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Testing the efficiency of EMA and RSI during Covid and Pre Covid period: A Study on BRICS

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Abstract

The paper is based on testing the efficiency of EMA and RSI during the Covid and Pre Covid period on the BRICS nation. The research is conducted on the four years data set starting from 1st January 2018 to 31st December 2021. The data is divided into two sub period which are identified as Covid and pre Covid period. The pre Covid period is taken from 1st January 2018 to 31st December 2019 and Covid period is taken form 1st January 2020 to 31st December 2021. In the paper the researcher has used two different time period techniques of EMA which are EMA 5-20 and EMA 5-200. The researcher has used Relative strength index technique by using 50 crossover rule. In order to test the efficiency of the techniques the researcher has calculated Alpha returns for all the markets. The alpha returns are calculated by subtracting the index return i.e., the return of passive strategy, from the return as generated by the markets by using the different techniques under study. During the research it has been found that the efficiency of EMA and RSI is not found to be strong in any of case. There is a very low efficiency of EMA 5-200. EMA 5-20 and RSI has shown some efficiency but that was also not so strong that it can be said that the investor can use techniques of technical analysis (EMA and RSI) as the predicted tools and can generated the higher returns over the passive strategy.

Key Words: - Exponential Moving Average, Relative Strength Index, Efficiency, Alpha Returns, Covid Period, Technical Analysis and Fundamental Analysis.

Introduction

The fundamental proposition of technical analysis (TA) is that motif related to past prices of tools paddled in the asset markets can be used to foretell the direction of future prices. The purpose is to magnify the return of an investment portfolio by understanding the interconnection of price measures for the portfolio's holdings over a recognized time period. Technical Analysis is the study to predict future asset prices with previous data. The stock market is a main fulcrum in every growing and triumphant economy, and every financing in the market is aimed at maximising profit and minimising related risk. As a result, various studies aimed on the stock-market forecasting using technical or fundamental analysis by way of various soft-computing techniques and algorithms. According to Stanković et al. (2015), Technical Analysis is a way of detecting trends in asset prices based on the premise that the price series moves according to investors' perceived standards. The objective of our research was to probe the profitability of trading policies based on Technical Analysis in the stock markets of BRICS. To this edge, we evolved a robotic trading system based on the moving averages of past prices. The tools used by Technical Analysis can provide a guide of defiance and advocate as well. Indicators include the Relative Strength Index (RSI) and Moving Averages (MA). These measures pursue to gauge patterns of future conduct and forecast buy and sell opportunities only from the formerly substantiated pricing of assets. More particularly, Vandewalle et al. (1999, pp. 170–172) defined moving averages as transformations of a price series that allow us to identify trends from data smoothing.

Technical analysis centres on magnitude and price which are market measures. For examining the stocks, technical analysis is the only one loom. It is better to exercise that approach for appraising the stocks to buy or sell, with which you are most comfortable. Every independent should use unbiased set and attributes of technical apparatus considering the type of analysis he ought to do. All the instruments which are mentioned in this paper in fusion are helpful in the framing of business or trading strategies. Framing business strategy and collecting stocks with the help of technical apparatus is also possible with an investment objective, risk tolerance, and financial situation that the investor intends to achieve.

In order to determine the Exponential Moving Average, the given day's EMA depends on all the days preceding that day.

$EMA= Price(t)*k+ EMA(y)*(1-k)$

Where t and y represent today and yesterday respectively, N is the number of days in EMA and $K(smoothing)=2/(N+1)$.

RSI is an indicator that measures whether a stock bought is oversold or overbought.

$RSI = 100-(100/1+RS)$

where RS= average gain/ average loss

A capital market is said to be efficient if it completely and accurately considers all pertinent facts in ascertaining security prices. Efficiency can be ascertained at three levels. The weak form of the Efficient Market Hypothesis (EMH) declares that prices fully reflect the information contained in the historical sequence of prices. It is this form of efficiency that is associated with the term 'Random Walk Hypothesis'. The semi-strong form of EMH asserts that current stock prices reflect not only historical price information but also all publicly available information relevant to a company's securities. The strong form of EMH asserts that all information that is known to any market participant about a company is fully reflected in market prices.

Coronavirus (COVID-19), a disease which originated in the Chinese city of Wuhan in December 2019 and rapidly unfurl all over the world giving rise to a pandemic. Because the virus is highly contagious and fatal, the authorities imposed strict quarantines on their populations and ordered the shut-down of the bulk of business activity. In this paper we test the efficiency of Exponential Moving Average and Relative Strength Index during covid and pre covid period on the BRICS market behaviour. Nevertheless, COVID-19, may not necessarily be equally detrimental to all firms and industries. Whereas most sectors suffer and their stock prices collapse, some other may benefit from the pandemic and the resulting lockdown.

Literature Review

Sagala, Saputri, Mahendra & Budi (2020) in this paper predicted stock price movement using combination of technical and sentiment analysis. For conducting the experiment, researcher has used several algorithms like Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Naïve Byes. Web crawling is the process which is used to retrieve hyperlinks repeatedly starting from the list of initial URLs. It has been found that the highest accuracy is achieved when the combination of technical analysis feature and online media, sentiment label is implemented on ASII dataset using SVM.

Park, Chel-Ho & Irwin(2007) in this paper, to examine the profitability of technical trading rules, the empirical literature is categorized into two groups, "early studies" and "modern studies"(1988-2004), depending on testing procedures. Early studies resulted that the profitability of technical trading rules is applicable in foreign exchange markets and future markets, not in stock markets. However, modern studies show the consistent economic profits in speculative markets. Out of 95 studies, results of 56 are favourable, 20 studies give negative response and 19 studies indicates mixed results regarding technical trading strategies. Notwithstanding the positive evidence about profitability, improved procedures for testing technical trading strategies, and plausible theoretical explanations, many academics still appear to be sceptical about technical trading rules.

Ijegwa, Rebecca, Olusegun & Isaac (2014), in this paper has used four technical indicators namely Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Stochastic Oscillator (SO) and On Balance Volume (OBV) are used to deploy fuzzy inference to stock market. For testing, data of two Nigerian Banks were collected of two months. It has been found that Experiments were done with MATLAB using actual stock data of two Nigerian banks and results achieved were satisfactory.

Barroso, Cardoso & Melo (2021), has analysed a fusion between Technical Analysis indicators and Multi objective Portfolio optimization between 2012 and 2015 of four scenarios namely AT (considers only signs of technical analysis without optimization), OT(considers only risk and return optimization without using technical analysis), ATOT (uses technical analysis as first to indicate which assets should be considered in the optimization) and OTAT (first uses portfolio optimization to then carry out transactions using technical analysis indicators). It has been found that OTAT and OT portfolios outperformed the other portfolios & benchmarks and suitable for investors who wish to minimize risk and maximize return on investments.

Mizano, Kosaka, yajima & Komoda (1998) has proposed a neural network model for the technical analysis of stock market prediction, and its use in predicting the time to buy and sell for TOPIX. To verify the accuracy of Prediction system, weekly data of TOPIX has been collected. 260 weekly data from September 1982 to August 1987 have been used as learning samples for making prediction models and 119 weekly data from October 1987 to January 1990 are used as prediction samples for evaluation. Total 11 technical indexes of TOPIX are selected to form input patterns. It has been found that Experimental Simulation applied to practical data has demonstrated that the prediction system generates buying and selling signal at more proper timings on the whole and made higher profits compared with that yielded by a single use of each technical index.

Aguirre, Medina & Mendez (2020), in this paper tries to fill the gap existing in the literature on the use of Genetic Algorithms for predicting asset pricing of investment strategies into stock markets and investigate its advantages over its peers buy & hold and traditional technical analysis. The application of Genetic Algorithms to the oscillator in the asset investment strategy of the NASDAQ stock index was studied. These strategies examined the use of the indicator within technical strategies that generate buy and sell signals derived from the statistical calculation of moving averages and their transmission to the market. It has been found that technical analysis is a useful tool in the consistent search for price trends and asset behaviour with sufficient historical information availability.

Li, Wu & Wang (2020), in this paper has built up a stock prediction system with an approach to represent numerical price data by technical indicators, set up a layered deep learning model and also a fully connected neural network to predict stocks. Data of more than 5 years of Hong Kong stock exchange has been collected for experiment. It has been found that proposed approaches and models outperforms the baselines and models that only use either technical indicators or news sentiments.

Pramudya R., & Ichsani S. (2020), in this paper find out about the indicators capability to show more accurate signals of buy and sell. For this the researcher used LQ45 index with the help of Oscillator indicator Moving Average Divergent Convergent (MACD), Bollinger Band and Relative Strength Index (RSI). For this the researcher has used qualitative approach with the help of graph swapping listed on the indicator. It has been found that Bollinger band and RSI is good to capture the sell signals. On the other hand, MACD is too slow in capturing the buy signal when compared to Bollinger Bands and RSI.

Nti et al (2019), in this paper has attempted to do a systematic review of nearby 122 research works from 2007-2018 described in academic journals in order to predict stock market with the help of Machine learning. For this, techniques were grouped into three classes namely technical analysis, fundamental analysis and combined analysis. It has been found that there are two machine learning algorithms which are used for predicting the stock market namely Support Vector Machine and Artificial Neural Network.

Wolian Li A. & Bastos G. (2020), in this paper tried to find out the techniques which are helpful in forecasting the prices of the stocks using past data with the support of some technical indicators, in order to analyse the techniques, deep neural network (DNN), convolutional neural network (CNN), Long short-term memory (LSTM), and hybrid algorithms are used. The main objective of this literature is to review the articles on financial time series forecasting. For this, 34 articles were taken into consideration. It is found that in 35.3% of articles evaluated profitability and risk management was inscribed by only two. Furthermore, it has been found that some publications got losses with the model performance by 50%.

Shah D., Isah H. & Zulkerninr F. (2019), in this paper tried to give a review of stock markets and taxonomy of stock market forecasting tools. Researchers also paid their attention towards the research achievements in analysing the stocks and their prophecy. Researchers also accentuates on the theory of (EMH) Efficient Market Hypothesis. In this paper their main focus is on the grouping engagement for prophesying companies that are efficient or inefficient based on their one-year performance. ANN, (SVR) Support Vector Regression, (SVM) Support Vector Machine, Decision Trees, statistical and pattern recognition approaches and Machine learning approaches are used. In this paper, the researcher recommends a morphology of mathematical applications to stock market examination and forecast, present a comprehensive literature learning of the state-of-the-art design and procedure that are commonly applied to stock market forecast, and talk over some of the ongoing provocation in this region which need additional heed and dispense opportunities for hereafter evolution and exploration. Hybrid perspective that appreciates statistical and machine learning techniques will doubtlessly manifest to be more functional for stock prediction.

Research Methodology: -

Research methodology is one of the most important parts of any research. One has to put a great emphasis on research methodology. In this paper our main concentration is on the testing the efficiency of Exponential Moving Average (EMA) and Relative Strength Index (RSI) during Covid and Pre Covid period among the BRICS nation.

Objectives of the study: -

1. To test the efficiency of EMA among BRICS during Covid and Pre Covid period.
2. To test the efficiency of RSI among BRICS during Covid and Pre Covid period.

Data Period: -

The data is taken for four years from 1st January 2018 to 31st December 2021. The total data is divided into two block of two years each. The data is divided into two blocks as the first block is related to pre covid period from 1st January 2018 to 31st December 2019 and second block is related to Covid period from 1st January 2020 to 31st December 2021. The data will also be analysed for the aggregate period of four years.

Tools Used: -

Data is analysed by using the techniques of EMA and RSI. The researcher has used EMA 5-20, EMA 5-200 and RSI 50 cross over rule to find out the return of active strategy and then to judge the efficiency the researcher has calculated the Alpha returns by subtracting the return of passive strategy from the return of active strategy. Sharpe ratio is also calculated to find out the performance of a particular market.

Analysis and Interpretation

Table-I: Testing the efficiency of EMA 5-20 for Panel-I: Whole Sample Period i.e., 01st January 2018 to 31st December 2021)

	Index	No. of	Trade Repetition Time	Gross Returns (%)	T C (%)	Net Returns (%)	Sharpe Ratio	Alpha (↑Index

Markets		trades	(in days)	Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank	(%)	Return)
Brazil	Bovespa	54	18.27	43.98	9.51	**1**	0.55	43.43	9.44	**1**	41.02	11.81
Russia	RTS I	58	17.40	23.64	5.45	**3**	0.62	23.02	5.32	**3**	-34.77	-9.35
India	CNX Nifty	53	18.70	38.57	8.50	**2**	0.53	38.04	8.39	**2**	-59.52	-11.91
China	Shanghai	67	14.49	-33.87	-9.82	**4**	0.67	-34.54	-10.05	**4**	-237.64	-43.56
South Africa	FTSE	88	11.77	-88.82	-42.18	**5**	0.92	-89.74	-43.40	**5**	-395.66	-90.96

Table I interpreters the results of complete data set for the technique of EMA 5-20. The trade repetition time is found to be minimum in case of South African market hence one has to be most active in case of South African market. When EMA 5-20 is used on the complete data set it has not shown any great efficiency on the data set. Only one market out of five shows positive alpha returns. Brazilian market has shown positive alpha return and rest all markets shows negative alpha return. So, we can say that the low efficiency of EMA 5-20 is found for this given data period.

Table-II: Testing the efficiency of EMA 5-20 for Panel-II: Sub Sample Period i.e., 01st January 2018 to 31st December 2019)

Markets	Index	No. of trades	Trade Repetition Time (in days)	Gross Returns (%)			T C (%)	Net Returns (%)			Sharpe Ratio (%)	Alpha (↑Index Return)
				Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank		
Brazil	Bovespa	34	14.5	2.36	1.17	**2**	0.35	2.01	1.00	**2**	-194.48	-39.09
Russia	RTS I	38	13.31	-13.41	-6.95	**4**	0.40	-13.81	-7.16	**4**	-213.76	-43.20
India	CNX Nifty	30	16.37	-7.61	-3.88	**3**	0.30	-7.91	-4.04	**3**	-168.95	-22.37

China	Shanghai	26	18.73	7.62	3.74	**1**	0.26	7.36	3.61	**1**	81.70	15.45
South Africa	FTSE	54	9.57	-75.36	-50.36	**5**	0.56	-75.92	-50.93	**5**	-380.43	-68.25

Table II interpreters the results of first sub period for data set for the technique of EMA 5-20. The trade repetition time is found to be minimum in case of South African market hence one has to be most active in case of South African market. When EMA 5-20 is used on this period data set it has not shown any great efficiency on the data set. Only one market out of five shows positive alpha returns. Chinese market has positive alpha return and rest all markets shows negative alpha return. So, we can say that the low efficiency of EMA 5-20 is found for this given data period.

Table-III: Testing the efficiency of EMA 5-20 for Panel-III: Sub Sample Period i.e., 01st January 2020 to 31st December 2021)

Markets	Index	No. of trades	Trade Repetition Time (in days)	Gross Returns (%)			T C (%)	Net Returns (%)			Sharpe Ratio (%)	Alpha (↑Index Return)
				Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank		
Brazil	Bovespa	20	24.70	41.62	19.00	**3**	0.19	41.43	18.92	**3**	144.81	51.25
Russia	RTS I	20	25.15	55.77	24.81	**1**	0.22	55.55	24.72	**1**	162.91	52.57
India	CNX Nifty	23	21.74	46.18	20.90	**2**	0.23	45.95	20.81	**2**	41.88	10.45
China	Shanghai	41	11.80	-41.49	-23.51	**5**	0.41	-41.90	-23.78	**5**	333.01	-59.01
South Africa	FTSE	34	15.26	-13.46	-6.97	**4**	0.36	-13.82	-7.17	**4**	-83.71	-22.71

Table III interpreters the results of second sub period for data set for the technique of EMA 5-20. The trade repetition time is found to be minimum in case of Chinese market hence one has to be most active in case of Chinese market. When EMA 5-20 is used on this period data set it has shown more than average efficiency on the data set. Three markets out of five shows positive alpha returns. Brazilian, Russian and Indian market has shown positive alpha return whereas Chinese and South African markets have shown negative alpha return. So, we can say that the average efficiency of EMA 5-20 is found for this given data period.

Table-IV: Testing the efficiency of EMA 5-200 for Panel-I: Whole Sample Period i.e., 01st January 2018 to 31st December 2021)

Markets	Index	No. of trades	Trade Repetition Time (in days)	Gross Returns (%)			T C (%)	Net Returns (%)			Sharpe Ratio (%)	Alpha (↑Index Return)
				Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank		
Brazil	Bovespa	20	49.35	-3.83	-0.97	**2**	0.18	-4.01	-1.02	**2**	-123.83	-35.64
Russia	RTS I	32	31.53	-32.31	-9.30	**3**	0.36	-32.67	-9.42	**3**	-241.87	-65.04
India	CNX Nifty	23	43.08	4.25	1.05	**1**	0.22	4.03	0.99	**1**	-229.48	-45.92
China	Shanghai	35	27.74	-67.70	-24.61	**4**	0.35	-68.05	-24.82	**4**	-420.46	-77.07
South Africa	FTSE	68	15.23	-112.48	---	**5**	0.72	-113.20	---	**5**	-497.69	-114.42

Table IV interpreters the results of complete period for data set for the technique of EMA 5-200. The trade repetition time is found to be minimum in case of South African market hence one has to be most active in case of South African market. When EMA 5-200 is used on this period data set it has shown zero efficiency on the data set. All the five markets have shown negative alpha return. So, we can say that the zero efficiency of EMA 5-200 is found for this given data period.

Table-V: Testing the efficiency of EMA 5-200 for Panel-II: Sub Sample Period i.e., 01st January 2018 to 31st December 2019)

	Index	No. of	Trade Repetition Time	Gross Returns (%)	T C (%)	Net Returns (%)	Sharpe Ratio	Alpha (↑Index

Markets		trades	(in days)	Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank	(%)	Return)
Brazil	Bovespa	06	82.17	28.55	13.38	**1**	0.08	28.47	13.34	**1**	-64.58	-12.98
Russia	RTS I	22	23.00	-16.74	-8.75	**2**	0.24	-16.98	-8.88	**2**	-229.49	-46.38
India	CNX Nifty	18	27.28	-18.09	-9.50	**3**	0.18	-18.27	-9.60	**3**	-247.20	-32.73
China	Shanghai	26	18.73	-25.03	-13.41	**4**	0.26	-25.29	-13.57	**4**	-90.95	-17.20
South Africa	FTSE	54	9.57	-105.15	---	**5**	0.56	-105.71	---	**5**	-426.45	-98.04

Table V interpreters the results of first sub period for data set for the technique of EMA 5-200. The trade repetition time is found to be minimum in case of South African market hence one has to be most active in case of South African market. When EMA 5-200 is used on this period data set it has shown zero efficiency on the data set. All the five markets have shown negative alpha return. So, we can say that the zero efficiency of EMA 5-200 is found for this given data period.

Table-VI: Testing the efficiency of EMA 5-200 for Panel-III: Sub Sample Period i.e., 01st January 2020 to 31st December 2021)

Markets	Index	No. of trades	Trade Repetition Time (in days)	Gross Returns (%)			T C (%)	Net Returns (%)			Sharpe Ratio (%)	Alpha (↑Index Return)
				Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank		
Brazil	Bovespa	14	35.50	-32.38	-17.77	**4**	0.10	-32.48	-17.83	**4**	-63.99	-22.65
Russia	RTS I	10	50.30	-41.06	-23.23	**5**	0.12	-41.18	-23.31	**5**	-136.84	-44.16
India	CNX Nifty	5	100	22.34	10.61	**1**	0.05	22.29	10.58	**1**	-52.95	-13.21

China	Shanghai	09	53.78	-13.45	-6.97	**3**	0.09	-13.54	-7.02	**3**	-172.96	-30.65
South Africa	FTSE	14	37.07	-7.34	-3.74	**2**	0.16	-7.50	-3.82	**2**	-60.44	-16.39

Table VI interpreters the results of second sub period for data set for the technique of EMA 5-200. The trade repetition time is found to be minimum in case of Brazilian market hence one has to be most active in case of Brazilian market. When EMA 5-200 is used on this period data set it has shown zero efficiency on the data set. All the five markets have shown negative alpha return. So, we can say that the zero efficiency of EMA 5-200 is found for this given data period.

Table-VII: Testing the efficiency of RSI for Panel-I: Whole Sample Period i.e., 01st January 2018 to 31st December 2021)

Markets	Index	No. of trades	Trade Repetition Time (in days)	Gross Returns (%)			T C (%)	Net Returns (%)			Sharpe Ratio (%)	Alpha (↑Index Return)
				Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank		
Brazil	Bovespa	254	3.88	15.31	3.63	**3**	2.54	12.77	3.05	**3**	-65.53	-18.86
Russia	RTS I	194	5.20	34.71	7.73	**1**	1.98	32.73	7.34	**1**	1.34	0.36
India	CNX Nifty	225	4.40	18.12	4.25	**2**	1.15	16.97	4.00	**2**	-164.81	-32.98
China	Shanghai	237	4.10	2.76	0.68	**4**	2.36	0.40	0.58	**4**	-47.05	-8.62
South Africa	FTSE	286	3.62	-48.85	-15.43	**5**	2.88	-51.73	-16.65	**5**	-230.32	-52.95

Table VII interpreters the results of complete data set for the technique of RSI. The trade repetition time is found to be minimum in case of South African market hence one has to be most active in case of South African market. When RSI is used on the complete data set it has not shown any great efficiency on the data set. Only one market out of five shows positive alpha returns. Russian market has shown positive alpha return and rest all markets shows negative alpha return. So, we can say that the low efficiency of RSI is found for this given data period.

Table-VIII: Testing the efficiency of RSI for Panel-II: Sub Sample Period i.e., 01st January 2018 to 31st December 2019)

Markets	Index	No. of trades	Trade Repetition Time (in days)	Gross Returns (%)			T C (%)	Net Returns (%)			Sharpe Ratio (%)	Alpha (↑Index Return)
				Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank		
Brazil	Bovespa	138	3.57	-31.13	-17.01	**4**	1.39	-32.52	-17.85	**4**	-367.83	-73.97
Russia	RTS I	98	5.16	0.79	0.39	**3**	1.00	-0.21	-0.11	**3**	-146.46	-29.60
India	CNX Nifty	106	4.63	-4.17	-2.11	**3**	0.55	-4.72	-2.39	**3**	-144.86	-19.18
China	Shanghai	110	4.43	25.10	11.85	**1**	1.10	24.00	11.36	**1**	169.70	32.09
South Africa	FTSE	146	3.54	-33.35	-18.36	**5**	1.48	-34.83	-19.27	**5**	-151.39	-27.16

Table VIII interpreters the results of first sub period data set for the technique of RSI. The trade repetition time is found to be minimum in case of South African market hence one has to be most active in case of South African market. When RSI is used on the complete data set it has not shown any great efficiency on the data set. Only one market out of five shows positive alpha returns. Chinese market has shown positive alpha return and rest all markets shows negative alpha return. So, we can say that the low efficiency of RSI is found for this given data period.

Table-IX: Testing the efficiency of RSI for Panel-III: Sub Sample Period i.e., 01st January 2020 to 31st December 2021)

Markets	Index	No. of trades	Trade Repetition Time (in days)	Gross Returns (%)			T C (%)	Net Returns (%)			Sharpe Ratio (%)	Alpha (↑Index Return)
				Aggregate	CAGR	Rank	Aggregate	Aggregate	CAGR	Rank		
Brazil	Bovespa	116	4.26	46.44	21.01	**2**	1.16	45.28	20.53	**2**	155.71	55.11
Russia	RTS I	96	5.24	61.30	27.00	**1**	0.98	60.32	26.62	**1**	177.69	57.34
India	CNX Nifty	119	4.20	22.29	10.58	**3**	0.60	21.69	10.31	**3**	-55.35	-13.81
China	Shanghai	127	3.81	-22.34	-11.88	**5**	1.27	-23.61	-12.60	**5**	-229.67	-40.72
South Africa	FTSE	140	3.71	-15.51	-8.08	**4**	1.40	-16.91	-8.85	**4**	-95.13	-25.80

Table IX interpreters the results of second sub period data set for the technique of RSI. The trade repetition time is found to be minimum in case of South African market hence one has to be most active in case of South African market. When RSI is used on the complete data set it has not shown any great efficiency on the data set. Only two market out of five shows positive alpha returns. Brazilian and Russian market has shown positive alpha return and rest all markets shows negative alpha return. So, we can say that the below average efficiency of RSI is found for this given data period.

Conclusion: -

The study is conducted on BRICS nation and we have tried to test the efficiency of EMA and RSI during the Covid and pre Covid period. The results shows that there is not a very good efficiency of EMA and RSI on the BRICS nation for the given data set. There is very low efficiency is shown by EMA 5-200. Whereas EMA 5-20 and RSI has shown some efficiency. We have tried to find out the efficiency during two sub period also but the results are not so supporting the fact that markets can be predicted by using the techniques of technical analysis for the given data set. The applicability of techniques does not show any great results during covid times too, though there is some hint of more efficiency of techniques during covid times in some markets. But in last we have reached at a conclusion that the efficiency of techniques is not so strong on the selected markets for the given data period.

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