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Effect of factor investing on stock returns at the Nairobi Securities Exchange in Kenya.

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EFFECT OF FACTOR INVESTING ON STOCK RETURNS AT THE NAIROBI SECURITIES EXCHANGE IN KENYA

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the proposal contains no material previously published or written by another person except where due reference is made in the proposal itself.

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ABSTRACT

Factor investing is the investment process to gain selective exposure to factors which explain an asset's risk and return. The purpose of this study was to establish the extent to which stock returns from factor investing were profitable at the Nairobi Securities Exchange. The two factors under study were value and momentum. The study used daily stock prices of large-capitalization stocks during the period January 2010 to December 2019. For each factor, three portfolios were formed: high (value and winning portfolio), low (growth and losing portfolio), and an intermediate portfolio. The stock returns from the factor portfolios were then analysed using descriptive statistics and regression analysis with the estimated parameters tested for significance. The study found out that factor investing was not profitable at the NSE: momentum factor earned positive returns albeit with mixed results while value factor and the combined factor portfolio lost money. The study also reported that stock returns from factor investing were highly cyclical: the stock returns exhibited high drawdown, long durations to prior peaks, and fluctuating returns in bull and bear markets. Finally, the studied showed that CAPM was a suitable model to explain the returns of long-only portfolios (value and winning), but ineffective in explaining the returns of long-short portfolios (value and momentum premium). A limitation of this study was its focus on large-capitalisation stocks. Prior studies focused on factors that explain stock returns at the NSE; therefore, this study added to knowledge the analysis of the profitability of stock returns from factors at the NSE.

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LIST OF ABBREVIATIONS

CAPM – Capital Asset Pricing Model

CMA - Capital Markets Authority

EMH – Efficient Market Hypothesis

MSCI – Morgan Stanley Capital International

NASI – Nairobi All Share Index

NSE – Nairobi Securities Exchange

UK – United Kingdom

US – United States

DEFINITION OF TERMS

Factor - Any characteristic that is useful in explaining the risk and return of any group of securities (Bender, Briand, Melas, & Subramanian, 2013).

Factor Investing - The investment process to earn returns through selective exposure to factors (K. G. Koedijk, Slager, & Stork, 2016).

Value Factor – Refers to the purchase of that stocks appear cheap relative to some measure of fundamental value, and the avoidance or sell of stocks that sell above the same fundamental values (Pätäri & Leivo, 2017).

Momentum Factor – Refers to the purchase of stocks captures that have increased in value over a certain period in the past, and the avoidance or sell of stocks that decreased in value (C. Asness, Frazzini, Israel, & Moskowitz, 2014).

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CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Our bodies require a number of nutrients – carbohydrates, proteins, vitamins et cetera - to power through a day's activities (Ang, 2010). According to Ang (2010), we access these nutrients by buying different foods: proteins from meat, carbohydrates from rice, and vitamins from fruits and/or vegetables. To create a balanced diet, we need to know what nutrients constitute the different foods. This knowledge enables us to mix and match foods to produce what best suites our bodies. Correspondingly, in the investment world, portfolios are the human bodies whereas *asset classes* - real estate, equities, treasury bonds (bills) - are the different types of food. Nutrients, on the other hand, are proxied by *factors* such as economic growth, inflation, size, and momentum. Therefrom, investors who want to maximize portfolio returns and/or minimize risk should not only invest in several asset classes, but they should also take cognizance of factors (nutrients).

Bender, Briand, Melas, & Subramanian (2013) define a factor as any characteristic that is useful in explaining the risk and return of any group of securities. Ang & Kjaer (2012) identify two types of factors: fundamental and style. Fundamental factors include economic growth, inflation, and liquidity. These factors explain returns across asset classes. Style factors include value, momentum, size, quality, and minimum volatility. These explain returns within an asset class. Ilmanen & Kizer (2012) note that it is difficult for investors to gain exposure to fundamental factors as they are characteristically difficult to invest in. Most investors according to the authors use market-based proxies for fundamental factors: commodities for inflation, treasuries for deflation, and equities for economic growth. Under style, some factors cut across different asset classes. Value – buying assets with low prices and selling those with high prices – for example is called "carry" in the foreign exchange market, "value investing" in equities, "riding the yield curve" in treasuries and the "roll" in commodities (Ang & Kjaer, 2012; Asness, Frazzini, Israel, & Moskowitz, 2015).

The development of factors can be traced to the work of William F. Sharpe (Koedijk, Slager, & Stork, 2016). Sharpe (1964) demonstrated that risk was broken into two: avoidable and unavoidable. Avoidable risk is reducible through effective diversification, and therefrom it is unrewarded by returns. Unavoidable risk (*systematic risk*), which is caused by general economic developments, is irreducible by diversification, and hence it is compensated by returns. These insights led to the development of the first factor: the sensitivity of an asset's return to general economic activity (proxied by the return to a broad-based portfolio of all assets in the investible universe). Research has shown, however, that other factors play a pivotal role in explaining assets` returns (Cerniglia & Fabozzi, 2018; Idzorek & Kowara, 2013). Therefore, factor investing is the investment process to earn returns through selective exposure to factors (Bender et al., 2013; Koedijk et al., 2016).

Factor investing has been profitable across time and different markets. Angelidis & Tessaromatis (2017) combined equities return from 23 developed and 21 emerging market countries to create global single-factor portfolios. Between 1980 and 2015, size, value, beta, and momentum generated higher returns than the world equity market portfolio. In addition, the authors combined the global single-factor portfolios to form a global multifactor portfolio. The performance of the global multifactor portfolio was better than the world equity market and the four global single-factor portfolios. Koedijk et al. (2016) reported that an equally weighted portfolio of low volatility, momentum, size, and value generated higher returns than the market average in the US between 1929 and 2012. The authors carried out the same study for the European market between 1990 and 2012, and they came to the same conclusion. Dimson, Marsh, & Staunton (2017) reported similar returns for various factors. In the UK equities market, value earned higher returns than the market portfolio between 1955 and 2016. Momentum was also put under the scope by the authors. In the US, momentum generated an average return of 17.5% while in the UK it earned an average return of 14.1%. Flint, Seymour, & Chikurunhe (2016) provided similar evidence for the South African equities market, but it was muted. Between 2002 and 2016, of the seven factors studied, only momentum generated returns above the market average.

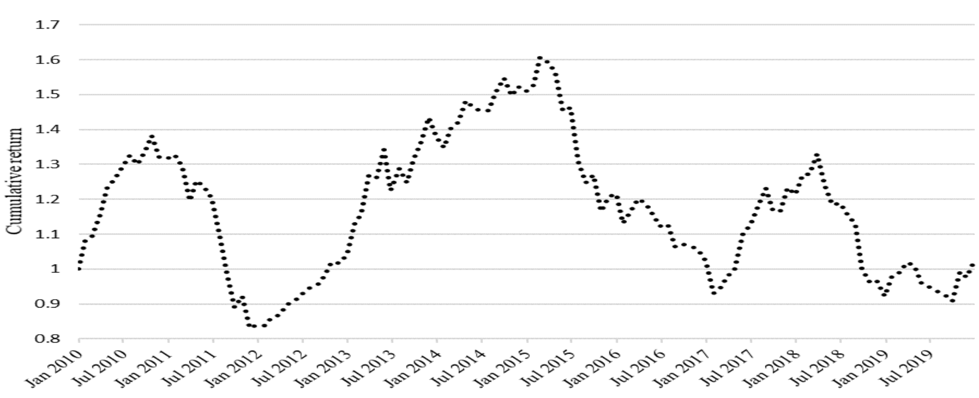
Factor investing is not only associated with profitability, but it is also associated with effective diversification. Ilmanen & Kizer (2012) advocated for factor investing instead of the traditional route of allocating moneys to various asset classes. Their assertion lay in the weak co-movement between the different factor returns in the US equities market between 1927 and 2010. To prove their point, they compared the returns of asset diversified and factor diversified portfolios between 1973 and 2010. The factor diversified portfolio generated higher returns than the asset diversified portfolio. Further, due to the weak co-movement in factor returns, portfolio risk was reduced, thereby, raising the *Sharpe ratio* of the factor diversified portfolio. Blitz (2015) showed the same diversification benefit, but it was between factor portfolios and the market portfolio for US equities. Between 1963 and 2014, both the equally and capitalization weighted factor portfolios generated higher Sharpe ratios than the market portfolio. Nevertheless, Idzorek & Kowara (2013) argued that both asset class and factor approaches could be superior over a given time period.

Despite the benefits of factor investing, two concerns have been raised: persistence and cyclicity of factor returns. Under persistence, two reasons have been brought forth to try and predict the continuation of factor returns. The first is that factor returns are a compensation for bearing some sort of unavoidable risk (Ilmanen, 2011). For example, the return to value necessitated the assumption of higher risks. Chan & Lakonishok (2004) rejected this metaphysical approach to risk. Their study showed that value was less risky across different measures for example *volatility* and *downside risk*. Nonetheless, the risk argument has not been laid down (Njogo, 2017). The second reason uses human psychology with a focus on behavioral biases such as overconfidence and overreaction. Overconfidence is where investors over evaluate the probability of success and private information, and overreaction causes investors to overweight new data instead of long-term information (Zhang & Zheng, 2015). Such biases lead to momentum in stock returns that can be exploited by well-informed investors. Under cyclicity, factors failed to generate returns in certain time periods. For example, Dimson et al. (2017) showed that the size factor had prolonged periods of underperformance. Bender et al. (2013) identified three approaches to deal with cyclicity: investing in multiple factors to increase diversification, setting an explicit time for initial investment, and setting a suitably long-time horizon.

Factor investing has been made accessible to investors through professional investment managers (Warren & Quance, 2019). They pointed to the development of passive investment vehicles that have been developed to replicate single or multiple factors. These passive investment vehicles have come to be known as *smart-beta funds*. McGee (2019) defined smart-beta funds as passive investment vehicles that select and track securities which exhibit desired factor exposure. This is contrasted from *index funds* which weigh and track securities by market capitalization. Dimson et al. (2017) reported that asset owners – pension plans, governments, and corporations – who used smart-beta funds increased from 2% in 2014 to 20% in 2016. They also highlighted the over 1,000 smart-beta products from 145 providers spread-out in 32 countries. Bender, Briand, Melas, Subramanian, & Subramanian (2015) stressed that in selecting factor indexes (smart-beta funds) investors should consider factor exposure and investability of the index. According to the authors, factor exposure is the extent to which the fund captures the pure return to a factor. Conversely, investability refers to how tradeable and liquid the fund is. These two dimensions create an unavoidable tradeoff for the investor. To gain the pure factor return, an investor sacrifices investability and vice versa. The authors, hence, advised investors to consider their own preference and select which dimension is key to them.

In Kenya, style and fundamental factors have been studied. Under fundamental factors, Ouma & Muriu (2014) reported that exchange rates, inflation, and money supply were important determinants of stock returns at the NSE. Likewise, Kirui, Wawire, & Onono (2014) reported that exchange rates had the strongest impact on stock returns at the NSE. Under style factors, two factors have been shown to exist in the Kenyan equities market: value and momentum. The two have been documented by researchers trying to discover what factors explain returns of stocks listed at the NSE (Achola & Muriu, 2016; Riro & Wambugu, 2015). Njogo (2017) also documented the presence of value and momentum factor when testing for stock anomalies present at the NSE. In Kenya, the studies have not only focused on what factors explain stock returns but also returns from factor portfolios have been reported: Otinga (2017) documented the returns calculated from momentum factor portfolios at the NSE. The figure below presents the cumulative return of the Nairobi All Shares Index between 2010 and 2019:

Figure 1. 1: **Nairobi All Share Index Cumulative Return between 2010 and 2019**



Source: NSE (2020)

According to the graph, by the end of 2019 NASI had failed to return money to its investors. Factor investing and its associated returns posits a solution for Kenyan investors to generate returns at the NSE.

1.2 Problem statement

Investing in any stock market exposes investors to the market factor: the expected or realized return of a broad equity index less a short-term riskless asset (Ilmanen, 2011). In Kenya, investors have been poorly rewarded by the market factor. Financial Sector Regulators (2020) reported the underperformance of Kenyan equities proxied by the Nairobi All Share Index between 2013 and 2019. Equities generated an average return of 4.76% per annum, but fixed income securities (treasury bonds) earned 10.3% per annum. Zamara (2019) also reported that Kenyan equities - proxied by NASI - churned out an average return of 12.5% between 2009 and 2018. The returns were slightly below that of Kenyan bonds at 13.1%; however, equities return exhibited higher volatility (standard deviation) than Kenyan bonds, and thus equities generated a lower Sharpe ratio (0.1 versus 0.4). Due to the unattractive and high volatility of equities returns, the report highlighted that pension funds allocated 67% of their funds in fixed income securities and 26% in equities. Nevertheless, Zamara stated that the poor run of returns and minimal asset allocation did not imply equities were poor investments. Rather, a buy and hold strategy should be augmented with an active approach to generate superior returns.

Factor investing and its associated returns posits an active approach that has been shown to be relatively profitable (Angelidis & Tessaromatis, 2017; Koedijk et al., 2016). Moreover, factor investing has enabled investors to generate returns above the market average. In Kenya, the existence of value and momentum factor provides the avenue for local investors to boost their equities portfolio performance. The two factors have generated returns despite being evidently clear to investment practitioners (Cakici & Tan, 2014; Dimson et al., 2017; Fama & French, 2012). Not only have Kenyan equities investors seen low returns, but also their portfolios have exhibited high volatility (Zamara, 2019). Factor investing, particularly, combining different factors has been shown to reduce portfolio volatility (Blitz, 2015; Ilmanen & Kizer, 2012). Asness, Moskowitz, & Pedersen (2013) documented the performance of portfolios combining value and momentum. The authors showed that the two factors were negatively correlated. A combination of the two, hence, lowered volatility and improved Sharpe ratios. Flint et al. (2016) and Koedijk et al. (2016) provided evidence of the same in South Africa and Europe respectively. An appreciation of factor investing can also uncover whether investors knowingly or unknowingly expose themselves to factors, in this case value and/or momentum (Dimson et al., 2017).

Research on factors in Kenya has primarily been focused on finding out which ones are important in explaining returns at the NSE. This research has highlighted value and momentum as pertinent to the local exchange (Achola & Muriu, 2016; Riro & Wambugu, 2015). A gap, however, remains as to whether value and momentum - independently or jointly - generate returns that enhance the performance of investors' portfolios. This study, therefore, aimed at answering the question: can Kenyan investors boost their equity portfolios returns by investing in factors: value and momentum.

1.3 Objectives of the study

1.3.1 General objective

The general objective of this study was to establish the profitability of stock returns from factor investing. The factors were value and momentum.

1.3.2 Specific objectives

1. To examine the profitability of stock returns from factor investing
2. To assess the cyclicity of stock returns from factor investing
3. To determine the source of stock returns from factor investing

1.3.3 Research questions

The following were the research questions:

1. Do stock returns from factor investing - value and momentum - independently and jointly generate profitable returns at the NSE between 2010 and 2019?
2. Do stock returns from factor investing exhibit periods of underperformance or overperformance at the NSE between 2010 and 2019?
3. Does the Capital Asset Pricing Model explain the stock returns from factor investing?

1.4 Scope of the study

The study was conducted on stocks listed on the NSE between January 2010 and December 2019. This period was adequate as it coincided with the introduction of the NSE All-Share Index (NASI) as well as being concurrent with the literature on equities performance at the Kenyan bourse. The target population for this analysis were stocks that lay above the median market capitalization at the NSE.

1.5 Justification

1.5.1 Researchers

This study acted as a foundation for other researchers to expand on factor investing at the NSE. This made factor investing comprehensible and helpful to those who desire to grow the body of knowledge. Factor investing has a long history of research as it challenges market efficiency and, is highly persistent. The focus of this study can also be extended to markets outside Kenya such as Dar es Salaam Stock Exchange, Uganda Securities Exchange, and Rwanda Stock Exchange.

1.5.2 Investment practitioners

The study highlighted the extent to which factor investing is feasible in Kenya. This was done by looking into the construction of the factor portfolios. Further, the analysis of the profitability, cyclicity and source of stock returns from factor investing offered insights to the desirability and riskiness of the proposed portfolios amongst investment practitioners and the market in general.

1.5.3 Investment clients

The research by extending its findings to investment practitioners will eventually find itself to investment clients who potentially can earn high risk adjusted returns than the general stock market. In addition, investment clients will have a general sense of the riskiness of factor investing strategies offered to them by their financial advisors.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter covered the theoretical and empirical review of existing literature. Section 2.2 reviewed theories relevant to this study. Section 2.3 reviewed studies done on stock returns from factor investing, cyclicity of stock returns from factor investing, and source of stock returns from factor investing. Section 2.4 detailed the research gap, and section 2.5 presented the conceptual framework between the independent and dependent variables.

2.2 Theoretical review

Several theories were instrumental in the formation and analysis of factor investing and stock returns. The theories were: Efficient Market Hypothesis (EMH), Behavioral Finance, and Capital Asset Pricing Model (CAPM). EMH provided a risk-based explanation for the existence of factors. Behavioral finance extended the conceptualization of risk, as defined in EMH, to encompass human tendencies (both rational and irrational), and CAPM provided the background on the formation of factors. A multi-theoretical approach was appropriate because the theories offered competing analysis for the existence and continuation of stock returns from factor investing. No theory had the upper hand in the analysis of the objectives of the study.

2.2.1 Efficient market hypothesis

Fama (1970) was credited with the development of the efficient market hypothesis. In the hypothesis, a market that always "fully reflects" available information was considered "efficient". Market efficiency was tested on several levels: weak form efficiency which concerned itself with past returns (or price), semi-strong form efficiency which concerned itself with the speed of price adjustment to publicly available information (for example earnings announcement), and strong form efficiency which tested whether any group or investor (for example managements of unit trusts) had monopolistic access to any information relevant to the formation of prices (Fama, 1991). Verheyden, De Moor, & Van den Bossche (2013) highlighted the activities that failed to generate abnormal returns in an efficient market: in a weak form market, trading on past prices or returns (that is technical analysis) was rendered obsolete, in a semi strong form market, trading on public information (for example announcements of earnings, rights issue et cetera) would not generate abnormal returns, and in a strong form market, utilizing private information (for example market insights) would likewise fail to generate abnormal returns.

Under weak form, empirical analysis was initially centered on the random walk model with its assertion that successive price changes or commonly one-period returns were independent of each other (Fama, 1970). Jegadeesh & Titman (1993) reported contrary findings to the random walk model from their study of momentum - stocks that performed well in the past sustained their price advance, but poor performers continued to decline. Since past returns partially explained variation in returns, tests for weak form efficiency were improved by variables such as earnings yield (E/P) which were known to predict stock returns (Fama, 1991). Fama (1991) concluded that this predictability of stock returns was not a result of irrational bubbles – deviations from a fundamental value – but rational variation in expected returns. Chan & Lakonishok (2004) carried conflicting opinion to the rational variation in expected returns. They sighted behavioral considerations such as investor overreaction that resulted in irrational bubbles. Asness et al. (2015) reinvigorated the rejection of rational variation in expected returns. Though studies on semi-strong form efficiency (event studies) yield considerable insight, the findings did not augur well with the research question at hand, so no material was presented.

Is it profitable to expend resources searching for little known information? Are these activities even profitable? And who are the "professionals" in the financial world who have access to this "special information"? (Fama, 1970). This concern added the final layer to the market efficiency debate (strong form or tests of private information) by leaning on professional investment managers (mutual fund managers). In an efficient market, ex post values for average returns and standard deviation would lie along a straight line, so higher values of standard deviation would be associated with higher average returns (Sharpe, 1966). Sharpe (1966) observed the hypothesized phenomenon. Some portfolios, however, generated both greater values of average returns and smaller standard deviations. This led to the development of the Sharpe ratio. Sharpe ratio was used to test whether fund managers were "informed professionals. Lemeshko & Rejnuš (2015) reported the underperformance of fund managers from 27 emerging economies in times of crisis (2008 to 2010) and in times of economic recovery and growth (2011 to 2014). Still, there were a small number of mutual fund managers, who regardless of overall macroeconomic condition, outperformed their peers. Fang & Wang (2015) reported contrary evidence for Chinese fund managers between 2008 and 2011. The fund managers earned high Sharpe ratios; precisely, a Masters in Business Administration and the Chartered Financial Analyst designation were important qualities in distinguishing poor from good fund managers. In short, there was contradictory evidence on whether fund managers were “informed professionals” who by research generated abnormal returns beyond the costs of doing so.

EMH presented the ideal for a well-functioning market. Through EMH, factor investing could be viewed as compensation for bearing systematic risk. EMH provided the impetus for continued investment for those willing to bear the risk.

2.2.2 Behavioral finance

Modern finance assumes: rational investors, portfolios are mean-variance efficient, efficient markets, and expected returns are a function of risk (Fama, 1970; Markowitz, 1952; Sharpe, 1964). Behavioral finance, on the other hand, assumes: investors are “normal” not rational, portfolios are designed using behavioral theory, inefficient markets, and expected returns follow behavioral asset pricing theory (Statman, 2008).

Daniel Kahneman and Amos Tversky are regarded as the first scholars to help evolve the theory of behavioral finance (Antony, 2020). According to Antony (2020), behavioral finance is an interdisciplinary approach that combines knowledge from psychology, sociology, and economics. In behavioral finance, investors decision making are affected by psychological factors that affect all investors, therefore, influencing asset prices through inefficient allocation of resources (Huang, Shieh, & Kao, 2016). According to Huang et al. (2016) investor irrationality displays itself in speculative bubbles, excessive volatility of securities market, group behavior, overconfidence, overreaction, and under-reaction. This peculiar investors’ habits have been blamed for observed phenomenon such as momentum returns in asset prices. Ramiah, Xu, & Moosa (2015) noted that behavioral phenomena such as disposition effect, conservatism in expectations, biased self-attribution, selective information conditioning, and expectation extrapolation gave credible evidence for the existence of momentum returns. The authors also highlighted that asset pricing models such as the Fama and French three-factor model failed to explain momentum returns. Ilmanen (2011) also pointed out that representative bias caused people to neglect “base rate” information and put focus on new data. This single-mindedness on new information eventually pushes prices upwards. Similarly, underreaction to new information can lead to momentum in stock returns. One of the key observations of behavioral finance is that investors are “normal” not rational. Such a view can explain the existence of returns to value investing. For example, Munson & Spivey's (1981) definition of value-expressive products and utilitarian products is helpful. Value-expressive products are those which give positive expression of an individual’s self-concept and values, and utilitarian products are those which user categorizations are relatively inconsequential. The analogy of a Rolex and Timex watch is useful. The two are identical in the utilitarian sense (they have identical accuracy and reliability) but the former sells for Kshs 1,000,000 while the later sales for Kshs 5,000. To express the difference, we must look to value-expressive characteristics. Value factor or value and growth stocks lend themselves to the same analogy: value stocks are equivalent to a Timex, and growth stocks are equivalent to a Rolex. The penchant for growth stocks will lead to higher prices and lower returns, but the disdain for value stocks will lead to lower prices and higher returns (Statman, 1999). Whether Rolex will maintain its price advantage over Timex or in the case of stocks, growth versus value, what is known is utilitarian and value expressive characteristics determine expected returns (Statman, 1999).

Behavioral finance extends the utilitarian concept of an investor. It does so by challenging the homo economicus model of man by showing the systematic errors plaguing man. In turn, the theory offers a competing analysis to the EMH for the existence and continuation of factors. This advancement was key to this study as it provided a suitable groundwork for continual factor investing.

2.2.3 Capital asset pricing model

CAPM was introduced by William F. Sharpe in 1964 (Flint et al., 2016). Based on the framework of Markowitz (1952), CAPM asserted that beta (the slope in the regression of a security’s return on the market’s return) was the only measure of risk sufficient to explain the cross-section of expected returns (Sharpe, 1964). In the model, beta represented unavoidable risk as diversification would not eliminate it. Unavoidable risk characterized general economic developments that affected all securities (Koedijk et al., 2016). As compensation, beta (unavoidable risk) earned returns. Therefore, according to CAPM, securities with higher beta (more responsive to changes in economic developments) would have had higher expected returns than those with lower beta (less responsive to changes in economic developments). At the outset, empirical validity for the CAPM was weak. Portfolios formed from book-to-market equity and past returns challenged the validity of CAPM (Fama & French, 1992; Jegadeesh & Titman, 1993). The apparent failure of CAPM led to its extension to include book-to-market equity ratio and size (Fama & French, 1993). Later on, Carhart (1997) added past returns (momentum) to improve the explanatory power of the CAPM.

Without CAPM anomalies would not exist. This model, therefore, provided the necessary background for understanding factor investing. Despite its failings, it led to the formation of other asset pricing models that discovered factors – value and momentum.

2.3 Empirical review

This section discussed literature on stock returns from factor investing. The section introduced factor investing and stock returns, reported the stock returns from factor portfolios, documented the cyclicity of stock returns from factor portfolios, and detailed the source of stock returns from factor investing. In each section, the review started from global markets, Africa and then Kenya.

2.3.1 Factor investing and stock returns

Blitz (2015) identified three sources of return for investors: managerial skill (active investing), exposure to the market risk premium (broad equity index less a risk-free rate of return), and factor exposure for example value or momentum. According to the author, the first source of return failed to produce market beating returns, thus, investors chose to passively invest in the second source of returns. The author, however, contended the investors who chose the second source of return would fail to capture factor premiums for which evidence of returns was available. Dimson et al. (2017) supported the foregoing discussion. According to the authors, investors' choices of geographical exposure, sectors, and securities had some bearing on portfolio returns. The authors also emphasized that investment returns were influenced by whether a portfolio leant towards, for example, value or growth stocks and/or large or small companies. They, therefore, observed investors were knowingly or unknowingly exposed to such factors. Consequently, they underscored the importance to understand factor exposures when developing an investment strategy and measuring its performance. Cerniglia & Fabozzi (2018) propose that in employing a factor strategy an investor should consider whether the goal is to enhance returns or improve diversification. As per the authors, factor strategies can improve returns because some factors generated larger returns than the market portfolio. Pertaining to diversification, the authors noted that combined factors offered investors unique diversification benefits as some factors had low correlations than traditional asset classes. Concisely, Koedijk, Slager, & Stork (2016) remarked that factor investing presented an opportunity for investors to identify and understand what drives returns and risks. Therefrom, investors could construct portfolios based on knowledge of underlying factors.

2.3.1.1 Value factor and stock returns

Value investing entails buying stocks which provide high current income and/or appear to be cheap relative to some measure of fundamental value; moreover, value investing also entails avoiding or selling stocks that are selling above the same fundamental values (Pätäri & Leivo, 2017). Pätäri & Leivo (2017) differentiated value stocks from growth stocks by individual valuation ratios. The authors thought of these ratios as output/input ratios. Output was defined as any measure of profitability: earnings, book-value of equity, cash flow or dividends. Inputs were enterprise value or market value of equity. Accordingly, the more output one could get for every input, the better in terms of relative value. This implied the higher (lower) the output/input ratio the more the stock exhibited characteristics of a value stock (growth stock).

Fama & French (2012) used data spanning 23 countries divided into four regions: North America, Japan, Asia Pacific, and Europe to study the value factor. The authors additionally combined the four regions to form a global portfolio. To sort stocks as either value or growth, the authors used the ratio of book equity to market equity (B/M). Between November 1990 and March 2011, the study reported that the value premium per month (value stocks return less growth stocks return) was 0.33%, 0.55%, 0.48% and 0.62% for North America, Europe, Japan, and Asia Pacific, respectively. These regional returns were likewise statistically different from 0 apart from North America. Comparing the four regions value premium to their respective market portfolio average returns, only Japan generated a value premium higher than its respective market portfolio return. The value premium for the regions combined in the study stood at 0.45% per month. This return was statistically different from 0, and it was correspondingly higher than the average return for the global market portfolio. Cakici & Tan (2014), on the other hand, worked with twenty-three developed countries individually rather than in regions. The authors used stocks from 16 markets in Europe, 5 from Asia and 2 from North America. To split stocks to either value or growth, the study used the ratio of book equity to market equity (B/M). Between January 1990 and March 2012, the study established that value premium was statistically significant from 0 in 9 European countries, all Asian countries, and Canada. Angelidis & Tessaromatis (2017) also undertook to study value factor returns, but the authors used country dollar total return indexes from MSCI. The authors focused on 23 developed markets and 21 emerging markets to make global factor portfolios. To form the global value factor portfolio, the authors combined price-to-cash flow, price-to-book, and dividend yield ratios to rank country indexes as either value or growth. Between July 1980 and December 2015, the authors observed that value portfolio generated 14.77% per annum while growth portfolio generated 10.99% per annum. In the same period, the world market portfolio proxied by the MSCI All-Country World index generated 10.64%. The value portfolio similarly generated a higher Sharpe ratio than the growth portfolio and MSCI All-Country World index. The study also reported that alpha of the value portfolio vis a vis the world market portfolio was statistically different from 0 at the 5% level of significance. For the growth portfolio, the return was indistinguishable from zero.

The return to value investing followed through to specific markets. Koedijk et al. (2016) reported the return to value in the US market. The authors used the ratio of book value to market value of equity to distinguish value stocks from growth stocks. Between January 1929 and July 2012, the study reported that value stocks generated an average return of 11.14% per annum. In the same period, the market portfolio earned 8.73% per annum. Likewise, value stocks generated a higher Sharpe ratio than the market portfolio (0.40 versus 0.35). The study was then carried out for a relatively recent period. Between January 1990 and July 2012, the authors showed that value stocks earned 9.89% per annum whereas the market portfolio generated 8.82% per annum, and value stocks earned a Sharpe ratio of 0.46 compared to 0.40 for the market portfolio. Dimson et al. (2017) documented comparable returns but from the UK market. The authors used the book-to-price ratio to separate value stocks from growth stocks. Between 1955 and 2016, high book-to-price stocks (value) earned 16% per annum, and low book-to-price stocks (growth) earned 10.3% per annum. In the same period, the UK market generated 12.1% per annum. In Asia, Perez (2018) tested for returns to value in the South Korean market by employing two different methodologies. The first methodology used MSCI style indexes: MSCI South Korea Value index and MSCI South

Korea Growth index. Between 1997 and 2016, Perez reported there was no statistically significant difference between value and growth indexes. The second methodology employed by the author relied on individual stocks. Perez used price-to-book, price-to-earnings, last 5 years average sales growth, and cash flow per share to differentiate value stocks from growth stocks. Between 1997 and 2016, the author reported that portfolios of low values of price-to-book, price-to-earnings, and last 5 years average sales growth outperformed those that exhibited higher values. Cash flow per share showed the reverse. Perez noted that in majority of the years the difference between value and growth was not statistically different from 0. The author, however, observed there was a substantial difference in the final values of value and growth portfolios.

In Africa, Hsieh (2015) showed the return to value in the South African market. The author used earnings-to-price, book-to-price, and sales-to-price to differentiate value stocks from growth stocks. Between January 1997 and December 2013, the study observed value portfolios formed from earnings-to-price and sales-to-price outperformed their growth counterparts, but value portfolios formed from book-to-price underperformed growth portfolios. In addition, the value portfolios formed from earnings and sales ratio outperformed the broad South African market portfolio. For risk-adjusted returns, only value portfolios formed from earnings-to-price ratio generated a higher Sharpe ratio than the market portfolio. Hsieh then compared the performance of value and growth stocks in bull and bear markets. The author reported that value stocks earned higher returns in bull markets, but value stocks generated huge losses in bearish markets compared to growth stocks. Flint et al. (2016) carried out the same analysis for the South African market and came to an opposite conclusion. The authors used the ratio of book value to market value to separate value stocks from growth stocks. Between December 2002 and August 2016, the authors reported the value premium at 1.98% per annum against the market portfolio return of 8.66% per annum. To cap the poor performance of the value premium, it generated a negative Sharpe ratio unlike the positive Sharpe ratio for the market portfolio. The authors then split the period to three distinct phases: December 2002 to June 2007, June 2007 to December 2011, and December 2011 to August 2016. The value premium was 11.40%, 0.78% and -5.24% per annum in the first, in the second, and in the third period, respectively. The value premium was only higher than the market portfolio returns between June 2007 and December 2011. In Kenya, between 2009 and 2013, Riro & Wambugu (2015) documented that the value premium as captured by the Cahart four-factor model was a significant variable in explaining returns at the NSE. Achola & Muriu (2016) tested the applicability of the Fama and French three-factor model at the NSE. They confirmed the existence of the value premium between 2004 and 2014. Njogo (2017) provided further evidence. Between 2009 and 2014, Njogo reported that the value anomaly was statistically significant at the NSE. The author confirmed that there was a positive relationship between book-to-market equity ratio and stock returns at the NSE.

2.3.1.2 Momentum factor and stock returns

Momentum factor captures the return to a strategy that buys stocks that have increased in value (winning) over a certain period in the past, and the strategy sells or avoid those that decreased in value (losing) (Asness, Frazzini, Israel, & Moskowitz, 2014). Precisely, this strategy selects stocks on the basis of past returns in J months, and the strategy holds the stocks for K months (J and K being either three, six, nine or twelve months) (Jegadeesh & Titman, 1993). This combination of J and K produces 16 different ways to capture momentum return. Nevertheless, the use of twelve months past return while skipping the most recent month return to avoid one month reversal in stock returns and high bid-ask spreads was common in the literature (Asness et al., 2013; Fama & French, 2012).

Fama & French (2012) used the 11 months past return while skipping the most recent month return to capture the momentum factor. The study grouped countries into four regions: North America, Japan, Asia Pacific, and Europe. Between November 1990 and March 2011, the momentum premium (winner portfolio less loser portfolio) was 0.64%, 0.08%, 0.69% and 0.92% per month for North America, Japan, Asia Pacific, and Europe, respectively. These returns were statistically different from 0 in Europe and Asia Pacific only. Comparing the momentum premium to each region’s market portfolio, the momentum premium was higher than the market return in only Europe and Japan. The authors also combined the four regions into one global portfolio. The momentum premium for the global portfolio was 0.62% per month, and it was statistically different from 0 and higher than the global portfolio average. Cakici & Tan (2014), in contrast, used individual data from 23 developed markets to capture the momentum factor. The authors used the 11 months past return while skipping the most recent month return to capture momentum returns. Between January 1990 and March 2012, the momentum premium was statistically different from 0 in 13 countries. Angelidis & Tessaromatis (2017), likewise, reported returns to the momentum factor. Rather than individual stock data, the authors used country indexes from MSCI that encompassed 23 developed markets and 21 emerging markets. The study utilized the past 11 months return while skipping the most recent 2 months return. Between July 1980 and December 2015, the average return to the winning portfolio was 13.84% per annum, and the average return to the losing portfolio was 6.92% per annum. In the same period, the world market portfolio generated an average return of 10.64% per annum. Additionally, the winning portfolio generated a higher Sharpe ratio than the losing portfolio and the world market portfolio.

The return to the momentum factor was observed in specific markets. In the US, Blitz (2015) reported the return to the momentum factor. Blitz used the past 12 months return while skipping the most recent month return. Between July 1963 and December 2014, the returns to an equally and capitalization weighted winning portfolio averaged 9.7% and 8.1% per annum, respectively. The market portfolio earned 5% per annum in the same period. Furthermore, the winning portfolio, from equally and capitalization weighted portfolios, earned a higher Sharpe ratio than the market portfolio. The author replicated the same study but for a shorter period, January 2010 to December 2014. The winning portfolio, still, outperformed the market portfolio; however, the winning portfolio generated a lower Sharpe ratio than the market portfolio. In the UK, Dimson et al. (2017) deployed the past 12 months return while skipping the most recent month return to capture the momentum factor. Between 1900 and 2016, the authors reported that the cumulative difference between the winning and the losing portfolio averaged 10.2% per year. Pirie & Chan (2018) reported contrary findings from 9 countries in Asia. The authors used the past 6 months return to distinguish winning portfolios from losing portfolios. Thereafter, the authors held the portfolios for a variety of months ranging from 1 to 24 months. Between 1997 and 2009, momentum premium was negative across all holding periods. The authors attributed this poor performance to conflicting pressures, changing market conditions, and behavioral biases.

What about Africa? Between 2001 and 2009, Ushad (2012) reported that all 16 momentum trading strategies at the Stock Exchange of Mauritius generated a lower Sharpe ratio than the market portfolio. The author blamed isolation from developed capital markets and restrictions on foreign investor participation as some of the factors that limited the performance of momentum strategies. On the contrary, Flint et al. (2016) documented the strong performance of the momentum premium in South Africa. The study utilized the prior 12 months return while skipping the most recent month return. Between December 2002 and August 2016, the momentum premium averaged 20.88% per annum against the market average of 8.66% per annum. Equally, momentum premium generated a higher Sharpe ratio than the market portfolio (0.89 versus 0.54). The authors then split the period under study to three distinct phases: December 2002 to June 2007, June 2007 to December 2011, and December 2011 to August 2016. In each period, the authors reported the momentum premium was higher than the market average; however, the Sharpe ratio for the momentum premium was higher than the market portfolio in the first two periods only. Charteris, Rwishema, & Chidede (2018) documented similar results for South Africa. The study used the past 11 months return while skipping the most recent month return. Between 2000 and 2013, momentum premium averaged 1.65% per month compared to the market portfolio which averaged 0.60% per month. Momentum premium was also statistically different from 0 at the 1% significance level. The Kenyan evidence was akin to that of South Africa. Between 2009 and 2013, Riro & Wambugu (2015) documented that the addition of momentum premium to Fama and French's three-factor model improved the model's explanatory power at the NSE. Otinga (2017) broke down his study period into two: 2011 to 2013 and 2014 to 2016. He reported statistically significant momentum premium for the period 2011 to 2013, but only on the three- and six-months formation and holding period strategy.

2.3.1.3 Combined factor portfolio and stock returns

So far, it is evident that factor investing, and its associated returns cut across many markets in the world despite some conflicting evidence. Factor investing, especially, multifactor investing has multiple benefits. The primary benefit of multifactor investing is the negative or weak correlation between value factor and momentum factor. Asness et al. (2013) reported the results of combining value factor and momentum factor between 1972 and 2011. They reported that the two factors exhibited negative correlations in the US, in the UK, in European, and in Japanese stock markets. In addition, the authors combined the four markets into one global portfolio, and they reported a negative correlation between value factor and momentum factor. In terms of return, the combined factor portfolio generated superior statistically significant returns than the separate factor portfolios in all regions and in the global portfolio. Similarly, alpha - the intercept from the regression of each return series on the return of the market portfolio - was greater than the separate factor portfolios in all regions and in the global portfolio. Cakici & Tan (2014) reported comparable results, but they used individual data from 23 developed markets between 1990 and

2012. The authors documented that the value factor and momentum factor exhibited negative correlations in all countries. These correlations were also statistically significant in 15 countries. In terms of return, the authors reported that the combined factor portfolio generated statistically significant returns in all 23 countries unlike the separate factor portfolio returns. Grobys & Huhta-Halkola (2019) also reported a negative correlation between value factor and momentum factor but from Nordic countries. The authors reported the combined factor portfolio generated superior statistically significant returns than the separate factor portfolios. The evidence from Africa was not different. In South Africa, Flint et al. (2016) reported a negative correlation between value factor and momentum factor between 2002 and 2016.

The diversification benefit brought about by multifactor investing was tempered by portfolio choice: long-only or long-short. Long-only portfolios carry market exposure; Long-short portfolios eliminate market exposure by investing equal value in the long and short side of value or momentum factor (Ilmanen & Kizer, 2012). Ilmanen & Kizer (2012) put across this distinction clearly. In their study, the correlation between value and momentum in a long-short portfolio was -0.53, but in a long-only portfolio, correlation increased to 0.73. This in turn lowered the Sharpe ratio of the combined value and momentum factor portfolio from 1.44 to 0.86. Nevertheless, the authors pointed out the long-only combined factor portfolio still did its work of raising the Sharpe ratio. Flint et al. (2016) reported similar results but from the South African market. The correlation between value and momentum from the long-short portfolio was -0.41, but the correlation between value and momentum from the long-only portfolio was 0.76. Despite long-only portfolios reduced impact, Blitz (2015) argued the long-only approach was the preferred method after taking consideration of: factor decay, tracking error constraints in the case of passive investing, and implementation costs.

2.3.2 Cyclicity of stock returns from factor investing

At the outset, several studies picked on the cyclicity of stock returns from factor investing. For example, in the "dot com period" (1996 to 1999), Chan & Lakonishok (2004) reported that the value portfolio underperformed the growth portfolio by 11.8% per annum in the US. In the subsequent period, however, the authors reported the dramatic fall of the growth portfolio by 24.51% and the rise of the value portfolio by 22.82%. Bender et al. (2013) underscored the procyclical nature of factor returns. In their study, they reported that factors at a minimum went through two to three years of underperformance. Hsu (2014) split his analysis into three distinct periods, and he showed that the value premium in the US was as high as 60.3% in 2000, -33.1% in 2006, and 44.4% in 2009. Sebastian & Attaluri (2016) also conveyed that factors go in and out of favor for long periods of time. In their analysis, this offers an opportunity for skilled investors to add returns to their portfolios. Those who do not wish to take an active approach were advised by the authors to consider investing for the long-term despite the underperformance from time to time. In India, Agarwalla, Jacob, & Varma (2017) reported that the value factor and momentum factor recorded a maximum loss of 53% and 48.5%, respectively. The authors also noted that it took more than 7 years and 2 years for the value factor and momentum factor to reach their previous peaks, respectively. Kalesnik & Linnainmaa (2018) similarly reported large maximum losses for value factor and momentum factor in Europe, in Developed Markets, and in Asia Pacific excluding Japan between 1990 and 2017. The authors concluded that factor investing is a valuable tool for investors to achieve their long-term goals, but it requires: investors who are willing to weather periods of underperformance, have tempered expectations of the factors, and have the skill to carry through the investment. Recently, Warren & Quance (2019) noted that factor returns were influenced by the changing economic environment. For example, the authors highlighted that when an economy was in a recovery phase, value portfolios tended to do well as they were trading at a discount. Conversely, when the economy or stock market was experiencing rapid growth, value portfolios tended to disappoint.

2.3.3 The source of stock returns from factor investing

Several studies have endeavored to explain the source of stock returns from factor investing. Among the many asset pricing models used to explain stock returns, CAPM has featured prominently. CAPM postulates that an asset's return is explained by its sensitivity to an economy wide source of risk. It has become the norm to use a country's stock market index to proxy the source of risk. To explain the source of stock returns from factor investing using CAPM, factor portfolio returns are regressed on the returns of a market index (Fama & French, 1993). According to Fama & French (2006), if the CAPM holds, alpha (the intercept) is indistinguishable from 0. Similarly, beta (the slope) is statistically significant and close to the hypothesized value of 1.

The effectiveness of CAPM to explain stock returns from factor investing has varied from study to study. Asness et al. (2013) reported that of the four asset pricing models used to explain value factor and momentum factor returns, CAPM produced the largest pricing error (alpha). Additionally, CAPM explained the least variation of value factor and momentum factor returns. The authors concluded that CAPM did a poor job in explaining value factor and momentum factor returns. In a similar study but using 23 developed stock markets independently, Cakici & Tan (2014) reported that value premium generated statistically significant alpha in 15 countries. In all countries, beta of the value premium was small and statistically insignificant. The authors replicated the same study for the momentum premium. In all countries, alpha was statistically different from 0 and betas were negative. On the contrary, Ushad (2012) reported that in the Mauritius Stock Exchange momentum factor generated statistically insignificant alpha. The author concluded that investors are unable to generate significant positive excess return (alpha) by investing in momentum strategies. Similarly, Blitz (2015) reported that value factor and momentum factor generated inferior risk-adjusted returns (alpha) in the US between 2010 and 2014. This finding contrasted with the longer period (1963 to 2014) where value factor and momentum factor generated statistically significant alpha.

2.4 Research gap

A review of literature established the returns to factor investing across different markets and time periods. By and large, the returns were above the market average and statistically significant from 0 (Angelidis & Tessaromatis, 2017; Blitz, 2015; Flint et al., 2016). The returns were also boosted by investing in multiple factors due to low or weak correlation between factors (Asness et al., 2013; Ilmanen & Kizer, 2012). Factor investing, however, failed to earn returns in certain markets, and in others, the returns were statistically insignificant (Cakici & Tan, 2014; Hsieh, 2015; Ushad, 2012). Additionally, factor returns were cyclical, thus, investors were likely to experience periods of loss (Bender et al., 2015; Dimson et al., 2017). The long-only versus long-short approach to factor investing was also pertinent (Ilmanen & Kizer, 2012).

In Kenya, the existence of factors has been documented through tests of asset pricing models and stock market anomalies at the NSE (Achola & Muriu, 2016; Njogo, 2017; Otinga, 2017; Riro & Wambugu, 2015). These studies identified the existence of value and momentum that are germane to this research. Apart from Otinga (2017), none of the above studies explicitly formed portfolios to try and capture returns from value factor and momentum factor. Moreover, none of the studies combined the two factors into a portfolio and reported the subsequent returns. Thus, there was a research gap that pertained to reporting the profits earned from value factor and momentum factor together and separately.

The table below provides a matrix capturing studies, findings, research gaps and how the study sought to fill these gaps:

Table 2. 1: Research gaps matrix

Study	**Finding**	**Research gap and the proposed solution**
Koedijk et al. (2016)	Factor investing presents an opportunity to understand what drives returns and risks.	The gap is on the applicability of the inference at the NSE. To address this gap, the study sought to establish the profitability of stock returns from factor investing.
Fama & French (2012)	Value factor generated positive and statistically significant returns in 23 developed countries.	The gap is on the similarity of the findings at the NSE. To close the gap, the study sought to evaluate the profitability of the value factor at the NSE.
Angelidis & Tessaromatis (2017)	Value factor generated positive and statistically significant returns in 23 developed and 21 emerging countries.	The gap is on the resemblance of the findings at the NSE. To fill the gap, the study sought to evaluate the profitability of the value factor at the NSE.
Hsieh (2015)	Value factor generated positive and statistically significant returns in South Africa.	The gap is on the similarity of the South African evidence in Kenya. To bridge the divide, the study sought to evaluate

		the profitability of the value factor at the NSE.
Njogo (2017)	The study confirmed a positive relationship between book-to-market equity ratio and stock returns at the NSE.	The gap is on the translation of the value anomaly into a factor portfolio that could be exploited. To fill the gap, the study constructed value factor portfolios, and measured its return.
Cakici & Tan (2014)	Momentum factor generated positive and statistically significant returns in 23 developed countries.	The gap is on the resemblance of the findings at the NSE. To fill the gap, the study sought to evaluate the profitability of the momentum factor at the NSE.
Dimson et al. (2017)	Winning portfolio generated higher returns than the losing portfolio in the UK.	The gap is on the similarity of the findings at the NSE. To close the gap, the study sought to report the results of the winning portfolio.
Pirie & Chan (2018)	Momentum factor returns were negative across 9 Asian countries.	The gap is on the resemblance of the findings at the NSE. To fill the gap, the study sought to evaluate the profitability of the momentum factor at the NSE.
Otinga (2017)	Momentum factor return was statistically significant for the	The gap is whether momentum factor returns at

	period 2011 to 2013 at the NSE.	the NSE were profitable between 2010 and 2019. To bridge the gap, the study sought to evaluate the profitability of the momentum factor at the NSE.
Asness et al. (2013)	The combined value and momentum factor portfolio generated positive and statistically significant returns in developed markets.	The gap is on the applicability of the inference at the NSE. To address this gap, the study sought to establish the profitability of stock returns from the combined factor portfolio.
Grobys & Huhta-Halkola (2019)	The combined value and momentum factor portfolio generated positive and statistically significant returns in Nordic countries.	The gap is on the resemblance of the findings at the NSE. To address this gap, the study sought to establish the profitability of stock returns from the combined factor portfolio.
Ilmanen & Kizer (2012)	The benefit of the combined factor portfolio is tempered by portfolio choice: long-short or long-only portfolio.	The gap is on the similarity of the findings at the NSE. To address this gap, the study sought to establish the correlation between value and momentum factor using either long-short or long-only portfolios.

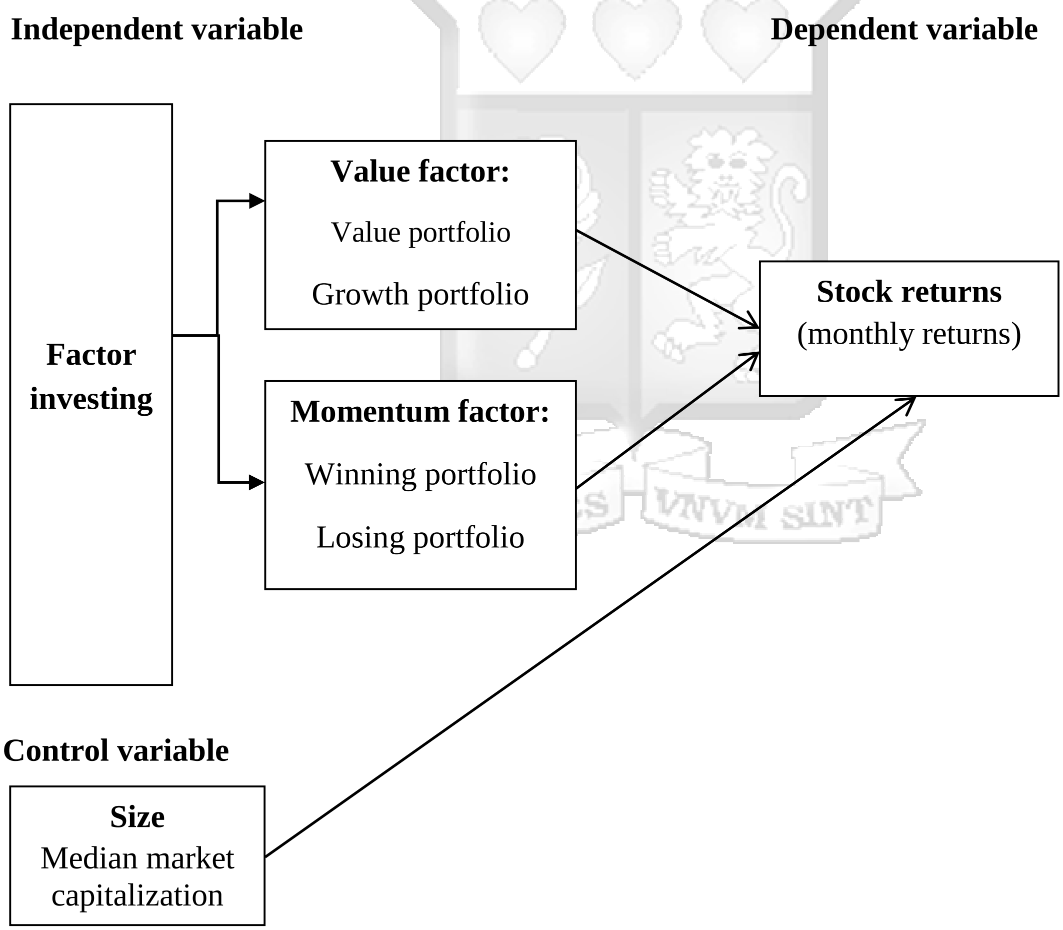
Bender et al. (2013)	Stock returns from factor investing are cyclical in the US.	The gap is on the resemblance of the findings at the NSE. To address this gap, the study sought to evaluate the cyclicity of stock returns from factor investing.
Agarwalla et al. (2017)	Stock returns from factor investing are cyclical in India.	The gap is on the similarity of the findings at the NSE. To close this gap, the study sought to evaluate the cyclicity of stock returns from factor investing.
Kalesnik & Linnainmaa (2018)	Stock returns from factor investing are cyclical in developed markets.	The gap is on the likeness of the findings at the NSE. To close this gap, the study sought to evaluate the cyclicity of stock returns from factor investing.
Ushad (2012)	The CAPM was effective in explaining the stock returns of the momentum factor at the Mauritius Stock Exchange.	The gap is on the similarity of the findings at the NSE. To close this gap, the study sought to evaluate the source of stock returns from factor investing.
Blitz (2015)	The CAPM was effective in explaining the stock returns of the momentum and value factor in the US.	The gap is on the similarity of the findings at the NSE. To close this gap, the study sought to evaluate the source

		of stock returns from factor investing.

2.5 Conceptual framework of factor investing and stock returns

This study sought to analyze stock returns generated from factor investing. The independent variable was factor investing (value factor and momentum factor) whereas the dependent variable was stock returns. The study sought to analyze how the independent variables related with the dependent variable.

Figure 2. 1: Conceptual framework of stock returns from factor investing



Source: Researcher (2021)

2.6 Operationalization of variables

Table 2. 2: Study variables

Variables	Indicator	Measure	Supporting Literature
Independent variables:			
Value factor			
	Value portfolio	Low price-to-book ratio	Pätäri & Leivo (2017); Asness et al. (2015)
	Growth portfolio	High price-to-book ratio	
Momentum factor			
	Winning portfolio	High past continuously compounded monthly stock returns	Asness et al. (2014); Dimson et al. (2017)
	Losing portfolio	Low past continuously compounded monthly stock returns	
Dependent variable:			
Stock returns	Monthly returns	End month price/beginning month price	Otinga (2017); Blitz (2015)
Control variable:			
Size	Median market capitalization	Number of shares outstanding times market price	Asness et al. (2013); Fama & French (2012)

2.7 Chapter summary

This chapter begun by discussing relevant theories that underpin this research, namely the Efficient Market Hypothesis, Behavioral Finance and Capital Asset Pricing Model. The chapter also included an empirical analysis of the returns to value factor and momentum factor, cyclicity of stock returns from factor investing, and source of stock returns from factor investing. It concluded by presenting the conceptual framework in diagrammatic form and the operationalization of variables.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter explains the strategies that were used to obtain the information relevant to achieving the objectives of the study. This chapter, therefore, shows the research design, population and sampling, data collection, data analysis, research validity, and ethical considerations for the study.

3.2 Research philosophy

The study adopted a positivist approach to research. The aim of positivist studies is to consistently be rational and use logical approaches to seek objectivity (Saunders, Lewis, & Thornhill, 2012). In positivism studies, the researcher collects and interprets data in an objective way by using statistical and mathematical procedures to make inferences from the study. In these types of studies, research findings are usually observable and quantifiable. In addition, according to Saunders et al. (2012), the positivist approach emphasizes that researchers should be detached from the study. Yet, the authors contend it is difficult to be completely removed from a research endeavor. This is because the researcher still needs to make choices about: what to study, the objectives to put together, and the data to collect. The positivist approach is appropriate for this study as it used secondary data to determine relationship between variables.

3.3 Research design

According to Saunders et al. (2012), research design is the arrangement of procedures for collection and analysis of data to align it with the research objective. This study employed a descriptive research design as it sought to report information regarding the variables as they existed (Kothari, 2008). According to Kothari (2008), the descriptive research approach is applicable when the researcher clearly knows what to measure, the measurement methods, and a clear definition of 'population' under study. This method was advantageous because its rigidity and focus on attention ensured the problem at hand was adequately treated. Conversely, the drawback of this method was its requirement for careful planning because its aim was to obtain complete and accurate information. This design was applicable to this study because what was being measured was returns to factor investing at the NSE. The methodology to calculate the returns was also well articulated with respect to value and momentum factor.

3.4 Population and sampling

The target population for this study comprised all listed companies at the NSE between 2010 and 2019. As at the fourth quarter of 2019, 65 companies traded on the bourse (Capital Markets Authority, 2019). For this study, purposive sampling was adopted to collect data. Purposive sampling is a non-probability technique where the researcher deliberately selects particular units from a population to qualify as the sample (Kothari, 2008). For this study, purposive sampling entailed the selection of stocks that were above the median market capitalization at the beginning of each year t. The goal was to concentrate the study on large-capitalization stocks (Asness et al. 2013). Table 3.1 below shows the number of companies sampled. Appendix III to VI displays the sampled companies.

Table 3. 1: Target population and sample

	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Primary listed	55	58	61	61	64	64	66	67	67	65
Delisted	0	0	0	-1	0	-1	0	-3	-3	-3
Suspended	0	-2	0	-2	-2	0	-1	-1	-3	-4
Population	**55**	**56**	**61**	**58**	**62**	**63**	**65**	**63**	**61**	**58**
Sample	27	27	29	30	30	32	32	33	32	32

Source: CMA and NSE (2020)

3.5 Data collection

This study used secondary data to achieve the first, the second, and the third objective. The objectives were to examine the profitability of stock returns from factor investing, assess the cyclicity of stock returns from factor investing, and determine the source of stock returns from factor investing. The secondary data collected was book value of equity, market value of equity, daily closing stock prices, daily closing NASI price levels, and the 91-day treasury bill rates. To achieve the first objective, book value of equity, market value of equity, daily stock prices, daily NASI price levels, and the 91-day treasury bill rates were used. Book value of equity was obtained from the sampled companies' annual reports. Book value of equity was for the fiscal year ended in calendar year $t-1$. Market value of equity or market capitalization was obtained from the NSE daily price list. Market value of equity was for the end of December of calendar year $t-1$. The ratio of market value-to-book value of equity was used to construct value and growth portfolios. To construct the winning and losing portfolios for the momentum factor, stocks were sorted based on the cumulative past return which were calculated from daily closing stock prices. The daily closing stock prices and daily closing NASI index levels were obtained from the daily price list provided by the NSE. To capture the excess returns of the value and momentum portfolios, the 91-day treasury bill rate was used. This data was retrieved from the Central Bank of Kenya website.

The second and third objective relied on the data already obtained. The returns of NASI, value, and momentum portfolios were calculated from the daily NASI price level and closing stock prices.

3.6 Data analysis

Saunders et al. (2012) defined data analysis as the application of statistical tools, in a methodical way, to process data into meaningful information. For this study, secondary data was cleaned, sorted, and coded before descriptive and inferential statistics were carried out. The first objective of this study was to examine the profitability of stock returns from factor investing. To achieve this objective, the sampled stocks were sorted to value or growth portfolio and winning or losing portfolio. Value or growth portfolio corresponded to the value factor; winning or losing portfolio corresponded to the momentum factor. Value or growth portfolios were formed from the ratio of book value-to-market value of equity at the beginning of each year t . Winning or losing portfolios were formed from past returns. Specifically, in any given month t, portfolios were formed from the ranking of stocks from continuously compounded returns over the past 12 months, in ascending order, while skipping the most recent month. In addition, the portfolios formed in month $t-12$ were closed out.

After the definition of the factor portfolios, three equal portfolios were constructed for the value and momentum factor. The value factor had value and growth portfolio, and the momentum factor had winning and losing portfolio. The intermediate portfolios were the bridge between value or growth portfolio and winning or losing portfolio. Value portfolio consisted of stocks that exhibited the lowest market value-to-book value of equity, and growth portfolio consisted of stocks that exhibited the highest market value-to-book value of equity. Winning portfolio consisted of stocks that had the highest 12 months cumulative returns, and losing portfolio consisted of stocks that had the lowest 12 months cumulative returns. The combined factor portfolio was constructed by an equal weight of each factor.

The weight of each stock in the portfolio was constructed by either value-weight or equal weight. Value-weight weighed each stock in the portfolio by its ratio of market capitalization to total portfolio capitalization, and equal weight weighed each stock equally. The realized return from each portfolio was calculated every month for the next 12 months. The mean return and standard deviation of return for each portfolio was computed each year for the entire period under study. These analyses were done in Microsoft Excel. To test the statistical significance of a portfolio's return, the following hypothesis test was carried out in Stata:

$$Ho: Xi = 0$$

$$Ha: Xi \neq 0$$

where Xi was the mean return of either the value or momentum portfolio (independently or jointly). The test statistic to test whether to accept or reject the null hypothesis was computed as follows in Stata:

$$t - statistic = \frac{\mu - 0}{\sigma/\sqrt{n}}$$

where μ was the mean of the return series, σ was the standard deviation of the return series, and n was the number of months. The chosen significance level was 5% which translated to a t-critical value of 1.96.

To assess the risk-adjusted return of the factor portfolios, the Sharpe ratio was calculated. The Sharpe ratio measures a portfolio's return in excess of a risk-free rate relative to its standard deviation. The Sharpe ratio was the chosen metric as it is ubiquitous in the literature. This analysis was done in Microsoft Excel. The formula was:

$$Sharpe\ ratio = \frac{(R_i - R_f)}{\sigma_i}$$

where $(R_i - R_f)$ was portfolio $i`s$ excess return and $\sigma_i$ was portfolio $i`s$ standard deviation. To carry out the correlation analysis, the Pearson correlation coefficient was calculated. The correlation coefficient measures the degree of linear association between two variables and the direction of the relationship (Brooks, 2011). This analysis was carried out on the returns of the value and momentum portfolios, and it was done in Microsoft Excel. The formula for the correlation coefficient was:

$$\rho_{xy} = \frac{Cov(x, y)}{\sigma_x \sigma_y}$$

where ρ_{xy} was the correlation coefficient, $\mathrm{Cov}(x, y)$ was the covariance between the value and momentum portfolio, σ_x was the standard deviation of the value portfolio, and σ_y was the standard deviation of the momentum portfolio. After 12 months, the factor portfolios were recalibrated to reflect new book value of equities, past 12 months return, and the new crop of stocks that fell above the median market capitalization.

The second objective was the assessment of cyclicity of stock returns from factor investing. To achieve this objective, maximum drawdown, average drawdown, and duration to previous peak were computed. Additionally, stock market cycles were identified, specifically bull and bear market periods. Maximum drawdown, average drawdown and duration to previous peak were calculated from the factor portfolio returns. Maximum drawdown was defined as the maximum peak-to-trough loss. Maximum drawdown was computed in Microsoft Excel as:

$$MDD_T = \max_{0 \le t \le T} D_t \qquad \text{with} \qquad D_t = \max_{0 \le x \le t} S_x - S_t$$

where D_t is the drawdown from the previous maximum value at time t. Average drawdown was defined as the average of the peaks-to-troughs losses (drawdown loss). Average drawdown was computed in Microsoft Excel as:

$$ADD = \sum_{t=1}^{T} D_t / n$$

where D_t is the drawdown from the previous maximum value at time t and n is the number of drawdowns. Duration to previous peak measured how long stock returns from factor investing took to reach their previous highs. The measure was computed from a conditional statement in Microsoft Excel:

$$Duration\ to\ previous\ peak\ = if\ return_t < 0, current\ month\ + 1\ otherwise\ 0$$

To identify the stock market cycles, the troughs and peaks that defined the change in market direction had to be identified. To carry out the analysis, daily NASI index price levels were used. At any point in time in the analysis period, if the price of NASI was the highest (lowest) in the 8 preceding months and 8 succeeding months, the index price was considered as the peak (trough). There is a peak if:

$$[P_{t-8}, \dots P_{t-1} < P_t > P_{t+1}, \dots P_{t+8}] \text{ , and}$$

a trough if:

$$[P_{t-8}, \dots P_{t-1} > P_t < P_{t+1}, \dots P_{t+8}]$$

where P_t denotes the NASI index price level. To conclude the objective, the computed monthly returns for the value and momentum portfolios (independently and jointly) were plotted on a line graph in Microsoft Excel, and a visual inspection was carried out.

The third objective was the determination of the source of stock returns from factor investing. To achieve this objective, the CAPM was chosen as the asset pricing model to try and explain the factor portfolios returns. The following regression analysis was ran in Stata:

$$R_t - RF_t = \alpha + \beta_1(RM_t - RF_t) + \beta_2(SMB - RFt) + \varepsilon$$

where $R_t - RF_t$ was portfolio $i's$ risk-adjusted return in period t, α was alpha, β_1 the factor loading of portfolio i on the risk-adjusted return of NASI, and β_2 the factor loading of portfolio i on the risk-adjusted return of the small-cap portfolio (control variable). Thereafter, two hypothesis tests were carried out in Stata to test the appropriateness of CAPM in explaining stock returns from factor investing. The first hypothesis test was:

$$Ho: \alpha = 0$$

$$Ha: \alpha \neq 0$$

where α was the alpha of either the value or momentum portfolio (independently or jointly). The test statistic to test whether to accept or reject the null hypothesis was computed as follows in Stata:

$$t - statistic = \frac{\mu - 0}{\sigma/\sqrt{n}}$$

where μ was the alpha of the portfolio and $\sigma/\sqrt{n}$ was the standard error of alpha. The second hypothesis test was:

$$Ho: \beta = 0$$

$$Ha: \beta \neq 0$$

where β was the beta of either the value or momentum portfolio (independently or jointly). The test statistic to test whether to accept or reject the null hypothesis was computed as follows in Stata:

$$t - statistic = \frac{\mu - 0}{\sigma/\sqrt{n}}$$

where μ was the beta of the portfolio and $\sigma/\sqrt{n}$ was the standard error of beta. The chosen significance level was 5% which translated to a t-critical value of 1.96.

3.6.1 Diagnostic tests

Brooks (2011) stresses the challenges of financial data when it violates the underlying assumptions of linear regression. When these assumptions are violated, the regression results will be invalid. Diagnostics tests, hence, were necessary before any meaningful analysis could be done. Three diagnostic tests were done: unit roots, serial correlation, and normality.

3.6.1.1 Unit roots

Unit root test was conducted to determine whether the variables in the study were weakly dependent. Time series data with unit roots would lead to misleading results if the linear regression model assumptions were violated (Wooldridge, 2013). The test carried out for unit roots was an Augmented Dickey-Fuller (ADF) test for a unit root. The null hypothesis was H_o = Existence of unit root against H_1 = Non-existence of unit root in the data.

3.6.1.2 Serial correlation

The serial correlation test was conducted to determine whether the residuals from the regression model were uncorrelated. Regression coefficients with serial correlation in the residuals would render the coefficient estimates inefficient. In the case of positive serial correlation, standard error estimates would be biased downwards relative to the true standard error estimates. The positive serial correlation would lead to an increase in the probability of a type I error (Brooks, 2011). The test carried out for serial correlation was the Breusch-Godfrey test for serial correlation. The null hypothesis was H_o = No serial correlation against H_1 = Presence of serial correlation.

3.6.1.3 Normality

Normality test was done to ensure the error term in the regression model was normally distributed. A normally distributed variable is symmetric about its mean, is not skewed, and is defined to have a coefficient of kurtosis of 3. Normality of residuals is important to conduct hypothesis tests about the model coefficients. Most financial data, however, has been observed to exhibit fat tails - a characteristic of non-normally distributed data (Brooks, 2011). For sufficiently large sample sizes, the violation of the normality assumption is inconsequential. The test carried out for normality of the residuals was the Bera-Jarque test. The null hypothesis was H_o = Normally distributed errors against H_1 = Non-normally distributed errors.

3.7 Research quality

The validity of a research can either be internal or external. External validity is the ability to generalize the research findings. External validity shows how the findings of a study can be applied to a different environment. This study was generalizable to stocks listed on different exchanges. Internal validity is the extent to which a study establishes cause and effect relationship between variables as opposed to a spurious relationship. To ensure this, the data collected was subjected to careful analysis such that the quality of the output was of high standards.

3.8 Ethical considerations

Since the data (stock prices, NASI index levels, companies' annual reports and 91-day treasury bills) was collected from public resources, no ethical considerations arose in the due course of carrying out this study.

CHAPTER FOUR

PRESENTATION OF RESEARCH FINDINGS

4.1 Introduction

The results of the data analysis and research findings of the study are presented in this chapter. The chapter organization is based on the specific objectives of the study. Section 4.2 presents general information about the study. Section 4.3 covers the first objective which aims at the examination of the profitability of stock returns from factor investing. Section 4.4 discusses the second objective which assesses the cyclicity of stock returns from factor investing. Section 4.5 presents the source of stock returns from factor investing, and section 4.6 presents the chapter summary.

4.2 Data and sample

The study collected secondary data which included companies' annual reports, stock prices, NASI index levels, and 90-day treasury bill rates. The study sampled large-capitalization stocks at the NSE between 2010 and 2019. 10 portfolios were formed for the value factor, and 121 portfolios were formed for the momentum factor. Thereafter, the stocks in each factor portfolio were held in either value or equally weighted portfolios for comparison. The large-cap stocks market capitalization as a percentage of total market capitalization is presented below:

Table 4. 1: Sampled stocks market capitalization as a % of total market capitalization

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
% of total market cap	94.99	95.73	95.09	96.17	95.77	96.59	97.10	97.84	98.04	98.07

Source: Researcher (2021)

4.3 To examine the profitability of stock returns from factor investing

The first objective of the study examined stock returns from value and momentum factor portfolios (independently and jointly) at the NSE. The stock returns were calculated from value and equally weighted portfolios. Value-weighted portfolios weighed each stock relative to its market capitalization, and equally weighted portfolios weighed each stock evenly. The equally weighted portfolios were formed to control for the effects of large capitalization stocks on portfolio returns. Independent t-tests were computed to assess the statistical significance of the factor returns. The factor returns were adjusted for risk by subtracting the 91-day treasury bill rate. Additionally, the Pearson correlation coefficient, standard deviation and Sharpe ratio were computed. The Pearson correlation coefficient was used to measure the strength of a linear association between two variables. The measure ranges from +1 to -1. +1 indicates a strong positive linear relationship between the variables, and -1 indicates a strong negative linear relationship between the variables. 0 indicates no linear relationship between the variables. Standard deviation measured the dispersion of returns relative to its mean, therefore, a high standard deviation signified increased dispersion of returns from its mean. The Sharpe ratio adjusted the return earned by the amount of risk taken to generate the return. Risk was proxied by standard deviation of returns. The portfolio with the highest Sharpe ratio generated high returns with minimal risk.

4.3.1 Stock returns from value factor

The value factor was defined by the ratio of market value of equity to book value of equity. High market value of equity to book value of equity stocks were placed in the value portfolio, and low market value of equity to book value of equity stocks were placed in the growth portfolio. Value premium was defined as value portfolio return less growth portfolio return. In the analysis, the value portfolio was bought, and the growth portfolio was sold short. Value premium combined the long and short side of the value and growth portfolio, respectively. Table 4.2 on the following page presents the returns from the value factor.

Table 4. 2: Annualized risk-adjusted stock returns from value factor

Panel A: Value-weighted portfolio				
	NASI	**Value portfolio**	**Growth portfolio**	**Value premium**
Mean %	1.49	-8.05	2.90	-10.95
(t-stat)	*(0.32)*	*(-1.38)*	*(0.64)*	*(-2.3)*
Standard deviation %	15.85	20.21	15.64	16.30
Sharpe ratio	0.09	-0.4	0.19	-0.67
Panel B: Equally weighted portfolio				
	NASI	**Value portfolio**	**Growth portfolio**	**Value premium**
Mean %	1.49	-7.24	-3.98	-3.25
(t-stat)	*(0.32)*	*(-1.32)*	*(-0.9)*	*(-0.8)*
Standard deviation %	15.85	18.96	15.40	13.68
Sharpe ratio	0.09	-0.38	-0.26	-0.24

Source: Researcher (2021); critical *t*-value of 1.96 at $\alpha=0.05$

Between 2010 and 2019, the value portfolio lost 8.05% per year. The value portfolio return was also statistically insignificant as shown by the low t-statistic value. Panel B of Table 4.2 shows slightly lower value returns; however, the value portfolio return remained statistically insignificant. In both Panel A and B, the value portfolio returns underperformed NASI, and they also generated a negative Sharpe ratio. Unlike the value portfolio, the growth portfolio earned 2.90% per year; however, the return was statistically insignificant. When compared to NASI, the growth portfolio generated a higher Sharpe ratio. In Panel B, the growth portfolio lost 3.98% per year, and it generated statistically insignificant returns. The growth portfolio also produced a negative Sharpe ratio, and it therefore underperformed NASI. Value premium lost 10.95% per year, and generated statistically significant returns; nonetheless, value premium underperformed NASI with its negative Sharpe ratio. In Panel B, value premium was slightly negative. Since the growth portfolio was sold short in the value premium calculation, the negative growth portfolio return reduced the negative value premium return. Nevertheless, value premium became statistically insignificant, and it still underperformed NASI.

In conclusion, the value portfolio lost money, and it generated statistically insignificant returns at the NSE. The same insights for the value portfolio can be gleaned from the equally weighted portfolio. The growth portfolio earned a positive return, but the return was statistically insignificant. From the equally weighted portfolio, the growth portfolio lost money, and it generated statistically insignificant returns. Finally, value premium generated negative returns that exhibited statistically significant returns. On the other hand, value premium from the equally weighted portfolio generated statistically insignificant returns.

4.3.2 Stock returns from momentum factor

The momentum factor was formed from the past 12 months return while skipping the most recent month. The recent month was skipped to avoid one-month reversals in stock returns and high bid-ask spreads. Stocks that generated the highest returns in the past 12 months were placed in the winning portfolio, and stocks that generated the least returns in the past 12 months were placed in the losing portfolio. Momentum premium was defined as winning portfolio return less losing portfolio return. Like the value factor, the winning portfolio was bought, and the losing portfolio was sold short. Momentum premium combined the long and short side of the winning and losing portfolio, respectively. Table 4.3 presents the returns from the momentum factor.

Table 4. 3: Annualized risk-adjusted stock returns from momentum factor

Panel A: Value-weighted portfolio				
	NASI	**Winning portfolio**	**Losing portfolio**	**Momentum premium**
Mean %	1.49	4.52	-3.69	8.21
(t-stat)	*(0.32)*	*(0.95)*	*(-0.70)*	*(2.01)*
Standard deviation %	15.85	16.47	18.35	14.16
Sharpe ratio	0.09	0.28	-0.20	0.58
Panel B: Equally weighted portfolio				
	NASI	**Winning portfolio**	**Losing portfolio**	**Momentum premium**
Mean %	1.49	-1.52	-7.55	6.03
(t-stat)	*(0.32)*	*(-0.35)*	*(-1.35)*	*(1.54)*
Standard deviation %	15.85	14.84	19.40	13.61
Sharpe ratio	0.09	-0.10	-0.40	0.44

Source: Researcher (2021); critical *t*-value of 1.96 at α=0.05

Between 2010 and 2019, the winning portfolio earned 4.52% per year, but the return was statistically insignificant. In comparison with NASI, the winning portfolio generated a higher Sharpe ratio despite its higher standard deviation. In Panel B, the winning portfolio lost 1.52% per year. The negative return was due to control of Safaricom's weight in the equally weighted portfolios. In contrast to the winning portfolio, the losing portfolio lost 3.69% per year, and the return was statistically insignificant. According to Panel B, the losing portfolio negative returns increased slightly, but the returns were still statistically insignificant. Momentum premium earned 8.21% per year, and the return was statistically significant. The strong performance was due to the winning portfolio and the losing portfolio performing as expected: the winning portfolio made money, and the losing portfolio lost money. Given the high return and low standard deviation of returns, momentum premium generated a higher Sharpe ratio than NASI. In Panel B, momentum premium reduced to 6.03%, and as a result, momentum premium became statistically insignificant, but it still generated a higher Sharpe ratio than NASI.

In conclusion, the winning portfolio earned a positive return, and the losing portfolio generated a negative return. Furthermore, both portfolios' returns were statistically insignificant. Lastly, momentum premium generated a positive and statistically significant return; however, the momentum premium from the equally weighted portfolio was lower and statistically insignificant.

4.3.3 Stock returns from the combined factor

The combined factor portfolio was formed by holding value and momentum factor equally. The portfolio was formed from either value and momentum premium (long-short portfolio) or value and winning portfolio (long-only portfolio).

The data in Table 4.4 on the following page presents the long-short portfolio returns.

Table 4. 4: Annualized risk-adjusted stock returns from long-short factor portfolios

Panel A: Value-weighted portfolio				
	NASI	**Long-short portfolio**	**Value premium**	**Momentum premium**
Mean %	1.49	-1.37	-10.95	8.21
(t-stat)	*(0.32)*	*(-0.66)*	*(-2.3)*	*(2.01)*
Standard deviation %	15.85	7.22	16.30	14.16
Sharpe ratio	0.09	-0.19	-0.67	0.58
Correlation (Val, Mom)			-0.56	
Panel B: Equally weighted portfolio				
	NASI	**Long-short portfolio**	**Value premium**	**Momentum premium**
Mean %	1.49	1.39	-3.25	6.03
(t-stat)	*(0.32)*	(0.68)	(-0.8)	(1.54)
Standard deviation %	15.85	7.08	13.68	13.61
Sharpe ratio	0.09	0.20	-0.24	0.44
Correlation (Val, Mom)			-0.46	

Source: Researcher (2021); critical *t*-value of 1.96 at α=0.05

According to Panel A of Table 4.4, the long-short portfolio generated a negative return lower than value premium, but it fared poorly when compared to momentum premium. The long-short portfolio return, unlike value and momentum premium, was statistically insignificant. The insignificant returns were unexpected given the anticipated benefit of multifactor investing. In particular, the negative correlation between value and momentum premium was futile. In comparison with NASI, the long-short portfolio generated a negative Sharpe ratio despite the lower standard deviation of returns. In Panel B, however, the long-short portfolio generated a higher Sharpe ratio than NASI because of the lower standard deviation of returns.

The data in Table 4.5 on the following page presents the long-only portfolio returns.

Table 4. 5: Annualized risk-adjusted stock returns from long-only factor portfolios

Panel A: Value-weighted portfolio				
	NASI	**Long-only portfolio**	**Value portfolio**	**Winning portfolio**
Mean %	1.49	-1.77	-8.05	4.52
(t-stat)	*(0.32)*	(-0.34)	*(-1.38)*	(0.95)
Standard deviation %	15.85	16.64	20.21	16.47
Sharpe ratio	0.09	-0.11	-0.40	0.28
Correlation (Val, Mom)			0.65	
Panel B: Equally weighted portfolio				
	NASI	**Long-only portfolio**	**Value portfolio**	**Winning portfolio**
Mean %	1.49	-4.38	-7.24	-1.52
(t-stat)	*(0.32)*	(-0.87)	(-1.32)	(-0.35)
Standard deviation %	15.85	15.87	18.96	14.84
Sharpe ratio	0.09	-0.28	-0.38	-0.10
Correlation (Val, Mom)			0.77	

Source: Researcher (2021); critical *t*-value of 1.96 at α=0.05

The long-only portfolio performed better than the value portfolio, but it performed worse than the winning portfolio and NASI; however, none of the portfolios generated statistically significant returns. Unlike the long-short portfolio, the long-only portfolio failed to reproduce the diversification benefit of multifactor investing. The positive correlation coefficient between value factor and momentum factor failed to substantially lower the standard deviation of returns of the long-only portfolio. As a result of the high standard deviation of returns and the negative return, the long-only portfolio generated a negative Sharpe ratio which was better than the value portfolio, but the Sharpe ratio was worse than the winning portfolio and NASI. The same analysis applied to the data in Panel B.

In conclusion, regardless of the portfolio construction choice, the long-short portfolio and long-only portfolios generated statistically insignificant returns. Similarly, the anticipated benefits of multifactor investing, through the weak correlation of value and momentum factor, remained unrealized. The combined factor portfolios failed to improve the risk-adjusted returns (Sharpe ratio) of the separate value and momentum factor.

4.4 Assessment of the cyclicity of stock returns from factor investing

The second objective sought to understand the cyclicity of stock returns from factor investing. To assess cyclicity, maximum drawdown, average drawdown, and time to previous peak were computed. Additionally, stock market cycles were identified, and factor returns were evaluated in the bull and bear market periods. The results of the analysis are presented below.

4.4.1 Maximum drawdown, average drawdown, and time to previous peak

Maximum drawdown was defined as the worst loss among successive losses during a given period; similarly, average drawdown was defined as the mean loss among successive declines during a given period. Time to previous peak measured how long it took the stock returns from factor portfolios in years to reach previous highs.

4.4.1.1 Value factor

The data in Table 4.6 presents the maximum drawdown, average drawdown, and time to previous peak for the value factor.

Table 4. 6: Value factor drawdown measures and duration to previous peak

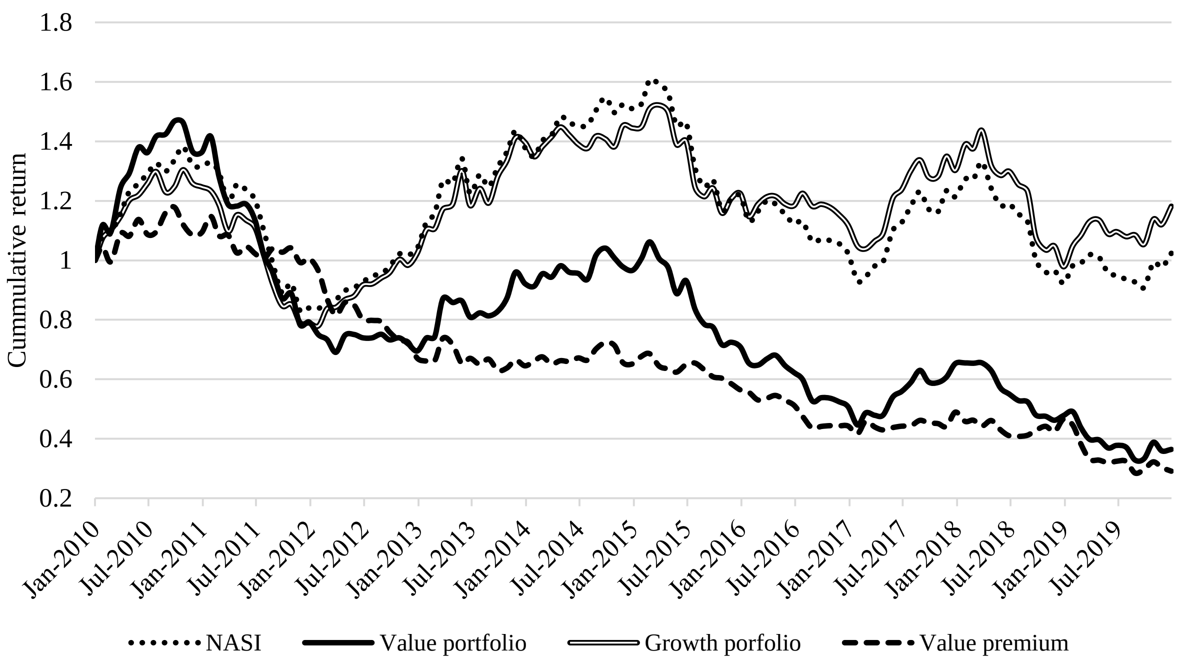
Panel A: Value-weighted portfolio				
	NASI	**Value portfolio**	**Growth portfolio**	**Value premium**
Maximum drawdown %	-43.45	-77.65	-40.21	-75.84
Average drawdown %	-23.52	-48.29	-18.72	-45.31
Max time to previous peak (in years)	4.83	9.25	4.75	9.25
Panel B: Equally weighted portfolio				
	NASI	**Value portfolio**	**Growth portfolio**	**Value premium**
Maximum drawdown %	-43.45	-74.70	-69.20	-51.52
Average drawdown %	-23.52	-46.26	-35.93	-37.80
Max time to previous peak (in years)	4.83	9.25	6.08	9.67

Source: Researcher (2021)

Between 2010 and 2019, the value portfolio witnessed a maximum loss of 77.65%, and its average loss was 48.29%. By the end of 2019, the value portfolio had not reached its previous peak. Within the same period, the growth portfolio's maximum loss was 40.21%, and its average loss was 18.72%; however, its maximum duration to previous peak was lower than that of the value portfolio. Lastly, value premium's performance was akin to that of the value portfolio; its maximum loss was 75.84%, and its average loss was 45.31%. In the same vein, value premium's duration to previous peak was as long as that of the value portfolio. The prior conclusions were also observed from equally weighted portfolios, but the measures were slightly better.

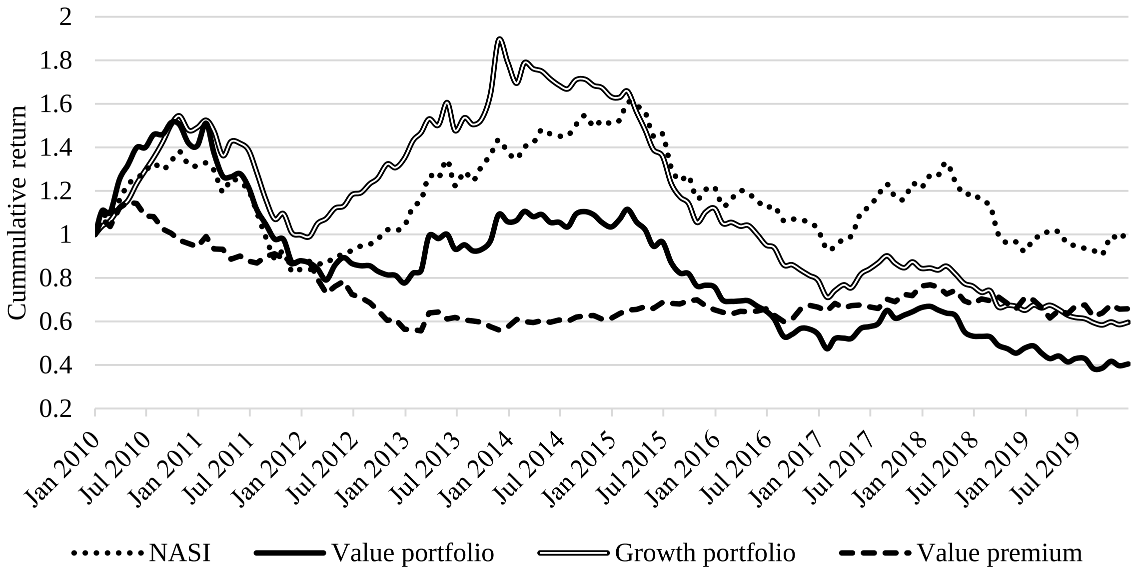
In conclusion, the value factor underwent long periods of underperformance as demonstrated by the large drawdown measures and the long duration to previous highs; moreover, the value factor performed worse than NASI. Figure 4.1 and 4.2 sum up the prior discussions.

Figure 4. 1: Value-weighted stock returns from value factor



Source: Researcher (2021)

Figure 4. 2: Equally weighted stock returns from value factor



Source: Researcher (2021)

4.4.1.2 Momentum factor

The data in Table 4.7 presents the maximum drawdown, average drawdown, and time to previous peak for the momentum factor.

Table 4. 7: Momentum factor drawdown measures and duration to previous peak

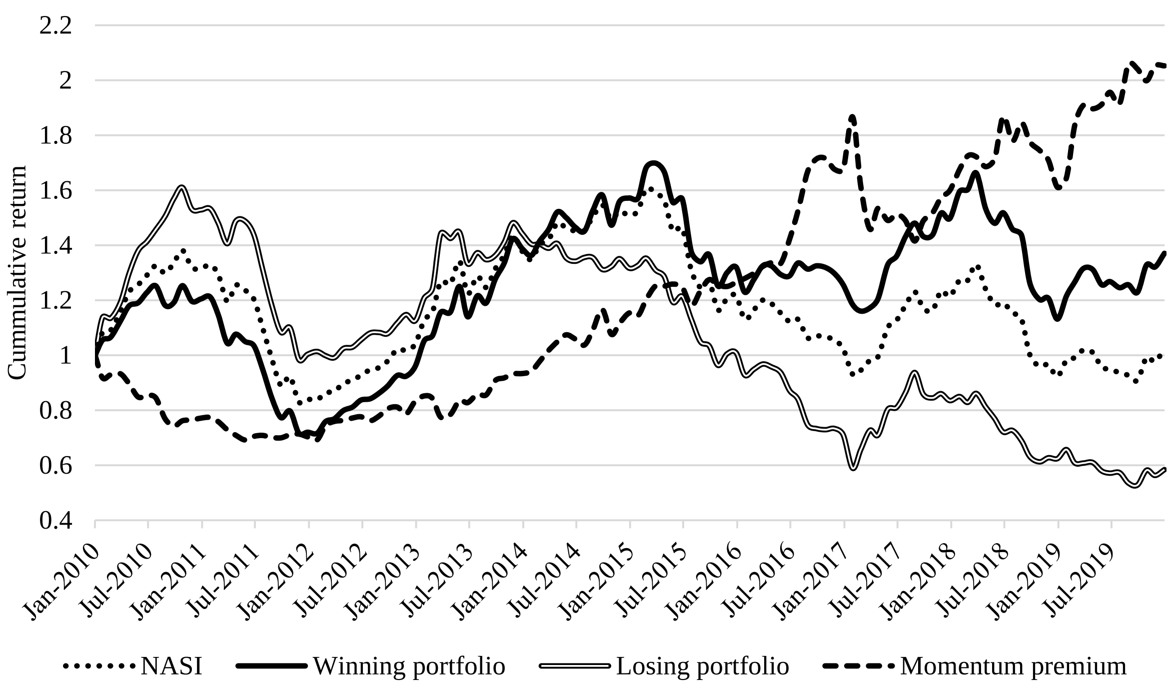
Panel A: Value-weighted portfolio				
	NASI	**Winning portfolio**	**Losing portfolio**	**Momentum premium**
Maximum drawdown %	-43.45	-42.83	-67.18	-30.83
Average drawdown %	-23.52	-19.04	-35.66	-13.88
Max time to previous peak (in years)	4.83	4.75	9.17	4.17
Panel B: Equally weighted portfolio				
	NASI	**Winning portfolio**	**Losing portfolio**	**Momentum premium**
Maximum drawdown %	-43.45	-58.27	-77.90	-23.36
Average drawdown %	-23.52	-30.46	-45.96	-9.42
Max time to previous peak (in years)	4.83	5.25	9.17	2.17

Source: Researcher (2021)

Between 2010 and 2019, the winning portfolio lost a maximum of 42.83%, and it registered an average loss of 19.04%. The longest time the winning portfolio remained below its previous peak was 4.75 years. Unlike the winning portfolio, the losing portfolio recorded a higher maximum loss and average loss; also, the losing portfolio never attained its high peak in the studied period. Finally, momentum premium's maximum and average loss were lower than that of the winning portfolio, and momentum premium took slightly less time than the winning portfolio to reach its previous peak. The same observations can be said of the data in Panel B of Table 4.7, but the measures deteriorated slightly; however, momentum premium from Panel B performed better than its counterpart in Panel A.

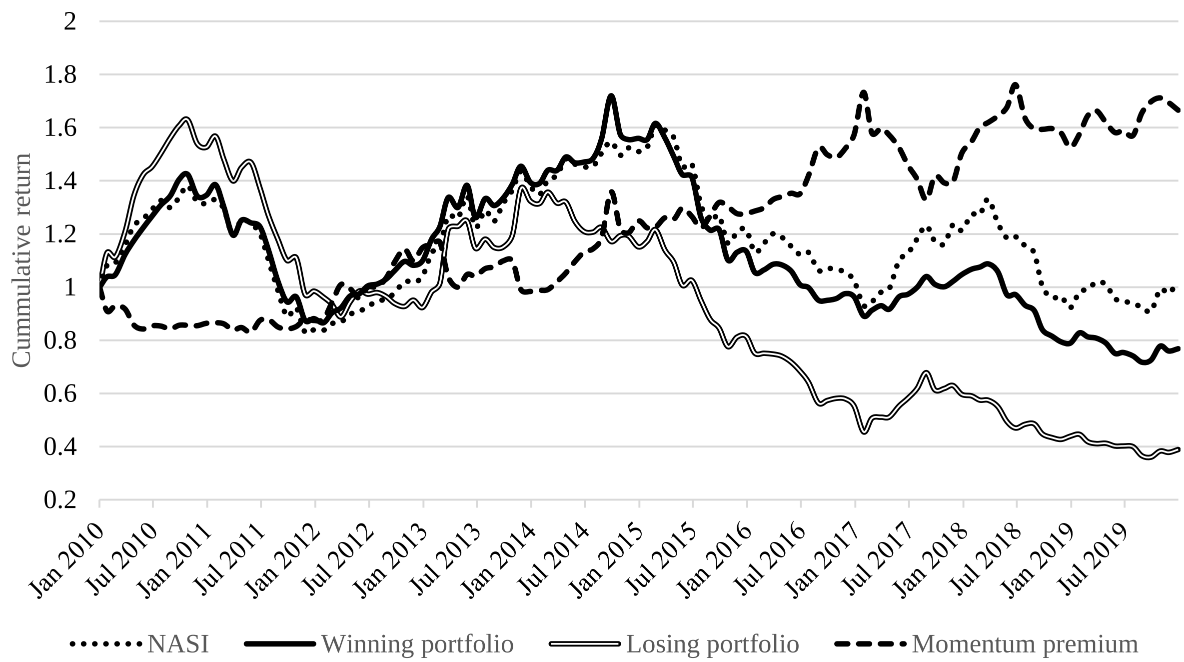
In conclusion, momentum factor exhibited periods of underperformance, but it performed slightly better than NASI. Figure 4.3 and 4.4 sum up the prior discussions.

Figure 4. 3: Value-weighted stock returns from momentum factor



Source: Researcher (2021)

Figure 4. 4: Equally weighted stock returns from momentum factor



Source: Researcher (2021)

4.4.1.3 Combined factor portfolio

The combined factor portfolio was formed by holding value and momentum factor equally. The portfolio was formed from either value and momentum premium (long-short portfolio) or value and winning portfolio (long-only portfolio).

The data in Table 4.8 on the following page presents the maximum drawdown, average drawdown and time to previous peak for the long-short combined factor portfolio.

Table 4. 8: Long-short portfolio drawdown measures and duration to previous peak

Panel A: Value-weighted portfolio				
	NASI	**Long-short portfolio**	**Value premium**	**Momentum premium**
Maximum drawdown %	-43.45	-24.90	-75.84	-30.83
Average drawdown %	-23.52	-13.35	-45.31	-13.88
Max time to previous peak (in years)	4.83	9.75	9.25	4.17
Panel B: Equally weighted portfolio				
	NASI	**Long-short portfolio**	**Value premium**	**Momentum premium**
Maximum drawdown %	-43.45	-24.12	-51.52	-23.36
Average drawdown %	-23.52	-9.66	-37.80	-9.42
Max time to previous peak (in years)	4.83	6.5	9.67	2.17

Source: Researcher (2021)

According to Panel A of Table 4.8, the long-short portfolio registered better drawdown measures than value and momentum premium; however, the long-short portfolio took twice as long to reach its previous peak compared to momentum premium. In Panel B of Table 4.8, the long-short portfolio drawdown measures were better than value premium's, but they were slightly inferior to momentum premium. Table 4.9 presents the data for the long-only combined factor portfolio.

Table 4. 9: Long-only portfolio drawdown measures and duration to previous peak

Panel A: Value-weighted portfolio				
	NASI	**Long-only portfolio**	**Value portfolio**	**Winning portfolio**
Maximum drawdown %	-43.45	-51.39	-77.65	-42.83
Average drawdown %	-23.52	-28.60	-48.29	-19.04
Max time to previous high peak (in years)	4.83	9.17	9.25	4.75
Panel B: Equally weighted portfolio				
	NASI	**Long-only portfolio**	**Value portfolio**	**Winning portfolio**
Maximum drawdown %	-43.45	-63.55	-74.70	-58.27
Average drawdown %	-23.52	-34.87	-46.26	-30.46
Max time to previous high peak (in years)	4.83	9.17	9.25	5.25

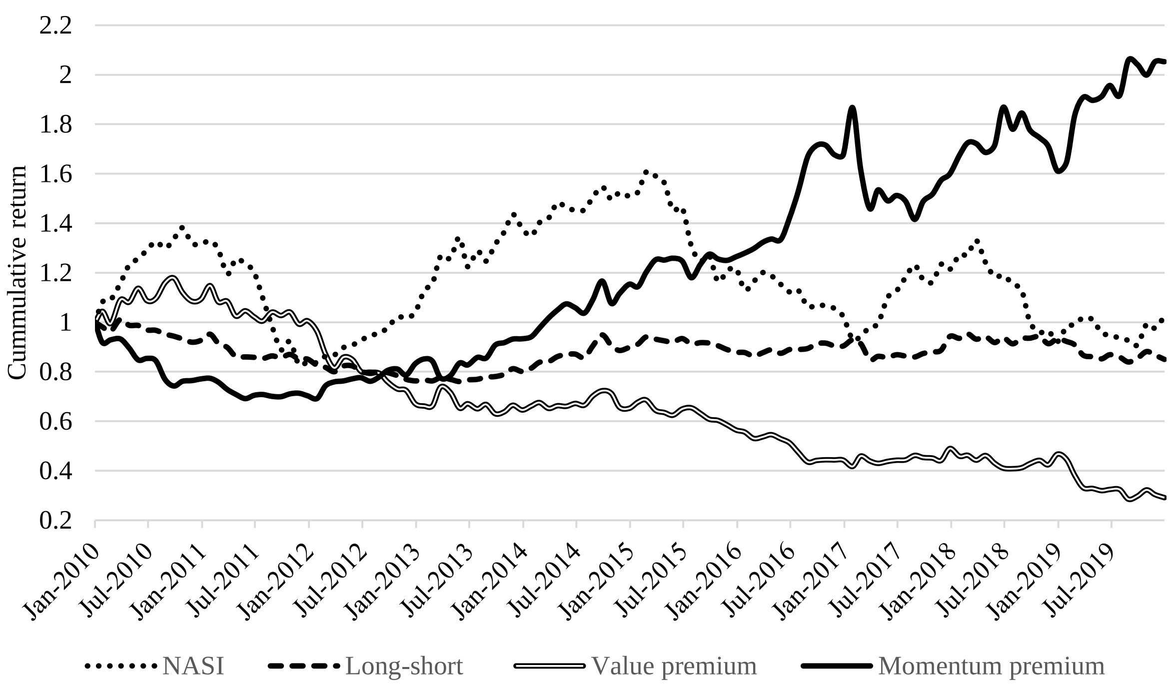
Source: Researcher (2021)

According to Panel A of Table 4.9, the long-only portfolio registered better metrics than the value portfolio, but it did worse than the winning portfolio. The preceding conclusions were also arrived from Panel B of Table 4.9; however, the metrics for the long-only portfolio were slightly worse than those recorded in Panel A.

In conclusion, the long-short factor portfolio did better on some metrics than its separate arms that is value premium and momentum premium. In contrast, the combined long-only portfolio improved the performance of the value portfolio and not the winning portfolio. Additionally, the long-short portfolio registered better drawdown measures and duration to previous peak than NASI, but the long-only portfolio registered inferior metrics than NASI.

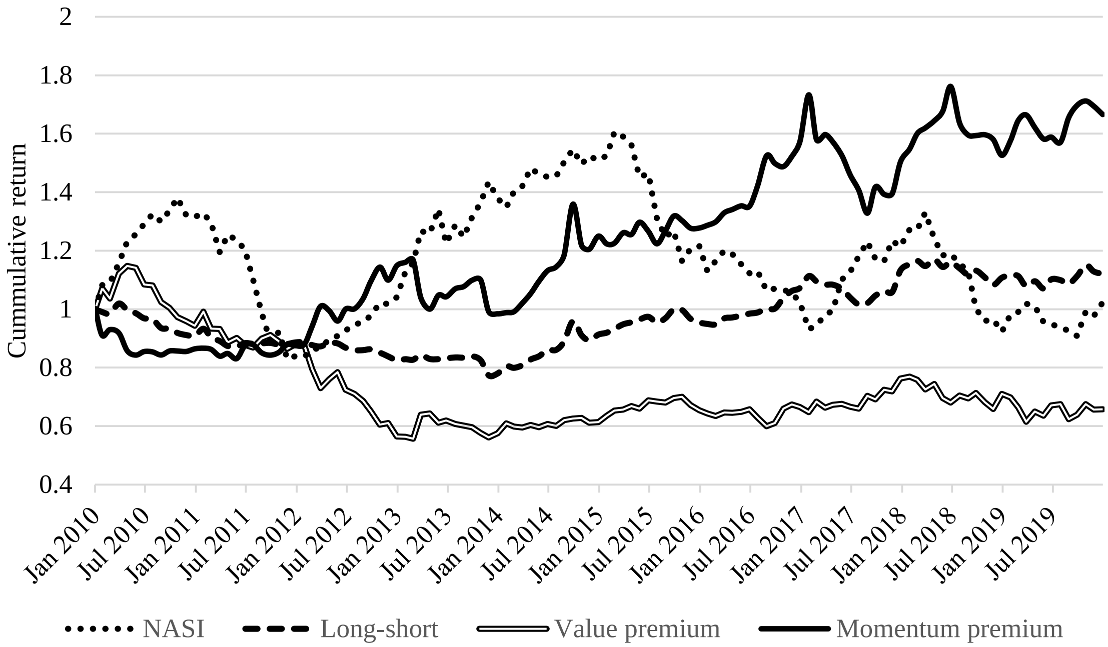
Figures 4.5 to 4.8 sum up the discussions.

Figure 4. 5: Value-weighted stock returns from long-short combined factor



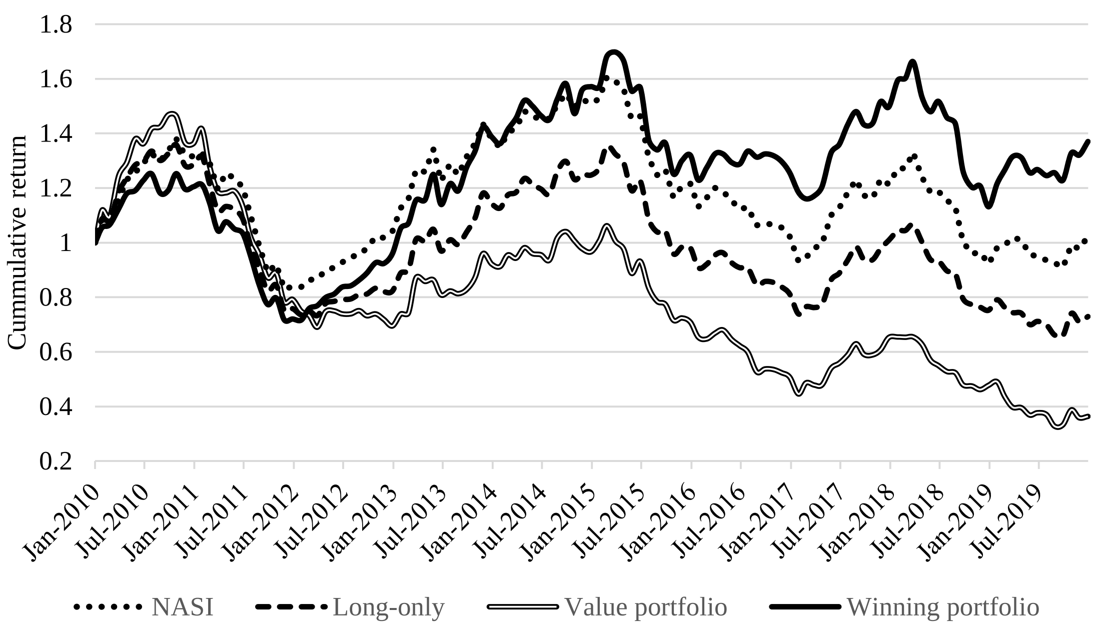
Source: Researcher (2021)

Figure 4. 6: Equally weighted stock returns from long-short combined factor



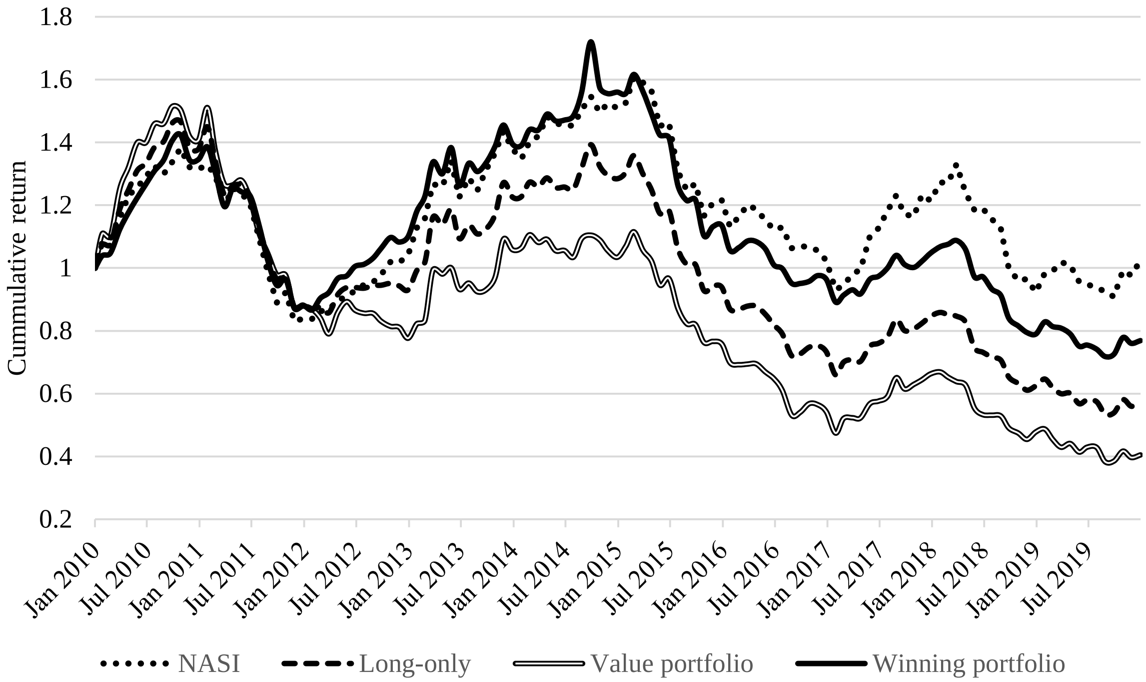
Source: Researcher (2021)

Figure 4. 7: Value-weighted stock returns from long-only combined factor



Source: Researcher (2021)

Figure 4. 8: Equally weighted stock returns from long-only combined factor

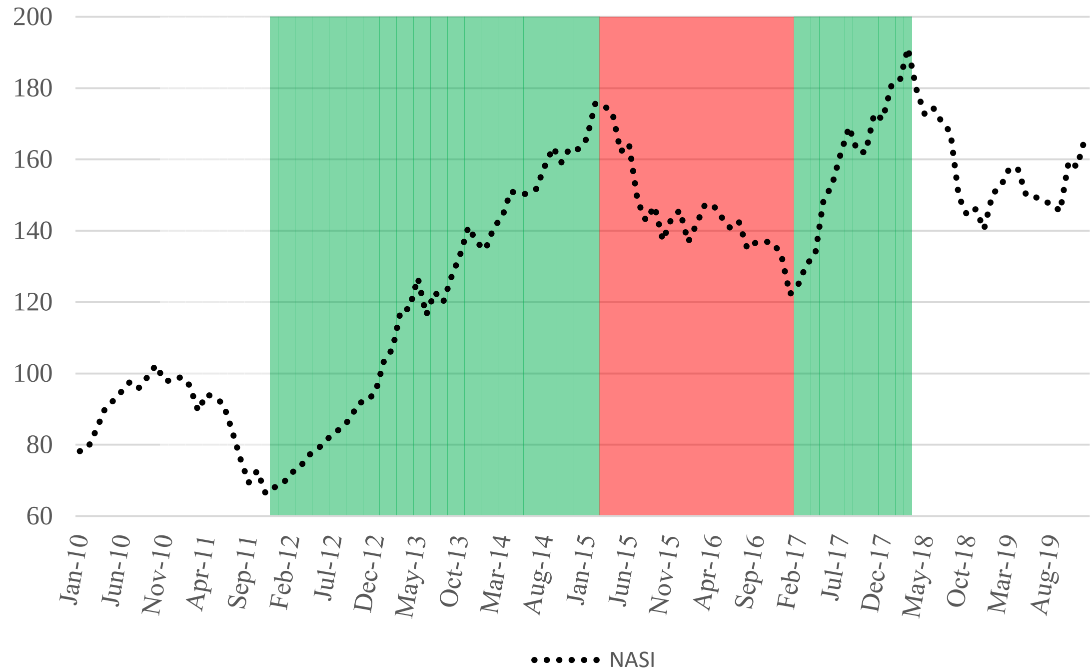


Source: Researcher (2021)

4.4.2 Stock market cycles

Bull and bear markets were identified within a window of 8 months. At any point in the analysis period, if the price of NASI was the highest (lowest) in the 8 preceding months and 8 succeeding months, the index price was considered as the peak (trough). This methodology identified 3 bull markets and 3 bear markets. The results presented in the following sections are for the three longest stock market cycles: the bull market between December 2011 and February 2015 (3.25 years), the bear market between March 2015 and January 2017 (1.90 years), and the bull market between February 2017 and March 2018 (1.20 years). The graph on the following page identifies the 2 bull markets and 1 bear market.

Figure 4. 9: Stock market cycles



Source: Researcher (2021); shaded areas: red (bear market) and green (bull market)

4.4.2.1 Value factor

The data in Table 4.10 on the following page presents the annualized returns, standard deviation, Sharpe ratio, and maximum drawdown for the value factor in bull and bear markets. In the analysis, the value portfolio was bought, and the growth portfolio was sold short. Value premium combined the long and short side of the value and growth portfolio, respectively.

Table 4. 10: Value factor stock market cycle metrics

Panel A: Value-weighted portfolio					
Statistic	**Period**	**NASI**	**Value portfolio**	**Growth portfolio**	**Value premium**
Annualized return %	Dec 2011 – Feb 2015	33.90	21.83	35.47	-10.95
	Mar 2015 – Jan 2017	-17.10	-26.90	-8.97	-19.66
	Feb 2017 – Mar 2018	44.08	40.88	43.93	-2.86
Standard deviation %	Dec 2011 – Feb 2015	12.11	17.34	13.27	15.98
	Mar 2015 – Jan 2017	13.99	15.89	13.47	10.62
	Feb 2017 – Mar 2018	13.19	18.07	14.67	18.07
Sharpe ratio	Dec 2011 – Feb 2015	1.99	0.69	1.93	-1.30
	Mar 2015 – Jan 2017	-1.89	-2.28	-1.36	-2.73
	Feb 2017 – Mar 2018	2.76	1.84	2.47	-0.58
Maximum drawdown %	Dec 2011 – Feb 2015	-8.27	-8.60	-8.15	-37.60
	Mar 2015 – Jan 2017	-30.20	-45.15	-17.73	-35.43
	Feb 2017 – Mar 2018	-4.24	-5.41	-3.60	-9.98
Panel B: Equally weighted portfolio					
Statistic	**Period**	**NASI**	**Value portfolio**	**Growth portfolio**	**Value premium**
Annualized return %	Dec 2011 – Feb 2015	33.90	19.87	29.88	-8.65
	Mar 2015 – Jan 2017	-17.10	-26.47	-26.36	-0.14
	Feb 2017 – Mar 2018	44.08	29.47	22.34	5.60
Standard deviation %	Dec 2011 – Feb 2015	12.11	18.12	15.22	16.15
	Mar 2015 – Jan 2017	13.99	15.53	12.12	9.96
	Feb 2017 – Mar 2018	13.19	16.67	12.33	12.75
Sharpe ratio	Dec 2011 – Feb 2015	1.99	0.55	1.32	-1.14
	Mar 2015 – Jan 2017	-1.89	-2.31	-2.95	-0.95
	Feb 2017 – Mar 2018	2.76	1.31	1.19	-0.16
Maximum drawdown %	Dec 2011 – Feb 2015	-8.27	-7.97	-8.92	-36.95
	Mar 2015 – Jan 2017	-30.20	-44.53	-44.36	-13.93
	Feb 2017 – Mar 2018	-4.24	-4.77	-4.77	-5.65

Source: Researcher (2021)

In the 3 stock market cycles, the value portfolio underperformed NASI and the growth portfolio: in the bull markets, the value portfolio earned lower annualized returns, and in the bear market, the value portfolio lost more money. The weak annualized returns were accompanied by high standard deviation of returns, therefore, the value portfolio exhibited weaker Sharpe ratios than NASI and the growth portfolio. To cap the poor performance of the value portfolio, it exhibited higher maximum drawdown than NASI and the growth portfolio in the 3 stock market cycles. The weak performance of the value portfolio in relation to the growth portfolio led to the negative value premium returns in the 2 bull markets and subpar performance in the bear market. Value premium also exhibited higher standard deviation of returns than NASI, value portfolio, and growth portfolio; value premium, therefore, showcased lower Sharpe ratios than the market, value, and growth portfolio. The poor performance of the value premium culminated in the portfolio exhibiting higher maximum drawdown than NASI, value portfolio, and growth portfolio. In Panel B, the value portfolio's performance improved slightly in the bear market and in the second bull market. The improved value portfolio's performance, however, showed its benefit in the value premium portfolio in the bear market.

In conclusion, the value factor did abysmally in bull markets and the bear market. In bull markets, the value portfolio underperformed NASI and the growth portfolio, and in bear markets, the value portfolio lost more money than the growth portfolio and NASI. In both bull and bear markets, the underperformance of the value portfolio and the overperformance of the growth portfolio led to the negative return of the value premium.

4.4.2.2 Momentum factor

The data in Table 4.11 on the following page presents the annualized returns, standard deviation, Sharpe ratio, and maximum drawdown for the momentum factor in bull and bear markets. In the analysis, the winning portfolio was bought, and the losing portfolio was sold short. Momentum premium combined the long and short side of the winning and losing portfolio, respectively.

Table 4. 11: Momentum factor stock market cycle metrics

Panel A: Value-weighted portfolio					
Statistic	**Period**	**NASI**	**Winning portfolio**	**Losing portfolio**	**Momentum premium**
Annualized return %	Dec 2011 – Feb 2015	33.90	44.39	21.42	18.53
	Mar 2015 – Jan 2017	-17.10	-8.24	-26.24	22.39
	Feb 2017 – Mar 2018	44.08	48.07	38.79	4.32
Standard deviation %	Dec 2011 – Feb 2015	12.11	14.23	13.49	12.60
	Mar 2015 – Jan 2017	13.99	14.18	16.32	12.59
	Feb 2017 – Mar 2018	13.19	13.19	23.04	20.49
Sharpe ratio	Dec 2011 – Feb 2015	1.99	2.43	0.86	0.69
	Mar 2015 – Jan 2017	-1.89	-1.24	-2.18	1.04
	Feb 2017 – Mar 2018	2.76	3.07	1.35	-0.16
Maximum drawdown %	Dec 2011 – Feb 2015	-8.27	-7.99	-7.15	-10.18
	Mar 2015 – Jan 2017	-30.20	-20.17	-44.20	-5.84
	Feb 2017 – Mar 2018	-4.24	-2.57	-8.34	-14.22
Panel B: Equally weighted portfolio					
Statistic	**Period**	**NASI**	**Winning portfolio**	**Losing portfolio**	**Momentum premium**
Annualized return %	Dec 2011 – Feb 2015	33.90	33.82	18.97	10.29
	Mar 2015 – Jan 2017	-17.10	-17.37	-30.47	16.88
	Feb 2017 – Mar 2018	44.08	25.50	21.75	0.96
Standard deviation %	Dec 2011 – Feb 2015	12.11	14.03	18.90	17.44
	Mar 2015 – Jan 2017	13.99	12.36	16.78	10.37
	Feb 2017 – Mar 2018	13.19	7.44	20.64	16.58
Sharpe ratio	Dec 2011 – Feb 2015	1.99	1.71	0.48	0.03
	Mar 2015 – Jan 2017	-1.89	-2.16	-2.37	0.73
	Feb 2017 – Mar 2018	2.76	2.40	0.68	-0.40
Maximum drawdown %	Dec 2011 – Feb 2015	-8.27	-7.98	-8.92	-18.17
	Mar 2015 – Jan 2017	-30.20	-30.63	-50.17	-5.46
	Feb 2017 – Mar 2018	-4.24	-2.40	-11.26	-17.72

Source: Researcher (2021)

In the bull markets and bear market, the winning portfolio generated better annualized returns than NASI and the losing portfolio. The winning portfolio returns were less volatile than the losing portfolio returns, but NASI exhibited lower volatility of returns than the winning portfolio; nonetheless, the winning portfolio generated higher Sharpe ratios than NASI and the losing portfolio in the 3 stock market cycles. The superior performance of the winning portfolio was also captured by the low maximum drawdown than NASI and the losing portfolio in the stock market cycles. The strong performance of the winning portfolio did not translate to the momentum premium, especially in the bull markets. Since the losing portfolio was sold short, the positive returns in the bull markets led to lower annualized returns than the winning portfolio and NASI. In the bear market, the losing portfolio lost more money than the winning portfolio, thus, the loss translated to a positive return for the momentum premium. In line with the positive performance of the losing portfolio, momentum premium generated lower Sharpe ratios and higher maximum drawdown than the winning portfolio and NASI in the bull markets, but in the bear market, momentum premium generated a higher Sharpe ratio and lower maximum drawdown than the winning portfolio and NASI. In Panel B, the winning portfolio still outperformed the losing portfolio in all cycles and metrics, but the winning portfolio's performance was weaker than NASI. Momentum premium exhibited the same patterns as captured in Panel A.

In conclusion, the momentum factor exhibited a positive but mixed performance. In the bull markets and bear market, the winning portfolio outdid the losing portfolio and NASI. The strong performance of the winning portfolio, however, failed to translate to the momentum premium as the losing portfolio generated positive returns, particularly in the bull markets.

4.4.2.3 Combined factor portfolio

The data in Table 4.12 on the following page presents the annualized returns, standard deviation, Sharpe ratio, and maximum drawdown for the combined factor portfolio in bull and bear markets. In the analysis, the combined factor portfolio was formed by holding value and momentum factor equally. The combined factor portfolio was formed from either value and momentum premium (long-short portfolio) or value and winning portfolio (long-only portfolio).

Table 4. 12: Combined factor portfolios stock market cycle metrics

Panel A: Value-weighted portfolio				
Statistic	**Period**	**NASI**	**Long-short portfolio**	**Long-only portfolio**
Annualized return %	Dec 2011 – Feb 2015	33.90	3.58	32.97
	Mar 2015 – Jan 2017	-17.10	-0.14	-17.93
	Feb 2017 – Mar 2018	44.08	1.26	44.70
Standard deviation %	Dec 2011 – Feb 2015	12.11	7.48	14.14
	Mar 2015 – Jan 2017	13.99	4.64	13.93
	Feb 2017 – Mar 2018	13.19	10.39	13.24
Sharpe ratio	Dec 2011 – Feb 2015	1.99	-0.84	1.64
	Mar 2015 – Jan 2017	-1.89	-2.04	-1.96
	Feb 2017 – Mar 2018	2.76	-0.61	2.80
Maximum drawdown %	Dec 2011 – Feb 2015	-8.27	-10.42	-6.83
	Mar 2015 – Jan 2017	-30.20	-7.43	-31.52
	Feb 2017 – Mar 2018	-4.24	-7.35	-3.99
Panel B: Equally weighted portfolio				
Statistic	**Period**	**NASI**	**Long-short portfolio**	**Long-only portfolio**
Annualized return %	Dec 2011 – Feb 2015	33.90	1.46	26.98
	Mar 2015 – Jan 2017	-17.10	8.43	-21.95
	Feb 2017 – Mar 2018	44.08	3.69	27.60
Standard deviation %	Dec 2011 – Feb 2015	12.11	8.17	14.33
	Mar 2015 – Jan 2017	13.99	5.58	13.23
	Feb 2017 – Mar 2018	13.19	8.81	11.44
Sharpe ratio	Dec 2011 – Feb 2015	1.99	-1.02	1.20
	Mar 2015 – Jan 2017	-1.89	-0.16	-2.37
	Feb 2017 – Mar 2018	2.76	-0.45	1.75
Maximum drawdown %	Dec 2011 – Feb 2015	-8.27	-13.54	-7.02
	Mar 2015 – Jan 2017	-30.20	-5.23	-37.82
	Feb 2017 – Mar 2018	-4.24	-7.58	-3.46

Source: Researcher (2021)

The long-short portfolio generated higher annualized returns than NASI in the bear market only. Due to the negative correlation between value premium and momentum premium, the long-short portfolio exhibited lower volatility than NASI in the stock market cycles; however, the low portfolio risk failed to translate to the Sharpe ratio. Again, in the bear market only, the long-short portfolio displayed a lower maximum drawdown than NASI. Similar insights on the long-short portfolio are replicated from Panel B. The long-only portfolio, on the other hand, closely matched the performance of NASI in the bull markets and bear market. In Panel B, however, the long-only portfolio slightly underperformed NASI.

In conclusion, the combined factor portfolios did not yield any positive outcomes for investors in the stock market cycles: the long-short portfolio underperformed NASI, and the long-only portfolio closely matched NASI's performance.

4.5 Determination of the source of stock returns from factor investing

The third objective sought to determine the source of stock returns from factor investing. The CAPM was the chosen asset pricing model to determine the source of factor investing returns. Additionally, the small-cap premium variable (SMB) was added to CAPM to control for the impact of small capitalization stocks. The independent variables in the regression analysis were the returns of NASI and the long-short small-cap portfolio. In the long-short small-cap portfolio, small-cap stocks were bought, and large-cap stocks were sold short. The dependent variable was the factor portfolio returns. In the regression analysis, beta on NASI was hypothesized to be statistically different from 0, and alpha (intercept) was hypothesized to equal 0.

4.5.1 Value factor

The data in Table 4.13 on the following page presents the regression model's alpha (intercept), beta coefficients, R^2, and t-statistics.

Table 4. 13: Alpha, beta coefficients, t-statistics and R^2 for value factor

Panel A: Value-weighted portfolio			
	Value portfolio	**Growth portfolio**	**Value premium**
Alpha	-0.0068	0.0004	-0.0073
(t-stat)	*(-1.95)*	*(0.31)*	*(-1.69)*
β_{NASI}	1.0169	0.8919	0.1249
(t-stat)	*(12.50)*	*(29.22)*	*(1.26)*
β_{SMB}	0.1366	-0.1101	0.2467
(t-stat)	*(1.67)*	*(-3.59)*	*(2.47)*
R^2	0.5860	0.9026	0.0507
Panel B: Equally weighted portfolio			
	Value portfolio	**Growth portfolio**	**Value premium**
Alpha	-0.0054	-0.0035	-0.0019
(t-stat)	*(-1.57)*	*(-1.63)*	*(-0.52)*
β_{NASI}	0.9374	0.8644	0.0729
(t-stat)	*(11.71)*	*(17.35)*	*(0.86)*
β_{SMB}	0.2173	0.1083	0.1089
(t-stat)	*(2.70)*	*(2.16)*	*(1.28)*
R^2	0.5447	0.7326	0.0152

Source: Researcher (2021); critical *t*-value of 1.96 at α=0.05

According to Table 4.13, value portfolio's beta was statistically significant from 0, but alpha was statistically insignificant. CAPM, therefore, captured the variation of the value portfolio's return, even after controlling for size. Additionally, value portfolio's R^2 was high at 0.58. The same pattern is replicated in Panel B. CAPM did an even better job in explaining the growth portfolio's return. The beta t-statistic was high at 29.22, and the R^2 was 0.90. The data in Panel B displays the same pattern. Unfortunately, CAPM failed to explain value premium's return: beta was statistically insignificant, and the R^2 was only 0.05. In Panel B, CAPM's explanatory power was weaker.

In conclusion, CAPM was an appropriate asset pricing model for the value and growth portfolio; however, another asset pricing model is required to explain value premium's return.

4.5.2 Momentum factor

The data in Table 4.14 on the following page presents the regression model's alpha (intercept), beta coefficients, R^2, and t-statistics.

Table 4. 14: Alpha, beta coefficients, t-statistics and R^2 for momentum factor

Panel A: Value-weighted portfolio			
	Winning portfolio	**Losing portfolio**	**Momentum premium**
Alpha	0.0019	-0.0037	0.0056
(t-stat)	*(1.44)*	*(-1.40)*	*(1.50)*
β_{NASI}	0.9597	0.9944	-0.0346
(t-stat)	*(30.98)*	*(15.95)*	*(-0.40)*
β_{SMB}	-0.0794	0.0676	-0.1470
(t-stat)	*(-2.55)*	*(1.08)*	*(-1.67)*
R^2	0.9096	0.7050	0.0237
Panel B: Equally weighted portfolio			
	Winning portfolio	**Losing portfolio**	**Momentum premium**
Alpha	-0.0017	-0.0053	0.0036
(t-stat)	*(-0.97)*	*(-1.64)*	*(1.02)*
β_{NASI}	0.8615	1.0143	-0.1528
(t-stat)	*(20.78)*	*(13.28)*	*(-1.84)*
β_{SMB}	0.0741	0.2639	-0.1897
(t-stat)	*(1.78)*	*(3.43)*	*(-2.28)*
R^2	0.8006	0.6040	0.0517

Source: Researcher (2021); critical *t*-value of 1.96 at α=0.05

According to Table 4.14, CAPM strongly explained the variations of the winning portfolio's return: beta was statistically different from 0, alpha was statistically insignificant, and the R^2 was 0.9096. Similarly, the losing portfolio's return was captured by CAPM. The same analysis applies to the winning and losing portfolio in Panel B. Like the value premium, CAPM failed to explain momentum premium's return variation: beta was statistically insignificant, and R^2 was low at 0.0237. Panel B replicates the same findings.

In conclusion, the winning and losing portfolio returns were well captured by CAPM. Like value premium, another asset pricing model is required to explain momentum premium's return.

4.5.3 Combined factor portfolio

Table 4. 15: Alpha, beta coefficients, t-statistics and R^2 for the combined factor portfolio

The data in Table 4.15 presents the regression model's alpha (intercept), beta coefficients, R^2, and t-statistics.

Panel A: Value-weighted portfolio		
	Long-short portfolio	**Long-only portfolio**
Alpha	-0.0007	-0.0024
(t-stat)	*(-0.41)*	*(-1.51)*
β_{NASI}	0.0451	0.9883
(t-stat)	*(1.01)*	*(26.08)*
β_{SMB}	0.0498	0.0286
(t-stat)	*(1.10)*	*(0.75)*
R^2	0.0138	0.8676
Panel B: Equally weighted portfolio		
	Long-short portfolio	**Long-only portfolio**
Alpha	0.0008	-0.0035
(t-stat)	*(0.46)*	*(-1.61)*
β_{NASI}	-0.0399	0.8994
(t-stat)	*(-0.91)*	*(17.49)*
β_{SMB}	0.0403	0.1457
(t-stat)	*(-0.91)*	*(2.82)*
R^2	0.0103	0.7324

Source: Researcher (2021); critical *t*-value of 1.96 at α=0.05

According to Table 4.15, CAPM failed to explain the variation of the long-short portfolio's return: beta was statistically insignificant, and R^2 was low at 0.0138. On the other hand, CAPM did well in explaining the long-only portfolio's return: beta was statistically significant, alpha was statistically insignificant, and R^2 was high at 0.8676. The same pattern of analysis was replicated in Panel B.

In conclusion, the CAPM failed to capture the returns of the long-short combined factor portfolio, but CAPM performed well with the long-only combined factor portfolio.

4.5.4 Diagnostic tests

Three diagnostics tests were conducted on the data collected. This was done to ensure that the analysis carried out did not lead to spurious regression analysis. Prior to running any regression, the variables studied were tested for the existence of unit roots. After running the regression model, the residuals from the model were tested for serial correlation and normality.

4.5.4.1 Unit root test

The unit root test was conducted to determine whether the variables in the study were weakly dependent. According to Appendix VII, the p-values for all variables were 0.00 which was less than 0.05. This implied we failed to accept the null hypothesis of unit roots, and we concluded the data for all variables were weakly dependent.

4.5.4.2 Serial correlation

The serial correlation test was conducted to determine whether the residuals from the regression model were uncorrelated. According to Appendix VIII, the p-value for all regressions were above 0.05 which implied we failed to reject the null hypothesis of no serial correlation.

4.5.4.3 Normality test

Normality of error terms is one of the assumptions of the classic linear regression model. According to Appendix IX, the p-values for 8 out of the 16 regressions were below 0.05. This implied we rejected the null hypothesis of normally distributed errors. Due to the large sample size of 120 months, no corrective action was taken.

4.6 Chapter summary

This chapter presented the study findings based on three objectives: to examine the profitability of stock returns from factor investing, assess the cyclicity of stock returns from factor investing, and determine the source of stock returns from factor investing. The findings of the first objective revealed momentum factor generated a positive return, but the value factor earned negative returns. The factor returns had varying levels of statistical significance which depended on the portfolio weighing scheme (value-weighted or equally weighted). The findings of the second objective indicated factor returns were highly cyclical with long periods of underperformance. The third objective demonstrated CAPM's effectiveness to capture the variations of the long-only factor portfolio returns (value or winning portfolio), but CAPM'S ineffectiveness to capture the variations of the long-short factor portfolio returns (value and momentum premium).

CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary, discussions, conclusions, and recommendations from the study. Discussions of the findings based on the objectives is given in section 5.2, conclusions in section 5.3, recommendations in 5.4, areas for further studies in 5.5, and limitations of the study is in section 5.6.

5.2 Discussion of the findings

The general objective of the study was to establish the profitability of stock returns from factor investing at the NSE. The study focused on two factors: momentum and value. The sample consisted of large capitalization stocks: stocks that are greater than or equal to the median capitalization at the NSE. Below are the discussions of the study's findings in comparison with previous research.

5.2.1 Examination of stock returns from factor investing

The first objective sought to assess the profitability of stock returns from factor investing. Broadly, the findings showed that stock returns from the value factor underperformed, and stock returns from the momentum factor outperformed albeit with mixed results. Like the stock returns from the value factor, the stock returns from the equally weighted combination of the factors underperformed. The prior conclusions were observed from the equally weighted portfolios as well.

5.2.1.1 Stock returns from value factor

At the global level, the findings of stock returns from the value factor resembled Fama & French (2012) who reported statistically insignificant stock returns from the value factor. Furthermore, the study stated that stock returns from the value factor were lower than those of the global market portfolio. Likewise, Cakici & Tan (2014) reported statistically insignificant stock returns from the value factor in 8 countries spread across Europe and North America. Additionally, this findings were in agreement with Perez (2018) who reported no value effect in the South Korean equity market. In South Africa, Flint et al. (2016) concluded that stock returns from the value factor generated lower returns and Sharpe ratio than the broad market portfolio. Specifically, the authors reported that stock returns from the value factor underperformed the market portfolio in the bull market of December 2002 to June 2007 and the weak economic period of December 2011 to August 2016. Similarly, in South Africa, Hsieh (2015) reported that the value portfolio generated lower returns and Sharpe ratio than the growth portfolio and the market proxy.

On the contrary, at the global level, the findings differed with Koedijk et al. (2016) who reported stock returns from the value factor earned higher returns and Sharpe ratio than the broad market portfolio in the US and in Europe. The findings were also contrary to Angelidis & Tessaromatis (2017) who showed the value portfolio generated a higher return and Sharpe ratio than the growth portfolio and the MSCI All-Country World index. The authors also reported that the value portfolio generated statistically significant alpha. In the UK, Dimson et al. (2017) reported that an investment in the value portfolio outperformed an investment in the growth portfolio and a broad market portfolio index. The study computed that an investment in the value portfolio would have grown an investor's capital 21 times more and 9 times more than an investment in the growth portfolio and market portfolio, respectively. In Kenya, the findings contrasted with Njogo (2017) who reported statistically significant stock returns from the value factor at the NSE. Similarly, the findings differed with Riro & Wambugu (2015) who reported statistically significant excess returns over the NASI index from the value portfolio.

5.2.1.2 Stock returns from momentum factor

At the global level, the study findings were similar to Angelidis & Tessaromatis (2017) who reported the winning portfolio generated higher returns and Sharpe ratio than the losing portfolio and MSCI All-Country World index. Likewise, in the US, Blitz (2015) reported that stock returns from the momentum factor generated the highest return among 5 factors – value, size, volatility, profitability and momentum. Similarly, in Europe, Koedijk et al. (2016) reported that stock returns from the momentum factor generated the highest return among 3 factors - size, value and momentum. The authors also reported that stock returns from the factor earned a higher return and Sharpe ratio than the market portfolio. In South Africa, Charteris et al. (2018) reported comparable results to this study: winning portfolio returns were statistically significant at the 10%, 5% and 1% significance level. Comparably, in South Africa, Flint et al. (2016) reported that stock returns from the momentum factor earned the highest return and Sharpe ratio among seven factors. The authors noted that the factor was highly profitable in both bull and bear markets. In Kenya, the findings were similar to Njogo (2017) who documented a positive momentum return, but the return was statistically insignificant.

On the contrary, at the global level, the findings of the study differed with Fama & French (2012) who reported statistically insignificant momentum returns in Japan. Similarly, Pirie & Chan (2018) reported negative momentum returns across 9 Asian markets. According to the authors, the losses ranged from 37% to about 1% per annum. In Europe, Cakici & Tan (2014) reported that 7 countries generated statistically insignificant stock returns from the momentum factor. In Africa, Ushad (2012) reported statistically insignificant momentum returns at the Stock Exchange of Mauritius. The author also reported that momentum returns were below the market benchmark. In Kenya, the findings differed with Otinga (2017) who reported statistically insignificant momentum returns at the NSE between 2011 and 2016.

5.2.1.3 Stock returns from the combined factor portfolio

The findings of stock returns from equally weighted combination of value factor and momentum factor contradicted empirical literature. In the US, Asness et al. (2013) reported statistically significant stock returns from the equally weighted combination of value and momentum factor. The authors noted that value and momentum combination generated higher returns and Sharpe ratio than either stock returns from momentum or value by itself. The study's findings also conflicted with Cakici & Tan (2014) who reported statistically significant returns from an equally weighted combination of the factors in 16 European countries, in 5 Asian Pacific countries, and in 2 North American countries. Additionally, this study's findings contradicted with Asness et al. (2015) who documented the superiority of the stock returns from the combined value and momentum factor portfolio.

The conclusion from the findings of the study was the unprofitability of stock returns from factor investing at the NSE. Value factor generated negative returns that went against the positive returns from stock markets around the world. Momentum factor earned positive returns, but the returns were largely statistically insignificant. Evidence from around the world showed momentum as a highly profitable investment strategy. Finally, the stock returns from the combined value and momentum factor portfolio failed to improve the performance of the separate factors.

5.2.2 Assessment of cyclicity of stock returns from factor investing

The second objective sought to assess the underperformance or overperformance of stock returns from factor investing. Drawdown measures and duration to previous peak were computed to show the cyclicity of stock returns. Additionally, the returns were studied in bull markets and bear markets. In the study, stock returns from value and momentum factor exhibited drawdowns greater than 30%. Momentum factor returns took 4 years to reach their previous peak; value factor returns, on the other hand, remained below their peak throughout the study period. Although stock returns from the multifactor portfolio were expected to perform better, the returns from the equally weighted combination of value and momentum factor displayed long periods of underperformance. In bull and bear markets, the value factor returns underperformed NASI. Stock returns from the momentum factor, particularly, the winning portfolio did well in bull and bear markets; however, the winning portfolio's return did not translate to the momentum premium. The stock returns from the combined factor portfolio failed to add value to investors in the stock market cycles.

The findings of the study were similar to Koedijk et al. (2016) who reported drawdowns of similar magnitude for the value and momentum factor returns in Europe and the US. The findings were also similar to Flint et al. (2016) who reported large drawdowns for value and momentum factor in South Africa. The authors also reported that the returns from the factors swung in stock market cycles. Similarly, Kalesnik & Linnainmaa (2018) observed drawdowns of the same degree from value and momentum factor returns in the US, in Europe, in Asia Pacific, and in Developed nations. In addition, the authors reported the longest duration to prior peaks was on average longer than 10 years for both value and momentum factor. Additionally, the study findings were in agreement with Grim, Pappas, Tolani, & Kesidis (2018) who reported value and momentum factor underperformed for more than 60 months. Furthermore, the authors reported that value and momentum underperformed a broad market index by at least 7% over a 1-year period. In India, Agarwalla et al. (2017) reported that value and momentum experienced maximum drawdown of similar magnitude as in this study. The duration to previous peak, however, for value and momentum factor in India were below the durations for this study. The findings of the study also echoed the sentiments of Sebastian & Attaluri (2016) who noted factor returns went in and out of favor for extended periods of time.

On the contrary, the findings of the study, on combined factor portfolio, contradicted the sentiments of Warren & Quance (2019) who advocated for multifactor investing to reduce the cyclicity of factor returns. Likewise, the findings of the study contrasted the results of Bender et al. (2015) who reported lower drawdowns and duration to previous peak from multifactor portfolios.

The study's findings showed that stock returns from factor investing at the NSE were highly cyclical. In the study period, value and momentum factor returns both lost more than 30% of their value. Additionally, the two factors witnessed poor performance for more than a year, and they exhibited fluctuating returns in bull and bear markets. Correspondingly, multifactor investing did not reduce the cyclicity of stock returns from factor investing in the study period.

5.2.3 Determination of the source of stock returns from factor investing

The third objective sought to determine the source of stock returns from factor investing. CAPM was used to try and explain the stock returns. The findings showed that CAPM explained the returns of the long-only portfolios: value and growth portfolio and winning and losing portfolio; however, CAPM failed to explain the returns of the long-short portfolios: value premium and momentum premium. A similar pattern is observed from the returns of the combined factor portfolios: CAPM was effective in explaining the returns of the combined factor portfolio formed from long-only portfolios, but CAPM was ineffective in explaining the returns of the combined factor portfolio formed from long-short portfolios.

The finding of the long-only portfolios was similar to Ushad (2012) who reported momentum returns in the Mauritius Stock Exchange were explained by the CAPM: 13 of the 16 momentum strategies generated statistically insignificant alpha. Similarly, in the US, Blitz (2015) reported that value and momentum factor generated inferior risk-adjusted returns (alpha). On the contrary, Asness et al. (2013) reported that CAPM poorly explained the returns of the 48 value and momentum portfolios in developed countries. According to the authors, in comparison with other asset pricing models, CAPM generated the highest pricing errors (alpha) and the lowest cross-sectional variation unexplained.

The finding of the long-short portfolios was similar to Cakici & Tan (2014) who reported CAPM failed to explain the return of value premium in 15 developed countries and momentum premium in 19 developed countries. In the countries, alpha was statistically different from 0. Additionally, the authors pointed out that beta for value and momentum factor stock returns were small and statistically insignificant. Similar result to the study was provided by Grobys & Huhta-Halkola (2019) who showed stock returns from value and momentum premium defied the CAPM in Nordic countries: alphas were statistically significant, and betas were negative. The authors also showed that the combined value and momentum factor portfolio challenged CAPM.

From the findings, the effectiveness of CAPM to explain stock returns from factor investing depended on the portfolio choice: long-only or long-short. CAPM was effective in explaining the stock returns from long-only factor portfolios, but CAPM was ineffective in explaining stock returns from long-short factor portfolios.

5.3 Conclusion

It is evident from the study that stock returns from factor investing at the NSE produced mixed results. Value factor produced negative returns, and momentum factor generated positive returns. Due to the negative returns of the value factor, the combined factor portfolio earned negative returns. The findings also showed that stock returns from factor investing were highly cyclical: stock returns exhibited large negative returns, stock returns took years to attain their previous peaks, and stock returns fluctuated in bull and bear markets. Finally, the study showed that CAPM was effective in explaining stock returns from long-only portfolios but not long-short portfolios.

5.4 Recommendations

5.4.1 Recommendation for investment practitioners

Investment practitioners (portfolio managers and investment analysts) should pick factors to invest in carefully. A solid understanding of the mechanisms of how the factors are formed and their past performance is paramount for success. Investment practitioners should also understand that factors go in and out of favor frequently. In response, investment practitioners should develop guidelines to guide their investment decision. Moreover, investment practitioners should develop the habit of back testing factor strategies before deploying clients` funds. To keep their clients' interest at heart, investment practitioners should develop the habit of communicating their investment performance in a clear and accurate manner. This would ensure that their clients will have the necessary information to make the right investment decision.

5.4.2 Recommendation for investment clients

Investment clients ought to be wary of investment products that market the success of factor-based strategies. Factor investing is risky, and lack of adequate information will lead to unsatisfactory results. To protect themselves, investment clients should insist on getting information about the returns as well as the risks of factor-based strategies. The information provided should cover enough time to enable effective decision making. The failure to receive the right level of information should make investment clients wary of further engagements.

5.4.3 Recommendation for policy

The Capital Markets Authority should develop guidelines for factor-based products. The guidelines for factor investing providers ought to encourage them to disclose the risks as well as the costs associated with factor-based strategies. Similarly, the guidelines for investors should aim at conveying the necessary information for adequate decision making. Failure to create guidelines will lead to manipulation of the investment public by unscrupulous individuals. This in turn will lead to distrust of the regulatory body, a situation nobody would want.

5.4.4 Recommendation for academicians

This study contributes to the understanding and implementation of factor investing. Precisely, this study exhibits the returns to value and momentum factor returns at the NSE. This study further combines literature on factor investing, and therefore it avails literature for future researchers in this area. Future research should be undertaken on whether factors such as volatility, profitability, and investment explain stock returns at the NSE. This will provide the basis for investing in such factors at the bourse.

5.5 Areas of further research

This study focused on value and momentum factor. The ratio of price to book value and the past 12 months return were used to measure the value and momentum factor, respectively. Future studies should measure the same factors differently: for example, price to earnings ratio and past

6 months returns can measure value and momentum factor, respectively. In addition, future studies should also consider small capitalization stocks. The research on stock returns from factor investing can also be studied in other East African markets to confirm or contradict this study's findings.

5.6 Limitations of the study

The study focused on large-capitalization stocks. It is feasible that small-capitalization stocks could have improved the return profile of both value and momentum factor. The study also had a narrow definition of value and momentum factor. This hampered the full understanding of the factors because a broader definition would have created diverse returns. The study likewise focused on the NSE, and thus the results could not be generalized to other markets. Other markets can be put under investigation to ascertain this study's findings.

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APPENDICES

Appendix I: Ethics approval letter

Strathmore
UNIVERSITY

23rd April 2020

Mr Chakaya, Muhwa
muhwa.chakaya@strathmore.edu

Dear Mr Chakaya,

RE: Effect of Factor Investing on Stock Returns at The Nairobi Securities Exchange

This is to inform you that SU-IERC has reviewed and **approved** your above research proposal. Your application approval number is **SU-IERC0790/20.** The approval period is **23rd April 2020 to 22nd April 2021.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-IERC.
iii. Death and life threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-IERC within 72 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-IERC within 72 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days upon completion of the study to SU-IERC.

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://oris.nacosti.go.ke and also obtain other clearances needed.

Yours sincerely,

Dr Virginia Gichuru,
Secretary; SU-IERC

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Appendix II: NACOSTI research license

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 300076

Date of Issue: 04/May/2020

RESEARCH LICENSE

This is to Certify that Mr.. Muhwa Chakaya of Strathmore University, has been licensed to conduct research in Nairobi on the topic: EFFECT OF FACTOR INVESTING ON STOCK RETURNS AT THE NAIROBI SECURITIES EXCHANGE for the period ending : 04/May/2021.

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300076

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Director General
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Appendix III: Sampled stocks between 2010 and 2012

	2010	2011	2012
1	Safaricom	ScanGroup	Athi River Mining
2	BAT	Centum	Kenol Kobil
3	Kenya Airways	COOP Bank	Nation Media Group
4	KPLC	Kenol Kobil	Jubilee Holdings
5	Athi River Mining	TPS Serena	ScanGroup
6	Mumias Sugar	DTK Bank	BAT
7	EABL	Standard Chartered Bank	DTK Bank
8	E.A.Portland Cement	Equity Bank	ABSA Bank
9	KCB Bank	Jubilee Holdings	TPS Serena
10	ABSA Bank	NCBA Bank	KPLC
11	DTB Bank	Athi River Mining	EABL
12	ScanGroup	CFC Stanbic Bank	Bamburi Cement
13	Jubilee Holdings	BAT	KCB Bank
14	Standard Chartered Bank	EABL	Equity Bank
15	COOP Bank	Mumias Sugar	COOP Bank
16	Kenya Re	NBK Bank	Transcentury
17	Total	Nation Media Group	Safaricom
18	NBK Bank	Kenya Airways	NCBA Bank
19	Nation Media Group	KenGen	Kenya Re
20	Bamburi Cement	ABSA Bank	Britam
21	Equity Bank	E.A.Portland Cement	Standard Chartered Bank
22	Centum	Bamburi Cement	Centum
23	KenGen	KCB Bank	Liberty Holdings
24	NCBA Bank	KPLC	E.A.Portland Cement
25	CFC Stanbic Bank	Kenya Re	Mumias Sugar
26	CMC Motors	CMC Motors	KenGen
27	Kenol Kobil	Safaricom	CFC Stanbic
28			NBK Bank
29			Kenya Airways

Source: NSE (2020)

Appendix IV: Sampled stocks between 2013 and 2015

	2013	**2014**	**2015**
1	Uchumi	Carbacid	CIC Insurance
2	BAT	Centum	Centum
3	KCB Bank	Britam	Britam
4	Kenya Re	Safaricom	Umeme
5	NCBA Bank	Athi River Mining	BAT
6	Safaricom	Sanlam Insurance	Housing Finance
7	ScanGroup	CFC Stanbic	Liberty Holdings
8	Nation Media Group	Jubilee Holdings	Sanlam Insurance
9	Kenol Kobil	CIC Insurance	Jubilee Holdings
10	Standard Chartered Bank	Nation Media Group	CFC Stanbic
11	EABL	DTK Bank	DTK Bank
12	Athi River Mining	KenGen	Equity Bank
13	DTK Bank	KCB Bank	Safaricom
14	Carbacid	NCBA Bank	COOP Bank
15	Equity Bank	Equity Bank	KCB Bank
16	Britam	COOP Bank	NCBA Bank
17	Bamburi Cement	Kenya Re	I&M Holdings
18	ABSA Bank	Transcentury	KPLC
19	Jubilee Holdings	Standard Chartered Bank	Standard Chartered Bank
20	COOP Bank	EABL	Kenya Re
21	KenGen	I&M Holdings	Kenol Kobil
22	KPLC	BAT	Athi River Mining
23	CFC Stanbic	TPS Serena	ABSA Bank
24	Mumias Sugar	ABSA Bank	EABL
25	Centum	Bamburi Cement	NBK Bank
26	NBK Bank	Kenya Airways	Nation Media Group
27	TPS Serena	Umeme	TPS Serena
28	Transcentury	KPLC	Bamburi Cement
29	CIC Insurance	ScanGroup	ScanGroup
30	Kenya Airways	Kenol Kobil	KenGen
31			Kenya Airways
32			Carbacid

Source: NSE (2020)

Appendix V: Sampled stocks between 2016 and 2017

	2016	2017
1	Kakuzi	Kenol Kobil
2	Kenya Re	Kenya Airways
3	Jubilee Holdings	Safaricom
4	Nairobi Securities Exchange	BAT
5	Safaricom	Kenya Re
6	Bamburi Cement	Sasini
7	COOP Bank	Jubilee Holdings
8	EABL	Bamburi Cement
9	Liberty Holdings	Standard Chartered Bank
10	KPLC	I&M Holdings
11	BAT	Kakuzi
12	Kenol Kobil	EABL
13	Equity Bank	Umeme
14	Umeme	CFC Stanbic Bank
15	DTK Bank	Centum
16	Sanlam Insurance	COOP Bank
17	ABSA Bank	KenGen
18	I&M Holdings	KCB Bank
19	Centum	DTK Bank
20	KenGen	Nairobi Securities Exchange
21	NBK Bank	Equity Bank
22	CFC Stanbic	ABSA Bank
23	ScanGroup	TPS Serena
24	KCB Bank	ScanGroup
25	NCBA Bank	Liberty Holdings
26	Standard Chartered Bank	KPLC
27	CIC Insurance	NCBA Bank
28	Kenya Airways	Housing Finance
29	Britam	Britam
30	Athi River Mining	Nation Media Group
31	Nation Media Group	CIC Insurance
32	Housing Finance	Sanlam
33		Athi River Mining

Source: NSE (2020)

Appendix VI: Sampled stocks between 2018 and 2019

	2018	2019
1	Crown Paints	Kenol Kobil
2	Nairobi Securities Exchange	CFC Stanbic Bank
3	DTK Bank	ABSA Bank
4	TPS Serena	Crown Paints
5	I&M Holdings	Total
6	KenGen	Bank of Kigali
7	CIC Insurance	KCB Bank
8	Equity Bank	Equity Bank
9	COOP Bank	Liberty Holdings
10	Safaricom	COOP Bank
11	NCBA Bank	Kakuzi
12	KCB Bank	Standard Chartered Bank
13	Sasini	Safaricom
14	KPLC	Kenya Airways
15	Kakuzi	Sasini
16	Nation Media Group	Jubilee Holdings
17	Britam	Bamburi Cement
18	CFC Stanbic	KenGen
19	Standard Chartered Bank	BAT
20	Bamburi Cement	EABL
21	ABSA Bank	TPS Serena
22	Centum	DTK Bank
23	Kenya Airways	ScanGroup
24	Jubilee Holdings	I&M Holdings
25	Liberty Holdings	NCBA Bank
26	Kenol Kobil	Kenya Re
27	ScanGroup	Britam
28	EABL	CIC Insurance
29	BAT	Centum
30	Kenya Re	Nation Media Group
31	Umeme	Umeme
32	Athi River Mining	KPLC
33		

Source: NSE (2020)

Appendix VII: Augmented Dickey-Fuller unit-root test

Variable	Value-weighted portfolio p-value	Equally weighted portfolio p-value
NASI return	0.00	0.00
SMB return	0.00	0.00
Winning portfolio return	0.00	0.00
Losing portfolio return	0.00	0.00
Value portfolio return	0.00	0.00
Growth portfolio return	0.00	0.00
Momentum premium return	0.00	0.00
Value premium return	0.00	0.00
Combined long-short portfolio return	0.00	0.00
Combined long-only portfolio return	0.00	0.00

Source: Researcher (2021)

Appendix VIII: Breusch-Godfrey test for serial correlation

Variable	Value-weighted portfolio p-value	Equally weighted portfolio p-value
Winning portfolio return	0.40	0.55
Losing portfolio return	0.84	0.62
Value portfolio return	0.07	0.31
Growth portfolio return	0.65	0.053
Momentum premium return	0.86	0.52
Value premium return	0.14	0.35
Combined long-short portfolio return	0.37	0.60
Combined long-only portfolio return	0.08	0.10

Source: Researcher (2021)

Appendix IX: Bera-Jarque test for normality

Variable	Value-weighted portfolio p-value	Equally weighted portfolio p-value
Winning portfolio return	0.57	0.00
Losing portfolio return	0.00	0.01
Value portfolio return	0.18	0.07
Growth portfolio return	0.71	0.00
Momentum premium return	0.00	0.00
Value premium return	0.25	0.09
Combined long-short portfolio return	0.02	0.00
Combined long-only portfolio return	0.19	0.20

Source: Researcher (2021)