-RESEARCH ARTICLE-

THE PROFITABILITY OF TECHNICAL ANALYSIS DURING VOLATILE PERIODS IN THE SOUTH AFRICAN FINANCIAL MARKETS

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─**Abstract**─

It is argued that technical analysis is effective in inefficient markets, citing volatility as a contributing factor. The dual moving average crossover and relative strength index were applied to the FTSE/JSE Top 40 Index from 2007 to 2019 to investigate this. Using regression analysis, the relationship between the returns of each technical trading rule and market volatility was determined, and the results indicate that there is little to no correlation between market volatility and the profitability of these trading rules. When the trades are divided into long and short trades, the study reveals that long trades generate higher returns than short trades.

Keywords: Technical Analysis, Moving Averages, Dual Moving Average Crossover, Relative Strength Index, Market Volatility, JSE

1. INTRODUCTION AND BACKGROUND TO THE STUDY

Investors in financial markets utilize various financial instruments to profit for themselves or their clients. Particularly, the stock market affords savvy investors opportunities to earn significant returns on their capital (Graham et al., 1934; Modigliani & Miller, 1959; Reilly & Brown, 2006; Fama & French, 2006; Bhalla, 2008). Many investors subscribe to fundamental and technical analysis (Menkhoff, 2010; Lim, 2015; Nti et al., 2020). (Reilly & Brown, 2006; Bhalla, 2008; AS, 2013; Nti, et al., 2020) define fundamental analysis as the investigation of company-specific variables such as profitability, financial strength and risk, the industry in which the company operates, and an assessment of economic variables that influence the company. The purpose of analyzing all of these variables is to determine the intrinsic value of a share (a perceivably objective determination of the share's true value), which is then compared to the current market price and results in an appropriate investment decision (Fama, 1965; Pinto et al., 2010; Nti, et al., 2020).

On the other hand, technical analysis (TA) is defined as the analysis of a security's historical price movements and market data to predict future price trends, thereby guiding an investment decision (Reilly & Brown, 2006). By utilizing diverse technical trading tools and strategies, such as price charts, indicators, volume data, and price pattern recognition, investors attempt to forecast future price movements and base their investment decisions on these forecasts (Brooks, 2006; Kirkpatrick II & Dahlquist, 2010; Nti, et al., 2020).

Due to its perceived contradiction with the Efficient Market Hypothesis (EMH) and Random Walk (RW) Theory (Menkhoff, 2010), the legitimacy of technical analysis as an investment analysis instrument has been debated in the academic community for decades. According to the EMH, a market is efficient when share prices contain all available information about those shares and adjust promptly to any changes in the information, preventing investors from earning excess returns (Fama, 1970). In addition, the arbitrary Walk Theory, a subset of the EMH, asserts that share price fluctuations are arbitrary and thus cannot be predicted. The fundamental tenet of technical analysis is to predict future price movements using historical price data (Fama, 1965). Despite this, 87% of fund managers use technical analysis in their investment analysis and decision-making (Menkhoff, 2010). In addition, Menkhoff (2010) states that TA is the most prevalent trading strategy in the commodity futures and foreign exchange markets, and 75% of TA profitability studies support its predictive power (Metghalchi et al., 2020). Some of these findings have been attributable to financial markets' efficacy, or lack thereof, during volatile periods. Numerous studies have confirmed that market volatility affects market efficiency and that technical trading rules can be implemented with a certain degree of success during such times (Noakes & Rajaratnam, 2014).

Market volatility occurs when investors are fearful and uncertain about the current and future stability of the market, resulting in a significant fluctuation of share prices over a

short period as investors attempt to decide whether to buy, sell, or hold shares (Danielsson et al., 2018). As a result, share prices trade at levels inconsistent with their intrinsic values, creating an opportunity for alternative investment strategies to capitalize on the mispricing. TA is especially profitable during periods of high market volatility, according to several studies (Efstathios et al., 2017; Luukka et al., 2016; McAleer et al., 2016; Patari and Vilska, 2014). Technical analysis strategies outperformed fundamental buy-and-hold strategies in the Russian and Greek share markets from 2003 to 2012, according to Efstathios et al. (2017) and Luukka et al. (2016), respectively. Patari (2016) noted similar results on the Finnish stock exchange between 1996-2012. McAleer et al. (2016) discovered that TA produced substantially higher returns than buy-and-hold strategies during the formation of 'bubbles' in 1997, 2000, and 2007. Markets are significantly less efficient during periods of high market volatility (Noakes & Rajaratnam, 2014), which may explain these findings. When markets are less efficient, the Efficient Market Hypothesis and Random Walk Model principles are compromised, allowing for more accurate price prediction using technical analysis and providing investors with profitable opportunities (Noakes & Rajaratnam, 2014). Volatility causes even the most efficient markets to experience periods of inefficiency, creating ideal conditions for applying technical trading tools such as indicators and chart patterns, which technicians believe can accurately predict future price movements. In addition, irrational investor behavior during volatile periods causes shares to trade at prices that are not in line with their true values, creating opportunities for investors to buy or sell mispriced shares with the expectation that their prices will return to their true values in the medium to long term. Due to the market's inefficiency, volatile markets or periods of volatility in stable markets may provide opportunities to profit from technical analysis strategies.

Despite being an emerging market, South Africa is considered to have a sophisticated, comparatively stable, and efficient stock market, with brief periods of inefficiency (Noakes & Rajaratnam, 2014). These brief periods of inefficiency may contribute to periods of volatility, which may present trading opportunities based on the rules of technical analysis. Campbell (2011), Du Plessis (2012), Bolton & von Boetticher (2015), De Souza et al. (2018), and Mulweli (2020) have produced contradictory findings regarding the profitability of technical analysis in the South African financial market, with the majority of the studies finding moderate to no evidence of profitability. De Souza et al. (2018) and Du Plessis (2012) generated moderate profits, which were considerably diminished by transaction costs. In contrast, none of the momentum indicators Bolton and von Boetticher (2015) employed on the FTSE/JSE Top 40 Index generated positive returns.

This study determines whether the technical analysis is a profitable investment strategy for the South African stock market, especially during periods of high market volatility. The study applies the dual moving average crossover (DMAC) and the relative strength index (RSI) to the FTSE/JSE Top 40 Index over 13 years. Using regression analysis, this

relationship between the profitability of these two technical trading strategies and market volatility, as measured by the South African Volatility Index (SAVI), is investigated further. This study contributes to the existing literature on technical analysis by providing a novel focus on the efficacy of technical analysis trading rules during volatile financial market periods.

The remaining sections are organized as follows. The literature review is presented in section 2, followed by an explanation of the data and methodology in section 3. Results are reported in section 4, and conclusions are shown in the final section.

2. LITERATURE REVIEW

2.1 The Difference between Fundamental and Technical Analysis

Fundamentalists base their investment decisions on economic, industry, and company-specific data. In contrast, technicians use market data, such as price and volume, and believe that price movements are driven by supply and demand forces, market sentiment, and market cycles or trends (Reilly & Brown, 2006). Lim (2015) distinguishes fundamental analysis from technical analysis by stating that fundamentalists are primarily concerned with intrinsic value, determining which specific companies to invest in, and comprehending the causes of potential market movements. Lim (2015) adds that technicians are more concerned with the dynamics of market and price movements, the effects of prospective market movements as opposed to their causes, and the precise timing of trades as opposed to determining intrinsic value. As a result, technicians are less concerned with the fundamental factors that led to price movements because they believe that the price already reflects all market information (Lim, 2015).

2.2 The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) posits that share prices reflect all available information about a stock at any given time (Fama, 1970). Fama identifies three additional types of Market efficiency and the incorporation of open data: Strong form - all available data. Semi-strong shape - all past and public data, and feeble form - all past data. Due to information asymmetry, there should be no opportunities to achieve above-average profits from trading a particular stock if this theory holds. Fama (1970) identifies three obstacles to market efficiency prevalent in most markets. This consists of transaction costs incurred in trading securities, the availability and cost of information, and investor consensus regarding the implications of the available data.

The arbitrary Walk Model, a weak form of market efficiency, asserts that future price movements are arbitrary and unpredictable, implying that any estimate of future price movements based on historical data is inaccurate, subjective, and risky (Fama, 1970). Technical analysis is incompatible with the Efficient Market Hypothesis and the Random Walk Model because it predicts future price movements based on past price movements.

In light of this, it should be challenging for an investor to consistently accomplish above-average profits over an extended period using technical analysis (Fama, 1970). With a few exceptions where the investor could profit from new public or non-public information, the rate at which the market processes further information and sets a new equilibrium price is such that the investor cannot consistently identify opportunities and earn above-average profits from them relative to the market (Ball & Brown, 1968; Fama et al., 1969).

Roux and Gilbertson (1977), Hadassin (1976), Morris et al. (2009), and Noekes and Rajaratnam (2014) all examined the JSE for weak-form efficiency utilizing different methodologies and samples. The studies found that shares on the JSE do not entirely follow a random walk motion, indicating that investors can apply and profit from technical analysis strategies on the JSE if they can identify shares or market conditions that are weak-form efficient or conditions that impact the efficiency of the market.

2.3 The Profitability of the Dual Moving Average Crossover

The dual moving average crossover (DMAC), also known as the moving average rule, is a well-known but straightforward technical trading rule. Numerous academic studies have examined its profitability and efficacy in financial markets. Brock et al. (1992), Cheung et al. (2011), Efstathios et al. (2017), Luukka et al. (2016), McAleer et al. (2016), Pätäri and Vilska (2014), Ratner and Leal (1999), and Taylor (2000) all tested the profitability of the DMAC strategy in different markets and periods and concluded that it is profitable. Brock et al. (1992) examined the profitability of a trading strategy on the Dow Jones Index over 90 years, from 1897 to 1986, using two basic trading rules: moving average and trading range break-out.t. Using standard statistical analysis and bootstrap techniques, they discovered substantial support for the strategies and that "buy" signals generated greater returns than "sell" signals. Moreover, Cheung et al. (2011) employed a simple moving average (using a variable length moving average and a fixed length moving average) and Trading Range Break strategy to the Heng Seng Index over 35 years from January 1972 to December 200. Standard statistical analysis was utilized for the conventional and non-sample tests. Before integrating the Hong Kong market in 1986, in which four Hong Kong share markets consolidated into one, the moving average strategy consistently outperformed the market. Subsequently, profits decreased due to increased market efficiency by computer-based matching systems, efficient information dissemination, and increased market liquidity. There is substantial evidence that increased market efficiency diminishes the profitability of technical analyses. This is also supported by the findings of De Souza et al. (2018), who examined the profitability of the DMAC strategy in the BRICS (Brazil, Russia, India, China, and South Africa) market.s. Using an automated trading system that simulated trades using technical analysis in a portfolio of assets, they discovered that the South African market, which is generally regarded as more efficient and stable than the other markets in the

group, generated returns from the DMAC that outperformed a buy-and-hold strategy over the short term at a more conservative, stable rate.

Moreover, the portfolio returns were especially robust for Russia and India. a. Studies by Luukka et al. (2016) and Pätäri and Vilska (2014), who applied the DMAC on the Russian stock market between 2003-2012 and 1996-2012, respectively, found the DMAC to be more profitable than buy-and-hold strategies during bearish periods compared to bullish ones. Ratner and Leal (1999) examined the profitability of DMAC and other variable average models in ten emergent stock markets in Latin America and Asia between January 1982 and April 1, 1999. Using a bootstrapping simulation, the study determined that excess returns could be attained compared to a buy-and-hold strategy; however, after adjusting for transaction costs, only Mexico, Taiwan, and Thailand demonstrated profitable strategies. Although there was no evidence of profitability in the seven other countries, the DMAC's ability to predict the direction of the trend in all the markets was demonstrated. Taylor (2000) tested the profitability of the DMAC on the FTA, FTSE-100, DJIA, and S&P-500 indices, as well as twelve UK shares and indices, using similar bootstrap methods and an ARMA-ARCH model. Statistical analysis revealed no random walk among the index or share prices; thus, a trading strategy could accurately predict and generate profitable trades. It was noted, however, that transaction costs could eliminate. There are, however, studies, such as Bolton and von Boetticher (2015), Du Plessis (2012), Ratner and Leal (1999), and Shynkevich (2016), that have found no evidence of profitability using moving averages. Shynkevich (2016) examined the profitability of the DMAC on a set of Dow Jones single-country indices representing developed equity markets in North America, Western Europe, and the Asia-Pacific region during the 1997 Asian and 2008 global financial crises. The study discovered that trading rules did not outperform a passive benchmark during the two financial crises. Following the global financial crisis, mes. Bolton and von Boetticher (2015) analyzed the performance of the JSE Top 40 Index between 2009 and 2014 using technical momentum indicators such as the simple moving average, the exponential moving average, and the relative strength index. They divided the analysis based on historical data, treating the data set as known and current data as unknown until realization. They discovered that none of the technical indicators generated positive returns over the investment period, leading them to the conclusion that the Top 40 exhibited no signs of momentum being present.

2.4 The Profitability of the Relative Strength Index

In a study that examined market efficiency in emergent BRIC markets, Chong et al. (2010) discovered that the RSI outperformed a buy-and-hold strategy in Russia, India, and China, with the highest return occurring in Russia. The RSI could not outperform the buy-and-hold system in Brazil, the BRIC country with the most mature market. This indicated that the RSI could generate significant excess returns in volatile and immature markets like Russia but not inefficient, mature, and stable markets like Brazil.

The RSI is not predictive across all markets and periods. Wu and Diao (2015) examined the RSI on the Shangai Share Index and the Shenzhen Share Index over eight years, from 2007 to 2015, and discovered that the oscillator was unable to accurately anticipate the future share price, regardless of whether the market was in a bull, bear, or normal period.

In a sample of 105 large-cap companies, including Apple, Amazon, and IBM, Halilbegovic et al. (2018) examined the RSI using regression and paired sample t-tests over five years from 2008 to 2013 as a stand-alone tool for generating reliable and consistent buy and sell signals that result in consistent, substantial, and sustainable profitability. According to the study, the correlation between signal strength and generated profit is very feeble, and the RSI as a stand-alone indicator is only 12.95 percent accurate. According to the study, RSI should only be used in conjunction with multiple other indicators when making investment decisions.

2.5   Market Volatility and Efficiency

Market volatility is characterized by the significant fluctuation of security prices over an extended period, driven primarily by the uncertainty or risk associated with the magnitude of changes in security fair values (Keupper, 2020). The greater a security's volatility, the greater the range over which its price can fluctuate, indicating that its price could change dramatically within a brief period (Danielsson et al., 2020). Ma et al. (2018) emphasize market liquidity as a significant factor during periods of turmoil, as market maker uncertainty hinders their ability to provide liquidity, resulting in share prices that are not closely aligned with their intrinsic values. An important finding of Noakes and Rajaratnam's (2014) study on the efficiency of the JSE was that the market was significantly weak-form efficient during the financial crisis, a period of high market volatility. This finding was echoed in Efstathios et al. (2017), Luukka et al. (2016), McAleer et al. (2016), Patari and Vilska (2014), and Shynkevich (2016), which all covered different markets with sample periods that included the global financial crisis, the Asian financial crisis, the dot-com bubble, the Greek crisis, and other periods considered to be periods of high market volatility.

According to a 2016 study by Luukka et al. (2016) the Russian stock market is one of the most volatile globally. The majority of technical trading strategies were unable to outperform the benchmark buy-and-hold strategy in the in-sample test, according to the study. However, the strategies that did outperform the benchmark did so even in the out-of-sample test, with superior performance during bearish periods and share market crashes. The sample period utilized by Patari and Vilska (2014) included both bullish and pessimistic market conditions. The study discovered that a technical strategy could outperform a fundamental buy-and-hold strategy, especially in adverse market conditions. According to the study, adverse market conditions on the Finnish stock exchange are typically caused by international institutional investors selling off their holdings during volatile times, bolstering the argument that technical analysis may be profitable.

Efstathios et al. (2017) examined the profitability of three technical trading rules, namely the simple moving average, the moving average envelopes, and the slope of regression, by applying them to the FTSE Large-Cap Index on the Athens Stock Exchange from 2005 to 2012, which included the period before and during the Greek financial crisis. The study discovered that technical trading principles were profitable even during the recession (2009-2012) and that technical trading strategies could predict price movement and recognize trends and patterns.

McAleer et al. (2016) discovered that the technical moving average strategies on the Hang Seng Index generated higher returns than a buy-and-hold strategy during the formation and bursting of bubbles, such as the Asian financial crisis of 1997, the dot-com bubble of 2000, and the global financial crisis of 2008.

The South African Volatility Index (SAVI)

The SAVI was introduced in 2007 and is based on the at-the-money FTSE/JSE Top 40 market volatilities. In 2010, it was modified to include volatility skews and to use a weighted average of call and put prices across a broad range of 3-month strike prices (Johannesburg Share Exchange, 2014). According to Shannon and Pillay (2006), a volatility index serves as an anxiety gauge for an emerging market, a timing tool for indicating market entry points, a political/country risk measure, and an underlying "spot" instrument for a volatility future.

Figure 1.1 SAVI and FTSE/JSE Top 40 Index (Feb 2007 to Mar 2020)
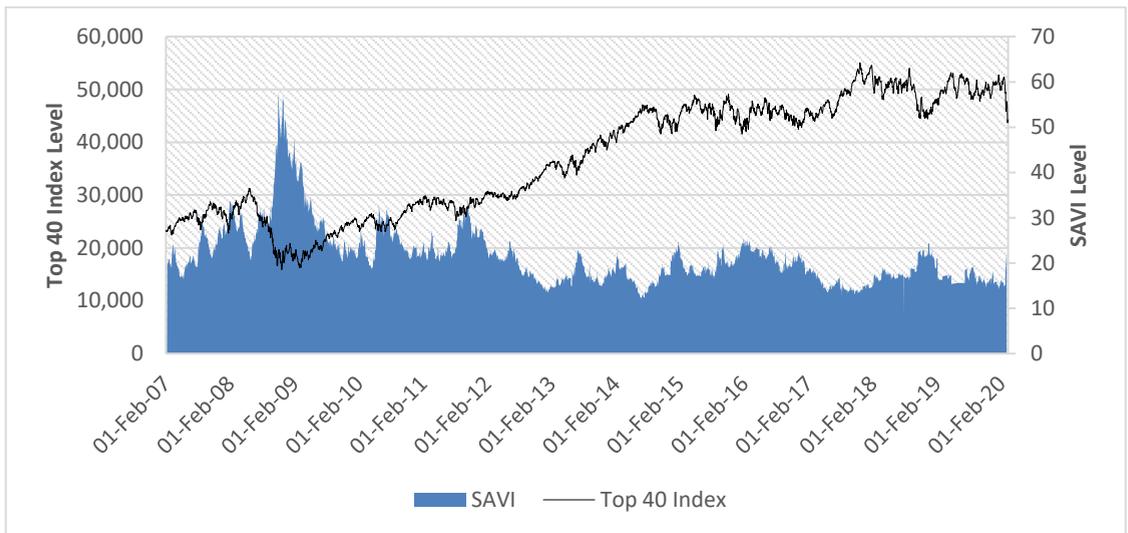**Source:** IRESS Database

The negative correlation between the FTSE/JSE Top 40 Index and the SAVI is depicted in Figure 1.1. When the market is stable and the Top 40 rises, the SAVI decreases and maintains levels at or below the 13-year average of 21,5 points. When market instability and the Top 40 Index begins a downward trend, the SAVI rises to levels above the

average of 21.5. A rise above this level indicates a possible increase in market volatility, while a drop below this level suggests a potential decrease in market volatility.

Despite its alleged incompatibility with the Efficient Market Hypothesis and the Random Walk Theory, many investors use technical analysis to make investment decisions. During periods of high market volatility that leads to less efficient markets, technical trading strategies have been shown to outperform buy-and-hold strategies (Efstathios et al., 2017; Lukka et al., 2016; McAleer et al., 2016; Patari & Vilska, 2014). In addition, testing the profitability of the DMAC and RSI trading principles on various markets yielded mixed results. The DMAC and RSI trading principles were more effective and profitable in emerging and less mature markets. It was discovered that developed and emerging markets with greater maturity were more efficient, and thus trading rules appeared less effective and profitable. In comparison to other emergent markets, the South African stock market is one of the most stable and efficient, making it difficult to consistently generate abnormal returns through technical analysis (De Souza et al., 2018). Several studies (Bolton & von Boetticher, 2015; De Souza et al., 2018; Du Plessis, 2012) that examined the profitability of the South African stock market using technical analysis found scant evidence of its profitability. In addition, transaction costs consistently reduce the profitability of trading rules, according to studies that consider transaction costs. Due to the contradictory findings of previous research on the subject, it is evident that there is insufficient evidence to determine whether the technical analysis is a profitable strategy to employ during volatile periods in the South African stock market.

3. DATA AND METHODOLOGY

The DMAC and RSI trading rules are applied to the closing price of the FTSE/JSE Top 40 Index, which has been used as a proxy for the South African stock market in other studies (Du Plessis, 2012; Bolton & von Boetticher, 2015). The rules were implemented over thirteen years, with the trading rules generating buy and sell signals and transaction costs for buying and selling the index calculated at 0%, 0.6%, 0.7%, and 0.8%. The period was chosen to ensure that sufficient periods of market volatility, such as the global financial crisis 2008 and other significant events in South Africa that may have contributed to inefficient or tumultuous periods on the JSE, are included. High volatility periods were designated as the in-sample data set, while stable periods were designated as the out-of-sample data set. According to Govender (2018), the level of the South African Volatility Index (SAVI) determines the beginning and ending points of volatile periods. Microsoft Excel Office 365 Pro was used to analyze the daily closing prices of the FTSE/JSE Top 40 Index from February 1, 2007,, to December 31 2019, downloaded from the iRESS database.

Using methodologies from previous studies (Brock et al., 1992; Wu & Diao, 2015; Luukka et al., 2016; Efstathios et al., 2017; Halilbegovic et al., 2018), the returns

generated by the trading rules are calculated and compared to determine the trading rules' profitability at each level of the transaction cost. The study then determined the returns generated by trading rules during periods of volatility. These were compared to the sample period's stable periods to determine if returns generated during volatile periods were greater than those generated during stable periods. The extent and significance of the relationship between the returns of the DMAC and RSI, and the SAVI was determined by regression analysis.

3.1 Technical Trading Rules

Moving Averages: *The Simple Moving Average*

The simple moving average (*SMA*) at time *t*, denoted by $SMA_{t,n}$ is given by:

$$SMA_{t,n} = \frac{1}{n}\sum_{i=t-n}^{t-1} C_i \qquad (1)$$

Where C_i is the closing price at time i. The moving average changes when adding a new period and simultaneously removing the oldest period. The moving average increases when the latest addition is larger than the value removed and decreases when the latest addition is less than the value removed (McAleer et al., 2016). Figure 3.1 (www.ig.com) shows a 50-day moving average overlaid on the daily FTSE/JSE Top 40 Index price. A buy signal is generated when the share's closing price is above the *SMA* and a sell signal is generated when the closing price is below the *SMA*. McAleer et al. (2016) also point out that since the *SMA* is a lagging indicator, it only works well when there is a clear trend and will not work during flat or volatile periods.

Figure 3.1 50-day Moving Average on FTSE/JSE Top 40 Index
Source: www.ig.com

The Exponential Moving Average

The $n-$day exponential moving average (EMA) at time t, denoted by $EMA_{t,n}$, is defined as:

$$EMA_{t,n} = \alpha C_t + (1 - \alpha)EMA_{t-1,n} \qquad (2)$$

With $EMA_{1,n} = C_1$ and $\alpha = \frac{2}{n+1}$. The exponential moving average reduces the lag effect of older periods by putting more weight on recent prices. The smoothing constant $\frac{2}{n+1}$ works as the weight that applies to the most recent price depending on the length of the moving average (McAleer et al., 2016). The EMA reacts faster to recent price changes with buy and sell signals similar to the simple moving average. Figure 3.2 (www.ig.com) shows a 15-day exponential moving average overlaid on the daily FTSE/JSE Top 40 Index price and illustrates how closely the EMA follows the price and how quickly it reacts to any changes in movements.

Figure 3.2 15-day Exponential Moving Average on FTSE/JSE Top 40 Index
Source: www.ig.com

3.2   Dual Moving Averages

This method combines two moving averages denoted by $DMA(n, m)$ with a short n=day SMA ($SMA_{t,n}$), a long m=day SMA ($SMA_{t,m}$) and $m > n$. The rule generates a buy signal when the short SMA rises above the long SMA and a sell signal when the short

SMA falls below the long *SMA* (McAleer et al., 2016). This rule works similarly with a short and long *EMA*. One of the benefits of the dual moving average is that, unlike the *SMA* and *EMA*, it is less affected by volatility due to the smoothing effect of the short moving average (McAleer at al., 2016).

This study will combine a 15-day EMA (15EMA) with a 50-day *SMA (50SMA)*. As illustrated in Figure 3.3 (www.ig.com), below, the buy signal will be generated when the *15EMA* rises above the *50SMA*, and the sell signal will be generated when the *15EMA* falls below the *50SMA*.

Figure 3.3 50-day SMA and 15-day EMA on FTSE/JSE Top 40 Index
Source: www.ig.com

The Relative Strength Index (RSI) Oscillator

The relative strength index (RSI) is calculated as follows:

$$RSI_t(n) = \frac{\sum_{i=0}^{n-1}(P_{t-i}-P_{t-i-1})1\{P_{t-i}>P_{t-i-1}\}}{\sum_{i=0}^{n-1}[P_{t-i}-P_{t-i-1}]} \times 100 \tag{3}$$

Where RSI_t is the relative strength index at time t, P_t is the value of the index at time t, n is the number of RSI periods, $1\{P_{t-i} > P_{t-i-1}\}$ is an indicator function which equals one when the statement inside the bracket is true and equals zero when it is false (Chong

and Ng, 2008). $[P_{t-i} - P_{t-i-1}]$ is an absolute value of x. The RSI ranges between 0 to 100 and is considered overbought when it is above 70, and oversold when it is below 30, giving a bullish signal when above 50 and a bearish signal when below 50 (Chong and Ng, 2008). This is illustrated in Figure 3.4 (www.ig.com), below, where a 14 day is applied to the FTSE/JSE Top 40 Index. As in Chong and Ng (2008), this study will use the popular 14-day RSI with a trading rule that triggers a buy signal when the RSI crosses the centre line from below and a sell signal when the RSI crosses the centre line from above.

Figure 3.4 14-day RSI on FTSE/JSE Top 40 Index
Source: www.ig.com

According to Bhandari (2016), divergence occurs when the price action and oscillator indicate contradictory information. These conflicts are frequently interpreted as a sign that the price is about to reverse course. A bullish divergence occurs when the RSI begins to move upwards out of the "oversold" zone and forms a "higher low", while the price continues to move sideways or downwards and forms a "lower low" (Bhandari, 2016; Lim, 2015). This signal is depicted in Figure 3.5 (Lim, 2015) and can be interpreted as an indication that the price is anticipated to reverse its current downward trend (Bhandari, 2016; Lim, 2015).

Figure 3.5 RSI - Bullish Divergence
Source: Lim (2015)

In a bearish divergence, the RSI moves downwards from the "overbought" zone while price action makes a higher high (Lim, 2015; Bhandari, 2016). This signal is depicted in Figure 3.6 (Lim, 2015) and can be interpreted as a prediction that the price will reverse its upward trend (Lim, 2015; Bhandari, 2016).
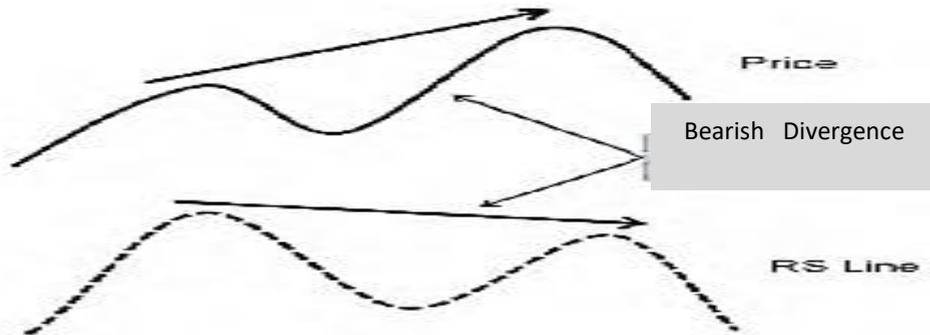

Figure 3.6 RSI - Bearish Divergence
Source: Lim (2015)

3.3 Applying the Trading Rules

The DMAC and RSI calculations will be applied to the data using Microsoft Excel formulas to determine purchase and sell signals. The transactions conducted by the DMAC and RSI were financed with an initial investment of R100,000. If the cash balance is depleted to the point where there are no longer sufficient funds to continue trading, an additional R100,000 will be invested to continue trading. The transaction costs will be calculated at 0.6%, 0.7%, and 0.8%, a range consistent with stockbroker rates in South Africa. Table 3.1 illustrates how calculations will be performed and how transactions will be affected by the DMAC and RSI strategies.

3.4 Dual Moving Average Crossover

Table 3.1 displays buy and sell signals generated by the DMAC trading rules based on the price movement of the FTSE/JSE Top 40 Index over 14 months, with five signals generated. On November 20, 2007, for R 26,703.16, the 15-day exponential moving average (EMA) crossed below the 50-day moving average (MA), generating a sell signal that triggered a short trade with transaction costs of R 160.22 (0.6% of the transaction). The trade was executed on February 19, 2008, for R 27,292.58, and transaction costs of R 163.76 are incurred when the 15-day exponential moving average crosses above the 50-day simple moving average to generate a buy signal. The buy signal also activates a long trade with additional transaction costs of R 163.76 (for a total of R 327.51 for both trades on the day). Over fourteen months, a total profit of R 9,910.45 is realized from all transactions.

Table 3.1 DMAC during Financial Crisis at 0.6% Transaction Cost

Date	Close	50-day MA	15-day EMA	MA/ EMA	Buy/ Sell	Trans Cost	Profit	Cum Profit
20-Nov-07	26 703,16	27 567,05	27 542,41	(24,64)	-1	(160,22)	(160,22)	(160,22)
19-Feb-08	27 292,58	25 778,66	25 873,62	94,96	1	(327,51)	(916,93)	(1 077,15)
17-Jun-08	29 655,55	29 689,54	29 656,57	(32,97)	-1	(355,87)	2 007,10	929,95
12-Dec-08	19 415,17	18 315,71	18 506,85	191,13	1	(232,98)	10 007,40	10 937,35
27-Jan-09	18 611,61	18 688,90	18 631,21	(57,68)	-1	(223,34)	(1 026,90)	9 910,45

SOURCE: IRESS DATABASE

Notes:
Date: February 1, 2007,, to December 31 2019; however, the dates reflected are the relevant dates that buy and sell signals were generated.
Close: Daily closing price of the FTSE/JSE Top 40 Index
50-day MA: 50-day moving average
15-day EMA: 15-day exponential moving average

EMA-MA: This represents the crossover between the MA and EMA. After a string of positive values, the first negative value indicates a sell signal as the EMA is below the MA. The short position will be held until the EMA exceeds the MA. After a string of negative values, the first positive value indicates a buy signal as the EMA is now above the MA. The long position will be held until the EMA crosses below the MA.

Buy/Sell: A buy signal is represented by 1, and a sell signal by -1.

Trans Cost: Transaction costs are calculated at 0.6%, 0.7% and 0.8% for the entry and exit of each trade.

Profit: This represents the daily profit and loss on each trade.

Cum Profit: This represents the cumulative profit from all trades in the period analysed.

3.5 Relative Strength Index

Table 3.2 displays buy and sell signals generated by the RSI trading rules based on the price movement of the FTSE/JSE Top 40 Index over three weeks, with five signals generated. The 14-day RSI crossed below 50 on October 22, 2007, for R 27,389.30, generating a sell signal that triggered a short trade with transaction costs of R 164.34 (0.6% of the transaction) incurred. When the RSI crosses above 50 and generates a buy signal on October 29, 2008, the trade is executed for R 28,335.75 and transaction costs of R 170.01 are incurred. The buy signal also activates a long trade with additional transaction costs of R 170.02 (for a total of R 340.03 for both trades on the day). During the three weeks, the cumulative loss on all transactions is R 3,184.38.

Table 3.2 RSI during Financial Crisis at 0.6 Transaction Costs

Date	Close	Change	14-day RSI	Buy/ Sell	Trans Cost	Profit	Cum Profit
22-Oct-07	27 389,30	(608,77)	43,97	-1	(164,34)	(164,34)	(164,34)
29-Oct-07	28 335,75	396,14	52,19	1	(340,03)	(1 286,48)	(1 450,81)
30-Oct-07	28 372,48	36,73	49,26	-1	(340,47)	(303,74)	(1 754,55)
08-Nov-07	28 209,04	334,63	52,42	1	(338,51)	(175,07)	(1 929,62)
15-Nov-07	27 281,66	(543,49)	41,07	-1	(327,38)	(1 254,76)	(3 184,38)

SOURCE: IRESS DATABASE

Notes:

Date: February 1, 2007, to December 31 2019. However, the dates reflected are the relevant dates that buy and sell signals were detected for the example.

Close: Daily closing price of the FTSE/JSE Top 40 Index

Change: Daily movement from the previous day's close.

14-day RSI: 14-day relative strength index indicates a buy signal when it moves above 50 and a sell signal when it moves below 50.

Buy/Sell: A buy signal is represented by 1, and a sell signal by -1.

Trans Cost: Transaction costs are calculated at 0.6%, 0.7% and 0.8% for the entry and exit of each trade

3.6 Identifying Volatile Periods

The SAVI can be expressed as (JSE, 2014):

$$SAVI = \sqrt{\sum_{i=1}^{n=F} w_{iP} P_i(K_i) + \sum_{i=n}^{\infty} w_{iC} C_i(K_c)} \tag{4}$$

Where F is the current (on value-date) forward of the FTSE/JSE Top 40 Index level. $P_i(K_i)$ and $C_i(K_t)$ are the put and call options with a strike price K_t. The prices of the put and call options are determined using the traded market volatility skew that expires in 3-months (JSE, 2014).

Table 3.3 identifies volatile and stable periods over the sample period.

Table 3.3 SAVI Closing Price

Date	Close	Vol/Sta
28-Feb-07	21,60	1
22-Mar-07	20,86	-1
08-Jun-07	21,73	1
11-Jun-07	21,28	-1
12-Jun-07	21,68	1
13-Jun-07	21,46	-1
27-Jun-07	21,88	1
02-Jul-07	21,30	-1
27-Jul-07	24,00	1
10-Oct-07	21,15	-1
16-Oct-07	21,65	1
16-May-08	21,25	-1

SOURCE: IRESS DATABASE

Notes

Date: February 1, 2007, to December 31 2019; however, the dates reflected are the relevant dates that volatile and stable signals were detected for the example.

Close: Daily closing level of the SAVI

Vol/Sta: The signal for the beginning of a volatile period is represented by 1, indicating that the SAVI closed above the average of 21.48 on the day. The signal for the end of a volatile period and the beginning of a stable period is represented by -1, indicating that the SAVI closed below the average of 21.48 on the day.

3.7 Relationship between the Profitability of Trading Rules and Market Volatility

The returns for the DMAC and RSI over the sample period were regressed against the SAVI, with the returns for the DMAC and RSI as the dependent variable and the SAVI as the independent variable for both models. A dummy variable was used for the SAVI with values above the average of 21.48, denoted by 1 (indicating volatile periods) and values below the average, represented by 0 (indicating stable periods). The hypothesis test for both models was as follows:

H_0: There is no relationship between the returns of the TA trading rules and the market volatility level.

H_a: There is a relationship between the returns of the TA trading rules and the market volatility level.

Correlation between the returns of the trading rules and the SAVI is also tested using the correlation coefficient denoted by R and the R^2, as a measure of the regression fit (Asteriou and Hall, 2011). A summary of the variables used is present in Table 3.4.

Table 3.4 Summary of Regression Variables

Variable	Description	
Regression 1		
SAVI South African Volatility Index	SAVI price over the sample period	*Independent variable* Dummy variable
DMAC Dual moving average crossover	Returns generated by the dual moving average crossover over the sample period	*Dependent Variable*
Regression 2		
SAVI South African Volatility Index	SAVI price over the sample period	*Independent variable* Dummy variable
RSI Relative strength index	Returns generated by the relative strength index over the sample period	*Dependent Variable*

Assuming that the coefficients a and β have a normal distribution and a 5% significance level, the null and alternative hypothesis can be set as $H\_0: \beta = 0$ and $H\_a: \beta \neq 0$ for a two-tailed test, and $H\_0: \beta = 0$ and $H\_a: \beta > 0$ for the one-tailed test (Asteriou and Hall, 2011).

4. RESULTS

The DMAC and RSI strategies were applied under two conditions. Firstly, the strategies were applied throughout the sample period, not considering any volatility. Secondly, they were applied over the sampled period with the trading rules specified to only come into effect when the volatility, indicated by the SAVI, exceeds the average level of 21.48.

4.1 Dual Moving Average Crossover (DMAC)

Performance of DMAC Irrespective of Market Volatility

Table 4.1 summarises all transactions executed during the sample period using the DMAC trading rules, regardless of market volatility. There were a total of 85 transactions with negative net returns at all levels of transaction costs. At 0% transaction costs, the R100 000 investment generated a negative 36% return. At transaction costs of 0.6%, 0.7%, and 0.8%, an R100,000 investment generated negative returns of 76%, 83%, and 89%, respectively, with an additional R100,000 investment required because the cash balance was depleted.

Since the DMAC trading principles generate both long and short trades during the sample period, it may be worthwhile to compare the profitability of long and short trades to determine which is more lucrative. Table 4.2 provides a breakdown of the long and short trades, revealing that 42 long trades and 43 short trades were executed with negative returns at all transaction cost levels. On an investment of R100 000, long trades yielded a negative 5% return. In comparison, short trades yielded a negative 31% return, indicating that although both trades are negative, the long trades yielded a higher return. This was the case regardless of the transaction cost level. This result is consistent with the findings of Brock et al. (1992), who examined the profitability of the DMAC on the Dow Jones Industrial Average over 90 years and discovered that "buy" signals generated higher returns than "sell" signals.

Performance of DMAC during Higher-than-Average Market Volatility

To evaluate the profitability of the DMAC trading rules during higher-than-average market volatility, the trading rules were modified to be activated only when the SAVI, the market volatility indicator, exceeded the average level of 21.48. Under these circumstances, the DMAC trading rules affected 43 transactions with negative returns at all transaction cost levels. This approach resulted in fewer overall trades than the one that disregards market volatility, resulting in lower transaction costs and higher returns at respective transaction cost levels than the one that disregards market volatility. At 0%

transaction costs, the R100 000 investment generated a negative return of 12%. At transaction costs of 0.6%, 0.7%, and 0.8%, an R100,000 investment yielded negative 26%, 28%, and 31%, respectively, with no additional investment required.

Table 4.2 provides a breakdown of long and short trades, revealing that 21 long trades and 22 short trades yielded negative aggregate returns at all transaction cost levels. On an investment of R100,000, the long trades generated a negative 2% return. In comparison, the short trades generated a negative 10% return, indicating that although both trades are negative, the long trades generated a higher return than the short trades. This was the case regardless of the transaction cost level.

This is consistent with Bolton and von Boetticher's (2015) findings, who examined the profitability of simple and exponential moving averages on the FTSE/JSE Top 40 Index and discovered that neither indicator generated positive returns over the investment period. The fact that the DMAC generated negative returns even during periods of high market volatility may indicate the South African stock market's efficacy. Cheung et al. (2011) and De Souza et al. (2018) discovered that enhanced market efficacy decreased the profitability of technical analysis.

4.2   Relative Strength Index (RSI)

Performance of RSI Irrespective of Market Volatility

Regardless of market volatility, Table 4.1 summarises all trades affected by the RSI trading criteria during the sample period. 382 transactions were executed with negative returns at all levels of transaction costs. At 0% transaction costs, the R100 000 investment generated a negative 24% return. At transaction costs of 0.6%, 0.7%, and 0.8%, an R100,000 investment yielded negative 190%, 218%, and 246%, respectively, with an additional R200,000 investment required because the cash balance was depleted twice. Compared to the DMAC, the RSI appears to have generated a significantly higher number of trades, which has resulted in significantly higher transaction costs and substantially reduced the trading strategy's profitability.

Table 4.2 provides a breakdown of long and short positions. Except for long trades with no transaction costs, both long and short trades generated negative returns. An R100,000 investment in long trades with no transaction costs generated a positive return of 2% over the sample period. Like the DMAC, the long positions generated higher returns than the short ones. Bhandari (2016) suggests that the RSI should not be utilized as a sole indicator but rather in conjunction with another indicator. The results of this study appear to support this recommendation, as the RSI generates numerous false buy and sell signals that result in losses.

Performance of RSI during Higher-than-Average Market Volatility

Similar to the DMAC during periods of high market volatility, the results demonstrate a significant reduction in the total number of affected trades, which has also significantly reduced transaction costs. Although returns at all transaction cost levels are negative, the returns for trades impacted only during periods of high market volatility are greater than those affected throughout the sample period. The RSI has generated significantly more trades than the DMAC, resulting in higher transaction costs and reduced returns for trades involved only during periods of high market volatility.

Table 4.2 provides a breakdown of long and short positions. Although returns for long and short trades were predominantly negative at all transaction cost levels, the results indicate that fewer long trades were negatively impacted, resulting in lower transaction costs and higher returns than short trades, with long trades at 0% transaction costs yielding a positive return. According to Halilbegovic et al. (2018), the RSI as a stand-alone indicator is only 12.95 percent reliable at generating consistent profits. Wu and Diao (2015) tested the RSI on the Shanghai and Shenzhen indices and discovered it was ineffective in both bull and bear market conditions.

4.3 The Relationship between the Profitability of the Trading Rules and Volatile Periods

The previous section's findings demonstrate that the technical trading rules, DMAC and RSI, generated negative returns throughout the sample period. It was also observed that these trading rules caused negative returns during a portion of the sample period when the trading rules were modified to be triggered only when volatility, as measured by the SAVI, is greater than the period's average. Intriguingly, despite the returns being negative even with 0% transaction costs, the returns are superior to the entire sample period regardless of market volatility.

4.4 Regression Model the DMAC Returns, RSI Returns and the SAVI

To better understand this relationship, the returns of the DMAC and RSI were regressed against the SAVI dummy variables, which represent market volatility. There is no statistically significant relationship between the returns of the DMAC and the SAVI or the returns of the RSI and the SAVI, as shown in Table 4.5. In contrast to the findings of Efstathios et al. (2017), Luukka et al. (2016), and Patari and Vilska (2014), who discovered that technical analysis tools are profitable in volatile markets, this finding indicates that technical analysis tools are not profitable in volatile markets.

Previous research on the profitability of technical trading rules, such as the DMAC and the RSI, has yielded contradictory results, with some studies finding the trading rules profitable in certain markets but not in others. In periods of market volatility, markets tend to be less efficient, according to the literature (Noakes and Rajaratnam, 2014). Particularly, the South African stock market has been shown to experience periods of inefficiency; as a result, these periods of volatility may present opportunities to generate profitable returns by applying technical trading rules.

Table 4.1 Summary of DMAC and RSI Trades over the Sample Period

	Summary of DMAC							
	Irrespective of Market Volatility				**Higher-than-Average Market Volatility**			
Transaction costs %	**0%**	**0.6%**	**0.7%**	**0.8%**	**0%**	**0.6%**	**0.7%**	**0.8%**
Total Investment	100 000	200 000	200 000	200 000	100 000	100 000	100 000	100 000
Number of trades	85	85	85	85	43	43	43	43
Transaction costs (R'val)	0	39 677	46 289	52 902	0	14 376	16 772	19 169
Net profit (R'val)	(36 286)	(75 963)	(82 576)	(89 189)	(11 711)	(26 087)	(28 483)	(30 879)
% Return	-36%	-76%	-83%	-89%	-12%	-26%	-28%	-31%
Number of recapitalisations	0	1	1	1	0	0	0	0
	Summary of RSI							
	Irrespective of Market Volatility				**Higher-than-Average Market Volatility**			
Transaction costs %	**0%**	**0.6%**	**0.7%**	**0.8%**	**0%**	**0.6%**	**0.7%**	**0.8%**
Total Investment	100 000	300 000	300 000	300 000	100 000	200 000	200 000	200 000
Number of trades	382	382	382	382	191	191	191	191
Transaction costs (R'val)	0	166 644	194 418	222 192	0	65 030	75 868	86 707
Net profit (R'val)	(23 835)	(190 479)	(218 253)	(246 027)	(15 504)	(80 534)	(91 372)	(102 210)
% Return	-24%	-190%	-218%	-246%	-16%	-81%	-91%	-102%
Number of recapitalisations	0	2	2	2	0	1	1	1

Source: Research Data

Table 4.2 Summary of DMAC and RSI Long and Short Trades over Sample Period

	Summary of DMAC Long and Short Trades							
	Irrespective of Market Volatility							
	0%		0.6%		0.7%		0.8%	
	Long	Short	Long	Short	Long	Short	Long	Short
Number of trades	42	43	42	43	42	43	42	43
Profit	(5 106)	(31 180)	(24 685)	(51 127)	(27 948)	(54 452)	(31 211)	(57 776)
% Return	-5%	-31%	-25%	-51%	-28%	-54%	-31%	-58%
	Higher-than-Average Market Volatility							
	0%		0.6%		0.7%		0.8%	
	Long	Short	Long	Short	Long	Short	Long	Short
Number of trades	21	22	21	22	21	22	21	22
Profit	(1 695)	(10 016)	(8 711)	(17 376)	(9 881)	(18 603)	(11 050)	(19 829)
% Return	-2%	-10%	-9%	-17%	-10%	-19%	-11%	-20%
	Summary of RSI Long and Short Trades							
	Irrespective of Market Volatility							
	0%		0.6%		0.7%		0.8%	
	Long	Short	Long	Short	Long	Short	Long	Short
Number of trades	191	191	191	191	191	191	191	191
Profit	2 079	(25 796)	(81 308)	(109 326)	(95 206)	(123 247)	(109 104)	(137 169)
% Return	9%	-26%	-81%	-109%	-95%	-123%	-109%	-137%
	Higher-than-Average Market Volatility							
	0%		0.6%		0.7%		0.8%	
	Long	Short	Long	Short	Long	Short	Long	Short
Number of trades	94	97	94	97	94	97	94	97
Profit	2 194	(17 698)	(30 274)	(50 260)	(35 685)	(55 687)	(41 097)	(61 113)
% Return	2%	-18%	-30%	-50%	-36%	-56%	-41%	-61%

Source: Research data

Table 4.5 Regression Models for DMAC and SAVI/RSI and SAVI

	DMAC Returns			RSI Returns		
	Model	*SAVI DV*	*Intercept*	*Model*	*SAVI DV*	*Intercept*
R^2	0,031994342			0,00031519		
Multiple R	0,178869622			0,01775354		
Standard error	2037,098859			996,546209		
Coefficient		743,5997429	-1842,82078		-35,446894	-46,4629
T-stat		1,656291171	-2,26838625		-0,345679	-0,67242
P-value		0,101438864	0,025902077		0,72977577	0,501726
Standard error		36,65149582	812,3928539		102,542809	69,09805

Source: Research data

This study's findings, however, indicate a correlation between the profitability of technical analysis trading principles and market volatility that is minimal at best. Moreover, several studies (De Souza et al., 2018; Shynkevich, 2016; Du Plessis, 2012) have demonstrated that transaction costs consistently reduce the profitability of technical trading rules. The study, therefore, considered transaction costs. Intriguingly, the DMAC and RSI generated negative returns at all transaction cost levels during the sample period, with the RSI performing worse than the DMAC.

5. CONCLUSION

This study was conducted to determine if technical analysis trading rules can be profitable during periods of high market volatility on the South African stock exchange and if there is a correlation between market volatility and profits generated by applying technical analysis trading rules. Several prior studies have demonstrated that technical analysis trading principles are profitable during times of high market volatility (Efstathios et al., 2017; Luukka et al., 2016; McAleer et al., 2016; Patari & Vilska, 2014). Periods of high market volatility have a negative impact on the market's efficiency, causing the market to be less efficient for the duration of the volatility (Noakes & Rajaratnam, 2014), thereby creating the potential for profitable technical analysis trading.

Even though the DMAC generated negative returns at all transaction cost levels under both conditions, the returns obtained by employing the DMAC only during periods of above-average market volatility were greater than those obtained when market volatility was ignored. This partially validates the findings of Luukka et al. (2016), Pätäri and Vilska (2014), and Noakes and Rajaratnam (2014), who discovered that the JSE was less

efficient during periods of high market volatility and that the DMAC generated higher returns during adverse periods. When the trades of the DMAC are segmented into long and short trades, the results indicate that long trade returns are greater than short trade returns. This is consistent with the findings of Brock et al. (1992), who evaluated the profitability of the DMAC on the Dow Jones Index and discovered that the "buy" signals generated greater returns than the "sell" signal.s. Nevertheless, the fact that the DMAC generated negative returns even during periods of high market volatility validates the findings of Bolton and von Boetticher (2015), Du Plessis (2012), Ratner and Leal (1999), and Shynkevich (2016), who found no evidence of profitability when applying the DMAC rules to different market environments.s. The RSI generated higher returns when used only during periods of above-average market volatility. When trades were segmented into long and short trades, long trades generated higher returns than short trades.s. When comparing the performance of the two technical trading instruments, the DMAC generated fewer trades but generated greater returns than the RSI. This indicates that the RSI generates more false signals that result in unprofitable transactions and supports the statement that the RSI generates more false signals. According to Bhandari (2016), the RSI should not be used as a solitary indicator but in conjunction with other technical indicators. A false trade signal occurs when the share price reverts to a level where the conditions for the trade are no longer met and no longer justifies the trade after the trade has been initiated.

Furthermore, the results demonstrate that there is no statistically significant correlation between the returns of the DMAC and the RSI and the level of market volatility during the sample period.d. This contradicts the findings of Efstathios et al. (2017), Luukka et al. (2016), and Patari and Vilska (2014), who discovered that technical analysis tools are profitable in volatile market conditions. One argument for the use of technical trading principles by technical traders is that markets are not always efficient, especially during volatile periods. Despite the fact that the South African stock market has limited periods of inefficiency due to market volatility, this study concludes that technical analysis trading rules cannot be used to exploit these periods of inefficiency profitably.s. Therefore, this study's findings may be of interest to active investors seeking investment strategies that perform consistently well, especially during periods of high market volatility when most of the market is apprehensive and uncertain. Corporate investors and fund managers restricted to liquid, mid- to large-cap shares, or hedge fund managers who are less restricted and can take long and short positions can use the study's trading criteria to determine to buy and hold signals.s. Retail investors who, like hedge fund managers, are not limited in the shares they can invest in can use the findings to take both long and short positions, as one of the advantages of technical analysis is that it does not require extensive or costly research on the fundamentals of security. This study adds to the existing literature by focusing on the relationship between technical analysis and market volatility and testing the profitability of technical analysis in volatile market conditions in the South African market context.t.

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