Evaluation of traditional and residual momentum strategies during the Covid period on the Johannesburg Stock Exchange

MPHATHI YENGWA

G17Y6396

ORCID: https://orcid.org/0000-0002-6328-8318

Thesis submitted in partial fulfilment of the requirements for the degree of

MASTER OF COMMERCE (FINANCIAL MARKETS) Department of Economics and Economic History

Rhodes University

Supervisor: David Fryer

Co-supervisor: Prof Sibanisezwe Khumalo

February 2024

Abstract

Traditional momentum is a concept which was first discovered by Jegadeesh and Titman (1993), defined as a tendency of stocks to experience a continuation in their relative performance. A stock that performed relatively well will continue to perform relatively well, and vice versa. It has been observed by other researchers that during market crises, traditional momentum tends to produce large negative returns for investors, defined as a momentum crash. To mitigate momentum crashes, many researchers have developed new momentum strategies which have better performance than traditional momentum during market crises; such strategies include residual momentum. While both residual and traditional momentum have been studied in international markets and locally, the performance of both the residual and traditional momentum strategies have not been examined in the most recent Covid-fuelled financial crisis on the Johannesburg Stock Exchange.

The study compares the performance of hypothetical long-only winner traditional and residual momentum portfolios (from 2018–2022) using various risk metrics, which include the tracking error, Sharpe ratio, Jensen's alpha and information ratio. To compare the statistical significance of the difference in mean returns of residual and traditional momentum strategies to the benchmark (FTSE/Johannesburg Stock Exchange (JSE) Top 40) the study uses Welch's t-test. The study uses an Auto regressive distributed lag (ARDL) regression to examine the effect that various market conditions (bull market, bear market and extreme volatility) have on the returns of residual and traditional momentum strategies. Given the limited period examined in this study, the Monte Carlo simulation was used to extrapolate potential outcomes of how the momentum strategies might perform under different market conditions (as mentioned) in 1 000 iterations of each condition.

The simple return analysis undertaken in this research revealed that traditional momentum outperformed residual momentum both before and throughout the COVID period. In the risk-adjusted performance measures, traditional momentum outperformed at all four risk indicators during the 2020 COVID year. The statistical significance tests, which compared the strategies' mean returns to the benchmark, demonstrated no statistically significant difference in returns over the COVID year. Furthermore, when evaluating the strategies over a five-year period (2018-2022), the difference in mean returns was shown to be statistically insignificant. However, statistical significance in returns was shown in some individual years. The ARDL regression findings show that bull, bear, and volatility factors explain relatively little of the returns for both momentum strategies, which is consistent with previous research. The Monte Carlo simulation, using the bear variable, forecasted that traditional momentum would result in negative returns during market declines, but residual momentum would provide positive returns and surpass traditional momentum with a probability of 26%. When using the bull variable, the simulation discovered that both traditional and residual momentum strategies resulted in positive returns. However, the residual momentum strategy outperformed in terms of returns and had an 84% likelihood of outperforming the traditional momentum strategy across 1,000 iterations. Nevertheless, when the simulation included the volatility variable, it projected negative returns for residual momentum and positive returns for traditional momentum. Additionally, it estimated a 14% probability of residual momentum surpassing traditional momentum under volatile market circumstances.

.

Key words: Efficient Market Hypothesis, Traditional momentum, Residual momentum, Economic crisis

Declaration

I confirm that, I Mphathi Yengwa, Student number G17Y6396, enrolled for the qualification Master's in Commerce (Financial Market) in the faculty Department of Economics and Economic History at Rhodes University. I declare that my academic work is in line with the plagiarism policy of Rhodes University, with which I am familiar.

I declare that the work presented in this dissertation is authentic and original unless clearly stated otherwise, and in such instance, full reference to the provided. I declare that no unethical research practices were used and this dissertation has not been submitted at another institution.

Acknowledgements

"A smooth sea never made a skilled sailor" – Franklin D Roosevelt

This quote encapsulates the essence of my academic journey, where the challenges of balancing a full-time job with the rigorous demands of this thesis have been my testing grounds. In these moments of turbulence, I have not only discovered the depth of my abilities but also cultivated resilience and discipline that are integral to the pursuit of knowledge.

I would like to express my deepest gratitude to God for granting me strength, wisdom, and perseverance throughout this academic endeavour. His unwavering guidance has been my compass, navigating me through the complexities of both personal and academic challenges.

To my mother, whose boundless love and unwavering support have been my anchor in times of uncertainty. Your sacrifices and encouragement have shaped my journey, and I am profoundly grateful for your presence in my life.

A heartfelt thank you to Rorisang Shomang, whose friendship and encouragement have been a source of inspiration. Your belief in my abilities has been a constant motivator, and I am fortunate to have shared this journey with such a supportive companion. To my language editor Nikki Watkins, thank you for your patience and work you have done to edit this paper.

I extend my sincere appreciation to my supervisors, David Fryer and Dr. Khumalo, for their invaluable guidance, expertise, and unwavering support. Your mentorship has been instrumental in shaping the trajectory of my research, and I am grateful for the opportunities to learn and grow under your supervision.

This thesis stands as a testament to the belief that adversity is not a hindrance but a catalyst for growth. I am grateful for the lessons learned, the strength gained, and the unwavering support that has paved the way for my success.

Table of Contents

List of Tables

List of Figures

List of Abbreviations/Acronyms

ADF	Augmented Dickey-Fuller
ALSI	All-Share Index
ARDL	Auto regressive distributed lag
CAPM	Capital asset pricing model
CUSUM	Cumulative Sum
ECM	Error-Correction Model
EMH	Efficient Market Hypothesis
HML	High-Minus-Low
IR	Information ratio
JSE	Johannesburg Stock Exchange
PP	Philips-Perron
SAVI	South African Volatility Index
SMB	Small-Minus-Big
WML	Winner-Minus-Loser

CHAPTER 1: INTRODUCTION TO THE STUDY

1.1 Introduction and Background of the Study

All investors have the same objective within financial markets and that is to seek an investment strategy that can obtain optimal returns. However, this is a difficult task. The Efficient Market Hypothesis (EMH), a widely accepted theory, supports the difficulty of making abnormal returns (Fama, 1970). The EMH argues that past information on prices cannot predict future stock prices, in its weak form. Several market anomalies have been empirically observed, putting doubt on the ability of the EMH to correctly explain the behaviour of the financial market (Banz, 1981).

A very important anomaly is momentum, which has been observed in many markets across the globe. Momentum investing is an empirically observed time series anomaly where good-performing stocks tend to keep on rising in asset price and poor-performing stocks tend to fall in asset price (Fama and French, 2008). Investors saw an opportunity in this anomaly after Jegadeesh and Titman (1993) observed a continuation of a trend within stocks, as stocks with high past returns continue to have abnormal future returns in a 3-12 month holding period, and stocks with lower past returns continue to experience negative future returns in the same holding period. As a profit opportunity, investors would buy the best-performing stocks and short/sell the worst-performing stocks.

Daniel and Moskowitz (2016) conducted a study on a traditional momentum strategy from 1927–2013 in the United States equity market and found that during catastrophic crashes, such as the 2008 financial crisis, momentum has demonstrated a tendency to underperform despite its proven performance. The authors observed that momentum crashes occur because of a clustering of low and high beta stocks in winner and loser portfolios, respectively. The authors also observed that during market recovery, the momentum strategy experiences a notable decline. In a recent study, El Ghorayeb (2021) closely examined the behaviour of momentum during the latest financial crisis caused by Covid-19. The findings of the study confirmed that momentum experienced a significant decline during the recovery following the bear market triggered by the pandemic within the United States equity market.

Even if momentum strategies do work over the long period, the losses in times of market crisis do not fully offset abnormal returns, which leads investors to question if they can do better by using more sophisticated strategies like residual momentum. Residual momentum strategy involves building a portfolio based on integrating Fama-French risk factors such as size and value, in order to mitigate against risks specific to individual stocks or sectors. The diversification achieved by incorporating these factors in portfolio construction aims to reduce the volatility and downside risk of the portfolio (Blitz, Huij and Martens 2011). Residual momentum has shown remarkable improvements in risk-adjusted returns over traditional momentum strategies and is less prone to severe momentum crashes than traditional momentum (Blitz et al. 2011).

There is various literature that tries to explain the momentum effect and the drivers behind it. Behavioural finance theories like underreaction or overreaction state that investors do not always make rational decisions or take all available information into account. One of the things that drives momentum is investor sentiment, which considers how investors' heuristics and biases are influenced by their emotions and the general sentiment of the market. According to the findings of several academics in the field of finance (Antoniou, Doukas and Subrahmanyam, 2013), the sentiment of investors does have a substantial impact on momentum. The only times that momentum was seen to perform well was during moments of optimistic attitude among investors. In addition, Mian and Sankaraguruswamy (2013) discovered that the sentiment of investors was more sensitive in the case of tiny-high-growth stocks.

The Johannesburg Stock Exchange (JSE) is the biggest, most liquid, and best-regulated market in Africa, with a market capitalisation of $1.15 trillion. It is positioned among the top 20 worldwide exchanges and has been recognised as the leading regulated stock exchange by the World Economic Forum Competitiveness in 2011 (Dabengwa, 2017). Consequently, several scholars have investigated Momentum on the JSE such as Marx (2016), who looks at industrial momentum on the JSE. Chan, Hameed and Tong (2000), as well as Dittberner (2016), compare traditional momentum against passive portfolios. Viljoen (2016) looks at residual momentum on the JSE, where he investigated the effects of investor sentiment on residual momentum within the JSE and found that there is no statistical significance in the difference in returns of either traditional momentum or residual momentum during different sentiment states.

1.2 Problem Statement

One of the main questions about investment strategies is their performance during times of market volatility and in particular a "black swan event". A black swan event is defined as a significant occurrence that, under typical conditions, is difficult to anticipate but, when viewed in hindsight, appears to have been unavoidable (Yarovaya, Matkovskyy and Jalan, 2021).

Covid-19 can be characterised as a black swan event which triggered a freefall in stock prices in the Johannesburg Stock Exchange (JSE) and we saw historically large and rapid declines across all sectors. However, this all turned around mid-May as governments around the world began to release stimulus packages to respond to the crisis. This resulted in most stocks fully regaining their market losses and surpassing them as more money was circulating within the world economy. El Ghorayeb (2021) investigated the performance of traditional momentum during a Covid-driven flash bear crash in the United States equity market and found that traditional momentum behaved in line with existing literature by Daniel and Moskowitz (2016) that stated that momentum portfolios have large negative betas and during times of recovery, post-crisis, these portfolios go through massive crashes. Kaluba (2020) and Viljoen (2016) investigated how momentum strategies fared during the 2008-2009 black swan event in South Africa, though Kaluba (2020) did not consider residual momentum. This research updates on the performance of traditional and residual momentum strategies during the most recent economic black swan event, the Covid-19 crisis, in a South African context. This study approached this problem using the long-only winner approach for both residual and traditional momentum.

1.3 Objectives of the Research

The research objective is the evaluation of traditional and residual momentum strategies during the Covid period on the Johannesburg Stock Exchange. To accomplish this, the following sub-objective have been identified:

The first sub-objective investigates the relative risk and profitability of momentum strategies compared to the South African FTSE/JSE Top 40 before, during and after the Covid crisis period.

The second sub-objective is to test if the difference in mean return between traditional momentum, residual momentum and the benchmark is statistically significant before, during and after the Covid period.

Sub-objective three aims to test the persistence of traditional momentum and residual momentum under different market conditions that existed before, during and after the Covid crisis period. These conditions include a bear market, a bull market and high volatility.

1.4 Overview of sample and methodology

The study adopts a quantitative explanatory approach, utilizing various analytical methodologies. This research employs a pseudo-experimental design in which the FTSE/JSE Top 40 serves as the control group, while traditional and residual momentum strategies function as experimental treatments. Secondary monthly data pertaining to the top 40 shares by market capitalization on the Johannesburg Stock Exchange, spanning the period of January 2017 to December 2022, are employed for analysis. A total of ten portfolios are constructed for the investment period: five portfolios represent the traditional momentum strategy, and the remaining five reflect the residual momentum strategy.

1.5 Outline of the Study

Chapter 2 delves into the literature to gain a deeper understanding of momentum and build knowledge on the subject. The chapter aims to thoroughly examine and consolidate existing literature to establish a comprehensive framework and theoretical foundation for the analysis and discussion of the data. In addition, the chapter aims to demonstrate the significance of different momentum styles in the field of investment, drawing on existing literature. It also discusses various studies that examine the historical aspects of momentum, specifically in relation to the JSE. Finally, it delves into the phenomenon of momentum crashes and residual momentum and explains the profitability associated with momentum.

Chapter 3 provides an overview of the research techniques employed in this study. The methodology section provides a detailed explanation of the methods necessary to conduct a thorough profitability and risk-adjusted analysis for each research question. This chapter outlines the research design, data collection methods and investment strategy analysis approach used to address the research questions. Finally, the study's validity and reliability are examined and explained.

Chapter 4 analyses and examines the findings of the study by drawing comparisons with previous research. The results are carefully examined to determine if they align with or challenge the conclusions drawn from previous studies. This process helped to confirm the validity of the findings or identify areas that required further investigation.

Chapter 5 discusses the accomplishment of the research objectives and the valuable contribution that the study has made to both theory and practice. The chapter also explores theoretical and practical recommendations for future studies on momentum within the JSE. Finally, the research paper explores its limitations.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Over the last few decades, many studies have confirmed the existence of the momentum anomaly, demonstrating its robustness across a variety of financial markets, including equities, fixed income, currencies and commodities. This anomaly challenges the notion of market efficiency and has practical implications for investment strategies and portfolio management, which has piqued the interest of researchers. The purpose of this chapter is to provide background literature on momentum investing strategies and examine the literature on the drivers of the phenomenon known as momentum. The chapter also examines the findings of other authors who looked at the momentum anomaly in international markets and within the JSE.

This chapter is structured as follows. Section 2.2 gives detail of the theories surrounding momentum and is divided into subsections: Section 2.2.1first describes the EMH as developed by Robert (1967). Section 2.2.2 gives background literature on the Capital Asset Pricing Model and its effect on the pricing of financial anomalies. Section 2.2.3 gives the literature on financial anomalies which have been discovered, that challenge the EMH. Section 2.2.4 gives background literature on traditional momentum and section 2.2.5 discusses the imperfection of traditional momentum and how it experiences crashes. Section 2.2.6 examines the literature on residual momentum, an alternative momentum strategy discovered after the 2008 financial crisis. Section 2.2.7 delves into the explanations as to why momentum strategies exist.

Section 2.3 examines the empirical literature pertaining to momentum and is structured into five distinct subsections. Section 2.3.1 critically analyzes the global empirical evidence surrounding the Efficient Market Hypothesis (EMH), with a particular focus on studies that have identified market inefficiencies across various international markets. Section 2.3.2 narrows the scope to investigate the empirical literature concerning the EMH within the context of the Johannesburg Stock Exchange (JSE). The subsequent two subsections explore the momentum phenomenon: Section 2.3.3 provides a comprehensive review of empirical findings on momentum effects in global markets, while Section 2.3.4 concentrates specifically on empirical evidence of momentum within the JSE. Finally, Section 2.3.5 synthesizes the empirical research on momentum crashes, examining their characteristics, causes, and implications for investment strategies.

2.2 Theoretical literature underlying Momentum

2.2.1 Efficient Market Hypothesis

Ever since Robert (1967) published the EMH theory, there has been much discussion about it. The capital market is efficient if it fully and correctly reflects all relevant information about the price discovery of securities (Malkiel, 2005). This implies that a security's price would not be influenced by disclosing the information to all stakeholders, which would make it impossible for one to make an excess return above the market from trading a security.

Based on three different types of information, Robert (1967) distinguished three levels of market efficiency:

1. The weak-form of EMH argues that the current price of a security fully represents the information contained in all past prices of the security. This implies that an investor cannot implement a trading strategy that analyses past price patterns (technical analysis) to make abnormal gains.
2. The semi-strong EMH argues that the current price of a security does not only include past information but also all public information relevant to that security. This implies that an investor cannot implement a trading strategy that uses both technical analysis and fundamental analysis (the analysis of a company's financial statements) to make abnormal gains.
3. The strong EMH argues that all information/data, public or not, is completely reflected in the current price of a security. This implies that no information, even privileged information, can be used to give an investor an advantage in the market by making abnormal gains.

Years after the introduction of the EMH, financial economists began to question the theory and claim that it is incomplete. Grossman and Stiglitz (1980) argue that it is not possible for a market to be informationally efficient. They argue that information is costly and stock prices are unable to perfectly reflect information, which is available because if they did, then investors who spent time and resources on analysis would not receive gains. LeRoy and Porter (1981) find that markets experience excess volatility and therefore reject the EMH. Excess volatility refers to an unusually large fluctuation in the price of stocks. In an efficient market, it is expected that prices will fluctuate based on changes in supply and demand and other market factors, but excess volatility suggests that there may be other factors in play that cause the stock prices to fluctuate more than would be expected based on normal market conditions (LeRoy and Porter, 1981).

To test the weak version of the EMH Malkiel (2005) compared the returns of mutual funds, which implement active strategies to make abnormal gains and passive index funds. Malkiel (2005) argues that if stock prices are irrational and the movement of stock prices is predictable, then actively managed investment funds (mutual funds) should be able to outperform a passive index fund. Malkiel (2005) finds that when compared to the S&P 500, actively managed funds underperform the index by 200 basis points. The underperformance of the actively managed funds can be the result of the increasing transactional cost from switching from security to security. Therefore, if transactional costs are reduced, actively managed funds would have outperformed the passively managed funds, which disputes even the weak-form of EMH. Wilson and Marashdeh (2007) found that cointegrating stock prices support Malkiel (2005). This implies that in the long-term there is a relationship between stock prices that is consistent with the EMH. However, Wilson and Marashdeh (2007) also found that cointegrating stock prices are inconsistent in the short-term, as they may be deviations from the expected relationship between stock prices. This inconsistency in the short-term is a departure from efficient market behaviour, indicating possible arbitrage opportunities. Therefore, one can conclude that the elimination of arbitrage opportunities means that stock market inefficiency in the short-run results in stock market efficiency in the long-run.

2.2.2 Capital Asset Pricing Model

Ang (2011) stated that an empirical review of tests on market efficiency is generally divided into two parts, namely test on prices and test on investment managers and institutions. Tests on prices generally attempt to find the fair price of a security in terms of its exposure to common risk factors (beta and volatility). The most common of these tests is the Capital Asset Pricing Model (CAPM). CAPM stems from the work of Markowitz (1952) into modern portfolio theory as well as updates made by Sharp (1964), Lintner (1965), Mossin (1966) and Black (1972), which encourages investors to view returns achieved by a security only in the context of the risk incurred while generating that return. CAPM argues that the appropriate measure of risk to be priced for a security is its sensitivity to non-diversifiable risk (beta). Therefore, according to CAPM, the expected return of a financial security is proportional to the expected market return. Notwithstanding the above, CAPM is not without criticism and or shortcomings. In this light, Wan (2021), echoes the principles found by Jagadeesh and Titman (1993) who posited that smaller companies achieve better risk-adjusted returns than larger companies, proving CAPM and its inherent beta factor wrong. The aforementioned scholars find fault with the CAPM assumption that the beta factor alone can explain the risk premium earned by various market anomalies. Fama and French (1992) propose the addition of other factors to help explain financial anomalies.

2.2.3 Financial Anomalies

Momentum can be classified as a financial market anomaly. A financial market anomaly is defined as a distortion in gains that goes against the EMH (Frankfurter and McGoun, 2001). There are a few financial market anomalies, other than momentum, that have been discovered such as the January effect, which states that the average return in January is greater than other months of the year and the effect is particularly strong for small-cap firms (Haugen, 2001).

The way an investor receives, and processes information explains why market anomalies exist, therefore making the market inefficient. Hong, Lee and Swaminathan (2003) argue that lagged dispersion of information is a possible reason for market inefficiency. In emerging markets, stocks are found to be less liquid than developed market stocks, market capitalization is smaller and analyst coverage is slow (Lesmond, 2005). Hong, Lee and Swaminathan (2003) observe that there is slow dissemination of new information and ultimately inefficiency in small and less liquid stocks.

The joint hypothesis problem observed by Fama (1991) challenges the concept of market inefficiency. Fama (1991) argued that when testing market efficiency, researchers tend to use mathematical models. If there is any evidence of strange behaviour (anomalies) in the market, it might not necessarily mean the market is inefficient. Instead, it could indicate that the researcher's model of the market is incomplete or not accurate enough. In other words, anomalies might be due to flaws in how researchers are modelling the market, not necessarily a sign of market inefficiency. This view is supported by Ang et al (2011) who also argue that efficiency tests are implicitly joint tests of the pricing model and factors not captured by the beta inherent in the pricing model. It underscores the challenge of distinguishing between real inefficiencies and limitations in our understanding or modelling of the market.

Investors' reaction to new information is found to be also a contributing factor to market inefficiency and anomalies. A study conducted by Dimson and Mussavian (1998) considers several tests of underreaction and overreaction with the aim of return predictability. The tests confirm positive and negative correlations in returns over different time horizons. This is an important explanation of why momentum profits exist, which will be discussed in greater detail later in the chapter.

2.2.4 Momentum

Momentum in finance is defined as the tendency of investments to experience a continuation in their relative performance (Griffin, Ji and Martin, 2005). An investment that performs relatively well, will continue to perform relatively well and vice versa. Momentum starts to gain traction after the influential work of Jagadeesh and Titman (1993). The authors observe a continuation of a trend within stocks, as stocks with high past returns continue to have abnormal future returns in a 3 to 12-month holding period, and stocks with lower past returns continue to experience negative future returns in the same holding period.

The Jagadeesh and Titman (1993) work has since been labelled as the traditional momentum strategy (also known as price momentum) by investors. The strategy is constructed as follows. At the beginning of each month, the stocks are ranked in ascending order based on their returns in the past months. Based on these rankings, 10 decile portfolios are formed that equally weigh the stocks contained in the top decile, second, and so on. The top decile is called the “winner decile” while the bottom is the “loser decile”. Each month, the investor must buy the winner’s portfolio, sell the loser’s portfolio and hold this position for the period mentioned above.

Various investors have tested the strategy and shown abnormal returns. Griffen, Ji and Martinet (2005) investigate momentum in various stock markets around the world and find that momentum profits are economically significant around the world. They also find that momentum profits also exist across different asset classes such as currencies, commodities, bonds and futures (Asness, Moskowitz and Pedersen, 2013).

Investors and financial academics find that traditional momentum incorporates earnings momentum (Chordia and Shivakumar, 2006). Earnings momentum, implies that companies that unexpectedly report high earnings subsequently outperform firms that report unexpectedly low earnings. The abnormal performance lasts for 9 months after the earnings announcement. The theory surrounding earnings momentum suggests that investors can potentially make abnormal returns by ranking companies based on the magnitude of their earnings announcement.

Hong, Lee and Swaminathan (2003) found that traditional momentum strategies are only profitable in countries that experience earnings momentum. Hong, Lee and Swaminathan (2003) propose explanatory reasons for the interrelation of earnings momentum and traditional momentum. The first explanation is that both the momentum phenomena are manifestations of similar cognitive biases inherent to human market interactions; secondly, in both instances, momentum is associated with country-specific information dissemination issues (also behaviourally induced). Hirshleifer (2018) supports this, as the author notes that stocks with the strongest price momentum effects also experience the strongest earnings momentum effects. Earnings momentum will therefore not be independently tested in this research due to the assumption that it is incorporated in traditional momentum.

2.2.5 Momentum Crashes

According to Daniel and Moskowitz (2016), the momentum strategies return exhibit a negative skewness with pronounced and persistent negative returns, during momentum crashes. Negative skewness refers to a distribution of returns where the majority of returns are clustered around a central value but there is a long tail of negative returns. This means that even if the current return might be positive there is a high probability of experiencing larger losses than gains (Vogel, 2015). It is argued that momentum crashes are a consistent feature of the WML strategy and that a specific market environment is associated with these periods, allowing for the predictability of momentum crashes. During periods of intense market stress, particularly after a bear market with anticipated high volatility, the occurrence of severe crashes becomes more prevalent. Daniel and Moskowitz (2016) explain that past losers exhibit low down-market betas and high up-market betas, creating an option-like payoff structure. This is not typically reflected in their prices, leading to high expected returns and a reversal of the momentum effect during these times. This asymmetry between winners and losers is robust across different markets, asset classes, and time periods.

It is widely accepted that the work of Daniel and Markowitz 2016 is the most definitive work into momentum crashes, however momentum crashes were also observed by Chabot et al (2014) who used 140 years' worth of market data from 1867 to 1907 and from 1926 to 2012, Chabot (2014) concluded that during both periods momentum exposed investors to large loses and crashes. According to Chabot (2014) crashes were more likely to happen just after momentum had recently performed well during times of times of low interest rates from 1867 to 1907.

Butt and Virk (2022) provide a novel explanation for momentum crashes, attributing them to unforeseen fluctuations in market liquidity. The researchers discover that the fluctuations in liquidity have a greater influence on the occurrence of momentum crashes compared to other elements that have been previously found, such as market recoveries, as emphasised in prior studies like Daniel and Moskowitz (2016). Their findings indicate that when there is an unexpected improvement in market liquidity, the value of portfolios including underperforming stocks (referred to as "loser" stocks) significantly rises. This is because these portfolios are more responsive to changes in liquidity compared to portfolios containing outperforming stocks (referred to as "winner" portfolios), resulting in a sudden decline in momentum. The asymmetrical liquidity exposure of portfolios with poor performance is connected to their previous significant losses, which causes them to be more responsive to favourable changes in liquidity. The research posits that the fluctuations in market liquidity, influenced by investor emotion, provide a more comprehensive explanation for the potential losses associated with momentum strategies under negative market circumstances, as opposed to only relying on market recoveries.

2.2.6 Residual Momentum

Traditional momentum has faced criticism after the 2008 financial crisis, as the strategy performed miserably during this period (2007–2008) which indicates a considerable risk. Blitz et al. (2011) therefore proposes an alternative momentum known as residual momentum to mitigate against momentum crashes. Residual momentum showed risk-adjusted profits that are twice as large as those associated with traditional momentum. The authors observe that residual momentum performs better than traditional momentum during periods of crisis and recession, as it reduces the volatility of the strategy. Residual momentum involves building a portfolio based on a stock's residual return rather than based on a stock's total return (Blitz et al., 2011). Residual momentum in the first year of formation produces the same results as traditional momentum, however, over the long-term traditional momentum reverses strongly while residual momentum continues to show profit.

Blitz et al. (2011) state that one of the key differences between traditional momentum and residual momentum is that traditional momentum returns are more volatile than residual momentum returns. This is one of the primary contrasts between the two types of momentum. Lastly, Gutierrez and Pirinsky's (2007) research of the variations in reversal patterns and volatility suggests that traditional momentum appears to be associated with overreaction, whereas residual momentum tends to be linked to underreaction.

2.2.7 Explanation of Why Momentum Profits Exist

The explanation behind momentum returns can be divided into two major categories, namely rational and behavioural. Rational thinkers believe that a momentum premium is a reward for the high risk taken on by momentum traders. Numerous studies have been conducted on risk-based momentum models to explain the momentum premium. Liu (2012) attempts to explain the momentum premium within the framework of a factor model such as the Fama-French model investigated in this study. He found that a combination of the beta and the leverage effect helped explain some of the momentum premium. Johnson (2002) presents a rational model that provides a theoretical link between expected growth rate and return-continuation patterns. Johnson (2002), using Jagadeesh and Titman's (1993) work as his base, argues that past winners experience positive shocks in their expected earnings growth rate, which then results in an instant increase in their stock prices and vice versa. An investor who is informed about this would use the information and exploit (risk) it to make abnormal returns. Dittmar, Kaul and Lei (2007) propose that the cross-sectional variation in stock prices could be the reason behind most momentum profits observed.

The second explanation belongs to advocates of behavioural finance. If momentum is not a risk-reward, its existence seems to challenge the weakest form of the EMH. In other words, momentum could be due to market inefficiency, perhaps due to investor behaviour. Behavioural biases can be divided into two categories known as underreaction, where investors tend to underreact to new information, and overreaction, where investors tend to overreact to new information (Barberis, Shleifer and Vishny, 1998). Underreaction and overreaction are argued to deviate stock prices from their intrinsic values, resulting in abnormal returns.

Underreaction in investors can be due to the gradual diffusion of information to the investing public. Investors tend to receive news from various sources and react to the news over different time horizons, in whichever way they choose. Underreaction can also be attributed to the disposition effect, which argues that investors tend to sell winning investments prematurely to lock in profit and hold on to losing investments for too long in the hopes that they will break even. This creates an artificial headwind: When good information is released, the stock's price does not immediately rise to its intrinsic value because of premature selling or lack of buying. Similarly, if bad news is released, the price of stocks falls less because investors are reluctant to sell (Abbes, Boujelbene and Bouri, 2009). Grinblatt and Han (2005) argue that investors in winning stocks tend to underreact to positive firm-specific news, while with losing stocks they underreact to negative firm-specific news as a result of deposition. Anchoring and adjustment is also seen to be an attribute of underreaction. It can be defined as a behavioural phenomenon in which individuals update their views only partially when faced with new information, slowly accepting its full impact. This is particularly true in a market dominated by institutional investors who underreact to information known to retail traders, as retail traders react to information that is irrelevant to stock pricing (Jedagessh and Titman,2023).

Secondly, the overreaction theory argues that investors overreact to new information, which deviates the stock price from its intrinsic value, causing short-term momentum. This is a theory supported by many academics that argue that investors' overconfidence and self-attribution cause market overreaction (Daniel, Hirshleifer and Subrahmanyam, 1998).Institutional investors, who are overconfident in nature, as defined by Jagadeesh and Titman (2023) pay more attention to their private information than public information since the gradual information model predicts that as private information is known across the market, pricing accuracy would improve, and asset prices would exhibit momentum (Lin, 2010). Self-attribution can be defined as a behavioural phenomenon by which investors attribute failures to being beyond their control (self-protecting: irrational denial of responsibility for failure) and take credit for successes (self-enhancing bias: irrational credit for success). Therefore, self-attribution results in more of an overreaction if public information validates private information (Biljana et al, 2016).

2.3 Existing Empirical Findings Surrounding Momentum

2.3.1 The Efficient Market Hypothesis Globally

Dias, Heliodoro, Teixeira, and Godinho (2020) performed an evaluation to investigate whether price indices demonstrate mean-reversion and to examine the form of market efficiency in both established markets (such as Japan and China) and emerging markets (such as Mexico and Brazil). The authors used Wright's variance test, using it on three distinct time periods: before the global financial crisis, during the global financial crisis, and after the global financial crisis. They also included delays of 2, 4, 8, and 16 days. The findings demonstrated the existence of mean-reversion and resulted in the rejection of the random walk and market efficiency hypothesis in their weak form. This pattern was seen in both established and developing economies, including European and non-European markets. Rossi (2015) posits that the prevalence of calendar anomalies in various global markets provides substantive evidence challenging the Efficient Market Hypothesis (EMH). These anomalies include the January effect, first documented by Rozeff and Kinney (1976) in U.S. markets; the day-of-the-week effect, initially observed by Osborne (1962) in U.S. markets and later corroborated by Cinko and Avci (2009) in the Turkish stock market; and the turn-of-the-month effect, first noted by Ariel (1987) and more recently observed by Yu Kyung Lee (2022) in the Korean stock exchange. The persistent manifestation of these financial anomalies across diverse global markets suggests that stock price movements are not entirely random and may be influenced by factors unaccounted for in the EMH framework. Consequently, these empirical observations provide a compelling basis for questioning the universal applicability of the Efficient Market Hypothesis.

2.3.2 The Efficient Market Hypothesis on the JSE

This study focuses on the JSE; therefore, it is important to investigate the efficiency of the market. The review of the empirical works begins with Affleck-Graves and Money (1975) who investigate if there is autocorrelation within the JSE. They estimate a random walk model, which tests for autocorrelation, for 50 shares on the JSE and conclude that there is very little evidence of autocorrelation in the JSE stock series. This indicates that there is market efficiency within the share prices. Other studies such as Bonga-Bonga (2012) find that the JSE is weak-form market efficient. Bonga-Bonga (2012) conducts a study to investigate the market efficiency of the JSE using a time-varying and fixed-effects GARCH model and finds that the JSE is efficient only in the weak-form of the EMH. Heymans and Santana (2018) investigate the efficiency of the JSE and found that sub-indices like the JSE Top 40 are not always as efficient as the All-Share Index, thus allowing actively managed strategies like momentum to make abnormal returns from information inefficiencies in the JSE.

Vincent (2018) conducted an empirical examination of the Efficient Market Hypothesis (EMH) on the Johannesburg Stock Exchange (JSE) utilizing Greenblatt's (2006) "Magic Formula" investment strategy. This approach involves ranking stocks based on two key metrics: earnings yield and return on capital, to construct portfolios. The study compared the performance of these portfolios against the JSE All Share Index, revealing that the constructed portfolios consistently outperformed the market benchmark, even after adjusting for risk factors. The author posits that the superior performance of this value investing approach provides compelling evidence against the validity of the EMH in the context of the JSE. This finding suggests the presence of exploitable market inefficiencies, challenging the notion that the JSE fully reflects all available information in stock prices.

2.3.3 Momentum A Global Phenomenon

Further research highlights the widespread and strong presence of momentum strategies across several markets and asset categories. Jegadeesh and Titman (1993) were early researchers that observed the momentum effect in the U.S. stock market. They found that equities that had strong previous performance tend to continue to succeed in the future, namely during short to medium time periods. Rouwenhorst (1998) expanded upon these discoveries by showing that momentum profits are not limited to the United States and can also be seen in European stock markets.

In their study, Chui, Titman, and Wei (2010) investigated the presence of momentum in international stock markets, including developing countries. They discovered that the momentum effect exists worldwide, albeit its intensity and endurance vary across various areas. In addition, Blitz, Huij, and Martens (2011) conducted a study on the effectiveness of momentum methods in bond markets and found evidence of profitable momentum trading in corporate bonds.

Geczy and Samonov (2016) made a noteworthy addition by analysing data spanning more than two centuries across several asset classes, such as stocks, bonds, currencies, and commodities, to get a comprehensive understanding of momentum over the long run. Their findings strengthen the concept that momentum is a widespread phenomenon that endures for long periods of time and applies to all types of assets.

Baltas and Kosowski (2013) investigated momentum techniques in commodities futures and found compelling evidence that momentum earnings are substantial in these markets. Their purpose is to emphasise the possibility for investors to attain exceptional profits by using momentum methods in commodities.

Moskowitz, Ooi, and Pedersen (2012) conducted a study that examined time-series momentum in several asset classes. Their findings indicate that a straightforward time-series momentum approach yields substantial returns in stocks, commodities, currencies, and bond futures. This research highlights the wide-ranging application and efficacy of momentum tactics in various investment possibilities.

2.3.4 Momentum on the Johannesburg Stock Exchange

Momentum is found to be a pervasive and persistent phenomenon within the JSE, which leads to its strategies becoming an attractive option for investors due to their potential for high returns (Muller and Ward, 2013). A study conducted by Daniel, Britten and Aurets (2013) finds that momentum strategies have a positive impact on returns in the JSE as they have the potential to increase investment returns by 10%. The authors note that their findings on momentum show that the magnitude of the effect depends on the period used to calculate momentum. Furthermore, they find that momentum has a more significant impact on the JSE during periods of high volatility.

Muller and Ward (2013) conduct a study and find that momentum strategies within the JSE generate profits superior to that of investment styles that are based on value and quality indicators. The authors' momentum portfolios are built based on traditional momentum over a three-month holding period. The study notes that momentum performs poorly compared to the All-Share Index (ALSI) from 2007 to 2011. This poor performance could be attributed to the effects of the 2008 financial crisis. Marx (2016) conducted a comprehensive examination of three distinct momentum strategies on the Johannesburg Stock Exchange (JSE): the traditional approach of Jegadeesh and Titman (1993), the industry momentum approach of Moskowitz and Grinblatt (1999), and the 52-week high momentum strategy of George and Hwang (2004). The study's findings revealed that investors on the JSE could consistently achieve momentum returns surpassing the market benchmark, providing robust evidence for the efficacy of momentum strategies in the South African equity market.

In a related study, Snyman (2011) investigated price momentum on the JSE using technical analysis and various price performance metrics. They benchmarked their results against both a market-capitalization-weighted All Share Index and an unweighted market representation. Their analysis, spanning from January 1990 to August 2009, demonstrated that even after accounting for maximum taxes and trading costs, the highest-ranking momentum stocks consistently outperformed the market. It is noteworthy that this study diverged from the traditional "winner minus loser" approach inherent in conventional momentum strategies, instead employing technical analysis for stock selection.

Residual momentum is first investigated by Viljoen (2016) on the JSE, where the author considers the effect of investor sentiment on residual momentum and the profitability of residual momentum compared to traditional momentum. The study concludes that residual momentum offers superior risk-adjusted returns compared to traditional momentum. Momentum strategies show sensitivity to changes in investor sentiment, with residual momentum showing the greatest potential for profit after pessimistic formation periods and traditional momentum showing the greatest potential for profit following non-pessimistic periods. Page, McClelland and Auret (2020) examined what they called idiosyncratic momentum on the JSE the authors found that idiosyncratic momentum outperforms price momentum and had better explanatory power in explaining momentum profits on the JSE.

These empirical investigations collectively underscore the persistent presence of momentum effects in the South African equity market, challenging the notion of market efficiency and suggesting potential opportunities for momentum-based investment strategies on the JSE

2.3.5 Momentum Crashes

Within the realm of finance, individuals engaged in investment activities must consistently navigate the delicate balance between risk and reward, which can occasionally result in significant market downturns. Daniel and Moskowitz (2016) conduct an extensive study on momentum crashes, focusing on US common stocks from 1927 to 2013. Their work is considered the most comprehensive in this area. It is discovered that the average annual excess return of the winner-minus-loser (WML) portfolio is 17.9%, accompanied by a Sharpe ratio of 0.71. By comparison, the average excess US equity return stands at 7.6% with a Sharpe ratio of 0.40. Nevertheless, they meticulously record the occurrence of extended periods during which previous losers consistently outperform previous winners, leading to sustained negative returns.

The primary factor behind the significant shift in momentum is the negative performance of the short positions in the WML portfolio. Market downturns are primarily caused by the underperformance of losing investments. During periods of panic, historically top performing stocks see small increases, while previously underperforming stocks see considerably greater rises. As a result, the portion of the strategy that bets against the underperformers by shorting them ends up losing more than the portion that bets on the top performers gains, resulting in substantial losses for the overall WML strategy.

In their study, Daniel and Moskowitz (2016) provide empirical evidence supporting the presence of significant fluctuations in the betas of momentum portfolios. They discover that the loser decile experiences a substantial increase in beta during periods of heightened market volatility. They conclude that the loser portfolio's beta, which changes over time, causes the momentum strategy to resemble a written call option on the market. This results in significant losses when the market experiences a sharp rebound.

Daniel and Moskowitz (2016) demonstrate the strength of their findings by thoroughly examining the consistency of their results across various periods, diverse equity markets and alternative asset classes. They discover that the WML strategy experiences crashes in all markets and asset classes. The researchers conclude that these reversals are caused by the optionality of losers in bear markets, which is consistently observed in various equity markets (Europe, the UK, Japan) and different assets (index futures, commodity, fixed income, currency).

De Backer and Frommel (2016) investigated the nature of momentum crashes in European market looking at 13,274 stocks from twelve European countries and found results similar to that of Daniel and Markowitz that the loser portfolio in the WML approach incurred large negative beta resulting in loses for the portfolio. Butt, Kolari and Sadaqat (2021) investigated momentum profits in emerging markets the authors found that the WML approach to momentum investing also experienced large negative beta following a market downturn leading to momentum portfolio crashes this finding also echoes the work of Daniel and Markowitz (2016) as far as emerging markets are concerned

2.4 Conclusion

The objective of the literature review was to provide the background and context of momentum-based investment strategies. The literature review discussed what is an efficient market, according to the EMH and presented conflicting evidence on market efficiency. Literature on the market efficiency of the JSE was explored with varying outcomes. Conflicting evidence on the EMH includes financial anomalies which can be a result of the gradual nature of information dispersion, different reactions to new information and the cost of information.

CAPM was explored in order to emphasize the inability of beta to explain the risk-return relationship of financial anomalies. Momentum was identified as a financial anomaly and specific momentum strategies were then discussed. A background explanation of the cause of momentum profits was explored, which was followed by momentum crashes. Residual momentum was discussed as an alternative momentum strategy to mitigate against momentum crashes. Lastly, the background of momentum within the JSE was discussed.

The study will evaluate whether the application of these two strategies in the South African financial market could yield excess profit during the pre-and post-Covid periods and determine which of the two performed best. This study will also indirectly test for weak-form efficiency since trading strategies based on past performance should not be able to produce abnormal returns in a weak-form efficient market.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This Chapter provides an overview of the research technique(s) employed to carry out a performance evaluation and statistical analysis of the research objectives. The study relied on secondary data to undertake the risk and statistical tests.

1. The first objective investigates the relative risk and profitability of momentum strategies compared to the South African FTSE/JSE Top 40 during the pre-and post-Covid as well as during the Covid crisis period.
2. The second objective is to test if the difference in mean return between traditional momentum, residual momentum and the benchmark is statistically significant during the pre- and post-Covid periods as well as during the Covid period.
3. Objective three aims to test the persistence of traditional momentum and residual momentum under different market conditions that existed during the pre-and post-Covid as well as during the Covid crisis period. These conditions include a bear market, a bull market and high volatility.

This chapter is structured as follows: Section 3.2 discusses the research paradigm which describes the nature of the study. Section 3.3 describes the research design which serves a blueprint for the study, outlining the methods and procedures that will be employed to answer research objectives. Section 3.3 also describes the data collection methods undertaken which include a description of the population as well as the proposed sampling methodology. Section 3.4 describes the data analysis methods which give details of the risk and statistical tests proposed to answer the research objectives. Section 3.5 discusses the reliability and validity of the study. Section 3.6 discusses the limitation and delimitation section of the study. Lastly, the chapter reaches its conclusion where a summary is given of the chapter and the methodologies employed across the study’s three research objectives.

3.2 Research Paradigm

This research is best described as post-positivist in nature, which means that the hypotheses can be tested through statistical data analysis (quantitative approach) (Aliyu et al., 2014). This method analyses variables using non-contextual, rigorous, and standardised research. In post-positivism, empiricism and rationality are preferred. A unification of methods that can establish cause-and-effect links and generate natural laws is sought (Green and Thorogood, 2018). Post-positivism views the researcher and the "object" as separate entities. "Judgement, interpretation, and other subjective mental operations devalue data" (Hughes, 1990). Positivist researchers seek a measurable "objective" reality. Thus, positivists prefer quantitative over qualitative methods. The nature of this research and the data used to answer the research objectives did not lend themselves to other research paradigms like the interpretive paradigm and advocacy paradigm.

Due to the numerical nature of the data employed in this study, it can be identified as quantitative, deductive, and explanatory in nature. Quantitative research aims to explain a phenomenon by gathering quantifiable data and performing statistical, mathematical or computational measures (Watson, 2015). Goertzen (2017) defined quantitative research as collecting and analysing numerical data. As the financial data associated with the stock market was ideally suited for this kind of analysis, a quantitative methodology was employed.

A deductive approach is concerned with developing a hypothesis based on existing theory and then designing a research strategy to test the hypothesis (Strang, 2015). Momentum is an existing theory and phenomenon developed by Jegadeesh and Titman (1993). The hypothesis for this study is that long-only traditional and residual momentum strategies can outperform the JSE during times of financial crisis and post-crisis recovery periods.

3.2.1 Rationale for using the quantitative approach

The research followed a quasi-experiment, whereby the market portfolio (FTSE/JSE Top 40) acts as the control and the different momentum strategies are the experiments. A quasi-experiment has the objective of establishing a cause-and-effect relationship between an independent variable and a dependent variable. However, unlike a genuine experiment, a quasi-experiment does not rely on a random assignment. Instead, subjects are assigned to groups based on criteria other than chance (LoBiondo-Wood, Haber and Cameron, 2014). When actual experiments cannot be conducted for ethical or practical reasons, a quasi-experimental design is a useful alternative (Thomas, 2023). The nature of the Fama-French three-factor model, employed to construct a residual momentum portfolio, is non-random in the sense that stocks are selected for inclusion based on factors such as market capitalization and book-to-market values. The three-factor model also checks for cause-and-effect of these factors in the return.

A quasi-experiment is especially valuable when undertaking practical research since it simulates a real-life scenario. Since a random unit assignment was not possible, a quasi-experimental approach was used. The units of analysis, i.e. stocks listed on the FTSE/JSE Top 40, were not amenable to traditional experimental analysis. This is because the inclusion of stocks in the FTSE/JSE Top 40 is non-random but follows established criteria.

3.3 Research Design

Research design refers to the overall structure, plan, and strategy that guides the process of collecting, analysing, and interpreting data in a research study. It serves as a blueprint for the entire research project, outlining the methods and procedures that will be employed to answer the research objectives.

3.3.1 Data collection

This study used secondary market data which was sourced from the JSE. A company must have been listed for at least three years before the stock could be considered for the momentum strategy. The aim of requiring stocks to have a minimum listing period of three years is to improve the persistence and robustness of momentum selection and avoid "momentum traps" caused by short-term price distortions (Grinold and Khan, 2000). The study used monthly data from 1 January 2017 to 31 December 2022. The period was chosen to examine the behaviour of momentum strategies during varying market conditions that existed before the Covid pandemic (2017–2019), during Covid-19 (2020) and those after (2021–2022). The study used the South African Volatility Index Top 40 (SAVI Top 40) as a proxy for South African market conditions pre-Covid, during Covid and post-Covid. The SAVIT40 is a forecast of equity market risk in the South African market. According to the SAVIT40 index, the average volatility between the period of 2017 and 2019 was 15. This period is defined as pre-pandemic. During the Covid pandemic period (2020) the SAVIT 40 recorded its highest average volatility since the 2008 financial crisis at 37. Post-pandemic, the SAVIT40 numbers have come down substantially, with an average volatility of 28. Volatility has come down post-pandemic, but it remains at levels higher than those that existed pre-pandemic. Volatility indexes have been proven to show long memory, as the statistical property that events in the past can be felt even after much time has passed (Koopman et al, 2005). The SAVIT40 is modelled in a manner that closely resembles the VIX. A widely recognised metric used to gauge the level of volatility within the S&P 500 index (JSE.co.za, 2023).

The pandemic resulted in a structural shift within the market (Mbatha and Alovopinhou, 2022). According to Bekaert and Harvey (2002), it is important when analysing a data set to look at it from a point of structural shift, not to distort the results.

3.3.2 Sampling

The research used the FTSE/JSE Top 40 because the index only selects the 40 largest companies ranked by investable market value in the FTSE/JSE ALSI. The FTSE/JSE Top 40 accurately reflects the South African stock market as a whole because, despite containing only 40 of the approximately 400 shares listed on the JSE, it represents approximately 80% of the total market capitalization of all JSE-listed companies (Bloomberg, 2023). The index's constituents are weighted according to their market capitalization, meaning that companies with a larger market cap influence the overall index more than companies with a lower market cap, and vice versa (Bloomberg, 2023).

To be representative of actual investing conditions, the study selected the FTSE/JSE Top 40 because the population of stocks has a greater market capitalization and a reduced non-commission trading cost per unit of value traded. Non-commission trading costs include the elasticity of the stock price to the demand for volume and the bid-ask spread. Small capitalization and illiquid equities have greater elasticity and wider bid-ask spreads, which could distort the return values of these stocks.

The momentum portfolio construction models within the study lent themselves to stratified sampling, which is defined as a probability sampling method that is used to divide a target population into distinct groups or strata, where within each stratum the elements are similar to each other concerning select characteristics of importance (Parsons, 2017). Sampling is the act or process of selecting a suitable representative part of a population to determine parameters or characteristics of the whole population (Verma, et al., 2017). There are different sampling techniques in research. In quantitative research, there are probability sampling techniques, namely stratified sampling, random sampling and cluster sampling (Taherdoost, 2016), whereas in qualitative research there are non-probability techniques, namely judgement sampling, quota sampling and volunteer sampling (Taherdoost, 2016).

3.3.3 Traditional momentum portfolio construction

The construction of the long-only traditional momentum strategy follows the same common approach as other studies, some of which have previously been covered in this study (Griffen, Ji and Martinet, 2005). The methods that were taken into consideration for this analysis chose shares based on their returns during the most recent 12 months. In the same vein, the holding periods for the shares will be over the subsequent 12 months.

The term “holding period” refers to the length of time over which shares are kept once they have been purchased, whereas the term "formation period" describes the number of months during which prior returns were tracked and used to construct the portfolio. Instead of using shorter formation and holding periods in the form of months, longer formation and holding periods in the form of years are employed to lower transaction costs, which are present in the real world, and create outcomes that are more realistic because of this change.

Shares will be ranked in descending order according to their past returns and placed into quintiles yearly. The application of quintiles is based on the research conducted by Fama and French (2008) and Hoffman (2012). Equal-weighted Quintile portfolios, referred to as sub-portfolios, are formed using the shares in each Quintile at the end of each year. Quintile 1 will encompass the stocks from the FTSE/JSE Top 40 that have exhibited the most substantial returns during the observed time frame, whereas Quintile 5 will encompass the stocks that have demonstrated the least favourable returns from the FTSE/JSE Top 40 during the observed time frame. In momentum investing, quantiles are used to divide stocks into groups based on their momentum characteristics (Jegadeesh and Titman, 1993). The standard WML momentum approach proposed in the literature, as discussed in section 2.6, is to go long the Quintile 1 portfolio and short the Quintile 5 portfolio. However, this study will only consider the Quintile 1 portfolio and disregard the Quintile 5 portfolio, therefore, going long on the “winners”.

The idea to use the long-only winner portfolio is based on the study of Manigault (2017), who concludes that the long-only momentum strategy outperforms the WML momentum in terms of performance and Sharpe ratio. Bojesen (2020) states that short selling is often restricted or prohibited for retail investors. Furthermore, short selling tends to be expensive and carries execution risks that are not adequately accounted for in theoretical models (Raju and

Chandrasekaran, 2019). According to Lesmond, Schill and Zhou (2004), a significant portion, up to 70%, of the gains generated by momentum trading strategies on long/short portfolios may be attributed to the short positions. The authors discover that short positions specifically have the greatest trading expenses linked to them. They contend that the excessively high transaction expenses linked to short selling would entirely negate the gains produced by the approach. These factors support our decision to implement a long-only strategy, which facilitates participation not only by institutional investors but also by retail investors.

3.3.4 Residual momentum portfolio construction

Following the steps outlined by Blitz et al. (2011) will result in the creation of the standard residual momentum strategy. At the beginning of each month (t), The researcher performed the time series regression for each stock using the Fama-French (1992) three-factor model. Fama and French (1992) expanded on the works of Lintner (1965) and Breeden (1979) on the asset pricing model. Fama and French (1992) documented that size and book-to-market equity are related to economic fundamentals, which improves the asset pricing model in explaining stock returns. Fama and French (1992) ran regressions to explain the correlation between the size and book-to-market equity in the regression they ran; for one of the factors, book-to-market, the slope increases monotonically from strong negative values for the lowest book-to-market stocks (growth stocks) to strong positive values for the highest book-to-market stocks (value stocks). The regression captures shared variation in stock returns that is not explained by the market or by the size factor. Fama and French (1992) expanded on the work of Banz (1981) who argues that market equity (ME) (a stock's price times shares outstanding), adds to the explanation of the cross-section of average returns that can be attributed to fluctuations in the stock price. It is further confirmed by Fama and French (1992) that historically, small-cap stocks over time have provided significantly higher returns than large-cap stocks.

Blitz, et al. (2011) incorporated the factors argued by Fama and French (1993), which came to be known as the Fama-French three-factor model, into the work of Jegadeesh and Titman (1993) to capture firm-specific returns for the residual return estimate. The formula for the Fama-French is as follows:

Equation 1: $r_{it} - r_{ft} = \alpha i + miMKT_t + siSMB_t + \text{h}iHMTL_t + \varepsilon_{it}$ (1).

Where:

- r_{it} is the return on stock *i* in month *t,*
- r_{ft} is the risk-free rate in month *t*. The risk-free rate in this study will be the South African 10-year generic government bond yield, and
- MKT_t is the market beta in month *t*. It represents the sensitivity of a stock's return to the changes in the overall stock market. It is calculated by regressing the security's excess returns against the market index's excess returns. The market beta is the regression's slope coefficient (Blitz et al ,2011).

The formula for the market beta (MKT_t) is:

MKT_t = Cov(r_{it}, r_{mt}) / Var(r_{mt})

Where:

- r_{it} is the excess return of security i at time t,
- r_{mt} is the excess return of the market index at time t,
- Cov(r_{it}, r_{mt}) is the covariance between r_{it} and r_{mt},
- Var(r_{mt}) is the variance of r_{mt} , and
- SMB_t is the size factor in month *t*. It represents the disparity between the returns of small-cap and large-cap stocks. It is calculated by subtracting the returns of a small-cap stock portfolio from those of a large-cap stock portfolio (Blitz et al ,2011).

The formula for the size factor is:

$SMB_t = r_s - r_b$

Where:

- r_s is the return of a portfolio of small-cap stocks,
- r_b is the return of a portfolio of large-cap stocks, and
- $HMTL_t$ is book-to-market in month *t*. The book-to-market ratio compares the book value to the market value of a company. The book value is the difference between the value of assets and the value of liabilities. The market value of a company is equal to the market price per share multiplied by the number of outstanding shares. $HMTL_t$ is

determined by subtracting the returns of a portfolio of stocks with a high book-to-market ratio from those of a portfolio of stocks with a low book-to-market ratio.

The formula for the book-to-market is:

- Book-to-market = Common Shares Equity Market Cap

$$HMTL_t = rh - rl$$

Where:

- rh is the return of a portfolio of high book-to-market ratio stocks, and
- rl is the return of a portfolio of low book-to-market ratio stocks.

Once we obtain the residual returns (ε_{it}) from Equation (1), we calculate the average residual return over the past 12 months, excluding the most recent month (i.e. from t−12 to t−2) standardised by the standard deviation of the residual returns over the same period. To construct the long-only residual momentum portfolio, stocks are ranked individually based on their values of the average standardised residual return into deciles. Stocks with an average standardised residual return ranked in the top 10 are defined as winners. These portfolios are equally weighted. Similarly to traditional momentum, the study will go long on the winner portfolio and disregard the loser portfolio.

Three distinct portfolios are constructed, two of which reflect the two momentum-based strategies, with the third being a "control" portfolio consisting of Top 40 stocks. Each momentum strategy will have one portfolio that is constructed, rebalanced, altered and maintained as proposed by George and Hwang (2004). The portfolios are long-only to determine how the strategy will perform from the perspective of an individual investor or portfolio manager who is unable to invest in zero-cost portfolios. Foltice and Langer (2015) argue that individual investors should consider the long-only winner portfolio approach due to the complexity and large fees associated with short-selling stocks. These portfolios are labelled as the "winner" portfolios. Table 3.1 gives a summary of the momentum-based portfolios.

Table 3.1: Momentum portfolio summary

Portfolio	*Abbreviation*	*Portfolio Construction*
Traditional Momentum Approach "Winner"	TMW	The winner portfolio is an equally weighted portfolio of the top 10 stocks with the highest past 11-month return. The traditional momentum strategy entails ranking stocks based on their total returns. Each year (from 2018 to 2022), a new portfolio is constructed based on the previous year's 11-month returns. The portfolio was held for a horizon of 12 months and reconstituted after the 12th month.
Residual Momentum Approach "Winner"	RMW	The winner portfolio is an equally weighted portfolio of the top 10 stocks with the highest past 11-month return. The residual momentum strategy entails ranking stocks according to their total excess returns, not explained by risk factors, over the formation period. Each year (from 2018 to 2022), a new portfolio is constructed based on the 11-month returns. The portfolio was held for a horizon of 12 months and reconstituted after the 12th month.
Top 40 Portfolio	Control	Top 40 shares in the JSE and held for 12-months.

Compiled by Author

3.4 Data Analysis

The data analysis section provides a more in-depth discussion of the recommended procedures that were used to accomplish the purpose of the research. Every one of the recommended procedures is connected to the corresponding objective.

3.4.1 Descriptive and inferential analysis

Descriptive statistics is a technique that summarises a particular numerical data set or multiple sets and delivers quantitative insights about that data through numerical or graphical representation (Lawless and Heyman, 2010). Descriptive analysis is used to analyse the returns of both momentum portfolios.

Inferential statistics draw conclusions, often known as inferences, based on the data that is available from a subset of the total population (Sinharay, 2010). The analysis of a random sample taken from a much larger data collection, such as a larger population, is frequently used as a method for accomplishing this goal. The inferences that can be drawn about the overall population are based on the findings of this sample. Inferential statistics are used in this study to make inferences about the returns of long-only traditional and residual momentum. Table

3.2 below shows the examples as well as differences between descriptive and inferential analysis.

Table 3.2: Differences between descriptive and inferential analysis

	Descriptive statistics	***Inferential statistics***
Purpose	Describe and summarise data	Make inferences and draw conclusions about a population based on sample data
Data Analysis	Analyses and interprets the characteristics of a dataset	Uses sample data to make generalisations or predictions about a larger population
Population vs Sample	Uses the entire population or dataset	Uses a representative subset (the sample) of the whole population to draw inferences about the complete population
Measurements	Provides measures of central tendency and dispersion	Estimates parameters, test hypotheses and determines the level of confidence or significance in the results
Examples	Mean, median, mode, standard deviation, range, frequency tables	Hypothesis testing, confidence intervals, regression analysis, ANOVA (analysis of variance), chi-square tests, t-tests, etc.
Goal	Summarise, organise and present data	Generalise findings to a larger population, make predictions, test hypotheses, evaluate relationships and support decision-making

Compiled by Author

Descriptive and inferential analysis are used to answer part of objective one and objective three of the research, by comparing the simple returns of the strategies against each other and the benchmark. Inferential statistics are also used to make inferences about the relationship the momentum strategies have to different market conditions.

3.4.2 To analyse the profitability of the momentum portfolios for the period 2018 to 2022

To address research objective one in terms of the profitability of the momentum strategies compared to the FTSE/JSE top 40, the study will measure the simple returns of the momentum portfolios. The portfolio returns are measured monthly and recorded. Therefore, this research will have an overall 58 sample monthly returns in each resultant time series. There are ten momentum portfolios constructed over the 5-year investment horizon, which are split between winners for each momentum strategy (residual and traditional). The returns of the portfolios will be calculated on a simple return basis and a risk-adjusted basis. To calculate the simple return of the portfolios, we will take the current price of each stock at the end of the portfolio holding period (12 months) and subtract the initial price of each stock at the portfolio construction, divided by the initial price of each stock at the portfolio construction. Once we have the returns of each stock, they are added together, giving the portfolio return.

Equation 1: Simple return of a stock Formula

$$R_t = \frac{R_{(t-1)} - R_1}{R_1}$$

Where :

- R_t is the return of a give stock over 12 months
- $R_{(t-1)}$ is the stock price after 12 months
- R_1 is the initial price of stock on portfolio construction

3.4.3 To analyse the risk-adjusted performance of momentum portfolios for the period 2018 to 2022

To address research objective one in terms of the risk-adjusted performance of the momentum strategies compared to the FTSE/JSE top 40, the study employs a tracking error, Sharpe ratio, Jensen's alpha and Information ratio.

Tracking error

According to Morningstar (2021), a tracking error is the difference in performance over a period between a portfolio and its benchmark. This difference is expressed as a percentage. A tracking error is one of the few important measures used to assess the performance of a portfolio. This study will use an ex-post tracking error, which is a tracking error calculated by using historical returns. Maxwell and Van Vuuren (2019) state that a tracking error with low errors indicates that the respective portfolio is performing close to the performance of the benchmark. These are common with ETFs and index funds that replicate the composition of major stock market indices. A tracking error with high errors indicates that the performance of the respective portfolio is significantly different from the performance of the benchmark, which signals that a portfolio significantly underperforms or overperforms the benchmark. Li and Shim (2019) conduct a study that looks at a combination of six factors in simple long-only investable portfolios. The authors investigate different factors to include within their portfolios to improve their tracking error. One of the factors they examine is momentum, and they observe that momentum has a significant impact on improving their tracking error. Even though this is not the aim of this study, the tracking error of momentum strategies is examined to see how well momentum strategies perform compared to their benchmark.

Equation 2: Tracking error Formula

T_0 = STD (R_p) - STD (R_B)

Where:

- STD (R_p) is the standard deviation of the return on the portfolio.
- STD (R_B) is the standard deviation of the return on the benchmark
- T_0 is the tracking error

Sharpe ratio

The Sharpe ratio is a finance metric that compares the excess returns of an investment to the volatility of the investment, as measured by the investment's standard deviation (Dowd, 1999).

Equation 3: Sharpe ratio Formula

R_p-R_f/*STD*(R_p) R_f

Where:

- R_p is the return on the portfolio,
- R_f is the return on the risk-free portfolio, and
- STD (R_p) is the standard deviation of the return on the portfolio.

The Sharpe ratio only gauges one aspect of risk, namely variation. Therefore, the Sharpe ratio is meant to be used for investment strategies with no anticipated return distributions; it cannot be used to evaluate investments with an asymmetric expected return distribution (Kidd, 2011). Fernando (2022) explains that a greater Sharpe ratio means better risk adjusted returns and according to the Corporate Finance Institute, a Sharpe ratio below 1 is "bad", a Sharpe ratio between 1 and 2 is "good", a Sharpe ratio between 2 and 3 is "very good" and a Sharpe ratio greater than 3 is "excellent".

Chang, et al. (2017) investigate the profitability of residual momentum and traditional momentum in the Japanese market. To observe the profitability of residual momentum and traditional momentum, the authors use the Sharpe ratio and observe that the risk-adjusted returns are more profitable for residual momentum than traditional momentum.

Jensen’s alpha

Jensen’s alpha is a risk-adjusted performance measure that represents the average return on a portfolio or investment, above or below that predicted by the CAPM, given the portfolio’s or investment’s beta and the average market return (Jensen,1968). Therefore, the Jensen’s alpha differs from the Sharpe ratio because the Sharpe ratio considers total risk, while the Jensen’s alpha considers systematic risk (beta).

Equation 4: Jensen’s Alpha Formula

$JA = Rp - Rf - \beta(Rm - Rf)$

Where:

- Rp represents the expected portfolio return,
- Rf denotes the risk-free rate of return,
- β symbolises the beta of the portfolio, and
- Rm denotes the expected market return.

Jensen’s alpha considers only the systematic risk of a β - factor, and the risk is always proportional to the chosen benchmark index or portfolio (Amencc and Le Sourd, 2003). If Jensen’s alpha is positive, the portfolio has performed better than the forecast in the CAPM model. Correspondingly, a negative value indicates lower performance.

Chang, et al. (2017) also use Jensen's alpha to investigate the profitability of residual momentum and traditional momentum in the Japanese market. They observe that the risk-adjusted returns are more profitable for residual momentum than traditional momentum.

Information ratio

Investors consider not just the profitability and risk associated with an investment strategy but also its effectiveness. The information ratio (IR) is a quantitative measure derived from modern portfolio theory and used to evaluate performance in the field of finance. The study of risk-adjusted returns and evaluating the skill set of investment managers has been a continuous subject of fascination. The IR became widely used as a measure of performance that considers the level of risk in the latter half of the 20th century. The constituents of the ratio, namely active return and tracking error, are deemed beneficial in assessing the extent to which a portfolio manager is enhancing value compared to the benchmark, taking into account the level of risk undertaken.

The IR is computed by:

The IR = the Active Return/the Tracking Error.

3.4.4 To determine if the returns between the momentum portfolios and the FTSE/JSE Top 40 for the period 2018 to 2022 are statistically significant

Welch's T-test is a comparison tool used to test for differences between two means; therefore, Welch's T-test is applied to each portfolio relative to one another (residual and traditional momentum) and the FTSE/JSE Top 40. Marx (2016) used a Student's t-test, similar to Welch's t-test, to evaluate the economic effectiveness of several momentum methods on the Johannesburg Stock Exchange (JSE). Marx selected the Student's t-test because the analysed strategies had similar features. Specifically, they were different versions of classic momentum strategies that did not reduce the inherent risks associated with volatility, such as the 52-week high momentum and industrial momentum strategies. Consequently, it was expected that the standard deviations of these techniques would not exhibit significant differences in the research. Contrary to Welch's t-test, which does not make any assumptions about equal variances, the Student's t-test assumes that the two samples have equal variances and follow a normal distribution. Daniel and Makowitz (2016) found that conventional momentum strategies exhibit high volatility and provide inconsistent returns, particularly in times of market upheaval. Blitz et al. (2011) introduced a different momentum method called residual momentum. This technique was shown to be less susceptible to significant market downturns and had fewer instances of negative returns under tumultuous market circumstances. Within the field of finance, it is typical for various approaches to display differing levels of volatility. Momentum techniques might vary in risk levels based on their specialised usage. Considering this, the research cannot make the assumption that the mean returns of the two momentum techniques have identical variances. Thus, the second study goal was addressed by using Welch's t-test to determine the statistical significance of the mean return differences between conventional momentum, residual momentum, and the benchmark over the pre-Covid, Covid, and post-Covid periods.

Equation 5: T-statistic formula

$t = X_1 - X_2 S_{21}\ N_1 \quad + S_{22}\ \ N_2$

Where:

- X_1 and X_2 are the sample means of residual momentum and traditional momentum, respectively,
- S_{21} and S_{22} are the sample variance of residual momentum and traditional momentum, respectively, and
- N_1 and N_2 are the sample sizes of residual momentum and traditional momentum, respectively.

The distinct null and the alternative hypothesis in the case of a comparison to the controlled portfolio can be described as:

- Null hypothesis: $H_0\ : U_{fi} \ = U_{f0}$ where U_{fi} is the mean return of the momentum portfolio and U_{f0} is the mean return of the controlled portfolio.
- Alternative hypothesis: H∂: $U_{fi} \ \not\approx U_{f0}$ where U_{fi} is the mean return of the momentum portfolio and U_{f0} is the mean return of the controlled portfolio.

The distinct null and alternative hypotheses in the case of a comparison between momentum portfolios (n-m) is:

- $H_0\ : U_{fn} \ = U_{fm}$ where U_{fn} is the mean return of the traditional momentum strategy portfolio and U_{fm} is the mean return of the residual momentum strategy portfolio.
- $H_1\ : U_{fn} \ \neq U_{fm}$ where U_{fn} is the mean of the traditional momentum strategy portfolio and U_{fm} is the mean return of the residual momentum strategy portfolio.

The difference in mean return of both momentum strategies is compared to each other and analysed for statistical significance. The difference in mean returns of the benchmark and the momentum strategies is also analysed for statistical significance. We can reject the null hypothesis and accept the alternative hypothesis if the p-value is less than or equal to the significance level of 0.05 (Temy and Abdelgawad, 2022).

3.4.5 Autoregressive distributed lag to analyse the effect of different market conditions on the returns of the momentum strategies from 2018 to 2022

To address objective three, the study used an autoregressive distributed lag (ARDL). The ARDL aims to observe the effect/relationship of different market conditions, namely: high volatility, bear market and bull market, have on the returns of the momentum strategies. ARDL is a regression model that was first introduced by Hendry (1970) and is used to analyse time series data and the presence of lagged variables. A lagged variable is a way to capture the effect of past values of a variable on its current value, and it is useful in time series analysis as it can account for the autocorrelation or time dependence of the data. Kaluba (2020) uses linear regression to test the relationship between volatility and market state on the returns of different momentum strategies on the JSE. The difference between the regression Kaluba (2020) runs and the ARDL run in this study is that the ARDL does not just account for the association between the variables but also checks for long- and short-term effects that variables like volatility, bear market and bull market have on the returns of the strategies.

Equation 6: The formula for ARDL for the two momentum portfolios

$$MomenTrad_t = 0 + i{=}1n1SAVIT40_{t-i} + i{=}1n2Bear_{t-i} + i{=}1n3Bull_{t-i}$$

$$MomenResi_t = 0 + i{=}1n4SAVIT40_{t-i} + i{=}1n5Bear_{t-i} + i{=}1n6Bull_{t-i}$$

Where $MomenTrad_t$ is the traditional momentum investment portfolio and $MomenResi_t$is a residual momentum investment portfolio. $MomenResi_t$and$MomenTrad_t$are the dependent variables at time *t*, β0 to β9 are the coefficients to be estimated; i=1n1$SAVIT40_{t-i}$ represents the lagged values of the South African Volatility index to the dependent variable; i=1n2$Bear_{t-i}$ represents the lagged values of the bear market to the dependent variable and i=1n3$Bull_{t-i}$represents the lagged values of the bull market to the dependent variable.

The ARDL is transformed into a dynamic error-correction model using a simple linear transformation (ECM). It is crucial to note that the ARDL model can account for both the long- and short-term correlations among the cointegrated variables. The ECM indicates the speed at which a system corrects deviations from the long-run equilibrium.

3.4.5.1 Explanation of the ARDL variables

- **Bull and bear markets**

The comprehensive characterisation of financial markets as either bullish or bearish effectively captures the whole behaviour shown by a given market. Nevertheless, it is important to note that these phrases lack a distinct and universally accepted meaning. In fact, multiple fundamentally diverse approaches exist for the identification and prediction of bull and bear markets (Kole and van Dijk, 2010). Lunde and Timmermann (2004) identify a bull-bear market as occurring only after a decrease or increase of 20% in the stock index. The study identifies a bull market as an increase of 20% over the last trough and a bear market as a 20% decrease since the last peak.

- **South African Volatility Index (SAVIT40)**

El Ghorayeb (2021) uses the VIX index as a regressor variable in trying to explain the returns of a momentum portfolio and finds it to be a negative coefficient and statistically significant. This study uses the South African equivalent of the VIX, the SAVIT40 index, as an independent variable in trying to explain the returns of both residual momentum and traditional momentum.

3.4.6 Diagnostic test

Before undertaking an ARDL, it is important to conduct several diagnostic tests to ensure the validity of the model and the reliability of the results. The study used the Augmented Dickey-Fuller (ADF) test, the Hausman test and Phillips Perrons as the diagnostic tests.

3.4.6.1 Test of stationary

A stochastic process is defined as stationary if it has a constant mean, variance and covariance over time. Hence, it is important to carry out a stationary test in a time series to clarify whether the series is stationary or time-invariant to avoid the model not being fit for policy prediction (Olasode, 2013).

The augmented ADF test is a statistical test used to determine whether a time series is stationary or not and therefore it is employed to verify these conditions. The ADF test evaluates the null hypothesis that the presence of a unit root in a time series indicates non-stationarity. According to the alternative hypothesis, the series is stationary. The unit root symbolises a random walk in which the series has a trend, and the current value is dependent on the previous value plus random noise. In time series analysis, the ADF test is valuable because it identifies the order of series integration. For a non-stationary series to become stationary, it may necessitate differentiation. Differentiation is the process of subtracting successive observations to eliminate trends or seasonality. In terms of differencing, the ADF test guides the decision-making process by providing evidence for or against stationarity.

The null hypothesis of this test is that H0= 1 for stationarity, while the alternative hypothesis is H0 ≠ 1 for non-stationary.

To improve the robustness of the study, the Phillips-Perron test is also conducted. The Phillips-Perron test is comparable to the ADF test, but it requires a higher level of expertise from the examinee. It examines the data points to determine whether they change in a pattern that may be anticipated (Leybourne and Newbold, 2017). If the data points are changing in a way that can be predicted, then the time series can be considered stagnant. A time series is considered non-stationary when the individual data points change in a manner that is not predictable. The Phillips-Perron test differs from the ADF primarily in its treatment of serial correlation and error heteroscedasticity. In particular, the ADF tests use parametric autoregression to approximate the ARMA structure of the errors in the test regression, while the Philips-Perron (PP) tests ignore any serial correlation in the test regression (Phillips and Perron, 1988).

3.4.6.2 Hausman test

Hausman (1978) devised a statistical test that enables researchers to select between two widely used approaches for panel data analysis, namely the fixed-effects estimator and the random-effects estimator.

The objective of the test is to examine the potential correlation between unobserved individual-specific traits and the independent variables in the regression analysis. To determine whether the regression model is fixed or random, the study will use the Hausman test. Using an inappropriate model has the potential to introduce bias or inefficiency into the estimation process, compromising the validity of the obtained results. The Hausman test serves as a valuable tool for academics to make informed decisions and improve the robustness of their econometric study through the application of a formal statistical test.

Fixed-Effects Model: This model posits that variations in the dependent variable are driven by individual-specific factors that are consistent throughout time (such as individual-specific traits that do not vary during the period of investigation). To account for these unobserved characteristics, the fixed-effects model incorporates individual-specific fixed-effects (Hausman, 1978).

Random-effects Model: Individual-specific heterogeneity is assumed to be random and unrelated to the independent variables in the random-effects model. Individual-specific impacts are treated as random departures from the general population average effect (Hausman 1978).

The null hypothesis stated by Hausman's (1978) test asserts that the random-effects model is both consistent and efficient, hence being acceptable. Conversely, the alternative hypothesis contends that the random-effects model is inconsistent and instead, the fixed-effects model should be favoured. The interpretation of a Hausman (1978) test outcome is simple: if the p-value is below the 0.05 significance level, the null hypothesis should be rejected.

3.4.7 Serial Correlation

The Breusch-Godfrey test, devised by Trevor Breusch and Leslie Godfrey in 1978, is a significant statistical test used in econometrics to identify the existence of serial correlation in the residuals of a regression model. The main purpose of the Breusch-Godfrey test is to examine the presence of higher-order autocorrelation in the residuals of a regression model. It represents an enhancement compared to the Durbin-Watson test, which examines first-order autocorrelation.

The test's null hypothesis posits that no serial connection is seen up to order p. If the test statistic is less than the crucial value of 0.005, we may reject the null hypothesis and infer the presence of serial correlation.

The significance of using the Breusch-Godfrey test in our research lies in its ability to enhance the model's validity. Serial correlation in the residuals of a model suggests that the model may be mis-specified or inadequate. Within the realm of financial analysis, serial correlation arises in time-series analyses when the residual errors from a certain time period persist and influence subsequent time periods. For instance, when forecasting the increase in stock dividends, an overestimation in one year is probable to result in subsequent overestimations. This might indicate that crucial variables or correlations are not being accounted for, resulting in incorrect forecasts or deductions (Williams, 2015). Furthermore, when assessing investment strategies or fund performance, the presence of serial correlation may result in distorted evaluations of risk-adjusted returns, such as Sharpe ratios. This may lead to inaccurate evaluations of managerial competence or the success of strategies.

3.4.8 Structural model stability

The Cumulative Sum (CUSUM) test be used in this study to identify disturbances in the data and to determine if there is a structural break in periods of economic uncertainty, i.e., Covid-19. The CUSUM test enables researchers to detect alterations or disruptions in the underlying process that generates the data. These structural changes may indicate alterations in trends, modifications to the system's behaviour or the occurrence of an event that influences the time series. By identifying these changes, researchers can gain insight into the causes or influencers of such shifts, allowing them to make informed decisions or forecasts based on the updated data (Lee, Ha and Na, 2003). Uribe (2017) uses the CUSUM test to examine the stability of this time series data which consists of momentum trading during regimes of high and low economic uncertainty.

Equation 7: The formula for the CUSUM test is as follows:

$CUSUM(n) = max[0, (x(n) - \mu 0) + CUSUM(n-1)]$

Where:

- CUSUM(n) is the cumulative sum at time n,
- x(n) is the value of the time series at time n, and
- μ0 is the reference value or target mean.

CUSUM(n-1) is the cumulative sum at the previous time point (n-1).

max[0, (x(n) - μ0) + CUSUM(n-1)] ensures that the cumulative sum does not become negative.

We can therefore formulate the hypothesis as follows:

H_0: 1=0 H_1: 1≠ 0

The null hypothesis (H_0) assumes that the mean of the time series does not undergo any structural change or shift, while the alternative hypothesis assumes the latter.

3.4.9 To analyse the impact of different market conditions on the momentum portfolio returns for the period 2018 to 2022 using Monte Carlo

To strengthen the analysis of the impact of different marker conditions on both momentum portfolios and answer objective 3 this study will also use the Monte Carlo simulation, which is a method that uses statistical sampling techniques to obtain a probabilistic approximation of a mathematical equation or model. It involves using sequences of random numbers as inputs into a model, which then produces results that indicate the performance of the developed model (Aderibige, 2014). Monte Carlo simulations have been used in professional fields such as physics, finance and system reliability (Dodds, 2023). The fundamental concept behind Monte Carlo involves using random sampling to analyse and estimate complex mathematical quantities, such as integrals, probabilities or solutions to optimisation problems. In this study, the Monte Carlo simulation will be modelled using Excel. Below are the steps that will be taken to run the simulation.

Struck and Cheng (2019) conducted a study developing a Monte Carlo back testing procedure to study time series momentum. They conclude that the strategies that outperform in-sample using a historical back test may out-of-sample underperform or outperform consistent with the predictions of the simulations.

Monte Carlo simulation steps:

1. Identify periods in which the FTSE/JSE Top 40 experienced a bear market, bull market and high volatility.
2. Calculate the average mean return for the residual momentum portfolio, FTSE/JSE Top 40 and traditional momentum portfolios in those periods using the "=Average()" function in Excel.
3. Calculate the average volatility (standard deviation) for both momentum portfolios and benchmark for periods in question using the function "=STDEV.S()".
4. Use the NORM.S.INV(RAND ())to extract a random probability using the mean and volatility of the momentum strategies and the benchmark for 12 months.
5. Run the Monte Carlo method for 1 000 simulations for both momentum strategies and benchmarks using the "What if analysis" function in the Data tab in Excel.
6. Calculate the average mean return for the simulation and the volatility.
7. Calculate the probability of mean returns of residual momentum being greater than the mean returns of benchmark using "=COUNTIF(>)/1000". This function counts the number of times the residual outperforms the benchmark within the simulation.

8. Calculate the probability of mean returns of residual momentum being greater than the mean returns of traditional momentum using "=COUNTIF(>)/1000". This function counts the number of times residual outperforms traditional momentum within the simulation.
9. Calculate the probability of mean returns of traditional momentum being greater than the mean returns of benchmark using "=COUNTIF(>)/1000". This function counts the number of times traditional momentum outperforms the benchmark within the simulation.

3.5 Reliability and Validity of Study

3.5.1 Reliability

Reliability refers to the ability of an investigation or test to produce the same result consistently. In other words, can the data collection techniques and analytic procedures reproduce consistent findings if they are repeated on another occasion or reproduced by another researcher (Robinson, 2008).

To ensure reliability in this investigation, the test-retest method was used. Lavrakas (2008) defines test-retest reliability as a measurement theory term that evaluates the stability of repeated measurements. In addition, it is essential to note that secondary data, data acquisition techniques and data sources all contribute to the study's reliability. Bloomberg, which is unlikely to contain bias or measurement errors, is this study's secondary data source. According to Saunders, et al. (2009), data integrity is crucial to the success of any database or organisation. Bloomberg has been in existence since 1981, making it a dependable source of secondary data due to its pervasive use.

This study is fully reproducible and therefore stable, and others will obtain the same results if conducted during the same period using the same sample. Financial information derived from a trustworthy source will endure over time.

3.5.2 Validity

Validity is the extent to which it can be demonstrated that a measure measures what it purports to measure (Cramer and Howitt, 2004). Internal and external validity are investigated in this study. Internal validity is the extent to which research demonstrates a causal relationship between the independent and dependent variables, whereas external validity is the extent to which the results of a study can be applied to other situations, people, locations and measurements (Slack and Draughlies, 2001).

To verify internal validity, the ARDL is used to quantify how much of the observed change in the momentum portfolios can be attributed to the various independent variables. A threat to internal validity is selection bias and history. The history threat pertains to any past occurrences between the first and second measurements that influence the dependent variable in addition to the independent variable (Kaya, 2014). The period in the study is one that observed a major financial disruption (Covid-19 crisis), which could influence the findings of this study. The ARDL regressions run for both traditional and residual momentum produced high R-squared values of above 0.50 in both cases meaning that the variables used explained most of the variation in the returns of the momentum strategies. This is in line with the work of Wang and Xu (2015) who found that market state and volatility regressed against momentum returns produced high R-squared values.

To verify external validity, back testing is employed to analyse the profitability of the momentum strategies. Back testing evaluates the performance of a trading/investment strategy based on historical market data, which gives insight into whether the results of the study could be applied in real-world situations (Harvey and Liu, 2015). Finally, the external validity of a quasi-experimental design could exceed that of a traditional randomised experimental analysis as field data is used rather than simulated laboratory data (Jensen, et al., 2008). Inferences could be drawn from a secondary data set and not a primary data set.

To further confirm external validity the study compares the findings of similar studies into momentum. In terms of risk-adjusted returns, Viljoen (2016) found the Sharpe ratio for the long-only-winner traditional momentum portfolio to be better than that of the long-only-winner residual momentum portfolio, which is in line with the findings of this study. The regression run by Kaluba (2020) found that the independent variables are not good explainers for momentum performance, which validates the findings of the ARDL regression in this study. El Ghorayeb's (2021) study used the WML approach to study momentum during Covid in the United States stock exchange, however, El Ghorayeb (2021) made an observation similar to this study, that the long-only winner traditional momentum portfolio outperformed its stated benchmark during the Covid period.

A threat to external validity is that a quasi-experimental design does not involve the random assignment of participants to the different groups being compared (Lund Research, 2012). This results in selection bias, which occurs when a researcher uses non-random procedures for selecting a sample population. The procedure followed in the creation of momentum portfolios is non-random, in the sense that the top-performing stocks are chosen for the winner portfolio, giving rise to selection bias.

3.6 Limitations and Delimitations

Delimitations are defined as a set of boundaries that one sets in their research. These boundaries are set for one to achieve their goals. Limitations are defined as potential flaws in research that one cannot control (Simon, 2011).

3.6.1 Limitations

Agyei-Ampomah (2007) observed that once transactional costs are accounted for within the profitability of momentum strategies, the momentum premium disappears for short-term horizons (6 months) but is present in longer-term horizons (12 months). A limitation of this study is that it does not account for cost in the performance evaluation of both momentum strategies, which may have changed the overall findings of the study. Secondly, the study's look-back period of five years is relatively short compared to other studies into momentum investing this presents an obvious limitation on the inferences that can be drawn about the performance of momentum strategies. However, the findings are backed up by other studies conducted on the performance of momentum strategies during the Covid period in other parts of the world like El Ghorayeb (2021) and Santoso (2021).

3.6.2 Delimitations

Page et al (2013) investigated momentum and liquidity on the JSE and found that liquidity momentum strategies achieve consistent significant average returns, yet the low liquidity momentum results are inconsistent and insignificant. As a Mitigation measure against the inconsistent results achieved by low liquidity momentum, this study limited its investment population to the FTSE/JSE Top40.

3.7 Conclusion

The chapter overviewed the study's overarching research design, sample design, and methodology. The measurement qualities were assessed, along with the constraints and boundaries. The study utilised a quantitative explanatory approach, incorporating secondary monthly data from the FTSE/JSE Top 40 listed shares by market capitalisation from January 2018 to December 2022. Three portfolios are built for each year, two of which correspond to the momentum techniques used, while the third is the control portfolio. In terms of data analysis methods, subsequent portfolio returns were compared using Welch's t-test; portfolio profitability risk-adjusted returns were compared using the tracking error; the Sharpe ratio; the IR and Jensen's Alpha. The ARDL was used to test for short-term and long-term market conditions on the momentum portfolios; the CUSUM test was used to detect structural breaks within the momentum portfolio returns. Lastly, the Monte Carlo was used to predict the potential outcomes of the momentum strategies in different market conditions.

CHAPTER 4: DISCUSSION AND INTERPRETATION OF THE RESULTS

4.1 Introduction

This chapter aims to present and interpret the results of the risk and profitability analysis conducted on both momentum strategies to answer the research objectives. The first objective is to investigate the relative risk and profitability of momentum strategies (traditional and residual) compared to the South African stock market. The second objective aims to observe if the difference in mean returns between the momentum strategies and the benchmark was statistically significant during the pre-Covid, Covid and post-Covid periods. The third objective aims to determine if momentum investing strategies are persistent under different market conditions including a bull market, a bear market and high volatility that were experienced during the Covid-19 crisis period and post-Covid-19 crisis period.

This chapter is structured as follows: Section 4.2 discusses the findings of the profitability and risk-adjusted analysis, conducted for research objective 1. Section 4.3, the findings of the Welch's test are presented and discussed, in the attempt to answer research objective 2. Section 4.4 – 4.5 discusses the diagnostic tests undertaken before one can conduct the ARDL. Section 4.6- 4.8 presents the tests undertaken to fulfil research objective 3 and discusses the findings of the ARDL and Monte Carlo simulation, which were undertaken to first show the effects of different market conditions and secondly provide a simulated prediction of the performance of residual and traditional momentum under the market conditions described above.

4.2 Descriptive Statistics

Two portfolios have been created: a long-only traditional momentum portfolio and long-only residual momentum portfolio which will be compared to the FTSE/JSE Top 40. The traditional momentum portfolio comprises stocks ranked according to the absolute price. The residual momentum portfolio comprises stocks based on the residual return, which considers common risk factors, small-minus-big (SMB) and high-minus-low (HML). Tables 4.1-4.2 show the descriptive statistics over the five years of the momentum strategies tracking the FTSE/JSE Top 40 from 2018 to 2022.

Table 4.1 captures the annual simple returns of both momentum strategies compared over different periods. The presentation of the annualised simple returns of both momentum strategies, aims to answer the profitability component of objective 1, by investigating the profitability of momentum strategies compared to the South African FTSE/JSE Top 40 during the pre-and post-Covid as well as during the Covid crisis period.

Table 4.1: The annualised simple returns of the momentum strategies during the pre-Covid, Covid and post-Covid periods

	Pre-Covid		**Covid**	**Post-Covid**	
Year	2018	2019	2020	2021	2022
Residual Momentum	-6.712%	28.035%	3.1232%	34.2158%	3.000%
Benchmark (FTSE/JSE Top 40)	-8.480%	8.633%	11.3778%	22.0398%	5.5640%
Traditional Momentum	-10.230%	36.237%	29.91756%	15.3212%	-3.0892%

Compiled by Author

4.2.1 Annualised simple return performance

The pre-Covid period is defined as occurring between 2018 and 2019. During this period, residual momentum returns -6.7% for 2018 and 28.03% for 2019, compared to traditional momentum which returns -10.23% for 2018 and 36.2% for 2019. The benchmark during this period returns -8.4% for 2018 and 8.6% for 2019. Overall, during this period residual momentum returns 19.44%, traditional momentum returns 22.30% and the benchmark returns -0.58%. Over the entire pre-Covid period, traditional momentum performs slightly better than residual momentum with a 3% outperformance. This is in line with the findings by Viljoen (2016), who studies residual momentum within the JSE and concludes that traditional momentum annual returns are slightly higher than those of residual momentum returns. Our findings also support the findings of Blitz et al (2011) who states that during market contraction as experienced in 2018, traditional momentum underperforms the market and residual momentum. While during market expansion as experienced in 2019, the strategy outperforms the market and residual momentum.

The Covid period is defined as one occurring in 2020, in which residual momentum returns 3.12319% compared to traditional momentum which returns 29.91759%. The benchmark during this period returns 11.37770%. During the Covid period, on an annualised basis, the residual momentum strategy underperforms the market and traditional momentum outperforms both. However, during the flash bear crash that happened in March 2020 and May 2020, both momentum strategies underperform the market and go negative, as shown in Appendix A. These findings are in line with those of Daniel and Moskowitz (2016), who illustrate that momentum strategies experience crashes during periods of persistent negative returns and high stress.

The post-Covid period is defined as one occurring between 2021 and 2022. During this period, residual momentum returns 34.21581% for 2021 and 3% for 2022, compared to traditional momentum which returns 15.32120% for 2021 and -3.0892% for 2022. The benchmark during this period returns 22.03978% for 2021 and 5.5640% for 2022. Overall, during this period, residual momentum returns 38.2%, while traditional momentum returns 11.8% and the benchmark 28.8%.

Post-Covid, the residual momentum portfolio outperforms the market for a single year but underperforms the market in the subsequent year. Traditional, on the other hand, underperforms the market in both years of the post-Covid period observed. It is worth noting that residual momentum outperforms traditional in both the post-recovery years. These findings complement the findings of Blitz et al (2011), who observes that post-financial crisis 2009 residual momentum outperforms traditional. It is worth noting that in the Blitz et al (2011) study, the residual portfolios are looked at from both a long and short point of view, unlike this study, which only looks at long-only winner portfolios.

Table 4.2: Risk metrics of Traditional momentum and Residual momentum during the Pre-Covid, Covid and post-Covid periods

Traditional Momentum					
	Pre-Covid		Covid	Post-Covid	
Year	2018	2019	2020	2021	2022
Tracking Error	15.650	16.6003	31.2772	13.97725968	18.16863928
Sharpe Ratio	-0.470	2.4745	0.87259	0.814002755	-0.250040694
Information Ratio	-0.05	1.92611238	0.901091389	-0.393073925	-0.471617843
Jensen's Alpha	-0.0586	0.38846	0.29732	-0.0843500	-0.09.397804

Residual Momentum					
	Pre-Covid		**Covid**	**Post-Covid**	
Year	2018	2019	2020	2021	2022
Tracking Error	9.17	11.1745	17.7716	13.4990	14.42407
Sharpe Ratio	-0.57	2.02639	0.17318	2.0063	-0.27522
Information Ratio	0.28	3.2244	-0.1958	0.6171	-0.38859
Jensen's Alpha	0.00132	0.272611	-0.036224	0.170475	-0.05375

Compiled by Author

Table 4.2 captures the risk-adjusted performance of both momentum strategies compared over different periods. The presentation of the risk-adjusted performance of both momentum strategies, aims to answer the risk-adjusted component of objective 1, by investigating the risk-adjusted returns of momentum strategies compared to the South African FTSE/JSE Top 40 during the pre- and post-Covid as well as during the Covid crisis period.

4.2.2 Tracking error

Traditionally, a tracking error is used in a passive strategy that seeks to reproduce as close as possible an index or a benchmark. However, El-Hassan and Kofman (2003) look at tracking errors in an active strategy that seeks to outperform an index and benchmark, as in the case in this study. A high tracking error will be interpreted as good since it indicates an outperformance or underperformance from the benchmark.

The tracking error of traditional momentum during the period defined as pre-Covid (2018–2019) is 15.65 and 16.60 respectively. This indicates that traditional momentum strategy returns deviate by 15.65 in 2018 and 16.60 percentage points in 2019 from the benchmark returns. During Covid, the tracking error is 31.28, which indicates that in 2020 the traditional momentum returns deviate by 31 percentage points from the benchmark's return. Post-Covid traditional momentum returns deviate by 13.98 and 18.17 percentage points, respectively, from 2021 to 2022.

The tracking error of residual momentum during pre-Covid is 9.17 and 11.17, respectively. This indicates that residual momentum strategy returns deviate by 9.17 percentage points in 2018 and 11.17 percentage points in 2019. During Covid, the tracking error is 17.77, which indicates that in 2020 the residual momentum returns deviate by 17.77 percentage points from the benchmark's return. Post-Covid residual momentum returns deviate by 13.49 and 14.42 percentage points, respectively, from 2021 to 2022.

The tracking errors of both traditional and residual momentum remain both high and positive throughout the periods observed in this study. Tracking errors can be used to evaluate the effectiveness of actively managed funds (El-Hassan and Kofman, 2003). Israel, et al. (2017), who looks at the returns of the long-only tax-agnostic and tax-managed US large-cap mutual funds, found the portfolios to have a tracking error of 0.80 percent, meaning the returns of these mutual funds deviate 0.80 percent from the returns of the Russell 2000 index on an annualised basis. The authors do not report whether this deviation from the index is positive or negative throughout the period observed. Similar to Israel, et al.'s (2017) findings, both momentum strategies exhibit significant deviations from the tracked index JSE top 40 in this case. It is important to note that traditional momentum achieves a higher tracking error throughout the investment horizon than residual momentum. In an active strategy such as momentum a high tracking error indicates a manager's attempt to achieve returns greater than the benchmark however this could also indicate excessive risk-taking on behalf of the manager.

4.2.3 Sharpe ratio

Baldridge and Curry (2023) state that a Sharpe ratio between 1 and 2 is considered good. A Sharpe ratio between 2 and 3 is very good and a ratio above 3 is excellent. The above results show that pre-Covid traditional momentum achieves a Sharpe ratio of -0.47 in 2018 and 2.47 in 2019. In 2020, the strategy's Sharpe ratio decreases to 0.87. Post-Covid the strategy achieves a Sharpe ratio of 0.81 in 2021 and -0.25 2022. A negative Sharpe ratio usually indicates two things: either the risk-free rate is greater than the portfolio's returns or the expected return is most likely to be negative. The negative Sharpe ratio experienced in 2022 can likely be attributed to the traditional momentum returns observed in that year being below the risk-free rate.

Residual momentum achieves a lower Sharpe ratio than traditional momentum of -0.57 in 2018 and 2.02 in 2019. In 2020, the strategy's Sharpe ratio decreases to 0.17. Post-Covid the strategy achieves a Sharpe ratio of 2.01 in 2021 and -0.27 in 2022. The negative Sharpe ratio experienced in 2022 can likely be attributed to the residual momentum returns observed in that year being below the risk-free rate.

It is interesting to note that traditional momentum achieves a higher Sharpe ratio than residual momentum except in 2021, when residual momentum achieves a higher Sharpe ratio. These findings are in line with the findings of Viljoen (2016) who compares the Sharpe ratios of long-only traditional and residual momentum portfolios in the South African market and finds that traditional momentum achieves a higher Sharpe ratio than residual momentum. This means that from a risk-adjusted perspective, a long-only traditional momentum portfolio achieves a better risk-adjusted return than a long-only residual momentum portfolio.

4.2.4 Information ratio (IR)

The IR differs from the Sharpe ratio because it measures a strategy's excess returns relative to its benchmark. Khan (2000) states that top-quartile active equity managers usually have an IR of 0.5 or higher. In another work, Grinold and Khan (2000) state that an IR of 1.0 or higher is "exceptional", 0.75 is "very good" and 0.50 is "good"; the inverse applies to a negative IR. According to Table 4.2, in the pre-Covid period, traditional momentum achieves an IR of -0.05 in 2018 and 1.93 in 2019. During Covid, the IR is 0.90 and post-Covid the IR is -0.39 in 2021 and -0.47 in 2022. The IR for residual momentum, as shown in Table 4.2, indicates that pre-Covid the strategy achieves a much higher ratio than the traditional of 0.28 in 2018 and 3.22 in 2019. During Covid, the strategy achieves an IR of -0.196. The strategy post-Covid achieves a poorer IR than traditional momentum, of 0.617 in 2021 and -0.388 in 2022.

In a study by Wroblewski (2022), EAM investors compare the returns of a traditional momentum portfolio and a value portfolio in the United States of America from 1985 until 2021 and find traditional momentum to have a better IR than the value portfolio. It must be noted that the period in which the authors of this study looked covers the Covid period, which is a similar period observed in this study. However, this study does not make a comparison to a value portfolio but to a residual momentum portfolio and tries to see which of the two has a superior IR. In this study, traditional is found to not have a superior IR during the pre-Covid and post-Covid periods; instead, residual momentum records a superior IR. This implies that residual momentum portfolios are generating better risk-adjust returns compared to the benchmark than traditional momentum. However, during Covid traditional momentum achieves a positive and superior IR than residual, which indicates that traditional momentum generates better risk-adjusted returns compared to the benchmark. Traditional momentum achieves a negative IR in the years 2018, 2021 and 2022, while residual momentum achieves a negative IR in 2019 and 2022. This implies that the momentum strategies portfolio returns are not compensating for the level of risk taken, and the momentum strategy is not adding value relative to the benchmark during the negative years.

4.2.5 Jensen's alpha

A positive and significant Jensen's alpha indicates that the investment strategy has beaten the market with the asset selection of the strategy (Ahmed, 2016). Table 4.2 shows that Jensen's alpha for traditional momentum, pre-Covid (2018–2019) is -0.0586 and 0.3887 respectively. During Covid (2020) the Jensen's alpha for traditional momentum decreases to 0.2973. The Jensen's alpha continues to decrease post-Covid (2021–2022) to -0.0843 and -0.0940 respectively.

Table 4.2 indicates that residual momentum achieves a Jensen's alpha of 0.00132 in 2018 and 0.2736 in 2019. During Covid residual momentum strategy achieves a Jensen's alpha of -3.62. Post-Covid, the strategy achieves a higher Jensen's alpha than traditional momentum of 0.1705 in 2021 and -0.0538 in 2022. Residual momentum achieves a higher Jensen's alpha than traditional momentum for most of the investment horizon. These findings of residual momentum achieving a higher Jensen's alpha are in line with Chang, et al. (2017), where residual momentum achieves a higher Jensen's alpha than traditional momentum in short-term periods within Japan. However, traditional momentum achieves a higher Jensen's alpha in the years 2019 and 2020. The fact that traditional momentum has a better Jensen's alpha during the year which has a Covid-fuelled bear crash contradicts widely accepted literature by Blitz, et al. (2011) that states that residual momentum is less susceptible to market risk than traditional momentum during times of high market volatility. The 2020 Jensen's alpha findings conclude that investors of long-only-winner traditional momentum portfolios are well compensated against market risk during times of high volatility. These findings must be taken with caution given that these are long-only winner portfolios of each strategy.

4.2.6 Overall assessment of risk-adjusted measures

The risk-adjusted measures indicate that traditional achieves better risk-adjusted returns during a year (2020) of high uncertainty and market volatility compared to residual momentum. However, in post-crisis years (2021-2022) residual momentum achieves better risk-adjusted returns compared to traditional momentum.

4.3 The Results of Welch's Test for Traditional Momentum and Residual Momentum

Tables 4.3 to 4.4 show the results of the Welch's t-test run on Excel. The Welch's test is run for each year of the investment period to answer objective 2: To observe if the difference in mean returns between the momentum strategies and the benchmark are statistically significant during the pre-Covid, Covid and post-Covid periods. The pre-Covid period is defined as the years 2018 and 2019; the Covid period is defined as the year 2020; and the post-Covid period is defined as the years 2021 and 2022.

Table 4.3: Welch's test between residual momentum, traditional momentum and the benchmark 2018-2022

Traditional	**2018**	**2019**	**2020**	**2021**	**2022**
Mean	-0.0563	0.143	0.082	0.088	0.085
Variance	0.00351	0.0169	0.02871	0.002	0.0103
Observations	12	12	12	12	10
DF	20	12	16	22	15
t-stat	-0.7206	2.204	1.685	-0.1777	-1.342
P(T<=t) two-tail	0.4794	0.047	0.111	0.860	0.993
t-Critical two-tail	2.0859	2.1	2.11	2.0738	2.131
FTSE/JSE Top 40					
Mean	-0.041	0.058	-0.008	0.0927	-0.0352
Variance	0.00189	0.0001	0.006	0.003	0.00355
Observations	12	12	12	12	10
Residual					
Mean	-0.006	0.120	-0.127	0.208	-0.005
Variance	0.001	0.0058	0.007	0.0103	0.0022
Observations	12	12	12	12	10
DF	22	14	22	17	17
t-stat	1.997	2.650	-3.4812	3.444	1.2424
P(T<=t) two-tail	0.058	0.019	0.002	0.003	0.230
t-Critical two-tail	2.073	2.1447	2.0738	2.1098	2.1098

2018-2022 (5-*year* horizon)

	Traditional Momentum	**FTSE/JSE Top 40**	**Residual Momentum**
Mean	0.038	0.015	0.039
Variance	0.019	0.006	0.019
Observations	58	58	58
DF	88		88
t-stat	1.178		1.141
P(T<=t) two-tail	0.2417		0.2567

Compiled by Author

- Null hypothesis: H_0 : U_{fi} = U_{f0} where U_{fi} is the mean return of the momentum portfolio and U_{f0} is the mean return of the benchmark (FTSE/JSE Top 40).

- Alternative hypothesis: H_α : U_{fi} $\not\approx U_{f0}$ where U_{fi} is the mean return of the momentum portfolio and Uf0 is the mean return of the benchmark (FTSE/JSE Top 40).

It is important to note that P(T<=t) two-tail value below 0.05, indicates that we reject the null hypothesis and conclude that there is statistical significance between the difference in mean returns of the momentum strategies and the benchmark. As observed in the above table, 2018 both traditional and residual momentum strategies have a P(T<=t) two-tail value above 0.05, which indicates that we fail to reject the null hypothesis and conclude that there is no statistically significant difference between the mean returns of both momentum strategies and the benchmark. In 2019 both momentum strategies report a statistical significance in the difference in mean returns against the benchmark as both P(T<=t) two-tail values are below the 0.05 significance level. The Covid year of 2020 traditional momentum shows the difference in mean returns that are statistically insignificant compared to the benchmark, while residual momentum mean returns indicate statistical significance against the benchmark. The post-Covid year 2021 traditional momentum produces mean returns that are not statically significant against the benchmark however residual momentum difference in mean returns continues to be statistically significant against the benchmark. In 2022, both strategies' differences in mean returns against the benchmark indicate no statistical significance against the benchmark. Table 4.3 also conducts a statistical significance test for the difference in mean returns for the entire investment horizon of five years and not just for the individual years. The difference in mean returns of both momentum strategies and the benchmark observed together over five years was not statistically significant.

The mean returns of the strategies compared to the benchmark are statistically significant in certain years, while in others they are not. For residual momentum, the strategy returns are significant for the years 2019–2021, while for traditional, the returns are only statistically significant for a single year in 2019. The fact that these returns are significant contradicts the findings of Foltice and Langer (2015) who examines the profitability of momentum strategies against the S&P 500 and finds that the returns of the various momentum portfolios have no statistical significance once compared to that of the S&P 500 at a 5% significance level, which is the level this study also uses. However, the author finds statistical significance in the strategies' returns against the S&P 500 only at 10% and 1% statistical significance levels. Marx (2016) compared the mean returns of various momentum strategies against the top 100 shares on the JSE. Marx's (2016) findings are similar to this study's in that different momentum strategies produce mean returns that are statistically significant to that of the benchmark or control portfolios in some instances but not all the time.

Table 4.4: Welch's test between residual momentum and traditional momentum 2018-2022

			Traditional		
	2018	2019	2020	2021	2022
Mean	-0.056	0.0582	-0.0083	0.0889	-0.0853
Variance	0.003	0.0008	0.0063	0.0023	0.0022
Observations	12	12	12	12	10
			Residual		
Mean	-0.007	0.1209	-0.1272	0.2082	-0.0052
Variance	0.002	0.0058	0.0076	0.0132	0.0103
Observations	12	12	12	12	10
DF	19	14	16	16	13
t-stat	2.393	2.651	-3.814	3.666	-2.25
			Statistical significance		
P(T<=t) two-tail	0.027	0.019	0.00152	0.0020	0.0422
t-Critical two-tail	2.093	2.145	2.1199	2.1199	2.1603

2018-2022	***Residual momentum***	***Traditional momentum***
Mean	0.038769381	0.014955029
Variance	0.019420814	0.005816197
Observations	58	58
DF	88	
t-stat	1.141652213	
P(T<=t) two-tail	0.256695675	
t-Critical two-tail	1.987289865	

Compiled by Author

H_0 : U_{fn} $=U_{fm}$ where U_{fn} is the mean return of the traditional momentum strategy portfolio and U_{fm} is the mean return of the residual momentum strategy portfolio.

$H_1 : U_{fn} \neq U_{fm}$ where U_{fn} is the mean of the traditional momentum strategy portfolio and U_{fm} Ufm is the mean return of the residual momentum strategy portfolio.

As stated, a value below the 0.05 P(T<=t) two-tail significance level indicates that we reject the null hypothesis and conclude that there is a statistically significant difference between the mean returns of traditional momentum and residual momentum. As indicated in Table 4.4 above, there is a statistically significant difference between the mean returns of traditional momentum and residual momentum, as the P(T<=t) two-tail for each year from 2018 to 2022 is below the 0.05 P(T<=t) two-tail significance level.

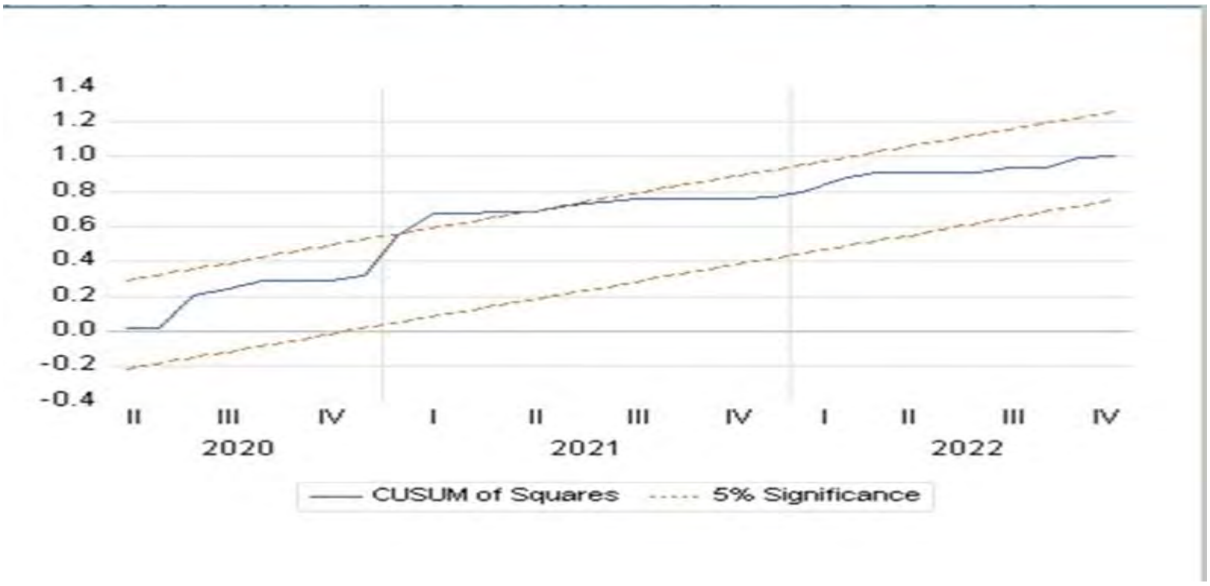
Table 4.4 also conducts a statistical significance test for the difference in mean returns for the entire investment horizon of five years and not just for the individual years. The difference in mean returns of both momentum strategies observed together over five years was not statistically significant.

The results above confirm that there is a statistically significant difference between the mean returns of both momentum strategies in the short-term, as there is a statistical significance in each year. What is interesting to note is that there is no statistically significant difference between residual momentum and traditional momentum over the accumulated five years. These results are in line with the findings of Viljoen (2016), that there is no statistical significance between the mean returns of residual and traditional momentum's winner portfolios over the long-term.

4.4 Structural Break Test of the Momentum Strategies During Covid and Post-Covid

To run the ARDL to answer objective 3 the CUSUMQ test is employed to detect structural breaks caused by the Covid-19 pandemic in the data set and account for them in the later regression model. Figure 4.1 and Figure 4.2 show the results of the test for structural breaks in traditional momentum and residual momentum respectively. Eviews is used to conduct the below test, with the dependent variable being the returns of traditional momentum and residual momentum. The independent variable within the test is volatility, which is represented by the SAVIT40, with the bull and bear markets being the dummy variables.

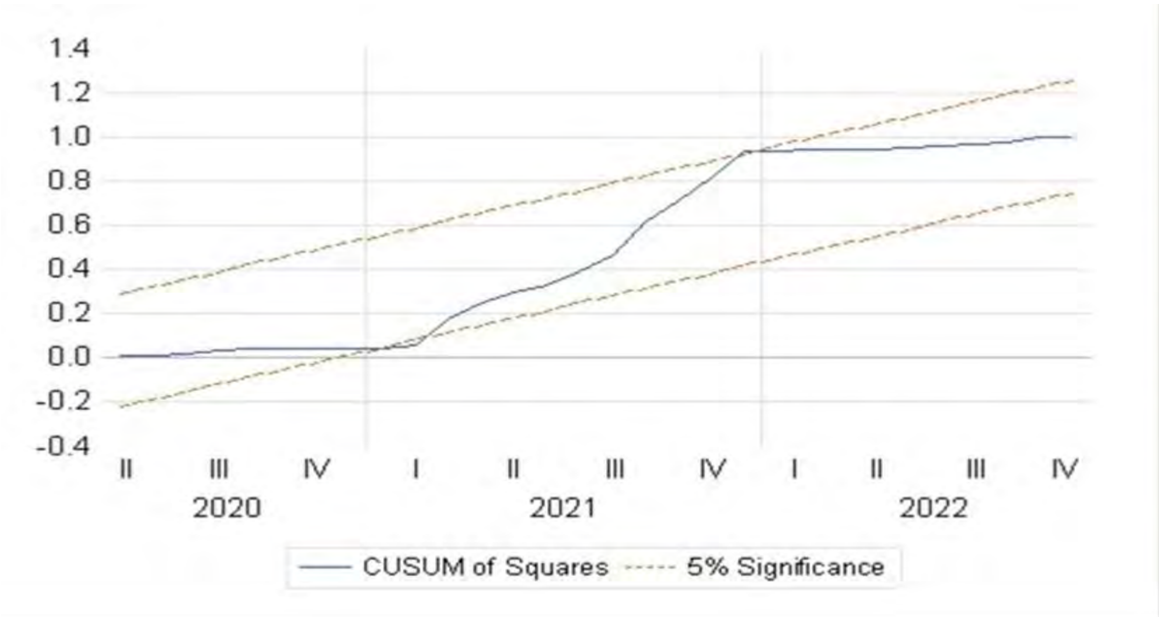
Figure 4.1: CUSUM Q test for traditional momentum



Compiled by Author

Figure 4.1 shows the CUSUM Q for traditional momentum. The model experiences structural change as reflected by the blue line statistic crossing through the 5% significance line (controlled limit) in 2020, therefore we reject the null hypothesis and conclude that there is a structural break within the dataset.

Figure 4.2: CUSUM Q test for residual momentum



Compiled by Author

Figure 4.2 shows the CUSUM Q for residual momentum. The model experiences structural change as reflected by the blue line statistic slightly crossing through the 5% significance line (controlled limit) in 2020, therefore we reject the null hypothesis and conclude that there is a structural break within the dataset/

4.5 Test for Stationarity of Variables at Level and First Difference

It is necessary to conduct unit root tests for all variables to confirm that none are integrated of order 2 or above before conducting ARDL in the pursuit to answer objective 3. Based on Table 4.5 below, tests for stationarity at level terms show mixed results. The SAVIT40 variable is observed to be stationary at a level for both the ADF and PP tests. FTSE/JSE Top 40 Returns, which is the benchmark, is observed to be stationary at level terms for both the ADF and PP. On the other hand, the traditional momentum returns variable is found to be non-stationary at level terms using the ADF but stationary when using the PP test, while the residual momentum returns variable is found to be non-stationary at level terms for both ADF and PP. The results show that at the first difference, all the variables are stationary using the ADF and PP tests.

The results from Table 4.5 imply that the data was made from a combination of I(0) and I(1) variables. Therefore, the suitable regression to use in such a scenario is the ARDL model. The ARDL model can accommodate purely I(0) or I(1) or a combination of the two. One of the advantages of the ARDL model is that it can show the relationship between variables in the short and long-run.

Table 4.5: Test for stationarity of variables at the level and first difference

Variable	***Augmented Dickey-Fuller***		***Phillips-Perron***	
	Level	First Difference	Level	First Difference
SAVIT40	0.0169***	0.000***	0.000***	0.000***
Residual Momentum Returns	0.2222***	0.000***	0.1777***	0.000***
FTSE/JSE Top 40 Returns	0.0346***	0.000***	0.0271***	0.000***
Traditional Momentum Returns	0.0517***	0.000***	0.0364***	0.000***

***/**/* depicts significance at 1%/5%/10% respectively

Compiled by Author

4.6 Short-run ARDL Regression with Residual Momentum Returns as Dependent Variable

Table 4.6: ARDL short-run estimate in the case of residual momentum

Dependent variable: Residual momentum portfolio returns			
Variable	**Coefficient**	**t-Statistic**	**Prob**.**
C	0.002040	0.234253	0.8160
Total Residual Momentum returns (-1)	-0.421212	-2.535364	0.0151
D(SAVIT40)	-0.007248	-1.930382	0.0605
D(SAVIT40)(-1)	-0.009648	-2.491143	0.0169
D(SAVIT40)(-2)	-0.0007060	-1.807934	0.0780
D(BULL_MARKET)	0.148486	3.994387	0.0003
D(BULLMARKET)(-1)	0.125621	2.125888	0.0396
D(BEAR MAKRET)	-0.132163	-2.491143	0.0169
D(BEAR MARKET)(-1)	-0.061886	-0.933964	0.3558
D(BEAR MARKET)(-2)	0.023852	0.390546	0.6982
D(BEAR MARKET)(-3)	-0.058556	-1.029911	0.3091
D(BEAR MARKET)(-4)	-0.117047	-2.285300	0.0275

R-SQUARED	0.520634	**MEAN DEPENDENT VAR**	0.000909
ADJUSTED R-SQUARED	0.392024	**S.D DEPENDENT VAR**	0.079925
S.E. OF REGRESSION	0.062320	**AKAIKE INFO CRITERION**	-2.516966
SUM OF SQUARED	0.159234	**SCHWARZ CRITERION**	-2.070862
LOG LIKELIHOOD	78.69961	**HANNAN QUINN CRITERIA**	-2.345416
F-STATISTIC	4.048152	**DURBIN-WATSON STAT**	2.098024
PROB(F-STATISTIC)	0.000493		

***/**/* depicts significance at 1%/5%/10% respectively

Compile by Author

Table 4.7: Breusch-Godfrey Serial Correlation LM test in case of residual momentum

Breusch-Godfrey Serial Correlation LM Test: Residual momentum as dependent variable			
F-Statistic	0.006942	**PROB. F(2,49)**	0.9931
OBS* R-SQUARED	0.001646	**PROB. CHI-SQUARE(2)**	0.9920

Compile by Author

The results of Table 4.6 show the short-run relationship between the dependent variable and independent variables. The results indicate that in the short-run, there is a statistically significant (0.0151) and negative association between the first lag of the dependent residual momentum returns (-1) and itself. This indicates that at first lag, residual momentum is to some degree affected by its past value.

The results indicate that SAVIT40 at first lag is a statistically significant factor and has a negative association with the residual momentum portfolio returns throughout the investment period, while at zero lags and two lags, SAVIT40 is found to be statistically insignificant and has a negative association with the residual momentum portfolio returns. A negative relationship implies that the momentum strategy tends to perform well in periods of low volatility and poorly in periods of high volatility (El Ghorayeb, 2021).

At zero lags and four lags, the bear market variable has a negative association with the returns of the strategy and is also shown to be a statistically significant factor. At first and third lags, the bear variable is statistically insignificant and negatively associated with the returns of the strategy. A negative relationship implies that the residual momentum tends to underperform during bearish periods, as investors tend to favour safer assets or defensive strategies over long-only momentum strategies that rely on positive trends. At two lags, the bear market variable is positively associated with the return of strategy, which indicates a favourable impact on strategy returns considering a time lag of two periods. However, this is shown to be statistically insignificant.

At zero and first lags, the bull market variable has a positive association with the returns of the residual momentum portfolio and is statistically significant. A positive relationship implies that residual momentum tends to perform well in a bull market.

The short-run model shows an R-squared of 0.520634, indicating the model fits the data fairly and explains the changes in residual momentum portfolio returns significantly. The short-run model also shows a Durbin-Watson statistic of 2.098024, which indicates there is no autocorrelation in the overall model. This is supported by Table 4.7 which shows the results of the Breusch-Godfrey test for serial correlation. The table shows that the likelihood of the Chi-Square statistic is 0.9920. The result exceeded the critical threshold of 0.005, allowing us to fail to reject the null hypothesis and conclude that there is no serial correlation in the model.

4.6.1 Bound test for long-run relationship in the case of residual momentum portfolio returns

The bounds test is typically employed to determine whether there is a cointegrating relationship between the variables under consideration. Cointegration implies a long-term relationship where variables move together in the long-run despite short-term fluctuations.

The bounds test also indicates the direction of the cointegrating relationship. For example, if the computed test statistic exceeds the upper bound, it suggests a positive cointegrating relationship, indicating that the variables move together in the long run.

H_0: there is no long-run relationship between variables

H_1: there is a long-run relationship between variables

Table 4.8: Bound Test for long-run relationship

F-statistic = 18.77959		
Level Significance	**I(0)**	**I(1)**
10%	2.72	3.77
5%	3.23	4.35
2.5%	3.69	4.89
1%	4.29	5.61

Source: Author

The results above show the F-statistic of 18.77959 is greater than the upper bound I(1) at all significant levels. This provides evidence that we reject the null hypothesis, accept the alternative hypothesis and conclude that this is a long-run and positive relationship between the variables.

4.6.2 ECM regression model

Table 4.9: ECM regression

ECM Regression			
Variable	**Coefficient**	**t-Statistic**	**Prob.**
C	0.002040	0.246500	0.8065
D(DIFFSAVI)	-0.007248	-3.050118	0.0040
D(DIFFSAVI(-1))	0.007060	2.351673	0.0236
D(DIFFBEAR)	-0.1321163	-2.868373	0.0065
D(DIFFBEAR(-1))	0.151750	2.465850	0.0179
D(DIFFBEAR(-2))	0.175602	0.053850	0.0022
D(DIFFBEAR(-3))	0.117047	0.040603	0.0063
D(DIFFBULL)	0.148486	0.023067	0.0000
ECM (-1)	-1.421212	0.158289	0.0000

Source: Author

The coefficient on the lagged error-correction component is statistically significant in the context of residual momentum returns, hence confirming the findings of the bound test for cointegration. The forecasted value of the error-correction term is -1.421212, which represents the speed at which the system returns to equilibrium after a disturbance. The high rate of adjustment implies the model predicts that residual momentum will overshoot its short-term equilibrium before oscillating and eventually converging toward its long-term equilibrium this suggests the model is overreacting to changes in the independent variables of volatility, bull and bear. Furthermore, the ECM coefficient exceeding 1 indicates that instead of monotonically converging to the equilibrium, the error correction process fluctuates around the long run value in a dampening manner this process is called oscillating convergence (Narayan and Smyth,2006).

4.7 Short-run ARDL Regression with Traditional Momentum Returns as a Dependent Variable

Table 4.10: ARDL short-run estimate in the case of Traditional momentum

Dependent Variable: Traditional momentum portfolio returns			
Variable	**Coefficient**	**t-Statistic**	**Prob*****
C	0.0099572	0.845774	0.4028
Total Traditional momentum returns _(-1)	-0.414613	-2.379923	0.0223
Total Traditional momentum returns _(-2)	-0.299911	-1.743466	0.0891
Total Traditional momentum returns _(-3)	-0.562052	-3.300453	0.0021
Total Traditional momentum returns _(-4)	-0.195277	-1402497	0.1687
D(SAVIT40)	-0.014612	-2.702798	0.0101
D(SAVIT40)(-1)	-0.024339	-3.533226	0.0011
D(SAVIT40)(-2)	-0.023655	-3.34162	0.0018
D(SAVIT40)(-3)	-0.014111	-2.823763	0.0074
D(BULL_MARKET)	-0.005157	-0.110665	0.9124
D(BEAR_MARKET)	-0.072438	-1.086950	0.2837
D(BEAR_MARKET)(-1)	0.025727	4.868753	0.7585
D(BEAR_MARKET)(-2)	0.406400	4.868753	0.0000
D(BEAR_MARKET)(-3)	0.169450	1.728750	0.0918

R-SQUARED	0.566116	**MEAN DEPENDENT VAR**	0.000658
ADJUSTED R-SQUARED	0.421488	**S.D DEPENDENT VAR**	0.105775
S.E. OF REGRESSION	0.080452	**AKAIKE INFO CRITERION**	-1.980731
SUM OF SQUARED	0.252431	**SCHWARZ CRITERION**	-1.460276
LOG LIKELIHOOD	66.48937	**HANNAN QUINN CRITERIA**	-1.780589
F-STATISTIC	3.814280	**DURBIN-WATSON STAT**	1.841086
PROB(F-STATISTIC)			

***/**/* depicts significance at 1%/5%/10% respectively

Compiled by Author

Table 4.11: Breusch-Godfrey Serial Correlation LM test in case of traditional momentum

Breusch-Godfrey Serial Correlation LM Test: Traditional momentum as dependent variable			
F-Statistic	0.985156	**PROB. F(2,49)**	0.3807
OBS* R-SQUARED	2.203396	**PROB. CHI-SQUARE(2)**	0.3323

Compiled by Author

The results of Table 4.9 show the short-run relationship between the dependent variable and independent variables. The results indicate that in the short-run, there is a statistically significant and negative association between the lags of the dependent traditional momentum returns (-1) and traditional momentum returns (-3). The results indicate that in the short-run, there is a statistically insignificant and negative association between the lags of the dependent traditional momentum returns (-2) and traditional momentum returns (-4). A negative association indicates some form of mean reverting behaviour within the strategy, implying that the strategy could experience periods of strong performance that are followed by corrections or reversals in subsequent periods. It could also indicate an overreaction within the market, which will be followed by a correction.

The results indicate that SAVIT40 at four lags is a statistically significant factor and has a negative association with the residual momentum portfolio returns throughout the investment period. A negative relationship implies that the momentum strategy tends to perform well in periods of low volatility and poorly in periods of high volatility (El Ghorayeb, 2021).

At zero lags, the bear market variable has a negative association with the returns of the strategy and is also shown to be a statistically insignificant factor. At first and third lags, the bear variable is statistically insignificant and positively associated with the returns of the strategy. A negative relationship implies that residual momentum tends to underperform during bearish periods, as investors tend to favour safer assets or defensive strategies over long-only momentum strategies that rely on positive trends. At two lags, the bear market variable is positively associated with the return of strategy, which indicates a favourable impact on strategy returns considering a time lag of two periods. This is shown to be statistically insignificant. At zero and first lags, the bull market variable has a negative association with the returns of the traditional momentum portfolio and is statistically insignificant. The short-run model shows an R-squared of 0.566166, indicating the model fits the data fairly and explains the changes in the traditional momentum portfolio returns significantly. The short-run model also shows a Durbin-Watson statistic of 1.841086, which indicates there is no autocorrelation in the overall model. This is further supported by table 4.11 which shows the Breusch-Godfrey Serial Correlation LM test in case of traditional momentum. According to table 4.11 a Prob. Chi-square value of 0.3323 is reported which is above the critical value of 0.005, which indicates that we fail to reject the null hypothesis and conclude that there is no serial correlation within the model.

4.7.1 Bound test for longrun relationship in the case of traditional momentum portfolio returns

H_0: there is no long-run relationship between variables

H_1: there is a long-run relationship between variables

Table 4.12: Bound Test for long-run relationship

F-statistic = 8.6349353		
Level Significance	**I(0)**	**I(1)**
10%	2.72	3.77
5%	3.23	4.35
2.5%	3.69	4.86
1%	4.29	5.61

Compiled by Author

The results above show that the F-statistic of 8.6349353 is greater than our upper bound I(1) at all significant levels. This provides evidence that we reject the null hypothesis, accept the alternative hypothesis and conclude that there is a long-run and positive relationship between the variables.

4.7.2 ECM regression model

Table 4.13: ECM regression

ECM Regression			
Variable	**Coefficient**	**t-Statistic**	**Prob.**
C	0.009572	0.893289	0.3772
D(DIFFTRAD(-1))	1.057240	3.391644	0.0016
D(DIFFTRAD(-2))	0.757329	3.210036	0.0027
D(DIFFTRAD(-3))	0.195277	1.534872	0.1329
D(DIFFSAVI)	-0.014612	-3.473231	0.0013
D(DIFFSAVI(-1))	0.037767	4.350265	0.0001
D(DIFFSAVI(-2))	0.01411	3.34146	0.0018
D(DIFFBEAR)	-0.072438	-1.259092	0.2155
D(DIFFBEAR(-1))	-0.575850	-5.157792	0.0000
D(DIFFBEAR(-2))	-0.169450	-1.910104	0.0635
ECM (-1)	-2.471853	-6.103995	0.0000

Compiled by Author

The coefficient on the lagged error-correction component is statistically significant in the context of traditional momentum returns, hence confirming the findings of the bound test for cointegration. The forecasted value of the error-correction term is -2.471853, which represents the speed at which the system returns to equilibrium after a disturbance. In a study by Loayza and Ranciere(2005)the authors found an error correction term of -2.36 similar to the one found in this study. Loayza and Ranciere (2005) argued that An error-correction term below -2, suggests dynamic instability within the model, this implies that the error-correction model has limitation in its ability to capture the short-term effects of the variables (volatility, bull and bear) on the long run performance of traditional momentum.

4.8 Discussion of ARDL regression for both momentum strategies

Kaluba (2020) conducts a study to test whether market volatility and market state can be explainers for varying momentum profits on the JSE. The author finds that volatility measured with the SAVI 40 as a proxy regressed against momentum strategy returns and proves to be a "bad explainer" for momentum returns. In another study by Viljoen (2016) that also tests momentum returns against volatility, the author finds a negative relationship to volatility. Volatility in this study is used as a proxy for market conditions as stated by research objective three – this study also finds a negative and significant relationship to exist between volatility measured by the SAVIT40 and the returns of traditional momentum; however, an insignificant relationship exists between volatility and the returns of residual momentum. This study uses volatility as a proxy for market conditions and the findings could imply that residual momentum strategies are agnostic to market volatility, while traditional momentum strategies returns are influenced to some degree by market volatility. These findings are in line with Viljoen (2016), who concludes that traditional momentum returns are aligned with market volatility within the JSE, while residual momentum returns are shown to not be influenced by market volatility within the JSE.

In Kaluba's (2020) aforementioned study, the author examines the market state as an explanatory variable for the market returns of momentum strategies on the JSE. The author of this work does a regression analysis to examine the impact of market conditions. According to Kaluba (2020), an upstate is characterised by a market that has seen 36 consecutive months of positive performance. Conversely, the author defines a market as being in a downstate if it does not meet this criterion. In the conducted regression analysis, the author discovers that the market state exhibits a low R-squared value and is statistically insignificant when applied to different momentum portfolios. In this study, the market state is characterised by bull and bear market variables. The bull market variable is characterised by a 20% increase on the JSE Top 40, whereas the bear market is characterised by a 20% decrease on the JSE Top 40.

Similar to Kaluba (2020), our analysis unveils the existence of a non-significant inverse relationship between traditional returns and bull and bear characteristics at zero lags. These results indicate that investors who use conventional momentum methods may need to consider other variables outside market fluctuations as explainers of traditional momentum returns. It is only at two lags that traditional momentum has a positive relationship with the bear variable explaining 40% of the traditional momentum return and having statistical significance.

At zero lags, residual momentum returns are shown to have a statistically significant and negative relationship with the bear market variable; however, the bull market variable is shown to have a statistical significance and a positive relationship with residual momentum returns. This finding collaborates with the findings of Viljoen (2016) who instead uses the consumer sentiment index as a gauge to measure market conditions on the JSE. The author observes that market sentiment influences the returns of residual momentum strategies. This suggests that a 20% increase or decrease in the JSE would promptly impact the returns of residual momentum portfolios, whereas it would not affect the returns of traditional momentum portfolios. The presence of a bear or bull market has little impact on the returns of residual momentum since the dummy variables (bull and bear) explain for less than 20% of the returns of residual momentum. Hence, it may be inferred that the success of residual momentum portfolios is mostly influenced by variables unrelated to market conditions.

4.8 Monte Carlo Simulation on Momentum Strategies

The Monte Carlo simulation presented in this section looks at how momentum strategies might perform under different market conditions – bull and bear market conditions and volatile market conditions. One thousand simulations of each condition are examined to test how well the strategy performs against the benchmark as well as against each other. This test is conducted to answer objective 3, which aims to test the persistence of traditional momentum and residual momentum under different market conditions that existed the pre- and post-Covid as well as during the Covid crisis period.

Table 4.14: Monte Carlo bear market simulation

Monte Carlo: Bear Market Simulation	
Average Return: Residual Momentum	-18%
Average Return: Traditional Momentum	-10%
Average Return: FTSE/JSE	-9%
Volatility: Residual Momentum	8%
Volatility: Traditional	10%
Volatility: FTSE/JSE Top 40	6%
Prob. Residual > FTSE/JSE Top 40	21%
Prob. Traditional > FTSE/JSE Top 40	51%
Prob. Residual > Traditional	26%

Compiled by Author

The bear market simulation took into consideration the flash bear market that happened from February 2020 to May 2020. According to the Monte Carlo simulation run, a mean return of -18% can be achieved by residual momentum; a mean return of -10% for traditional momentum and a mean return of -9% for the benchmark. There is volatility of 8%, 10% and 6% for residual momentum, traditional momentum and the benchmark, respectively. The probability of a long-only residual momentum strategy outperforming the benchmark given the condition of the flash bear crash is 26%, while the probability of a long-only traditional momentum strategy outperforming the benchmark is 51%. The probability of a long-only residual momentum portfolio outperforming a long-only traditional momentum portfolio is 26%.

It is safe to conclude that the Monte Carlo predicts that during a flash bear crash, the benchmark (FTSE/JSE Top 40) will outperform both strategies, with traditional momentum performing better than residual momentum. There is about a 50-50 chance for traditional momentum to outperform the benchmark and a small chance for residual momentum to outperform the benchmark. Overall, according to the Monte Carlo simulation during such a crisis, a long-only residual momentum is the worst performing. This contradicts the study of Blitz et al (2011) who argues that residual momentum returns will be less negative than those of traditional momentum in times of market crisis; however, Blitz et al (2011) is correct in arguing that the residual momentum strategy will be less volatile than traditional momentum in times of economic crisis, which is the finding of the Monte Carlo simulation run with the bear variable. It must be noted overall that the referenced study of Blitz et al (2011) looks at these strategies in the context of long and short which is not the case in this study which looked at long-only momentum portfolios.

Table 4.15: Monte Carlo bull market simulation

Monte Carlo: Bull Market Simulation	
Average Return: Residual Momentum	20%
Average Return: Traditional Momentum	11%
Average Return: FTSE/JSE	9%
Volatility: Residual Momentum	11%
Volatility: Traditional	5%
Volatility: FTSE/JSE Top 40	6%
Prob. Residual > FTSE/JSE Top 40	82%
Prob. Traditional > FTSE/JSE Top 40	71%
Prob. Residual > Traditional	84%

Compiled by Author

The bull simulation took into consideration the bull market rally within the JSE Top 40 in 2021, where the JSE returns about 22%. The results from the simulation indicate that the mean return for long-only residual momentum is 20%, while the mean return for the benchmark is 9% and the long-only traditional momentum portfolio is 11%. There is volatility of 11%, 5% and 6% for residual momentum, traditional momentum and the benchmark, respectively. The probability of a long-only residual momentum strategy outperforming the benchmark given the condition of the bull market rally is 82%, while the probability of a long-only traditional momentum strategy outperforming the benchmark is 71%. The probability of a long-only residual momentum portfolio outperforming a long-only traditional momentum portfolio is 84%.

The 2021 period in the context of this study represents a period of recovery. Daniel and Moskowitz (2016) argue that during times of economic recovery traditional momentum tends to return negatively due to high negative betas; however, the Monte Carlo simulation in this study finds that traditional momentum is not negative during the recovery period, since the study does not consider the short portfolio. The above results confirm the findings of Viljoen (2016) within the JSE, who concludes that residual momentum tends to outperform traditional momentum following a pessimistic formation period and one can classify the year 2020 as a pessimistic period for portfolio formation.

Table 4.16: Monte Carlo high volatility simulation

Monte Carlo: High Volatility Simulation	
Average Return: Residual Momentum	-13%
Average Return: Traditional Momentum	8%
Average Return: FTSE/JSE	-0.0071%
Volatility: Residual Momentum	9%
Volatility: Traditional	17%
Volatility: FTSE/JSE Top 40	0.0826%
Prob. Residual > FTSE/JSE Top 40	8%
Prob. Traditional > FTSE/JSE Top 40	70%
Prob. Residual > Traditional	14%

Compiled by Author

The year 2020 was a year of high volatility within the JSE market, where we see the SAVI Top 40 record its highest average volatility since the 2008 financial crisis at 37. The results indicate that a long-only residual momentum portfolio would achieve the mean return of - 13%, while a long-only traditional momentum portfolio would achieve the highest mean return of 8%. The benchmark would achieve a mean return of -0.0071%. The probability of a long-only residual momentum outperforming the benchmark under the circumstances experienced in 2020 would be 8%, while there is a 70% chance of a long-only traditional momentum portfolio outperforming the benchmark. A 14% probability is estimated for a long-only residual momentum strategy outperforming a long-only traditional momentum strategy. The volatility estimated is 8%, 10% and 6% for residual momentum, traditional momentum and the benchmark, respectively.

Venturato (2018) runs Monte Carlo simulations for momentum portfolios instead of using past stock prices as signals for investments. The author's positions are made based on forecast estimations of asset prices. The forecasts are based on a dynamic linear representation of the Farma-French-three-factor model. The author constructs portfolios with different rebalancing regimes. The rebalancing regimes range from three days to five days to seven days to ten days. The author also constructs portfolios with two stocks as well as one with 10. For this discussion, we will focus on the findings of his ten-day-stock portfolio. The author runs simulations from 1997 until 2017. In the author's observation, 2008 stands out as one of high volatility. During 2008, the portfolios all return above the benchmark in their study of the S&P 500. This might seem to contradict the findings of the Monte Carlo simulation run in this study, which shows residual momentum underperforming the benchmark during times of high volatility. Venturato (2018) concedes that, because of his frequent multi-day rebalancing regime in his portfolios, if trading costs are to be accounted for, his residual momentum portfolios would return negative, in line with the Monte Carlo simulations run in this study for residual momentum in times of volatility. The negative return for residual momentum inferred by the Monte Carlo simulation confirms the findings of Santoso (2021), who looks at residual momentum during Covid-19 in Indonesia and finds residual to also have a negative return as well as underperforming on the Indonesian stock market index. Santoso (2021) find absolute momentum to outperform residual momentum during this period, confirming the findings of the Monte Carlo simulation in this study.

El Ghorayeb (2021) also looks at the returns of traditional momentum using the WML portfolio during the Covid period which had a bear crash. El Ghorayeb (2021) observes extreme volatility in his portfolio over this period in line with the volatility of 17% for traditional momentum simulated by the Monte Carlo run in this stady. El Ghorayeb (2021) reports the WML momentum strategy to underperform the benchmark S&P 500 during this period, however, the long-only-winner portfolio similar to the one observed in this study outperforms the benchmark during this period in line with inferences made by the Monte Carlo simulation run in this study.

4.9 Conclusion

This chapter presented the findings of the measures implemented to answer the research objectives. Addressing objective 1 by investigating the profitability of momentum strategies compared to the South African FTSE/JSE Top 40 during the pre-and post-Covid as well as during the Covid crisis period. The study looked at the simple annualised returns of both momentum strategies and found that during a year of high market volatility and uncertainty, a long-only traditional momentum strategy outperforms a long-only residual momentum portfolio. Addressing objective 1 by investigating the risk-adjusted performance of both momentum strategies compared to the South African FTSE/JSE Top 40 during the pre-and post-Covid as well as during the Covid crisis period. The study used risk measures, namely:

tracking error, Sharpe ratio, IR and Jensen's Alpha. The risk-adjusted measures indicate that traditional achieves better risk-adjusted returns during a year (2020) of high uncertainty and market volatility compared to residual momentum. However, in post-crisis years (2021-2022) residual momentum achieves better risk-adjusted returns compared to traditional momentum.

The Welch's test was conducted to answer objective 2 by investigating if the difference in mean returns between the momentum strategies and the benchmark are statistically significant during the pre-Covid, Covid and post-Covid periods. Welch's test revealed that for residual momentum, the strategy returns are significant for the years 2019–2021, while for traditional, the returns are only statistically significant for a single year in 2019. The fact that these returns are significant contradicts the findings of Foltice and Langer (2015) but supports the findings of Marx (2016).

The ARDL and Monte Carlo simulation were used in the study to address objective 3 by investigating the persistence of traditional momentum and residual momentum under different market conditions that existed pre-and post-Covid as well as during the Covid crisis period. These conditions include a bear market, a bull market and high volatility. The ARDL regression results show the volatility variable to be mostly negatively associated with the returns of both momentum strategies. The bull variable for traditional momentum is both negative and insignificant, while at zero and first lags the bull variable for residual momentum show a positive association and is statically significant. The bear variable is only positively associated with the returns of the traditional momentum at two lags and found to be significant. For residual momentum, the bear variable at two lags is positively associated but is statistically insignificant. The regression findings indicates difficulty in finding causal relationships between market conditions volatility bull and bear and the returns of both traditional and residual momentum.

The Monte Carlo reveals that a long-only traditional momentum strategy will have a higher probability of outperforming the benchmark and a long-only residual momentum strategy during periods of high market volatility and a bear market. However, a long-only residual momentum strategy would have a higher probability of outperforming the benchmark and long-only traditional momentum, in a bull market following a pessimistic formation period like experienced in 2021.

CHAPTER 5: KEY FINDINGS, RECOMMENDATIONS AND CONCLUSION

5.1 Achievement of Research Objectives

The study set out to achieve three research objectives. The first was to analyse the profitability and risk-adjusted returns of momentum strategies during times of financial crisis on the JSE. The study uses four risk-adjusted return measures to do this, which was done to mitigate the shortcomings of a single risk-adjusted measure. The tracking error measure shows traditional momentum to be more volatile than residual momentum. The higher Sharpe ratio for the traditional momentum portfolio shows overall that the investors in traditional momentum are better compensated for the amount of portfolio risk they assume, considering that traditional momentum, according to generally accepted literature, is considered riskier than residual momentum. The findings of the Sharpe ratio confirm the work of Viljoen (2016), who concludes that a long-only traditional momentum portfolio has a better sharp ratio than a long-only residual momentum portfolio. The information ratios achieved by both traditional and residual momentum in this study show residual momentum to have a higher excess return above the benchmark than traditional momentum. Throughout the investment period, in the context of Jensen's alpha, there is a notable difference in the performance of residual momentum compared to traditional momentum. Residual momentum generally outperforms traditional momentum, as evidenced by its superior Jensen's alpha in the years 2018, 2021 and 2022. However, during the Covid-flash bear crash, the tables turn, and traditional momentum exhibits a stronger Jensen's alpha compared to residual momentum. Based on the analysis, it can be inferred that a long-only residual momentum strategy carries more portfolio risk, as evidenced by the lower Sharpe ratio. However, it is also capable of generating higher excess returns given the market risk its exposed to, as indicated by the higher Jensen's alpha achieved in three out of the five years examined in the study.

The second objective was to analyse the statistical significance of the difference in mean returns between the momentum strategies and the benchmark. Welch's test was used to answer the objective and it reveals there is statistical significance in the difference in mean returns of the benchmark and residual momentum strategy during the Covid period. It appears that the Fama-French three-factors model played a role in the strategy's underperformance compared to the benchmark, as the average returns of long-only residual momentum show a negative trend. This indicates that the portfolio selection criteria used by the residual momentum strategy is not proven beneficial during this particular period. However, the difference in the mean returns of traditional momentum and the benchmark shows no statistical significance during the Covid period of 2020. During the Covid period, the difference in mean returns of traditional momentum and residual momentum shows statistical significance. Overall, the results indicate that long-only traditional momentum may be a more effective strategy to employ than long-only residual momentum, especially during periods of crisis.

The third objective was to analyse the effect of market conditions such as bear market, bull market and high volatility on the performance of both momentum strategies. The ARDL reveals that a negative and significant relationship exists between volatility measured by the SAVIT 40 and the returns of traditional momentum, however, an insignificant relationship exists between volatility and the returns of residual momentum. The findings could imply that residual momentum strategies are agnostic to market volatility, while traditional momentum strategies returns are influenced to some degree by market volatility. The study finds a non-significant inverse relationship between traditional momentum returns and bull and bear characteristics, suggesting that traditional momentum returns do not show a significant association with market conditions without any time lag. Traditional momentum returns are positively influenced by past bear market conditions, accounting for 40% of their return at two lags. Residual momentum returns have a statistically significant and negative relationship with bear market conditions, indicating that they are influenced by bear market conditions without any time lag. However, at zero lags, residual momentum returns are positively associated with current bull market conditions. The findings suggest that both traditional and residual momentum returns are influenced by market conditions, but they respond differently to bull and bear markets.

The Monte Carlo simulation presented herein looks at how momentum strategies might perform under different market conditions. The Monte Carlo simulation predicts that during a flash bear crash, the benchmark (FTSE/JSE Top 40) will outperform both strategies, with traditional momentum performing better than residual momentum. When the market transitions from a pessimistic period into an optimistic bull market, Monte Carlo predicts that residual momentum would perform better out of the two momentum strategies. In 2020, the JSE market experienced high volatility, with the SAVIT40 recording its highest average volatility since the

2008 financial crisis. The results suggest that a long-only residual momentum portfolio would achieve the lowest mean return compared to a long-only traditional momentum strategy.

5.2 Contribution to Theory and Practice

Momentum on the JSE has been explored by various other researchers such as Marx (2016), who looks at industrial momentum on the JSE. Chan, Hameed and Tong (2000), as well as Dittberner (2016), compare traditional momentum against passive portfolios and Viljoen (2016) looks at residual momentum on the JSE. Viljoen (2016) studies long-short residual momentum against traditional momentum portfolios but when it comes to observing the Sharpe ratio, he finds it prudent to only examine the Sharpe ratios of long-only winner traditional momentum against long-only winner residual momentum – he finds that traditional momentum achieves a better Sharpe ratio than residual momentum. However, Viljoen (2016) stops at the Sharpe ratio as far as risk-adjusted measures are concerned. This study goes further by exploring other risk-adjusted measures so as not to subject the findings to the shortcomings of a single risk-adjusted measure. This study also adds to the literature on the behaviour of momentum strategies during times of crisis. Viljoen (2016) looks at the performance of residual momentum and traditional momentum using the WML approach in 2008. His findings are in line with those discovered by other researchers who look at WML momentum during crises around the world, such as Blitz et al. (2011) and Daniel and Moskowitz (2016). This study, instead of trying to replicate what is already established about how WML momentum portfolios perform during times of crisis, looks at long-only winner portfolios to see if the outcome might be different if the effect of the loser portfolio is not accounted for. The idea to use the long-only winner portfolio is based on the study of Manigault (2017), who concludes that the long-only momentum strategy outperforms the WML momentum in terms of performance and Sharpe ratio. Another study that looks at momentum on the JSE is that of Kaluba (2020), who does not look at residual momentum but only traditional momentum. He tries to establish whether volatility and market state drive momentum returns. Kaluba (2020) defines upstate as six months of consistent positive returns and downstate as having the past six months as negative. The conclusions for the market state in Kaluba (2020) are that the market state does not have statistical significance across all the momentum portfolios in his research. This study defines the market state slightly differently than Kaluba (2020). In this study, the market state is defined by the bull and bear variables, which are categorised as a 20% upward swing for the bull and a 20% downward swing for the bear market. This study does not just stop at running a regression to test the relationship between state and momentum returns but runs a Monte

Carlo simulation with both bull and bear variables. This allows the study to have a thousand iterations of each variable to test how well these strategies would do under these market states. The Monte Carlo predicts residual as the strategy that would achieve better returns compared to traditional momentum during the bull run that happened in 2021 and better returns than the benchmark. When running the Monte Carlo with the bear variable, it was predicted that traditional would outperform both residual and the benchmark. This also applies when running the Monte Carlo with the volatility variable; traditional performed better in this case too. The Monte Carlo simulations discussed earlier draw much clearer conclusions as to what potential effect market states might have on the returns of momentum on the JSE.

The contribution to practice this research makes is that it allows investors to consider the long-only-winner portfolio approach to momentum investing during times of adverse market conditions like the ones experienced during Covid-19 and the recovery period following Covid-19. This approach could potentially mitigate against the trading costs associated with the WML approach, which involves "shorting" as well as the tax implications of constant portfolio rebalancing, thus offering a unique perspective on momentum investing. This study only pursued rebalancing every 12 months instead of the frequent rebalancing strategies inherent in time-varying momentum. Venturato (2018) acknowledges the potential negative impact of constant rebalancing on momentum strategies. Despite the outperformance of residual momentum portfolios during the 2008 financial crisis, accounting for trading costs could have resulted in a negative return for the portfolio. Venturato (2018) pursues an aggressive rebalancing regime of three, five, seven and 10 days.

5.3 Limitations and Recommendations

The obvious limitation of the study is that it only looks at a short time frame to reach its conclusions about the potential performance of momentum strategies during different market conditions – and this limits the study's ability to form an accurate view of the behaviour and performance of long-only winner portfolios under these market conditions. The study pursues a 12-month rebalancing regime which according to accepted theory is more cost efficient due to lower transactional costs compared to a more aggressive rebalancing regime. The study does not however consider transactional costs in the calculation of the returns achieved by the momentum strategies even with this conservative regime in place. Lastly, the study does not take into account shorting the loser portfolio in any of the momentum strategies which could have altered the behaviour of both residual and traditional momentum.

5.3.1 Recommendations

The period chosen for this study is one of a Covid-fuelled flash bear crash. This chosen period updates various literature on the behaviour of momentum on the JSE during times of economic crisis. Viljoen (2016) looks through the 2008 crisis period, but it is not the focus of his research. Kaluba 2020 also looks through 2008 and their findings are in line with the work of Daniel and Moskowitz (2016) about the behaviour of momentum during times of crisis. Future researchers should conduct a longer-ranging back test investigation into the performance of residual and traditional long-only-winner momentum portfolios during times of economic crisis, such as those that existed on the JSE in the years 1974, 1987, 1998 and 2008, to add to this work which only looks through the Covid-fuelled financial crisis. It is also recommended to compare the performance of the winner-only approach used by this study against the widely accepted WML approach when conducting the longer-ranging back test during times of economic crisis within the JSE.

5.3.2 Recommendations for practice

The year 2020 was a year of high volatility and had a 20% market decline in March. During this period, traditional winner-long-only portfolios achieved better risk-adjusted measures in the Sharpe ratio, Jensen's alpha and IR as well as a high positive tracking error, meaning investors in this approach were well compensated from a risk-return perspective. However, in 2021, which is categorised as one of recovery and a bull run, a 22% upside was enjoyed by investors on the JSE. It was the residual winner-long-only portfolio that achieved the best risk-adjusted returns of the two strategies all around. From this outcome, it can be argued that if investors want a better risk-adjusted return during times of crisis, then the traditional momentum portfolio is better, and equally it can be argued that during times of recovery, investors are better off investing in the residual long-only momentum portfolio. However, without a comprehensive study analysing the performance of traditional and residual winner-long-only approaches during various crisis periods, it would be prudent for investors to refrain from adopting the long-only approach until additional research is conducted.

References

Abbes, M., Boujelbene, Y. and Bouri, A., 2009. Overconfidence bias: Explanation of market anomalies French market case. *Journal of Applied Economic Sciences*, 7, pp.12–25.

Aderibige, A., 2014. A term paper on Monte Carlo analysis/simulation. *Department of Electrical and Electronic Engineering.* Faculty of Technology. University of Ibadan

Affleck-Graves, J.P. and Money, A.H., 1975. A note on the random walk model and South African share prices. *South African Journal of Economics*, 43(3), pp.232-236.

Agyei-Ampomah, S., 2007. The post-cost profitability of momentum trading strategies: further evidence from the UK. *European Financial Management*, 13(4), pp.776-802

Ahmed, P. and Beck, K., 2016. Financial impact of green rankings in Newsweek. *International Research Journal of Applied Finance*, 6, pp.1163–1173.

Aliyu, A.A. et al., 2014). Positivist and non-positivist paradigm in social science research: Conflicting paradigms or perfect partners? *Journal of Management and Sustainability*, 4(3).

Antoniou, C., Doukas, J.A. and Subrahmanyam, A., 2013. Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis*, 48(1), pp.245–275.

Amenc, N. and Le Sourd, V., 2005. *Portfolio theory and performance analysis*. London: John Wiley & Sons.

Auret, C. and Page, D., 2013. Momentum and liquidity on the Johannesburg stock exchange. *International Journal of Economics and Finance Studies,* 5, pp.1309–8055.

Asness, C., Tobias, S., Moskowitz, J. and Pedersen, L.H., 2013. Value and momentum everywhere. *The Journal of Finance*, 68(3), pp.929–985.

Baldridge, R. and Curry, B., 2023. *Understanding the Sharpe ratio*. Available at: https://www.forbes.com/advisor/investing/sharpe-ratio/ [Accessed 10 December 2023].

Baltas, N. and Kosowski, R., 2013. Momentum strategies in futures markets and trend-following funds. *Available at SSRN:* http://dx.doi.org/10.2139/ssrn.1968996 [Accessed 4 Sept. 2024]

Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), pp.3–18.

Barberis, N., Shleifer, A. and Vishny, R., 1998. A model of investor sentiment. *Journal of Financial Economics,* 49(3), pp.307–343.

Bekaert, G. and Harvey, C.R., 2002. Research in emerging markets finance: looking to the future. *Emerging Markets Review*, 3(4), pp.429–448.

Bonga-Bonga, L., 2012. The evolving efficiency of the South African stock exchange. *International Business & Economics Research Journal*, 11(9), pp.997–1002.

Blitz, D., Huij, J. and Martens, M., 2011. Residual momentum. *Journal of Empirical Finance*, 18(3), pp.506–521.

Bloomberg.com., 2023. *Top40 quote - FTSE/JSE Africa top40 tradeable index*. Available at: https://www.bloomberg.com/quote/TOP40:IND?embedded-checkout=true> [Accessed 8 November 2023].

Breeden, D.T., 1979. An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of financial Economics*, 7(3), pp.265–296.

Bojesen, M., 2020. Time series momentum implemented: Testing the performance of long-only momentum strategies from a perspective of an individual investor, accounting for strategy costs (Masters Dissertation) pp.1-79.

Chan, K., Hameed, A. and Tong, W., 2000. Profitability of momentum strategies in the international equity markets. *The Journal of Financial and Quantitative Analysis*, 35(2), pp.153–172.

Chang, R.P., Ko, K.C., Nakano, S. and Rhee, S.G., 2017. Residual momentum in Japan. *Journal of Empirical Finance*, 45, pp.283–299.

Chordia, T. and Shivakumar, L., 2006. Earnings and price momentum. *Journal of financial economics*, *80*(3), pp.627-656.

Corporate Finance Institute., 2023. *Backtesting*. Available at: https://corporatefinanceinstitute.com/resources/data-science/backtesting/ [Accessed 10 December 2023].

Cramer, D. and Howitt, D.L., 2004. *The Sage dictionary of statistics: a practical resource for students in the social sciences*. Sage.

Daniel, K. and Moskowitz, T.J., 2016. Momentum crashes. *Journal of Financial Economics*, 122(2), pp.221–247.

Dabengwa, V.N., 2017. The financial effect of cross listing on Sub-Saharan African exchanges for Johannesburg Stock Exchange,(JSE), listed companies (Doctoral dissertation), pp. 1-10.

De Backer, U. and Frömmel, M., 2016. *Momentum Crashes in Europe* (Doctoral dissertation, GHENT UNIVERSITY).

Dias, Rui & Heliodoro, Paula & Teixeira, Nuno & Godinho, Teresa.,2020. Testing the Weak Form of Efficient Market Hypothesis: Empirical Evidence from Equity Markets. *International Journal of Accounting, Finance and Risk Management*, pp. 40-51.

Dimson, E. and Mussavian, M., 1998. A brief history of market efficiency. *European Financial Management*, 4(1), pp.91–103.

Dittberner, A.G., 2016. *Fundamental momentum: a new approach to investment analysis.* PhD Thesis. University of Pretoria.

Dittmar, R.F., Kaul, G. and Lei, Q., 2007. Momentum is not an anomaly. *Ann Arbor*, pp.1–40.

Dowd, K., 1999. A value at risk approach to risk-return analysis. *Journal of Portfolio Management,* 25(4) pp. 60–67.

El Ghorayeb, A.A., 2021. *Trading performance in a financial crisis: momentum and the Covid-19 flash bear market.* Master's thesis. LUISS.

El-Hassan, N. and Kofman, P., 2003. Tracking error and active portfolio management. *Australian Journal of Management*, 28(2), pp.183–207.

Fama, E.F., 1991. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), p.383.

Fama, E.F. and French, K.R., 1993. The cross-section of expected stock returns. *The Journal of Finance*, 47(2), pp.427–465.

Fama, E.F. and French, K.R., 2008. Dissecting anomalies. *The Journal of Finance*, 63(4), pp.1653–1678.

Foltice, B. and Langer, T., 2015. Profitable momentum trading strategies for individual investors. *Financial Markets and Portfolio Management*, 29(2), pp.85–113.

Frankfurter, G. and Mcgoun, E., 2001. Anomalies in finance: what are they and what are they good for? *International Review of Financial Analysis*, 10, pp.407–429.

Geczy, C.C. and Samonov, M., 2016. Two centuries of price-return momentum. *Financial Analysts Journal*, *72*(5), pp.32-56.

George, T.J. and Hwang, C.Y., 2004. The 52-week high and momentum investing. *The Journal of Finance*, *59*(5), pp.2145–2176.

Goertzen, M.J., 2017. Introduction to quantitative research and data. *Library Technology Reports*, 53, pp.12–18.

Green, J. and Thorogood, N., 2018. *Qualitative methods for health research Vol 4*, pp 1-440

Griffin, J.M., Ji, X.Q. and Martin, J.S., 2005. Global momentum strategies: a portfolio perspective. *Journal of Portfolio Management (Winter)*, pp.23–29.

Grinblatt, M. and Han, B., 2005. Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, 78(2), pp.311–339.

Grinold, R.C. and Khan, R.N., 2000. *Active portfolio management*. 2nd Edition. New York: McGraw-Hill.

Grossman, S.J. and Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. *The American Economic Review*, 70(3), pp.393–408.

Gutierrez Jr, R.C. and Prinsky, C.A., 2007. Momentum, reversal, and the trading behaviors of institutions. *Journal of Financial Markets*, 10(1), pp.48–75.

Harvey, C.R. and Liu, Y., 2015. Backtesting. *The Journal of Portfolio Management,* 42(1), pp.13–28.

Hausman, J.A., 1978. Specification tests in econometrics. *Econometrica: Journal of the Econometric Society,* pp.1251–1271.

Heymans, A. and Santana, L., 2018. How efficient is the Johannesburg stock exchange really? *South African Journal of Economic and Management Sciences*, 21(1).

Hirshleifer, D., 2018. Investor psychology and asset pricing. *The Journal of Finance*, 56(4), pp.1533–1597.

Hong, D., Lee, C.M. and Swaminathan, B., 2003. Earnings momentum in international markets. *SSRN Electronic Journal,* pp.4–39.

Israel, R.., Moskowitz, T.J., Ross, A. and Serban, L.., 2021. *Putting an academic factor into practice: the case of momentum*. Technical report, Working paper.

Jegadeesh, N. and Titman, S., 1993. Return to buying winners and selling losers: implication for stock market efficiency. *Journal of Finance*, 48(1), pp.65–91.

Jegadeesh, N., & Titman, S. 2023. Momentum: Evidence and insights 30 years later. *Pacific-Basin Finance Journal*, 82, pp. 2-6.

Jensen, M.C., 1968. The performance of mutual funds in the period 1945-1964. The *Journal of Finance,* 23(2), pp.389–416.

Johannesburg Stock Exchange., 2023. Savi dollar. Available at: https://www.jse.co.za/trade/derivitive-market/equity-derivatives/savi-top-40> [Accessed 6 November 2023].

Johnson, T.C., 2002. Rational momentum effects. *The Journal of Finance*, 57(2), pp.585–608.

Kaluba, M., 2020. *Can market state and market volatility explain time varying momentum profits in South Africa*. Master's thesis. University of the Witwatersrand.

Kent, D., Hirshleifer, D. and Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. *The Journal of Finance*, 53(6), pp.1839–85.

Kidd, D., 2011. The sharpe ratio and the information ratio. *Investment Performance Measurement Feature Articles*, 1, pp.1-4..

Kole, E. and van Dijk, D.J., 2010. *How to identify and predict bull and bear markets?* Econometrics Institute, Erasmus University Rotterdam..

Koopman, S.J., Jungbacker, B. and Hol, E., 2005. Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance*, 12(3), pp.445-475.

Langer, E.J. and Roth, J., 1975. Heads I win, tails it's chance: The illusion of control as a function of the sequence of outcomes in a purely chance task. *Journal of Personality and Social Psychology*, 32(6), p.951

Lawless, H.T. and Heymann, H., 2010. Descriptive analysis. *Food Science Text Series*, pp. 227–257.

Lavrakas, P.J., 2008. *Encyclopedia of survey research methods*. Sage.

Lee, S. and Na, O., 2005. Test for parameter change in stochastic processes based on conditional least-squares estimator. *Journal of Multivariate Analysis*, 93(2), pp.375–393.

LeRoy, S.F. and Porter, R.D., 1981. The present-value relation: Tests based on implied variance bounds. *Econometrica*, 49(3), p.55.

Lesmond, D.A., 2005. Liquidity of emerging markets. *Journal of Financial Economics*, 77(2), pp.411–452.

Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. Journal of Financial Economics, 71(2), 349‑380.

Leybourne, S., Newbold, P. and Vougas, D., 1998. Unit roots and smooth transitions. *Journal of Time Series Analysis*, 19(1), pp.83–97.

Li, F. and Shim, J., 2019. Trade-off in multifactor smart beta investing: factor premium and implementation cost. *The Journal of Portfolio Management*, 45(3), pp.115–124.

Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47(1), pp.13–37.

Liu, W., 2006. A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82(3), pp.631-671.

Loayza, N., and Ranciere, R., 2005. Financial Development, Financial Fragility, and Growth. *The International Monetary Fund,* pp. 10-15.

LoBiondo-Wood, G., Haber, J. and Cameron, C., 2014. Critical reading strategies: overview of the research process. In: *Nursing research in Canada-e-book: methods, critical appraisal, and utilization.* Elsevier, p.48.

Lunde, A. and Timmermann, A., 2004. Duration dependence in stock prices: An analysis of bull and bear markets. *Journal of Business & Economic Statistics*, 22(3), pp.253–273.

Malkiel, B.G., 2005. Reflections on the efficient market hypothesis: 30 years later. *The Financial Review*, 40(1), pp.1–9.

Manigault, P., 2017. *How can we adapt long-short strategies to long-only strategies?* HEC Paris MIF Program. Available at: https://www.vernimmen.net/ftp/Research_Paper_Paul_MANIGAULT.pdf [Accessed 10 January 2023].

Markowitz, H. M.,1952. Portfolio selection. *The Journal of Finance*, 7(1), 77-91

Moskowitz, T.J., Ooi, Y.H. and Pedersen, L.H., 2012. Time series momentum. *Journal of financial economics*, *104*(2), pp.228-250.

Marx, C., 2016. *The relative efficacy of momentum strategies in the South African equity market.* MCOM thesis. University of Johannesburg.

Maxwell, M. and van Vuuren, G., 2019. Active investment strategies under tracking error constraints. *International Advances in Economic Research*, 25, pp.309–322.

Mian, G.M. and Sankaraguruswamy, S., 2013. Investor sentiment and stock market response to earnings news. *The Accounting Review*, 87(4), pp.1357–1384.

MorningStar., 2021. *Explainer: What is tracking error*. Available at: https://www.morningstar.in/posts/65060/explainer-tracking-error.aspx [Accessed 8 October 2023].

Mossin, J., 1966. "Equilibrium in a Capital Asset Market." *Econometrica*, 34(4), pp768–83.

Muller, C. and Ward, M., 2013. Style-based effects on the Johannesburg Stock Exchange: A graphical time-series approach. *Investment Analysts Journal*, 42(77), pp.1–16.

Narayan, P.K. and Smyth, R.L., 2006. What determines migration flows from low-income to high-income countries? An empirical investigation of Fiji-US. *Contemporary Economic Policy Journal*. 24(2), pp. 332-342.

Page, D., McClelland, D. and Auret, C., 2020. Idiosyncratic momentum on the JSE. Investment Analysts Journal, 49(3), pp.180-198.

Olasode, O.S. and Babatunde, T.S., 2013. External debts and economic growth in Nigeria: An empirical study using autoregressive distributed lag model. *Business and Economics Journal,* 7.

Parsons, V.L., 2017. Stratified sampling. In: *Wiley statsref: statistics reference online.* Wiley. pp.1–11.

Phillips, P.C. and Perron, P., 1988. Testing for a unit root in time series regression. *Biometrika*, *75*(2), pp.335–346.

Prunier, L., 2016. Robustness tests of residual momentum strategies. Available at: https://matheo.uliege.be/bitstream/2268.2/1798/4/Master's thesis Laurent Prunier.pdf (Accessed: 29 February 2024).

Pronk, T., Molenaar, D., Wiers, R.W. and Murre, J., 2022. Methods to split cognitive task data for estimating split-half reliability: A comprehensive review and systematic assessment. *Psychonomic Bulletin & Review*, *29*(1), pp.44-54.

Roberts, H. 1967, Statistical versus clinical prediction of the stock market, Unpublished manuscript

Rossi, M., 2015. The efficient market hypothesis and calendar anomalies: A literature review. *International Journal of Managerial and Financial Accounting*, 7(3/4), pp.285-296.

Rozeff, M. S., and W. R. Kinney Jr. 1976. Capital market seasonality: The case of stock returns. *Journal of Financial Economics* 3:379–402.

Santoso, H., 2021. Momentum strategy alternatives during Covid-19 pandemic: an empirical study in Indonesia. In: AES, *7th Annual ECOFI Symposium,* Indonesia, July. AES.

Saunders, S.P, Zipkin, E.F., Zylstra, E.R., Wright, A.D.,., Finley, A.O., Dietze, M.C., Itter, M.S. and Tingley, M.W., 2021. Addressing data integration challenges to link ecological processes across scales. *Frontiers in Ecology and the Environment*, 19(1), pp.30–38.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium with risk. *The Journal of Finance*, 19(2), 425-442

Simon, M. K. 2011. *Dissertation and scholarly research: Recipes for success*. Seattle, WA: Dissertation Success LLC.

Sinharay, S., 2010. An overview of statistics in education. *International Encyclopedia of Education*, 3, pp.1–11.

Snyman, H.A., 2011. *Investigating momentum on the Johannesburg Stock Exchange* (Doctoral dissertation, Stellenbosch: University of Stellenbosch).

Strang, K.D., 2015. Selecting research techniques for a method and strategy. The Palgrave Handbook of Research Design in Business and Management, pp. 63–79.

Struck, C. and Cheng, E., 2019. Time-series momentum: A Monte Carlo approach. *The Journal of Financial Data Science*, 1(4), pp.103–123.

Taherdoost, H., 2016. Sampling methods in research methodology; how to choose a sampling technique for research. *SSRN Electronic Journal*, pp.1–10.

Temy, S. and Abdelgawad, I., 2022. *Statistical significance*. Sage.

Thomas, A.L., 2023. Evaluating the effect of CCTV on crime occurrence and case clearances in Fayetteville, North Carolina: A Microsynthetic Control Quasi-Experiment (Doctoral dissertation, City University of New York).

Uribe, J.M., 2017. Momentum pricing and trading, and economic uncertainty regimes. In: University of Barcelona, *26th European Financial Management Association*, Athens (Greece), June 28–July 1 2017. University of Barcelona.

Venturato, G., 2018. *Bayesian state space modelling of factor investing*. Copenhagen Business School.

Verma, S., Gautam, R., Pandey, S., Mishra, A. and Shukla, S., 2017. Sampling typology and techniques. *International Journal of Scientific Research & Development*, 5, pp.298–301.

Viljoen, L.E., 2016. Residual momentum and investor sentiment on the Johannesburg Stock Exchange. *Gordon Institute of Business Science University of Pretoria*, 1, pp.1–75.

Wan, Z., 2021,. Analysis of Size and Momentum Anomalies in CAPM. *Atlantis Press*, pp. 662-665

Wang, K.Q. and Xu, J. 2015. Market volatility and momentum. *Journal of Empirical Finance*, 30, pp.79–91.

Watson, R., 2015. Quantitative research. *Nursing Standard,* 29(31), pp.44–48.

Wilson, E.J. and Marashdeh, H.A., 2007. Are co-integrated stock prices consistent with the efficient market hypothesis? *The Economic Record*, 83(s1), S87–S93.

Yarovaya, L., Matkovskyy, R. and Jalan, A., 2021. The effects of a “black swan” event (COVID-19) on herding behavior in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money*, 75, p.10132

Appendix A: Monthly returns of FTSE/JSE Top 40, Traditional and Residual momentum

Date	Residual Montly Returns	FTSE/JSE Top 40 Monthly Returns	Traditional Monthly Returns
2018/02/28 00:00	4.41407%	-2.325%	-1.70600%
2018/03/30 00:00	-0.95832%	-6.520%	-9.75510%
2018/04/30 00:00	3.55022%	-1.174%	-4.92829%
2018/05/31 00:00	-1.81755%	-4.185%	-6.57391%
2018/06/29 00:00	0.01205%	-0.812%	2.81309%
2018/07/31 00:00	2.05693%	-1.132%	-1.99554%
2018/08/31 00:00	3.74369%	1.255%	-0.01130%
2018/09/28 00:00	0.75263%	-3.403%	-4.93499%
2018/10/31 00:00	-5.96745%	-9.862%	-16.06936%
2018/11/30 00:00	-7.14820%	-12.643%	-14.25341%
2018/12/31 00:00	-6.71275%	-8.480%	-10.23008%
2019/01/31 00:00	0.00000%	0.000%	0.00000%
2019/02/28 00:00	5.25503%	3.451%	5.96903%
2019/03/29 00:00	4.24830%	5.515%	2.17015%
2019/04/30 00:00	9.31898%	10.356%	2.32097%
2019/05/31 00:00	8.24032%	4.552%	0.21905%
2019/06/28 00:00	14.74607%	10.078%	13.44138%
2019/07/31 00:00	12.82077%	7.115%	11.03578%
2019/08/30 00:00	10.96670%	4.357%	23.36080%
2019/09/30 00:00	13.17808%	3.890%	16.67039%
2019/10/31 00:00	18.87457%	7.043%	32.70215%
2019/11/29 00:00	19.50022%	4.888%	27.62756%
2019/12/31 00:00	28.03538%	8.633%	36.23662%

2020/01/31 00:00	0.00000%	0.000%	0.00000%
2020/02/28 00:00	-6.74799%	-8.462%	-6.23948%
2020/03/31 00:00	-25.83889%	-18.210%	-24.45988%
2020/04/30 00:00	-18.15918%	-6.163%	-3.13246%
2020/05/29 00:00	-19.68245%	-5.585%	-5.79386%
2020/06/30 00:00	-17.84400%	1.781%	3.71028%
2020/07/31 00:00	-17.57955%	4.158%	25.70884%
2020/08/31 00:00	-16.17268%	4.155%	29.00831%
2020/09/30 00:00	-11.77046%	2.478%	21.65380%
2020/10/30 00:00	-17.16749%	-2.780%	13.70312%
2020/11/30 00:00	-4.87043%	7.249%	15.25799%
2020/12/31 00:00	3.12319%	11.378%	29.91759%

2021/01/29 00:00	0.00000%	0.000%	0.00000%
2021/02/26 00:00	7.99846%	6.055%	4.07186%
2021/03/31 00:00	16.49126%	7.467%	9.05862%
2021/04/30 00:00	15.96588%	8.104%	11.95268%
2021/05/31 00:00	18.37523%	9.262%	13.24048%
2021/06/30 00:00	17.38784%	6.560%	3.16767%
2021/07/30 00:00	22.99882%	11.394%	10.99408%
2021/08/31 00:00	25.49672%	8.763%	7.22024%
2021/09/30 00:00	29.42752%	4.950%	5.68858%
2021/10/29 00:00	30.16331%	10.432%	11.76017%
2021/11/30 00:00	31.33648%	16.330%	14.31195%
2021/12/31 00:00	34.21581%	22.040%	15.32120%
2022/02/28 00:00	2.103%	3.26%	9.67692%
2022/03/31 00:00	5.542%	2.41%	4.29181%
2022/04/29 00:00	2.946%	-1.71%	-3.0432%
2022/05/31 00:00	3.714%	-1.69%	-8.3187%
2022/06/30 00:00	-6.033%	-9.60%	-16.2050%
2022/07/29 00:00	-4.014%	-5.95%	-14.2035%
2022/08/31 00:00	-3.889%	-7.94%	-19.4045%
2022/09/30 00:00	-8.549%	-11.91%	-19.6226%
2022/10/31 00:00	-0.033%	-7.64%	-15.4504%
2022/11/30 00:00	3.000%	5.56%	-3.0892%

Note: Yellow highlight represent the annualised return achieved by the momentum strategies and the benchmark.

Appendix B: Split-Half Reliability using Spearman- Brown Prophecy

X	Y		Correlation
2.60461%	2.35447%		0.930597079
-0.10310%	-3.73888%		
2.72434%	0.63395%	2r	1.861194159
1.76583%	-1.44539%	1+r	1.930597079
1.65378%	1.38548%		
3.25667%	6.30793%	SPSS	0.964051059
4.02917%	8.03471%		
4.60774%	3.89104%		
5.17399%	5.32913%		
8.36370%	7.97099%		
14.66541%	17.81133%		