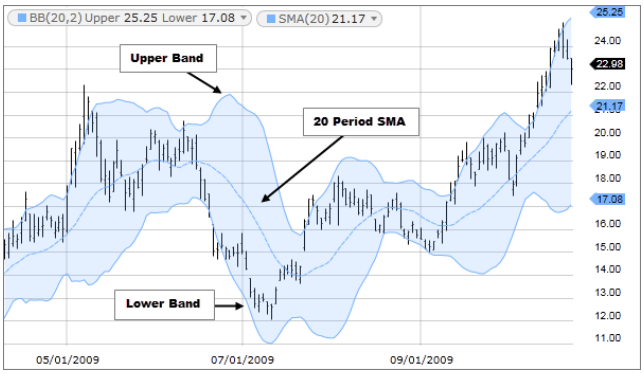

Figure4: Source: Fidelity.com

Significance of the Study

Research on the profitability of technical analysis during the COVID-19 pandemic is an unexplored area, considering the pandemic's profound impact on global financial markets, characterized by extreme volatility and uncertainty. Evaluating the effectiveness of technical analysis in this unprecedented crisis is essential for both investors and researchers. Lento & Gradojevic (2022) analyzed the profitability of technical analysis during the COVID-19 market meltdown, exploring pre-pandemic, pandemic crash, and recovery periods. Their study examined how market volatility influences traders' beliefs and the efficacy of technical analysis. Additionally, Menkhoff et al. (2012) studied high-interest-rate currencies and volatility's impact on returns, while Menkhoff and Taylor (2007) assessed technical analysis profitability for volatile currencies, illustrating the intricate relationship between market conditions and technical analysis effectiveness. The profitability of technical analysis, especially during market disruptions like the COVID-19 pandemic, remains a key focus of current research. Investors aim for enhanced market trend understanding, integrating traditional methods and for stock prediction, notably in challenging times like the COVID-19 pandemic. The pandemic-driven market volatility has prompted a reevaluation of the efficacy of technical trading strategies. Studies like Lento & Gradojevic (2022) have explored into this issue, shedding light on the relationship between market volatility and the success of technical analysis. This study evaluates the efficacy of technical indicators on listed companies at PSX in pre, during, and post-COVID periods. Sector-specific analysis is vital to grasp their relevance for the entire index and various sectors. A focused COVID-19 analysis explores potential impacts on the indicators' effectiveness in forecasting stock prices.

The paper is structured as follows: Section 2 reviews literature on the use of technical indicators. Section 3 outlines the research framework, methodology, data source, and the selected population and sample size. Section 4 presents the analysis, results, and discussion on the validity of technical indicators. The final section includes the conclusion, implications, limitations, and directions for future research.

LITERATURE REVIEW

Technical Analysis

Predicting stock market returns is acknowledged as a challenging task, as indicated by Teixeira et al. (2010). Vanstone and Finnie (2009) observed that techniques such as technical and fundamental analysis were developed for this purpose. Technical analysis, as described by Park & Irwin (2007), relies on past stock price information to predict future price returns, akin to using a toolkit of historical market data to forecast financial performance. Recent studies have integrated traditional technical analysis rules with advanced systematic methods and statistical models (Wei et al., 2011). Furthermore, there has been a growing emphasis on the application of technical indicators in recent research. These indicators serve as essential tools for market traders and investors engaged in modern quantitative portfolio management and investment strategies (Chincarini and Kim, 2006).

Taylor & Allen (1992) and Neely and Weller (2012) highlighted the significance of technical indicators in maximizing returns for investors, suggesting their use in stock investment decisions. However, Fama (1960) argued that markets reflect all available information at any given time, making it difficult to predict future stock prices based on past prices. Neftci (1991) supported this view, stating that future stock prices cannot be accurately predicted. Hudson et al. (1996) also advocated for the Efficient Market Hypothesis, suggesting that holding strategy is superior to attempting predictions using technical breakout rules. In contrast, Treynor and Ferguson (1985) were optimistic about using technical analysis for prediction, particularly in non-price data scenarios. Brock et al. (1992) found that breakout rules outperformed simple buy and hold strategies, further fueling research into the statistical evidence of technical indicators' applicability. Mills (1997) and Kwon & Kish (2002) provided empirical support for the effectiveness of breakout rules over buy and hold strategies in different stock markets. Yao & Tan (2000), however, found in their research on forex exchange prediction that technical indicators and neural networks were not reliable in an efficient market. Chen & Kuo (2006) proposed a neural network-based Decision Support System for transaction timing and strategies, showing improved predictions compared to solely applying stock indexes. Grigoryan (2015) utilized artificial neural networks and principal component analysis to predict stock movements in the NASDAQ stock exchange, emphasizing the importance of technical indicators. Aslam et al. (2021) predicted Islamic securities index using artificial neural networks, highlighting the impact of various technical indicators on the Islamic index. Pasaribu (2024) found that MACD crossovers alone without confirmation from other indicators like RSI tend to be weak and inaccurate for investment decisions in telecommunications companies on the Indonesia Stock Exchange. Tavakolipoura et al. (2024) introduced the NNARX model for forecasting financial indicators, showing promising accuracy in predicting technical analysis indicators influenced by economic conditions and company characteristics. Sheikhzadeh and Rahmany (2024) proposed a method using feature selection algorithms and classification techniques to improve the accuracy of stock price predictions, demonstrating its effectiveness in the Tehran Stock Exchange data.

Technical Indicators Role in Different Financial Crisis

After the Asian financial crisis, Singapore made some changes to improve its financial markets. Kung and Wong (2009) investigated the impact of changes in Singapore's financial markets on investors' profits, finding that trading rules were more effective in the period from 1988 to 1996 compared to 1999 to 2007. Shynkevich (2016) examined technical trading rules during financial crises, suggesting that such rules do not consistently outperform holding stocks, especially in chaotic market conditions. Híľovská et al. (2011) evaluated the effectiveness of artificial neural networks and technical analysis in predicting stock prices before and during financial crises, with mixed results. Sabbaghi and Sabbaghi (2018) assessed the

efficiency of developed markets during the global financial crisis, noting that technical analysis could aid in predicting returns, particularly in the USA. Yashina et al. (2022) developed new tools for technical analysis to improve investment decision-making during financial crises, with successful implementation in the Russian stock market. Kung et al. (2021) investigated the efficacy of technical rules in Asian markets during the 2008 financial crisis, highlighting factors influencing market policies. McAleer et al. (2016) studied the profitability of technical analysis strategies during stock market bubbles, suggesting that certain signals could enhance investor returns. Miletic (2019) analyzed the long-term economic impact of the European financial crisis on various countries, observing disparities in economic recovery. Bahrini (2016) examined the performance of Islamic banks in the MENA region during and after the global financial crisis, noting fluctuations in efficiency over time. Finally, Taylor and Allen (1992) surveyed foreign exchange dealers' reliance on technical analysis, emphasizing its importance, especially for short-term trading strategies.

The literature underscores the importance of technical analysis, particularly indicators like MACD, RSI, and Bollinger Bands, in predicting stock market movements. While some studies support its effectiveness, especially during crises, others stress the need for a nuanced approach and consideration of additional factors. Our objective is to assess the performance of these indicators in the Pakistani stock market during the COVID-19 pandemic, aiming to gauge their effectiveness amid pandemic-related challenges, leading to the hypothesis that these indicators will demonstrate varying degrees of effectiveness during this period. This hypothesis is grounded in the observed importance and utility of these indicators, as highlighted in the reviewed literature, especially during times of financial crises.

H1: There is difference between the predication accuracy of technical indicators before and after the Covid 19.

METHODOLOGY

This study employs a quantitative approach to analyze the impact of technical indicators on the Pakistan Stock Exchange (PSX), using secondary data from 2018 to 2022 sourced from dps.psx.com.pk, SCS Trade.com, and brokerage firms' sites. Focusing on the KSE-100 index and the top ten sectors representing 80.96% of market capitalization, firms with high volumes within these sectors are sampled using daily open, high, low, close, and volume data.

Table 1: Firms selected as sample

Sectors	**Name of Sample firms**		
Banks	Silk Bank	BOP	FABL
Oil and exploration	OGDC	PPL	PKOL
Cement	MLCF	FCCL	DGKC
Technology and Communication	WTL	TRG	HUMNL
Power	KEL	SPWL	TSPL
Automobile	GHNI	DFML	SAZEW
Oil and gas marketing	SNGP	PSO	SSGC
Pharmaceutical	SEARL	FEROZ	GLAXO
Chemical	GGL	EPCL	LOT CMEM

Lawrence, David & Maureen (1994) emphasized the unique information volumes provide in predicting stock prices, asserting its correlation with prediction precision. Shynkevich (2012) highlighted the significance of volumes in technical analysis, indicating their role in prediction accuracy. The selected sectors and corresponding firms based on market capitalization rate and high volume firms are given in table 1 and 2.

Table 2: Market capitalization of sample firms

Sectors	Market
Banks	24.17%
Fertilizers	12.73%
Oil and exploration	11.12%
Cement	8.43%
Technology and Communication	6.11%
Power	4.97%
Automobile	3.67%
Oil and gas marketing	3.41%
Pharmaceutical	13.18%
Chemical	3.17%

Technical indicators used in this study and the procedure of getting trading signals are as follows:

MACD:

MACD = exponential moving averages of 12-period - exponential moving averages of 26-period

The above calculation results in MACD line, then a nine-day EMA of MACD line are calculated to determine the signal line.

Signal Line = 9 Day EMA of MACD Line

Determining Signals:

Buy Signal = MACD > Signal Line

Sell Signal = MACD < Signal Line

RSI:

RSI = 100-(100/1+RS)

RS = average gain/average loss

Determining Signals:

Buy Signal = RSI >50

Sell Signal = RSI<50

BB:

BB indicator is defined by the trend lines that plot positive and negative standard deviation away from a 20 days simple moving average of a security price. A Bollinger band is formed by three bands; middle band, upper band and lower band and these bands provides support and resistance.

Determining Signals:

Buy Signal = Security Price > Lower Band

Sell Signal = Security Price < Upper Band

MFI

Calculate the Average Price by summing the day's high, low, and close prices, then dividing by the count. Compute the Money Flow by multiplying the Average Price by the day's volume. Determine the Money Flow Ratio by segregating positive and negative money flows based on price movements. Utilize

the formula MFI = 100 - [100 / (1 + Money Flow Ratio)] for the final MFI calculation. MFI values range from 0 to 100, with 70-80 indicating overbought and 20-30 suggesting oversold conditions in a stock.

Determining Signals:

Buy Signal = MFI>50

Sell Signal = MFI <50

This study analyzes four technical indicators applied individually to historical data from 29 companies over five years, aiming to generate buy and sell signals. These signals are compared with actual market movements across three periods: before, during, and after the COVID-19 pandemic, assessing indicator performance under diverse market conditions. Signals are categorized as true, false, or neutral, with verification against market behavior crucial for understanding indicator reliability. Percentage-based analysis quantifies indicator effectiveness in each period. Following descriptive examination, a two-tailed t-test determines significant differences in signal mean values before and after the COVID-19 period, adding depth to the analysis.

ANALYSIS AND RESULTS

Descriptive Analysis

The study assesses MACD, RSI, BB, and MFI signals' accuracy across 29 companies in three scenarios: 5 Years Results (See table 3), Before Covid (see table 4), and After Covid (see table 5). It involves computation, interpretation, and evaluation of trading signals in each scenario, followed by a detailed discussion on insights gained from individual company analyses. Furthermore, the research explores whether mean values of these indicators before and after the Covid period are equivalent or differ, emphasizing the interpretation of signal accuracy in each scenario. The descriptive results (tables shown in appendix) of all seniors of the selected companies revealed that each indicator showed strengths in identifying true buy signals, but they also had limitations in generating false signals, especially for sell opportunities. As a result, we recommend using a combination of indicators or additional technical and fundamental analysis for more accurate trading decisions. The analysis demonstrated mixed results for different stocks and market conditions. Some scenarios showed balanced accuracy between buy and sell signals, while others exhibited significant imbalances. This highlights the need for adaptability in applying these indicators and considering market conditions before making decisions.

Table 3: Five Years Accuracy Percentage

Sectors	MACD	RSI	BB	MFI
Bank	45%	46%	40%	47%
Fertilizer	50%	52%	48%	48%
OIL and Exploration	45%	51%	40%	53%
Cement	49%	50%	42%	50%
Technology and Communication	44%	47%	45%	46%
Power	51%	51%	46%	50%
Automobile	49%	50%	38%	51%
Oil and Gas Marketing	49%	50%	43%	51%
Pharmaceutical	48%	48%	42%	48%
Chemical	49%	18%	49%	53%

Table 4: Before Covid Accuracy Percentage

Sector	MACD	RSI	BB	MFI
Bank	45%	46%	40%	47%
Fertilizer	50%	52%	48%	48%
Oil and Exploration	45%	51%	40%	53%
Cement	49%	50%	42%	50%
Technology and Communication	44%	47%	45%	46%
Power	51%	51%	46%	50%
Automobile	49%	50%	38%	51%
Oil and Gas Marketing	49%	50%	43%	51%
Pharmaceutical	48%	48%	42%	48%
Chemical	49%	18%	49%	53%

Table 5: After Covid Accuracy Percentage

Sector	MACD	RSI	BB	MFI
Bank	45%	46%	40%	47%
Fertilizer	50%	52%	48%	48%
Oil and Exploration	45%	51%	40%	53%
Cement	49%	50%	42%	50%
Technology and Communication	44%	47%	45%	46%
Power	51%	51%	46%	50%
Automobile	49%	50%	38%	51%
Oil and Gas Marketing	49%	50%	43%	51%
Pharmaceutical	48%	48%	42%	48%
Chemical	49%	18%	49%	53%

The table 3 provides a concise overview of accuracy percentages for MACD, RSI, BB, and MFI across sectors over five years. Notable findings include comparable accuracy in banking (41% to 46%), moderate accuracy in fertilizers (48% to 51%), consistently high accuracy in oil and exploration (led by MFI at 52%), balanced accuracy in cement (46% to 50%), and varied rates in technology and communication (43% to 49%). Power, automobile, oil and gas marketing, pharmaceuticals, and chemicals sectors also present distinct accuracy ranges, aiding analysts and investors in decision-making based on historical indicator performance within specific industry contexts. The table 4 succinctly outlines pre-COVID-19 sector-wise performance for MACD, RSI, BB, and MFI, emphasizing their accuracy in generating signals. Notable highlights include MFI's exceptional 56% accuracy in banking and commendable rates (47%-52%) in fertilizers. Overall, accuracy spans 46% to 52%, with pharmaceuticals showcasing robust accuracy, especially MACD at 54%. RSI anomalies in the chemical sector warrant investigation, offering diverse insights. The table 5 Post-COVID-19, technical indicators show varied accuracy across sectors. Banking and technology sectors demonstrate moderate accuracy, while fertilizer and power sectors exhibit strong and consistent performance. The oil and exploration sector displays diverse results, with MFI standing out. The automobile sector's accuracy varies, and pharmaceuticals maintain a moderate level of accuracy. Overall, the performance of indicators differs across sectors after the COVID-19 period.

Table 6: Independent sample t test

Signal	Levene's Test for Equality of Variances	P value	Mean Difference	95% confidence [Lower tail]	95% confidence [Upper tail]
MACD	0.417	0.000	63.655	51.480	75.830
RSI	0.533	0.000	49.448	39.472	59.425
BB	0.612	0.000	52.862	41.840	63.884
MFI	0.097	0.000	60.345	34.412	86.278

The independent samples t-tests conducted across various technical indicators (MACD, RSI, Bollinger Bands, and MFI) in both company and sectorial analyses consistently reveal significant increases in post-COVID-19 values. Whether assuming equal variances or not, all indicators displayed substantial and sustained shifts, reflecting changes in market dynamics and company performance amidst the COVID-19 crisis. This suggests a notable impact of the pandemic on the performance of studied companies and sectors, reinforcing the significance of technical analysis in understanding and navigating market trends during challenging periods.

Through meticulous analysis, we've developed a specialized index focusing on individual sectors, integrating diverse technical indicators to assess sector performance during pre- and post-COVID periods. Evaluating the accuracy of results from these indicators individually and in combination, expressed as percentages, provides valuable insights into sector dynamics and performance, enhancing our understanding of their overall trajectory amidst various market factors.

Table 7: Proposed Technical Trading Index

Sector Wise Probabilities	MACD	RSI	BB	MFI
Bank	0.24	0.24	0.22	0.29
Fertilizer	0.25	0.25	0.24	0.24
Oil and exploration	0.25	0.25	0.22	0.26
Cement	0.25	0.25	0.23	0.25
Technology and communication	0.25	0.25	0.22	0.25
Power	0.25	0.26	0.23	0.25
Automobile	0.25	0.22	0.24	0.26
Oil and gas marketing	0.27	0.28	0.25	0.19
Pharmaceutical	0.25	0.26	0.23	0.25
Chemical	0.24	0.25	0.24	0.25

By utilizing the proposed index, investors can gain valuable assistance in shaping future buying and selling decisions through a comprehensive evaluation of the accuracy exhibited by diverse indicators. The index facilitates a deeper understanding by offering insights into the current percentage of accuracy demonstrated by each indicator. This information becomes instrumental in guiding decision-making process, as it allows us to assess whether it is prudent to initiate buying or selling actions at a given moment. The analysis not only sheds light on the accuracy of individual indicators but also empowers to make more informed decisions. Specifically, we can discern which indicators are proving to be more reliable under the prevailing market conditions. This knowledge is crucial for navigating the dynamic landscape of financial markets, enabling us to align our strategies with indicators that have demonstrated a higher level of trustworthiness in the present market scenario.

CONCLUSION

The study comprehensively assessed the reliability of MACD, RSI, BB, and MFI indicators for stock trading on the Pakistan Stock Exchange. While these indicators performed well in identifying genuine buy signals, challenges arose in generating false signals, particularly for sell opportunities. Post-COVID outcomes consistently showed positive results across company-specific and sectorial analyses. To enhance accuracy, a combination of indicators alongside technical and fundamental analyses is recommended. The research underscores the importance of adaptability in trading strategies, offering valuable insights for investors, brokerage firms, and fund managers. By understanding both strengths and limitations, investors can navigate the market confidently, utilizing specialized indices to guide decision-making and adapt strategies effectively. For future research, it is advisable to explore alternative technical indicators or integrate fundamental analysis to enhance overall predictive accuracy. Additionally, delving into the influence of market sentiment and macroeconomic factors on indicator performance could offer valuable insights for refining trading strategies. Embracing advanced technological methods for prediction, coupled with indicators, can yield more sophisticated and advanced results. These recommendations aim to broaden the scope of future research endeavors, incorporating a diverse range of indicators and considering broader market dynamics to further improve the precision of trading predictions.

REFERENCES

Aslam, F., Mughal, K. S., Ali, A., & Mohmand, Y. T. (2021). Forecasting Islamic securities index using artificial neural networks: performance evaluation of technical indicators. *Journal of Economic and Administrative Sciences*, *37*(2), 253-271..

Bagnoli, M., Clement, M., Crawley, M., & Watts, S. (2010). The relative profitability of analysts' stock recommendations: What role does investor sentiment play. *Availableat: http://www. ssrn. com*..

Bahrini, R. (2016). Technical efficiency Analysis of MENA Islamic banks during and after the global financial crisis. *Journal of Islamic banking and Finance*, *4*(2), 15-24.

Blume, L., Easley, D., & O'hara, M. (1994). Market statistics and technical analysis: The role of volume. *The journal of finance*, *49*(1), 153-181.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of finance*, *47*(5), 1731-1764.

Bulkowski, T. N. (2021). *Encyclopedia of chart patterns*. John Wiley & Sons.

Chen, C. L., & Kuo, M. H. (2006). An ETF trading decision support system by using neural network and technical indicators. In *The 2006 IEEE international joint conference on neural network proceedings* (pp. 2394-2401). IEEE.

Fama, E. F. (1960). Efficient market hypothesis. *Diss. PhD Thesis, Ph. D. dissertation*..

Grigoryan, H. (2015). Stock market prediction using artificial neural networks. Case Study of TAL1T, Nasdaq OMX Baltic Stock. *Database Systems Journal*, *6*(2), 14-23.

Híľovská, K., Lučkaničová, M., & Šterba, J. (2011). The impact of financial crisis on the predictability of the stock markets of PIGS countries–comparative study of prediction accuracy of technical analysis and neural networks. *Financial assets and investing*, *2*(3), 19-32.

Hudson, R., Dempsey, M., & Keasey, K. (1996). A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices-1935 to 1994. *Journal of banking & finance*, *20*(6), 1121-1132..

Kaufman, P. J. (2011). *Alpha trading: profitable strategies that remove directional risk*. John Wiley & Sons..

Kung, J. J., & Wong, W. K. (2009). Profitability of technical analysis in the Singapore stock market: Before and after the Asian financial crisis. *Journal of economic integration*, 135-150..

Kung, J. J., Lin, W. Y., & Chen, H. L. (2021). How effective are technical rules in predicting the 2008 global financial crisis? The case of the four Asian tigers. *Journal of the Asia Pacific Economy*, *26*(1), 13-33.

Kwon, K. Y., & Kish, R. J. (2002). Technical trading strategies and return predictability: NYSE. *Applied Financial Economics*, *12*(9), 639-653.

Lento, C., & Gradojevic, N. (2022). The profitability of technical analysis during the COVID-19 market meltdown. *Journal of Risk and Financial Management*, *15*(5), 192.

McAleer, M., Suen, J., & Wong, W. K. (2016). Profiteering from the dot-com bubble, subprime crisis and Asian financial crisis. *The Japanese Economic Review*, *67*, 257-279.

Menkhoff, L., & Taylor, M. P. (2007). The obstinate passion of foreign exchange professionals: technical analysis. *Journal of Economic Literature*, *45*(4), 936-972.

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012). Carry trades and global foreign exchange volatility. *The Journal of Finance*, *67*(2), 681-718.

Miletic, M. (2019). The impact of the financial crisis on the Gross Domestic Product: Technical Analysis..

Mills, T. C. (1997). Technical analysis and the London Stock Exchange: Testing trading rules using the FT30. *International Journal of Finance & Economics*, *2*(4), 319-331..

Neely, C. J., & Weller, P. A. (2012). Technical analysis in the foreign exchange market. *Handbook of exchange rates*, 343-373..

Neftci, S. N. (1991). Naive trading rules in financial markets and wiener-kolmogorov prediction theory: A study of" technical analysis". *Journal of Business*, 549-571..

Park, C. H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis?. *Journal of Economic surveys*, *21*(4), 786-826.

Pasaribu, M. K. (2024). Technical Analysis of Stock Investment Decisions in Telecommunication Companies Listed on the Indonesian Stock Exchange. *Indonesian Journal of Banking and Financial Technology*, *2*(1), 13-20.

Sabbaghi, O., & Sabbaghi, N. (2018). Market efficiency and the global financial crisis: evidence from developed markets. *Studies in Economics and Finance*, *35*(3), 362-385..

Sheikhzadeh, M. J., & Rahmany, S. (2024). Improved stock price forecasting by streamlining indicators: an approach via feature selection and classification. *International Journal of Computational Economics and Econometrics*, *14*(1), 42-60..

Shynkevich, A. (2012). Performance of technical analysis in growth and small cap segments of the US equity market. *Journal of Banking & Finance*, *36*(1), 193-208..

Shynkevich, A. (2016). Predictability of equity returns during a financial crisis. *Applied Economics Letters*, *23*(17), 1201-1205..

Sung, T., Kim, D., & Chincarini, L. (2006). Corporate scandals and the market response of dividend payout changes. Applied Financial Economics, 16(07), 535-549.

Tavakolipoura, H., Ahmadib, F., Abedinic, B., & Ranjbard, M. H. (2024). A Study of the Effective Factors on Error of Forecasting Technical Analysis Indicators in Iran Stock Exchange (NNARX Approach). Advances in Mathematical Finance and Applications, 9(1), 355-366.

Taylor, M. P., & Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of international Money and Finance*, *11*(3), 304-314..

Teixeira, N., Carreira, F. J. A., Pardal, P., & Mata, C. (2010). The contribution of financial information for stock price value. In *2010 British Accounting Association Annual Conference*..

Treynor, J. L., & Ferguson, R. (1985). In defense of technical analysis. *The Journal of Finance*, *40*(3), 757-773..

Vanstone, B., & Finnie, G. (2009). An empirical methodology for developing stockmarket trading systems using artificial neural networks. *Expert systems with Applications*, *36*(3), 6668-6680.

Wei, L. Y., Chen, T. L., & Ho, T. H. (2011). A hybrid model based on adaptive-network-based fuzzy inference system to forecast Taiwan stock market. *Expert Systems with Applications*, *38*(11), 13625-13631..

Yao, J., & Tan, C. L. (2000). A case study on using neural networks to perform technical forecasting of forex. *Neurocomputing*, *34*(1-4), 79-98..

Yashina, N., Kashina, O., Yashin, S., Pronchatova-Rubtsova, N., & Khorosheva, I. (2022). Digital Methods of Technical Analysis for Diagnosis of Crisis Phenomena in the Financial Market. *International journal of technology*, *13*(7), 1403-1411.