Efficiency and Predictive Power of Technical Trading Rules in Post-COVID-19 Era : A Study of BRICS Stock Market

Poonam [1]
N. S. Malik [2]

Abstract

Purpose : This study was an attempt to test the efficiency and revalidate the technical trading strategies based on the exponential moving average (EMA), relative strength index (RSI), and moving average convergence divergence (MACD) on stock returns in Brazil, Russia, India, China, and South Africa (BRICS) before and after the COVID-19 pandemic.

Methodology : The stock markets of BRICS were used from January 1, 2016, to February 29, 2024, to test the effectiveness of EMA, RSI, and MACD in a pre- and post-COVID sample.

Findings : The study did not suggest using EMA, RSI, and MACD indicators to generate buy and sell for a day trader because the technical rules under consideration failed to generate a positive alpha ratio ; hence, EMA, RSI, and MACD emerged as the low-performing technical trading rules for generating better stock returns than the "buy-hold" strategy in the BRICS stock market.

Practical Implications : Investors or traders in the stock markets of BRICS countries could clearly understand whether to use or not use the technical trading strategies studied in this research.

Originality : Unlike prior research on technical analysis, the current work provided a systemic way of back-testing technical trading strategies like EMA, RSI, and MACD.

Keywords : **technical trading, EMA, stock market, BRICS**

JEL Classification Codes : C58, G12, G14

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The COVID-19 pandemic has ushered in unprecedented volatility and uncertainty in global financial markets, impacting economies worldwide. Among the regions affected, the BRICS nations (Brazil, Russia, India, China, and South Africa) have been particularly scrutinized due to their significant contributions to the global economy and their unique market dynamics. In this context, understanding the efficacy and predictive power of technical trading rules in the BRICS stock markets becomes crucial for investors, policymakers, and researchers alike. Technical analysis, a popular approach in financial markets, relies on historical price and volume data to forecast future price movements (de Souza et al., 2018). Despite its widespread use, debates persist regarding its effectiveness, especially in emerging markets characterized by rapid economic changes and evolving regulatory environments (Tadas et al., 2023). The post-COVID-19 era presents an

[1] *Research Scholar,* Haryana School of Business, Guru Jambheshwar University of Science & Technology, Hisar - 125 001, Haryana. (Email : roshnipoonam07@gmail.com) ; ORCID iD : https://orcid.org/0009-0008-9358-1655
[2] *Professor (Corresponding Author),* Haryana School of Business, Guru Jambheshwar University of Science & Technology, Hisar - 125 001, Haryana. (Email : nsmalik2002@gmail.com) ; ORCID iD : https://orcid.org/0000-0002-0165-2719

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opportune moment to reevaluate the efficiency and reliability of technical trading rules in BRICS stock markets, given the paradigm shifts induced by the pandemic (de Souza et al., 2018).

This research paper aims to investigate the efficiency and predictive power of various technical trading rules within the BRICS stock markets post-COVID-19. By employing a comprehensive dataset spanning the pandemic period, we seek to analyze the performance of diverse technical indicators, trading strategies, and market conditions across the BRICS nations. Furthermore, we aim to assess the impact of COVID-19-induced market shocks on the effectiveness of technical analysis, considering factors such as market liquidity, volatility, and macroeconomic indicators. Through rigorous empirical analysis and statistical modeling, this study endeavors to provide insights into the viability of technical trading rules as decision-making tools for investors operating in the BRICS stock market post-COVID-19. By evaluating the consistency and profitability of various trading strategies, we aim to offer practical implications for market participants seeking to navigate the complexities of emerging market dynamics in the aftermath of the pandemic.

In summary, this research contributes to the ongoing discourse on the efficacy of technical analysis in BRICS stock markets, shedding light on its relevance and reliability in the post-COVID-19 landscape. By examining the interplay between technical indicators, market conditions, and economic shocks, we strive to provide valuable insights for both academic research and practical investment strategies in the BRICS region.

Review of Literature

The efficacy of technical trading rules in emerging markets, particularly within the BRICS nations, has been a subject of considerable academic inquiry in recent years. This section reviews existing literature to provide a comprehensive overview of the empirical evidence and theoretical frameworks relevant to the efficiency and predictive power of technical analysis in BRICS stock markets, focusing on the post-COVID-19 era.

Studies investigating the applicability of technical trading rules in emerging markets yield mixed findings. Some researchers argued that technical analysis is less effective in emerging markets due to market inefficiencies, limited liquidity, and informational asymmetries (Muruganandan, 2020). Others suggested that cultural and institutional differences may influence the behavior of market participants, thereby impacting the performance of technical indicators (Mohammed et al., 2021). Akhtar et al. (2021) found significant results by exponential moving average (EMA) considering leading stock markets worldwide. Vashishtha and Kumar (2013) also supported the predictability of technical analysis in their study on BSE-SENSEX employing Ralph Nelson Elliott Wave theory. However, contrasting results were reported by Reddy (2019). Raghuram (2017) argued that VMA trading rules did not profitably forecast future stock price movements when the trading cost was considered in most emerging stock markets.

Sobreiro et al. (2016) referred to technical analysis as a cheap proxy for Bayesian learning. Chong et al. (2010) found that various models employed to predict stock returns are now used as quantitative fund management tools. Khuntia and Pattanayak (2017) suggested that in the case of BRICS and emerging markets, the distinct combination of simple moving average (SMA) and EMA moving average techniques produced differing performances, among which the combination based on the SMA-SMA performed better than other combinations. Zhu et al. (2015) reported the dynamic conditional correlation (DCC) between bond returns, stock returns, and US financial stress in BRIC countries after the financial crisis in September 2008, except in India, where bond returns exhibited exceptional behavior. The deviation between BRIC bonds and the stock market was less than that of the deviation between the BRIC bond market and the measure of US financial stress in the long run.

Brock et al. (1992) demonstrated a direct relation between the persistence of stock returns for a large firm index, i.e., the Dow Jones index and trading volume employing a bootstrap simulation technique. Buchanan et al. (2011) examined the underlying sources of performance benefits in emerging countries by re-examining the

Chowdhury et al. (2024) paper. They reported that by focusing mainly on a limited set of stocks of emerging countries with a French civil law foundation and stocks that were moderately investable, an investor could benefit.

Agrawal et al. (2022) conducted a comparative analysis of the adaptive moving average and SMA by analyzing the Australian All Ordinaries, Dow Jones Industrial Average, and Standard and Poor's 500 stock market indices. They suggested that the adaptive moving average was an apparent natural progression of the trading system based on an SMA; however, they dismissed its ability to appropriately respond to changing market conditions. However, da Costa et al. (2015) found consistent results from SMA, EMA, and other techniques. Brock et al. (1992) utilized non-parametric techniques to explore the possibility of improved forecasting for stock returns and foreign exchange rates using observed nonlinearities in the two series. Forecast improvements were observed for both the series, i.e., stock returns and foreign exchange rates; however, the improvements were small/marginal for stock returns. Aggarwal and Khurana (2018) analyzed the effects of daily foreign exchange interventions in four Latin American countries, Chile, Columbia, Mexico, and Peru, while considering the inflation targets and reported asymmetrical effects. Nagendra et al. (2018) analyzed the relevance of moving averages for Physics by considering the Fractional Brownian motions and concluded that finance could contribute to Physics where specific transform could be used to investigate various structures in signals, such as trends, noise, cycles, etc.

Overall, the literature review highlights the multidimensional nature of the debate surrounding the efficiency and predictive power of technical trading rules in the BRICS stock markets. While some studies provide evidence of profitability and statistical significance for specific trading strategies, others emphasize the challenges posed by market inefficiencies, institutional factors, and external shocks. By synthesizing these diverse perspectives, this research paper aims to contribute to a nuanced understanding of the role of technical analysis in shaping investment decisions and market outcomes in the BRICS region post-COVID-19.

Research Methodology

Objective of the Study

The current study seeks to test and revalidate the effectiveness of the technical trading rule after the COVID-19 phase based on the EMA, relative strength index (RSI), and moving average convergence divergence (MACD) in the stock markets of the BRICS countries.

Hypotheses

The following null hypotheses have been framed to serve the purpose of the study:

- **$H_0$1** : There is no significant difference between the returns of the RSI-based strategy and the returns of the buy-hold (B-H) strategy.
- **$H_0$2** : There is no significant difference between the returns of the EMA-based strategy and the returns of the buy-hold (B-H) strategy.
- **$H_0$3** : There is no significant difference between the returns of the MACD-based strategy and the returns of the buy-hold (B-H) strategy.

Hypotheses Testing

To test the aforementioned hypotheses, the Brook *t*-test (Brock et al., 1992) has been applied to test the significant difference between buys/sells returns of technical trading rules and returns of the B-H strategy:

$$\frac{\overline{X}_r - \mu}{\sqrt{\left(\frac{\sigma^2}{N} + \frac{\sigma^2}{N_r}\right)}} \qquad (1)$$

where, μ and N are the unconditional mean and number of observations, $\overline{X}_r$ N_r is the mean return and number of signals for buy and sell, and σ^2 is the predicted variance for the sample.

Data Set

Five stock markets are considered a sample to serve the purpose of the study. The data set consists of the daily closing prices of Brazil, Russia, India, China, and South Africa stock indices, namely Bovespa, RTSI, Nifty 50, Shanghai Composite (SSEC), and FTSE_JSE Top 40. For consistent results, an equal number of observations from the pre- and post-COVID-19 period were obtained from investing.com from February 1, 2016, to February 29, 2024. The sample was divided from February 1, 2020, considering the date of introduction of the COVID-19 pandemic in the BRICS stock market, as shown in Figure 1.

Methodology

↳ **Computation of Returns :** The daily stock market returns (R_t) are calculated by taking natural logarithmic difference changes in the BRICS stock indices individually (Akhtar et al., 2021), i.e.,

$$R_t = \text{In}\left(\frac{P_t}{P_{t-1}}\right) * 100 \qquad (2)$$

where, P_t is the current closing price and P_{t-1} is the previous day's closing price.

↳ **RSI :** J. Welles Wilder developed the technical momentum indicator known as the RSI in 1978. It assesses an asset's overbought and oversold levels by comparing the size of recent gains to losses. The following formula is used to compute the RSI:

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

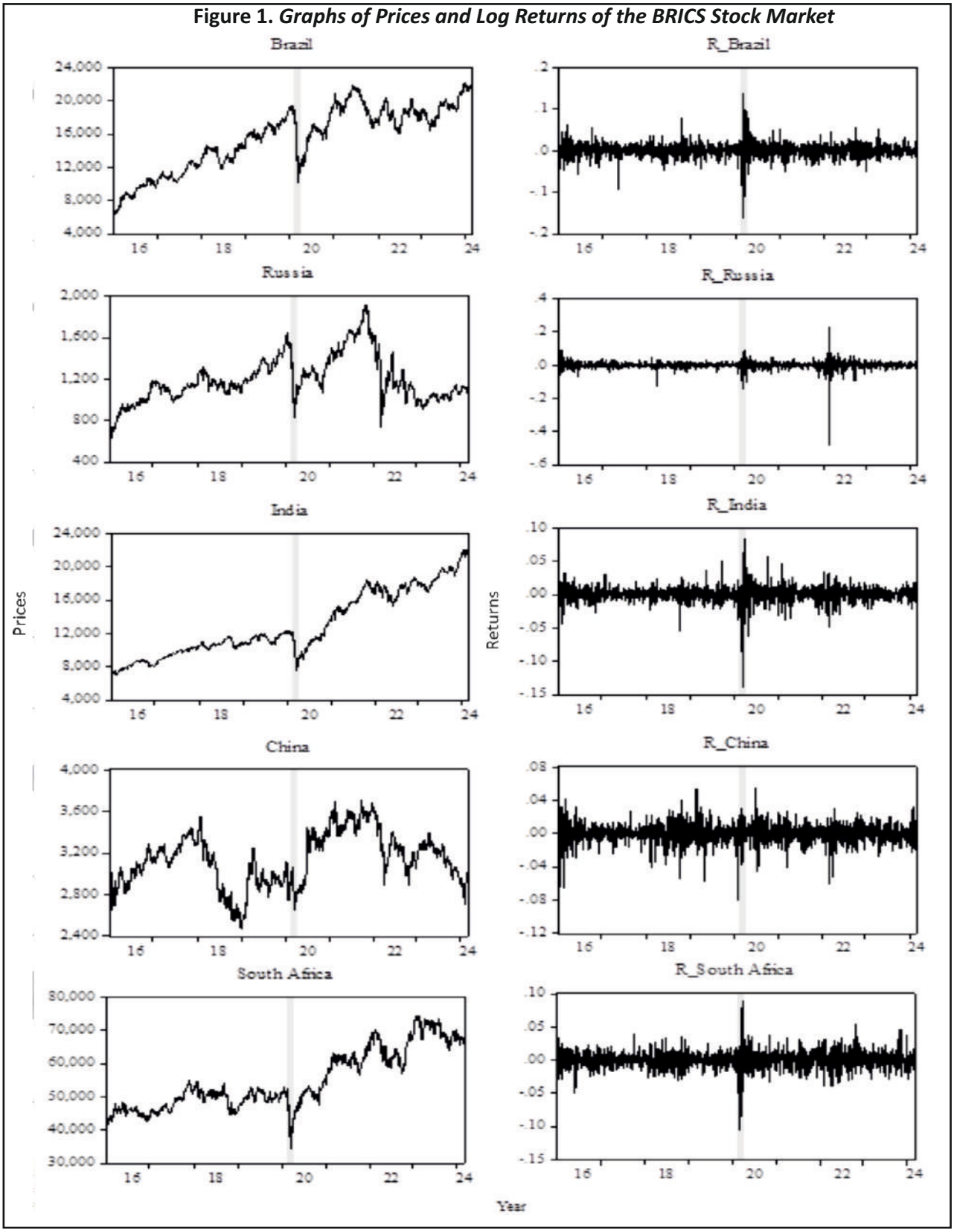
$$\text{where, } RS = \frac{\overline{U}_{t,p}}{\overline{D}_{t,p}} \qquad (3)$$

where, $\overline{U}_{t,p}$ Average Upward movement, $\overline{D}_{t,p}$ = Average downward movement, t is the sample period, p is the rolling period, and the default period is 14 days. The RSI ranges from 0 to 100, wherein 100 implies pure upward price movements (Overbought Market) and 0 implies pure downward price movements (Oversold Market).

↳ **RSI Rules :** The present study has used the two most widely used rules of RSI strategy, i.e., 70–30 and 50-crossover. The RSI trading rules at time t are defined as follows:

Signal	50-Crossover Rule	70–30 Rule
Buy	if $RSI_{Yesterday} < 50$ and $RSI_{Today} > 50$	if $RSI_{Yesterday} < 30$ and $RSI_{Today} > 30$
Sell	if $RSIY_{Yesterday} > 50$ and $RSI_{Today} < 50$	if $RSI_{Yesterday} > 70$ and $RSI_{Today} < 70$

Figure 1. ***Graphs of Prices and Log Returns of the BRICS Stock Market***



The rule specifies that when the RSI crosses 30 from below, a buy signal is generated, and when it crosses 70 from above, a sell signal is generated.

↳ ***Exponential Moving Average (EMA)*** **:** This is most common and frequently used by trend followers due to ease of computation and effective implementation. However, in spite of using an SMA, the EMA used in the study tends to be more sensitive and turns faster than the SMA due to higher weightage to current prices. The calculation of the *n-day* SMA and EMA is as follows:

$$\text{EMA} = \text{Initial } SMA\text{: SMA} = \frac{1}{n}\sum_{i=t-n+1}^{t} c_i \qquad (4)$$

$$C_i = (C_t + C_{t-1} + \ldots\ldots\ldots\ldots\ldots\ldots + C_{t-n+2} + C_{t-n+1})/n$$

$$5-day\ Multiplier = \frac{\mathbf{2}}{[\mathbf{1} + number\ of\ day\ (\mathbf{5})]} = 33.33\%$$

Similarly, multipliers for 20, 50, and 200 days are calculated.

$$EMA_t = [(P_t - EMA_{t-1}) \times \text{Multiplier}] + EMA_{t-1} \qquad (5)$$

where the closing price of the index at time t is represented by P_t and EMA_{t-1} is the exponential moving average at time t–1. For initial EMA *n-day,* a simple moving average is used. To generate buy (sell) signals, dual EMA is being computed, which tends to vary from investor to investor, wherein if the short-run moving average crosses (from below), the long-run moving average $[S_t(n) > L_t(m)]$ buy signal is generated and vice-versa. A dual strategy will follow in this study [(5, 20), (5, 50), (5, 200)] to help investors have both short-run and long-run views on the market to suit the risk-return profile of varied investors. To generate a buy (sell) signal, the short-term EMA (EMA_S) should cross the long-term EMA (EMA_L) from below (above).

↳ **MACD :** It is another important strategy for gaining abnormal returns, which relies upon 12-day and 26-day EMAs, the most used short and long-period EMAs. The MACD is reached by subtracting the longer period EMA's (26 days) from short period EMA's (12 days). Thereafter, in the second stage, the MACD signal line is reached, which is a 9-day EMA of MACD. The calculation of MACD is as follows :

MACD Line: (12-day EMA – 26-day EMA)
Signal Line: 9-day EMA of MACD Line
MACD Histogram: MACD Line – Signal Line

A buy (sell) signal is triggered when MACD crosses zero from below (above). A buy (sell) signal is triggered when the divergence between the signal line and MACD occurs (e.g., a MACD—9-day EMA > 0 buy signal is generated, and vice versa).

Empirical Analysis and Results

Summary Statistics

Table 1 presents the summary statistics of daily returns for BRICS stock markets for a sample and pre- and post-sample period. The mean returns of the sample countries are positive except China in the whole sample and

Table 1. ***Descriptive Statistics***

Whole Sample (January 1, 2016 – February 29, 2024)					
	Brazil	**Russia**	**India**	**China**	**South Africa**
Mean	0.065%	0.024%	0.061%	–0.005%	0.024%
Median	0.096%	0.124%	0.111%	0.034%	0.032%
Maximum	0.137	0.232	0.084	0.056	0.091
Minimum	–0.162	–0.483	–0.139	–0.108	–0.105
Std. Dev.	0.017	0.024	0.012	0.012	0.013
Skewness	–0.976	–5.092	–1.352	–1.055	–0.267
Kurtosis	19.106	112.315	22.117	11.703	10.475
Jarque–Bera	18545.070	849274.300	26265.560	5650.867	3957.192
Probability	0.000***	0.000***	0.000***	0.000***	0.000***
Obs.	1691	1691	1691	1691	1691
Pre-COVID Sample Period (January 1, 2016 – January 31, 2024)					
Mean	0.119%	0.090%	0.053%	–0.012%	0.016%
Median	0.156%	0.105%	0.078%	0.048%	0.034%
Maximum	0.079	0.090	0.052	0.054	0.039
Minimum	–0.092	–0.125	–0.055	–0.108	–0.050
Std. Dev.	0.015	0.015	0.009	0.012	0.010
Skewness	–0.219	–0.635	–0.143	–1.322	–0.216
Kurtosis	6.520	10.417	7.166	13.860	4.384
Jarque–Bera	442.552	1991.154	613.314	4393.603	73.899
Probability	0.000***	0.000***	0.000***	0.000***	0.000***
Obs.	844	844	844	844	844
Post-COVID Sample Period (March 1, 2020 – January 29, 2024)					
Mean	0.029%	–0.017%	0.081%	0.006%	0.045%
Median	0.048%	0.160%	0.154%	0.023%	0.034%
Maximum	0.137	0.232	0.084	0.056	0.091
Minimum	–0.162	–0.483	–0.139	–0.060	–0.105
Std. Dev.	0.019	0.030	0.014	0.011	0.015
Skewness	–1.197	–5.099	–1.587	–0.295	–0.224
Kurtosis	21.982	90.977	21.526	6.223	10.684
Jarque–Bera	12659.440	271270.600	12218.260	371.355	2048.633
Probability	0.000***	0.000***	0.000***	0.000***	0.000***
Obs.	830	830	830	830	830

Notes. *** marks indicate a significant *p*-value at 1% significant level.

pre-COVID sample. As the mean returns are found to be negative in the Russian stock market in post-COVID, this may be due to the Russia–Ukraine war. The daily returns of Russia are highly volatile compared to other countries in all the sample periods, as the standard deviation (*SD*) is highest for the Russian stock returns. The daily returns for all the sample countries are left-skewed, i.e., asymmetric, as the skewness values are found to be negative in all the sample periods. The kurtosis value is greater than the threshold value, i.e., 3, indicating that the returns are

leptokurtic with a heavier tail than the standard normal distributions. The *p*-value of the Jarque–Bera tests is used to determine whether the returns are distributed as normal. Since the *p*-value is less than the 5% significance level, the null hypothesis for the test, i.e., the returns are normally distributed, is rejected. Since the returns are not normally distributed, the median serves the most reliable result compared to the mean. The median is positive in the sample period.

Test of Significance

Table 2 reports the results of a test of significance obtained by Brock et al. (1992) for the technical trading strategy based on EMA, RSI, and MACD for the pre-COVID sample. The table contains information to determine the significant difference between active and passive strategies, such as the number of buy/sell signals, mean returns of Long/Short positions, and *t*-statistics of selected technical rules.

Table 2. ***Significance of t-test in Pre-COVID Sample***

Countries	Rules	No. of Buy	No. of Sell	Long (B)	Short (S)	Long-Short
Brazil	EMA 20	593	316	0.0006(–0.43)	0.0014(0.652)	–0.0001(–0.117)
	EMA 50	673	236	0.0003(–1.866)**	0.0025(1.719)**	–0.0004(–2.415)**
	EMA 200	845	64	0.0008(–0.106)	0.0018(0.515)	0.0007(0.394)
	RSI 50-Crossover	460	346	0.0001(–0.222)	0.0004(0.269)	–0.0002(–0.172)
	70–30	10	102	–0.0016(–0.582)	0.0001(–0.454)	–0.0002(–0.056)
	MACD	461	448	0.0011(0.299)	0.0007(–0.305)	0.0002(0.277)
Russia	EMA 20	569	360	0.000(–0.781)	0.0014(1.058)	–0.0005(–0.606)
	EMA 50	629	300	0.0003(–0.464)	0.0012(0.756)	–0.0002(-0.234)
	EMA 200	727	202	0.0003(–0.386)	0.0014(0.885)	–0.0001(–0.055)
	RSI 50-Crossover	459	348	0.0005(0.439)	–0.0011(–0.528)	0.0008(0.399)
	70–30	19	106	0.0041(1.17)	0.0013(0.431)	–0.0004(–0.144)
	MACD	452	477	0.0005(–0.087)	0.0006(0.084)	–0.0001(–0.092)
India	EMA 20	614	294	0.0004(–0.047)	0.0005(0.076)	0.0001(0.226)
	EMA 50	686	222	0.0004(–0.093)	0.0005(0.195)	0.0002(0.271)
	EMA 200	786	122	0.0002(–1.476)*	0.0016(1.551)**	0.005(2.150)*
	RSI 50-Crossover	539	268	0.0008(0.222)	0.0004(–0.352)	0.0004(0.542)
	70–30	20	97	0.0002(–0.096)	–0.0003(–0.731)	0.0003(0.175)
	MACD	455	453	0.0004(–0.007)	0.0004(0.007)	0.000(–0.004)
China	EMA 20	484	407	–0.0001(–0.168)	0.0001(0.188)	–0.0001(–0.15)
	EMA 50	448	443	0.000(–0.061)	0.0001(0.061)	0.000(–0.053)
	EMA 200	448	443	–0.0002(–0.405)	0.0003(0.408)	–0.0002(–0.351)
	RSI 50-Crossover	346	441	–0.0005(–0.518)	0.0001(0.44)	–0.0003(–0.382)
	70–30	29	59	0.0017(0.793)	–0.0002(–0.116)	0.0007(0.301)
	MACD	477	414	0.0002(0.293)	–0.0002(–0.322)	0.0002(0.268)
South Africa	EMA 20	508	409	–0.0002(–0.549)	0.0004(0.634)	–0.0003(–0.498)
	EMA 50	494	423	–0.0004(–0.835)	0.0006(0.926)	–0.0005(–0.752)
	EMA 200	559	358	–0.0007(–1.432)*	0.0012(1.926)**	–0.0009(–2.368)**

	RSI 50-Crossover	459	353	0.000(–0.45)	0.0007(0.536)	–0.0003(–0.374)
	70–30	30	48	0.0029(1.684)**	–0.0002(–2.135)***	0.0012(2.552)**
	MACD	492	425	0.0001(0.081)	0.000(–0.089)	0.000(0.079)

Note. *, **, and *** indicates the significant *t*-values at 10%, 5%, and 1%, respectively.

The empirical results highlight that mean returns of EMA 50 in Brazil's stock market are found to be significant for all the positions at a 5% significance level. Similarly, EMA 200 is found in all the positions in the Indian and South African stock markets. On the other hand, returns generated by RSI (70–30) rules are found to be significant for all positions in the South African stock market. That implies that the returns from the active strategy using RSI (70–30) are more than the passive strategy. However, none of the cases are significant based on the EMA-20, EMA-50, RSI (50-crossover), and MACD rules. This implies that returns from these strategies are either equal to or less than the buy-and-hold strategy.

Similarly, Table 3 presents the results of a test of significance obtained by Brock et al. (1992) for the technical trading strategy based on EMA, RSI, and MACD for the post-COVID sample. The empirical results highlight that the mean returns of RSI (70–30) are significant for all the positions in the Russian, Indian, and Chinese stock markets. Similarly, EMA 200 is found in all the South African stock market positions. That implies that the returns from the active strategy using RSI (70–30) are more than the passive strategy. However, none of the cases are significant based on the EMA-20, EMA-50, RSI (50-crossover), and MACD rules. The results imply that returns from these strategies are either equal to or less than the B-H strategy.

Table 3. ***Significance of t-test in Post-COVID Sample***

Countries	Rules	No. of Buy	No. of Sell	Long (B)	Short (S)	Long-Short
Brazil	EMA 20	448	358	0.0001(–0.12)	0.0003(0.139)	–0.0001(–0.082)
	EMA 50	475	331	0.0005(0.322)	–0.0001(–0.41)	0.0003(0.352)
	EMA 200	535	271	0.000(–0.283)	0.0006(0.444)	–0.0002(–0.201)
	RSI 50-Crossover	460	346	0.0001(–0.222)	0.0004(0.269)	–0.0002(–0.172)
	70–30	23	67	0.002(0.617)	0.0011(0.44)	–0.0003(–0.103)
	MACD	397	409	0.0003(0.06)	0.0002(–0.059)	0.000(0.048)
Russia	EMA 20	466	341	0.0006(0.499)	–0.0012(–0.614)	0.0009(0.458)
	EMA 50	474	333	–0.0001(0.05)	–0.0003(–0.063)	0.0001(0.033)
	EMA 200	367	440	0.0003(0.27)	–0.0005(–0.239)	0.0004(0.226)
	RSI 50-Crossover	459	348	0.0005(0.439)	–0.0011(–0.528)	0.0008(0.399)
	70–30	28	53	0.0133(2.269)***	0.0004(2.125)***	0.0043(1.962)*
	MACD	428	379	0.0008(0.587)	–0.0012(–0.637)	0.001(0.523)
India	EMA 20	525	282	0.0007(0.064)	0.0006(–0.096)	0.0002(0.355)
	EMA 50	564	243	0.0007(0.153)	0.0005(–0.267)	0.0004(0.524)
	EMA 200	717	90	0.0006(–0.063)	0.0009(0.232)	0.0005(0.446)
	RSI 50-Crossover	539	268	0.0008(0.222)	0.0004(–0.352)	0.0004(0.542)
	70–30	6	139	0.0062(1.47)*	0.0009(2.255)***	–0.0006(–2.166)*
	MACD	386	421	0.0009(0.402)	0.0004(–0.38)	0.0002(0.294)
China	EMA 20	333	454	–0.0005(–0.576)	0.0001(0.469)	–0.0003(–0.408)
	EMA 50	356	431	–0.0002(–0.037)	–0.0001(0.033)	0.000(–0.009)
	EMA 200	385	402	–0.0003(–0.201)	0.000(0.195)	–0.0001(–0.166)

	RSI 50-Crossover	346	441	–0.0005(–0.518)	0.0001(0.44)	–0.0003(–0.382)
	70–30	25	13	0.003(1.693)**	–0.0032(–2.007)*	0.0031(1.98)*
	MACD	392	395	–0.0006(–0.687)	0.0003(0.683)	–0.0004(–0.592)
South Africa	EMA 20	464	348	–0.0001(–0.552)	0.0008(0.669)	–0.0004(–0.468)
	EMA 50	468	344	0.0001(–0.338)	0.0006(0.415)	–0.0002(–0.265)
	EMA 200	557	255	0.0002(–2.204)***	0.0006(1.642)**	–0.0001(–2.082)*
	RSI 50-Crossover	459	353	0.000(–0.45)	0.0007(0.536)	–0.0003(–0.374)
	70–30	12	59	0.0027(0.646)	–0.0016(–0.89)	0.0017(0.467)
	MACD	417	395	–0.0003(–0.827)	0.0009(0.857)	–0.0006(–0.719)

Note. *, **, and *** indicates the significant *t*-values at 10%, 5%, and 1%, respectively.

Risk-Return Analysis

This section discusses the risk-return analysis of the long and short strategy of technical trading rules based on EMA, RSI, and MACD for the period pre- and post-COVID samples. The tables contain the information regarding the most used indicators for the risk-return analysis of securities through technical analysis, i.e., the numbers of trades executed during the sample period, time of trade repetition (in days), gross CAGR, transaction cost, net CAGR, alpha ratio, and Sharpe ratio.

The results in Table 4 highlight that out of six trading rules, only EMA 200 can generate a positive net CAGR (12.14%) in a pre-COVID sample of Brazil's stock market. In the Indian stock market, only EMA-20 (0.15%) and EMA-50 (2.35%) can generate positive net CAGR. Similarly, in the Chinese stock market, RSI 50-Crossover (1.93%) and MACD (0.61%) can generate positive CAGR. The remaining technical trading rules fail to generate a positive net CAGR, implying that the technical trading under consideration is not suggested in the BRICS stock market.

Table 4. ***Risk-Returns Analysis Pre-COVID***

Countries	Rules	No. of Trade	Trade Repetition	Gross Returns (%)		TC%	Net Returns (%)		Alpha Ratio	Sharpe Ratio %
				Aggregate	CAGR		Aggregate	CAGR		
Brazil	EMA 20	54	16.833	–9.526	–2.47%	10.690	–20.215	–5.49%	–91.613	–451.520
	EMA 50	41	22.171	–36.616	–10.77%	7.777	–44.394	–13.65%	–118.704	–585.038
	EMA 200	8	113.625	59.590	12.40%	1.475	58.114	12.14%	–22.497	–110.880
	RSI 50-Crossover	110	8.264	–44.988	–13.88%	21.981	–66.969	–24.19%	–127.075	–626.298
	RSI 70–30	52	2.154	–2.648	–0.67%	10.258	–12.907	–3.40%	–12.763	–62.901
	MACD	68	13.368	21.424	4.97%	13.411	8.013	1.95%	–60.663	–298.981
Russia	EMA 20	73	12.726	–46.781	–14.59%	14.030	–60.811	–20.88%	–98.515	–504.601
	EMA 50	44	21.114	–18.871	–5.09%	8.455	–27.327	–7.67%	–70.606	–361.648
	EMA 200	16	58.063	–5.041	–1.28%	3.117	–8.158	–2.11%	–56.775	–290.805
	RSI 50-Crossover	118	7.873	–12.388	–3.25%	22.859	–35.247	–10.30%	–64.122	–328.439
	RSI 70–30	60	2.083	–5.530	–1.41%	12.527	–18.057	–4.86%	–12.491	–63.981
	MACD	78	11.910	–6.952	–1.79%	15.061	–22.012	–6.03%	–58.686	–300.593
India	EMA 20	51	17.804	11.183	2.69%	10.567	0.616	0.15%	–27.066	–223.246
	EMA 50	24	37.833	14.585	3.46%	4.843	9.742	2.35%	–23.664	–195.187

	EMA 200	14	64.857	–0.012	0.00%	2.816	–2.828	–0.71%	–38.260	–315.580
	RSI 50-Crossover	89	10.202	15.794	3.73%	18.051	–2.257	–0.57%	–22.455	–185.213
	RSI 70–30	66	1.773	3.865	0.95%	12.723	–8.859	–2.29%	–1.064	–8.773
	MACD	71	12.789	–0.207	–0.05%	14.235	–14.442	–3.82%	–38.456	–317.195
China	EMA 20	59	15.102	–8.890	–2.30%	11.694	–20.584	–5.60%	–10.924	–69.905
	EMA 50	33	27.000	–3.116	–0.79%	6.519	–9.635	–2.50%	–5.149	–32.952
	EMA 200	19	46.895	–20.737	–5.64%	3.736	–24.474	–6.78%	–22.771	–145.720
	RSI 50-Crossover	86	10.360	24.959	5.73%	17.021	7.938	1.93%	22.926	146.713
	RSI 70–30	56	1.571	5.936	1.45%	11.252	–5.316	–1.36%	5.735	36.699
	MACD	67	13.299	15.827	3.74%	13.355	2.472	0.61%	13.794	88.273
South Africa	EMA 20	59	15.542	–29.183	–8.27%	11.772	–40.954	–12.34%	–33.464	–220.205
	EMA 50	45	20.378	–43.930	–13.47%	9.060	–52.990	–17.20%	–48.211	–317.246
	EMA 200	36	25.472	–81.641	–34.54%	7.140	–88.781	–42.13%	–85.922	–565.401
	RSI 50-Crossover	113	8.115	–20.838	–5.67%	22.436	–43.273	–13.21%	–25.119	–165.292
	RSI 70–30	54	1.444	9.628	2.32%	11.045	–1.416	–0.36%	9.264	60.961
	MACD	73	12.562	4.584	1.13%	14.510	–9.926	–2.58%	0.302	1.989

Notes. (1) No. of trade is counted as 1 for entering a long/short position, and another is for closing the long/short position. (2) TC is estimated to be 0.01 of closing prices because it typically varies among clients depending on the amount of transaction and is practically non-existent for stock exchange members when they purchase a seat for a one-time payment. (3) Sharpie ratio = alpha ratio/annual *SD.* (4) Annual Standard deviation (*SD*) = *SD* of daily return × $/\sqrt{(250\,Days)}$.

The risk-returns analysis of technical trading rules during the post-COVID sample period is presented in Table 5. The results highlight that only EMA-50 (4.66%) can generate positive CAGR and excess return over buy-hold, reparented by the alpha ratio (7.088) in Brazil's stock market during the post-COVID sample period. In the Russian stock market, positive net CAGR is generated by EMA 200 (7.32%), RSI 50-crossover (9.84%), RSI 70–30 (5.35%), and MACD (14.20%). Also, the highest alpha ratio is 93.55 by MACD in the Russian stock market. In India, EMA 20, 50, 200, and MACD outperformed during the post-COVID sample period. However, the EMA fails to generate an excess return over buy-hold in the post-COVID period. The net CAGR through RSI 70–30 is positive in China and South African stock markets with a positive alpha ratio.

Table 5. ***Risk-Returns Analysis Post-COVID***

Countries	Rules	No. of Trade	Trade Repetition	Gross Returns (%)		TC%	Net Returns (%)		Alpha Ratio	Sharpe Ratio %
				Aggregate	CAGR		Aggregate	CAGR		
Brazil	EMA 20	48	16.792	–5.868	–1.50%	9.606	–15.474	–4.12%	–24.247	–122.390
	EMA 50	28	28.786	25.466	5.84%	5.481	19.985	4.66%	7.088	35.776
	EMA 200	18	44.778	–15.169	–4.03%	3.484	–18.653	–5.03%	–33.548	–169.338
	RSI 50-Crossover	100	8.060	–12.386	–3.25%	20.118	–32.504	–9.36%	–30.764	–155.289
	RSI 70–30	52	1.731	–2.805	–0.71%	10.437	–13.242	–3.49%	–4.857	–24.517
	MACD	62	13.000	3.401	0.84%	12.518	–9.117	–2.36%	–14.977	–75.601
Russia	EMA 20	39	20.692	71.332	14.41%	7.480	63.852	13.14%	84.188	196.509
	EMA 50	31	26.032	5.170	1.27%	5.729	–0.559	–0.14%	18.026	42.075
	EMA 200	12	67.250	35.004	7.79%	2.362	32.642	7.32%	47.859	111.712

	RSI 50-Crossover	82	9.841	62.035	12.82%	16.487	45.548	9.84%	74.890	174.807
	RSI 70–30	56	1.446	34.981	7.79%	11.800	23.181	5.35%	36.271	84.663
	MACD	53	15.226	80.700	15.94%	10.623	70.076	14.20%	93.555	218.374
India	EMA 20	40	20.175	19.312	4.51%	7.851	11.461	2.75%	–33.458	–231.623
	EMA 50	24	33.625	29.652	6.71%	4.677	24.975	5.73%	–23.118	–160.041
	EMA 200	8	100.875	36.767	8.14%	1.562	35.205	7.83%	–16.003	–110.786
	RSI 50-Crossover	80	10.088	29.861	6.75%	15.774	14.088	3.35%	–22.909	–158.593
	RSI 70–30	58	2.500	–9.179	–2.38%	11.709	–20.888	–5.69%	–18.661	–129.184
	MACD	57	14.158	15.273	3.62%	11.443	3.830	0.94%	–37.497	–259.579
China	EMA 20	56	14.054	–22.031	–6.03%	11.405	–33.437	–9.67%	–10.262	–68.260
	EMA 50	30	26.233	–0.485	–0.12%	6.139	–6.624	–1.70%	11.284	75.060
	EMA 200	11	71.545	–8.883	–2.30%	2.207	–11.090	–2.90%	2.886	19.199
	RSI 50-Crossover	108	7.287	–20.552	–5.59%	21.889	–42.441	–12.90%	–8.783	–58.420
	RSI 70–30	42	0.905	11.736	2.81%	8.189	3.548	0.88%	12.305	81.846
	MACD	68	11.574	–31.608	–9.06%	13.648	–45.256	–13.98%	–19.839	–131.961
South Africa	EMA 20	55	14.764	–31.789	–9.12%	11.089	–42.878	–13.06%	–55.439	–297.471
	EMA 50	35	23.200	–18.038	–4.85%	7.008	–25.045	–6.95%	–41.688	–223.685
	EMA 200	19	42.737	–5.969	–1.53%	3.802	–9.770	–2.54%	–29.619	–158.926
	RSI 50-Crossover	105	7.733	–25.358	–7.05%	21.221	–46.578	–14.51%	–49.008	–262.961
	RSI 70–30	52	1.365	12.382	2.96%	10.376	2.006	0.50%	10.314	55.341
	MACD	75	10.827	–48.313	–15.21%	14.959	–63.272	–22.15%	–71.963	–386.131

Notes. (1) No. of trade is counted as 1 for entering a long/short position, and another is for closing the long/short position. (2) TC is estimated to be 0.01 of closing prices because it typically varies among clients depending on the amount of transaction and is practically non-existent for stock exchange members when they purchase a seat for a one-time payment. (3) Sharpie ratio = alpha ratio/annual *SD*. (4) Annual Standard deviation (*SD*) = *SD* of daily return × $/\sqrt{(250\ Days)}$.

Conclusion

Technical trading rules and momentum strategies have been widely investigated in financial markets, particularly stocks. However, most studies have been done on the developed financial system. This study attempts to test and revalidate the performance of technical trading strategy based on the EMA, RSI, and MACD on stock returns in BRICS before and after the COVID-19 pandemic. For this, the study analyses the pre- and post-COVID samples from January 1, 2016, to February 29, 2024. However, numerous studies have indicated that using technical trading strategies might provide many possibilities to outperform the returns given by the passive strategy (buy and hold). Interestingly, this study does not suggest the RSI (50-crossover and 70–30), EMA (20/50/200), and MACD indicators for day traders to generate buys and sells in the BRICS stock market because the technical rules under consideration have failed to generate positive alpha ratio because, in most of the cases, the null hypotheses are accepted ($H_0$1, $H_0$2, and $H_0$3). Hence, EMA, RSI, and MACD emerged as the low-performing technical trading rules for generating better stock returns than the "buy-hold" strategy in BRICS.

Managerial/Practical Implications of the Study

Investors or traders in the stock markets of BRICS countries can clearly understand whether to use or not use the technical trading strategies studied in this research.

Limitations of the Study and Scope for Further Research

Since the study focuses on the traditional methods of technical trading strategies, the model has some assumptions that cannot be fulfilled in recent times. Due to these limitations, further studies with some other econometric or machine learning models can be applied to check the efficiency of the stock market. Other aspects like volatility and fundament analysis can also be studied to make robust decisions regarding trade. Ultimately, the objective is to envisage the opportunities and threats of future research in this area and provide an effective solution with the best model for technical trading to invest in practice.

Authors' Contribution

Poonam conceived the idea of research in the context of technical trading in the BRICS stock market and extracted the existing pertinent literature with high repute, filtered these based on keywords, and generated concepts and codes relevant to the study design. Furthermore, she applied appropriate statistical tools to achieve the set objective and report the findings. Dr. N. S. Malik verified the analytical and conceptual methods.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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About the Authors

Poonam is a Research Scholar at the Haryana School of Business, GJUS&T, Hisar, Haryana (India). Her areas of interest include financial management, business statistics, and business research methods. Her research explores and analyses the approaches to technical trading in financial markets.

Prof. N. S. Malik is a Senior Professor at Haryana School of Business, GJUS&T, Hisar, Haryana (India). He is committed to contributing his knowledge to research in empirical asset pricing, trading strategies, financial markets, technical analysis, and personal financial planning. He is also a visiting faculty member for institutes of national and international repute.