Journal of
*Risk and Financial Management*

MDPI

*Article*

# Comparison of Multifactor Asset Pricing Models in the South African Stock Market [2000–2016]

**Lenia Mukoyi [1] and Kanayo K. Ogujiuba [2,]***

[1] School of Business and Finance, University of the Western Cape, Belville, Cape Town 7535, Western Cape, South Africa
[2] School of Development Studies, University of Mpumalanga, Nelspruit 1200, Mpumalanga, South Africa
* Correspondence: kanayo.ogujiuba@ump.ac.za

**Abstract:** The quest for parsimonious models has been a key objective in asset pricing. However, there appears to be no consensus on the most successful asset pricing strategy in the literature, especially for the South African Market. Using financial statements from January 2000 to December 2015, this article explores how market anomalies affect the performance of securities in the Johannesburg Stock Exchange's (JSE's) resources, industrial, and finance sectors. We investigated the efficacy of several asset pricing models and their capacity to account for market anomalies in the JSE's resources, industrial, and financial sectors, as well as the applicability of the Fama and French five-factor model. The study used multiple regression techniques and applied stationarity and cointegration methods to ensure robust results. Results also suggest that when the FF5FM is implemented, there is statistical significance at the 10% level for the CMA in the resources sector as the value factor disappears. The FF5FM results in the industrial sector show a significance level of 5% in the SMB. The financial sector seems to have the majority of the style-based risk factors as the SMB is positively significant at a 5% level, the HML is significant at a 1% level, and the CMA is negatively significant at a 10% level of significance. The results suggest that the Carhart Four Factor model is the best to use in all market conditions. Results also show that value becomes redundant in a bullish market, but the opposite holds in a bearish market for a model with operating profitably and investing factors. These findings highlight the necessity for investors to determine which investment risk elements produce abnormal returns in both bearish and bullish market circumstances before investing.

**Keywords:** asset; anomalies; EMH; Fama and French; JSE; risks; style; momentum; pricing

**JEL Classification:** C40; E70; G11; G40



**Citation:** Mukoyi, Lenia, and Kanayo K. Ogujiuba. 2023. Comparison of Multifactor Asset Pricing Models in the South African Stock Market [2000–2016]. *Journal of Risk and Financial Management* 16: 4. https://doi.org/10.3390/jrfm16010004

Academic Editor: Thanasis Stengos

Received: 2 October 2022
Revised: 23 November 2022
Accepted: 25 November 2022
Published: 22 December 2022



## 1. Introduction

According to the Efficient Market Hypothesis (EMH), all facts are accessible in the market; thus, current news is quickly assimilated into the price of securities, which renders attempts to pick individual stocks and outperform the market useless (Fama 1970). Against the backdrop of EMH, investors manage to use the performance of economic sectors to determine where to place assets and diversify their portfolios. Based on Fama and French's real work, it appears that investors would be better served by employing other factor models until this technique is verified by empirical data. A considerable increase in profitability paired with investment drove the FF5FM. In 2015, Fama and French proposed a new five-factor model based on their previous three but with significantly different definitions of investment and profitability. The FF5FM has yet to be shown to outperform previous variants. The classic Fama and French three-factor model is still used by most investors.

Nonetheless, in South Africa, there is no consensus on the causes of market irregularities or their impact on expected returns. Fama and French (1992), Fama and French (1993) Fama and French (1996) and Fama and French (2015) debated the CAPM's real-world application and effectiveness using the Fama and French three-factor model, the Carhart four-factor model, and the Fama and French five-factor model. Aside from market risk, several indicators have been discovered over time that can forecast typical stock returns. Banz (1981) found size anomalies; Basu (1977) identified value; Jegadeesh and Titman (1993) identified momentum; and Fama and French identified profitability and investment (Fama and French 2015). Various empirical studies have also shown cross-sectional diversity in average security returns.

The FF5FM's main flaw is that it ignores low normal earnings from small stocks, which behave similarly to firms that spend much despite low profit, and the model's performance is unaffected by the way its components are specified (Fama and French 2015). In addition, the model ignores low-normal earnings from small stocks with high speculation but poor profitability. Although the five-factor model has yet to be shown as superior to previous models, it has paved the way for better models to be developed in the future. Furthermore, various asset-pricing models have been developed (Cox and Britten 2019; McKane and Britten 2018; and Page and Auret 2019), but their findings have varied between economies and market conditions.

A large portion of South African asset pricing literature considers the identification of investment styles present on the Johannesburg Stock Exchange (JSE). Page and Auret (2019), in their study of the South African market, considered several popular investment styles that have been documented in the local and international literature, namely, size, value, momentum, low beta, currency risk, low volatility, and liquidity. As opposed to applying portfolio sorts based on styles and estimating factor premiums via Fama-Macbeth regressions, their study applied a panel data method on a share-by-share basis. The benefit of such an approach is the ability to test numerous styles in a multivariate parametric framework despite a limited investable universe of shares. The results of the study indicated that size, value, momentum, and low-market beta are priced factors that explain the average cross-sectional variation in share returns on the JSE. On the other hand, McKane and Britten (2018) explored the existence of a liquidity premium on the Johannesburg Stock Exchange (JSE) and its potential interaction with the size effect. It built on the stream of the South African literature that examines liquidity as a standalone factor and added further weight to its existence. Over the 2000–2015 sample period, this study found evidence of a significant liquidity effect. Importantly, the liquidity premium was found to be separate from the size effect. Furthermore, the liquidity premium captured a different underlying effect than the value premium. Their results showed that the Augmented Capital Asset Pricing Model (CAPM) was a useful asset-pricing model on the JSE and performed better than the Fama-French three-factor model.

An assessment of sectors and the relationship between style anomalies and security performance over time in the South African stock market is critical because of limited studies on the subject. Furthermore, the JSE has evolved significantly over the last 20 years, with several changes in composition, expansion, improvements, and reclassification; as a result, this study focuses on three primary sectors that have been stable throughout. By comparing the five-factor model to other models in explaining the cross-section of asset returns in the market, this research contributes to the growing literature on stock return predictability in the African market. In recent years, one of the most important and remarkable topics for academics, practitioners, and analysts in the financial industry has been the factors impacting stock returns and the determination of the explanatory capacity of asset pricing models.

This study compares multi-asset pricing models (Fama and French three-factor model; Carhart four-factor model; Fama and French five-factor model) to assess the relationship between investment style risks and JSE sectors between 2000 and 2016. The research covered the years leading up to and following the financial crisis of 2008. This article tries to answer two pertinent questions: (1) To what extent do investment-style risks influence securities selection and sector return performance on the JSE from 2000 to 2016? (2) Which asset pricing model better describes the JSE equities' predicted returns?

## 2. Review of Related Literature: Style-Based Risks

CAPM and EMH have surface abnormalities, according to research using cross-sectional and time series analysis. The most well-known anomalies, including value impact, size effect, and momentum effect, have been expanded and replicated in a large body of research in a variety of markets. Nonetheless, the impact of style-based risks on JSE sector results has been hotly contested throughout the years. Graham and Uliana (2001) tested 58 JSE industrial sector companies from 1987 to 1996 to see if there was a value growth effect in the South African market. The study found that throughout the study period, the value impact was more prominent. Bhana (2010) conducted a follow-up investigation on 120 stocks listed on the JSE from 1997 to 2012. On a risk-adjusted basis, Bhana discovered that value portfolios consistently beat growth portfolios. van Rensburg (2001) found earnings-to-price (value), market capitalization, and past 12-month positive returns (momentum) using industrial shares on the JSE from 1983 to 1999. In a separate study, van Rensburg and Robertson (2003) discovered evidence that small firms make greater returns on the JSE but that small firms had a smaller beta than larger firms, as well as evidence of a price-to-earnings relationship. This evidence contradicts CAPM's findings, which suggest that the model fails to explain fluctuations in JSE cross-sectional returns. Muller and Ward (2013), in a follow-up analysis to van Rensburg's, concluded that the beta coefficient as a single risk factor adequately explains security returns on the JSE, even though this study only uncovered evidence of momentum, not size. Auret and Cline (2011) used all ALSI constituents between 1988 and 2006 to study the link between price-earnings (P/E), size, and the January effect but found no meaningful support for the value and size impact anomaly on the JSE. Strugnell et al. (2011), building on the findings of van Rensburg and Robertson (2003), revealed the persistence, size, and value (proxied by price-earnings effects) in the cross-section of JSE returns. They did, however, show that beta has, if anything, a negative association with the predicted return. They discovered that beta has no predictive potential for JSE returns, rendering the CAPM based on ALSI as the market proxy worthless. The data offered by van Rensburg and Robertson (2003) suggesting that the CAPM is unable to explain the creation of returns on the JSE is unequivocally supported. According to Strugnell et al. (2011), developing a multifactor pricing model based on these findings would be a valuable addition to the research. Muller and Ward (2013) used JSE share price data to look at the potential benefits of styles and the persistence of numerous style-based strategies from 1985 to 2011. In contrast to prior studies, there was no indication of a small size impact, although there was evidence that bigger market capitalization shares underperformed.

The best results were from a combination style that included momentum, earnings yield, returns on capital, and cash flow-to-price, which consistently outperformed the ALSI by roughly 9% per year. Page and Way (1992) employed a methodology similar to De Bondt and Thaler (1985) to provide a thorough answer regarding mean reversion on the JSE. They discovered evidence of mean reversion, demonstrating that losers outperformed winners from 1974 to 1989. On the ALSI top 40, La Grange and Krige (2015) looked at the profitability of momentum strategies on the JSE over a 15-year period from 1998 to 2013. They discovered that investing long in the best-performing and momentum combo strategies generated large excess returns. Bolton and Von Boetticher (2015) performed an analysis of the financial crisis of 2008, looking at the years 2009 to 2014. The results revealed that the present data yield more negative findings on the indicators; therefore, no indication of the momentum effect on the ALSI top 40 effect or the reaction after the 2008 financial crisis was found. Chinzara and Kambadza (2014) used indices that reflect key JSE sectors, including the FTSE/JSE indices of industrials, general retailers, mining, and financials, to see if anomalies existed in daily JSE returns from 1995 to 2010. They discovered that JSE daily returns are highly favorable early in the week and strongly negative later in the week. As a result, their studies demonstrated that there are irregularities in the JSE's daily returns. According to Kruger and Toerien (2014), during the financial market crisis, firms with stronger cash flows were perceived by the market to be better positioned to outperform during periods of crisis. Three distinct momentum techniques were investigated by Gustafsson and Lundqvist (2010): 3-month momentum with a 3-month holding time, 6-month momentum with a 6-month holding period, and 12-month momentum with a 12-month holding period. The investigation employed the FF3FM and a single-factor model. The model found favorable momentum in the South African market, which is economically significant. Vardharaj and Fabozzi (2007) conducted a market segmentation study in South Africa and found a positive relationship between sector allocation decisions and investing methods.

Thus, this study's choice of FINI, INDI, and RESI is influenced by evidence of JSE market segmentation and indexation. Basiewicz and Auret (2010) investigated the validity of the Fama and French three-factor models on JSE-listed companies from June 1992 to July 2005 to explain the size and value effect. They proposed that the three-factor model could be used to explain the value and size impacts, and they found that these effects persisted even after accounting for liquidity. Philpott and Firer (1994) examined securities on the JSE from 1866 to 1991 to see how anomalies affected the JSE's efficiency. They discovered that some price differences are explained by liquidity on actively traded shares, but not all. When profitability and investment factors are considered, Fama and French (2014) found that the value component HML is superfluous for explaining average returns. For situations where anomalous returns are the primary concern, a four-factor or five-factor model can be utilized, but the five-factor model is the best to use if portfolio tilts are also a problem (Musarurwa 2019). Small, productive, and valuable enterprises with no substantial expansion potential provide the highest predicted returns, according to the new model (Fama and French 2014). Nonetheless, the five-factor model's core flaw is that it ignores small-cap companies' weak average returns, which behave like corporations that spend much despite low profitability and that performance is unaffected by how the elements are defined (Fama and French 2015).

Mosoeu (2017) discovered that the performance of the five-factor model varies depending on where it is tested, particularly in developing countries; however, when compared to the emerging market five-factor model, the five-factor model fails miserably. Except for India and South Korea, the market premium is consistent across all countries studied, as are some of the other differences. When looking at the overall picture for the locations covered in this study, large stocks outperform small ones on average. Firms having a larger profit margin generate better returns than those with a lower profit margin in terms of profitability. Even though the five-factor model was rejected in some countries, other countries' intercept values were minor and low, which is a contradiction. Finally, there is no consistent relationship that can be detected across countries to conclude the model's performance based on the market's status, i.e., developing or developed. Ozkan (2018) found that the recently proposed asset pricing models for developing markets have received less attention. They found that the Fama and French five-factor model is applicable and valid in ISE. During the 72-month analysis period, the market return gave the biggest premium, whereas the firm size premium appeared to have almost evaporated. During the analysis period, it appears that HML is not a redundant element in explaining common variations in stock returns. Subsequently, the value factor was revealed to be redundant in the FF5FM. Dirkx and Peter (2018), over the period 2002 to 2017, analyzed the Fama-French five-factor model for the German market. The results revealed that the five-factor model does not contribute substantial explanatory power to the analysis when compared to the three-factor model. They concluded that the validity of profitability and investment criteria in international asset pricing research cannot be applied to the German market's country-specific case. Asness et al. (2013) found extensive evidence on projected return premiums-to-value and momentum strategies, as well as a strong shared factor structure among their returns.

It takes years for stakeholders to accept a new paradigm, and there is no proof in South Africa at the moment. In asset pricing models, model parameters are critical, and determining which ones are appropriate for the South African market is critical. The research methods and objectives varied across all investment style risks, and there is still limited research that has focused on examining all five factors, market risk, value effect, size effect, momentum effect, profitability effect, and investment effect in the South African stock market. Furthermore, due to various study data samples of the validity of the FF5FM, there is no consensus on the conclusions offered; some have discovered evidence, while others have not. Graham and Uliana (2001) and Bhana (2014) discovered evidence of the value effect on the JSE, whereas van Rensburg and Robertson (2003) discovered evidence of the size and value effect, and Muller and Ward (2013) and La Grange and Krige (2015) discovered evidence of the momentum effect. In their cross-section regressions, the majority of these authors used fundamental ratios, and the Fama and French models. Auret and Cline (2011) found no evidence of a size or value effect on the JSE, and the momentum impact was not discovered by Bolton and Von Boetticher (2015). Thus, Ali and Ülkü (2021) concluded that in a world with an expanding number of factors, it is important to routinely examine asset pricing models and distinguish essential and redundant factors to keep models parsimonious.

However, Zaremba et al. (2019) demonstrated that there is no short-term reversal effect outside the stock-level equity data. The prior month's return positively predicts the returns in the cross-section in all asset classes, with the exception of government bonds, as well as across the asset classes. They also found that the short-term momentum strategies in equity indices, bonds, bills, and currencies share some common components and display weak but significant pairwise correlations. This result has implications for research practices and momentum measurement in various asset markets. Moreover, the findings of this study could be employed to optimize the implementation of the momentum strategies, both in individual asset classes and in a multi-asset framework.

The results of the literature discussed above suggest that, while the Fama French five-factor model is now comprehensively discussed and tested for all major developed and emerging markets, including the South African stock market (Cox and Britten 2019),there is no consensus yet on its efficiency. There is still limited research on the influence of market risk, value effect, size effect, momentum effect, profitability effect, and investment effect prior to and after the 2008 global financial crisis in the South African stock market. This motivates this study to examine the main sectors of the JSE between 2000 and 2016 (before and after the 2008 financial crisis) and make use of the Carhart four-factor model and Fama and French five-factor model to investigate the relationship between the investment style risks within JSE sectors.

## 3. Data and Methods

The cross-sectional analysis considered only the All-Share Index against the resources, industrial, and financial sectors. Portfolio sorts were conducted using financial statement data from IRESS Ltd. (Melbourne, Australia) [a fintech company], which delivers and develops software solutions for the financial services industries. Value is proxied by a book-to-market ratio, a price–earnings ratio, size, market capitalization operating profit, total assets, value, outstanding shares, total liabilities, valuation ratios, and momentum excess returns earned over previous 6-month intervals. The timeline was chosen to examine if the style-anomalies influenced returns the same way before and after the 2008 financial crisis and whether the restructuring of the JSE security prices differed from their intrinsic values prior to, during, and after a market crash.

The sample research includes 240 months, from 1 January 2000 to 31 December 2016, with a further split from 2000 to 2008 and 2009 to 2016 for the CH4FM and the FF5FM. The regressions determined whether the variables were adversely or positively linked with one another, as well as how all of the factors interacted to influence average stock returns. The models have to be compared together, particularly the five-factor model, to prove if it is an improvement to the other models and check whether there is room for improvement to be further developed in future research within the South African economy. The choice of assessment period has the distinct advantage of allowing the results of the tests in this study to be based on two distinct economic eras. Our analysis was unrestricted, and only the 6-month holding period was set to test the effects on the Carhart four-factor model. Preference shares were excluded from the sample because they are not purely equity. Secondly, to correct the slightly thin trading conditions on the JSE, shares not traded on the JSE for more than 12 months out of the 204 months in the testing period wwere excluded. Lastly, outliers—that is, values that lie outside most of the other values being either extremely large or extremely small—that fell less than the fifth percentile and beyond the 95th percentile were replaced by the smallest and largest values within the data set.

Table 1 below gives a description of the variables from the Fama and French models and the Carhart model. The FF3FM gives value and size, while the CH4FM gives momentum signal, and the FF5FM gives two additional profitability and investment variables. The variables are summarized below with descriptions of how they were derived in this study.

**Table 1.** Summary of the variables.

| Variables | Calculation | Formula |
|---|---|---|
| SMB (Size or Small Firm Effect Risk Premium) | Small minus large cap | *Small Market Cap* − *Large Market Cap (JSE Top 40)* |
| HML (Value Risk Premium) | Value minus growth (t − 6) | *Value (thus, high book-to-market)* − *Growth (thus, low book-to-market)* |
| WML (Momentum-Risk Premium) | Winner prior 6-month returns minus loser prior 6-month returns | $\frac{Total\ Return_t - Total\ Return_{t-6M}}{Total\ return_{t-6M}}$ |
| RMW (Profitability Factor) | Robust minus weak operating profitability | $\frac{Net\ Income\ before\ Interest\ and\ Tax_t}{ROE_t}$ |
| CMA (Investment Factor) | Conservative minus aggressive investing | $\frac{Total\ Assets_t - Total\ Assets_{t-1}}{Total\ Assets_{t-1}}$ |

Source: Compiled by the authors.

Justification of CAPM & Equation Specifications

*(a) Fama and French Three Factor Model:* Fama and French (1992, 1993) reveal that CAPM, as an EMH test, should be altered to cater for additional risk variable size and value premiums. Fama and French (1993) define non-diversified uncertainty in stocks more effectively than the CAPM when used jointly. The three explanatory variables ($Rm - Rf$), SMB, and HML form the model's foundation; these three variables are how the three-factor model is claimed to describe stock returns better than the CAPM. These attributes in their regression form are computed using:

$$R\_I = R\_f + \beta(i)(Rm - R\_f) + \beta\_SMB \times SMB + \beta\_HML \times HML \quad (1)$$

where:

$R\_I$: refers to the return on asset $i$
$R\_f$: refers to the risk-free rate
$\beta$: refers to the beta of the assets
$Rm$: refers to the return of the market portfolio
$HML$: refers to the return spread of small minus large securities (i.e., proxy for value).
$SMB$: refers to the return spread of small minus big market capitalization (i.e., firm size).

*(b) Carhart Four-Factor Model:* The Carhart (1997) four-factor model builds on the Fama and French three-factor model by adding one more factor: momentum, based on data presented by Jegadeesh and Titman (1993) on the existence of strong medium-term price momentum trends. This factor was included because in several studies, including those of Jegadeesh and Titman (1993), Fama and French (1996) discovered that you could raise your earnings by purchasing stock that was performing well in the previous 1–6 months and by selling stocks that were performing poorly in the previous 1–6 months. The FF3 model, according to Carhart (1997), does not account for asset returns influenced by momentum investment techniques. The so-called "factor wars" were really kicked off by Carhart's momentum factor. The momentum paradox is a market inefficiency caused by a sluggish

reaction to new information. The Carhart (1997) four-factor model is used in regressions to estimate monthly payoffs for each attribute, as illustrated in Equation (2):

$$R_i - R_f = \alpha_i + \beta_i\ (R_m \text{ - } R_f) + \beta_{SME} \times SMB + \beta_{HML} \times HML + \beta_{MOM} \times WML \qquad (2)$$

where:

$\alpha_i$: refers to Jensen's alpha
*WML*: refers to the return spread of winner's minus loser's stock (i.e., momentum risk factor)

*(c) Fama and French Five-Factor Model:* The Fama and French three-factor model (1993) was a significant improvement over the CAPM, but it failed to explain some of the key inconsistencies in justifying expected returns with a focus on profitability and investment impacts. The CH4FM is the standard performance metric currently in use. As a result, Fama and French recently suggested that several components were missing. As a result, a five-factor model incorporating size and value, as well as profitability and investment, was developed for anticipating patterns in security returns, which outperformed the three-factor model (Fama and French 2015). The five-factor model regression has the following equation when profitability and investment elements are added:

$$R_I - R_f = \alpha_i + \beta_I(R_m - R_f) + \beta_{SMB} \times SMB + \beta_{HML} \times HML + \beta_{RMW} \times RMW + \beta_{CMA} \times CMA + e \qquad (3)$$

where:

*RMW*: refers to the return of the most profitable firms minus the least profitable (i.e., profitability factor)
*CMA*: refers to the return spread of firms that invest conservatively minus aggressively (i.e., investment factor)

## 4. Findings and Discussion

### *4.1. Stationarity Test*

The early and pioneering work for detecting the presence of a unit root in time series data was developed by Dickey and Fuller (1979). The ADF results in Table 2 show that comparing the ADF test statistics with their corresponding critical values reveal that all the level series have unit roots, and all series became stationary at order 1 after the first differencing, at the 1% significance level. Thus, all variable series were integrated with a series into the same order I(1). To confirm the ADF test, the stationary tests are also represented graphically, which also shows that all the level series have unit roots; however, the first difference of all series made them stationary at the 1% significance level.

**Table 2.** Stationarity Test Result.

| | | **Augmented Dickey–Fuller** | | |
|---|---|---|---|---|
| **Variables** | | | **Prob Values** | **Order of Integration** |
| RESI_TOP_10 * | | −1483038 * | 0.0000 | I(1) |
| INDI_TOP_25 * | | −13.69089 * | 0.0000 | I(1) |
| FINI_TOP_15 * | | −13.86646 * | 0.0000 | I(1) |
| MRP * | | −14.88926 * | 0.0000 | I(1) |
| SMB * | | −13.15255 * | 0.0000 | I(1) |
| HML * | | −13.06093 * | 0.0000 | I(1) |
| RMW * | | −14.29083 * | 0.0000 | I(1) |
| CMA * | | −14.04376 * | 0.0000 | I(1) |
| ***Critical Value*** | ***1%*** | ***−3.462574*** | | |
| | ***5%*** | ***−2.875608*** | | |

Source: Own Computation; * denotes the rejection of the null hypothesis of unit root at 1% significance levels.

The RESI Top 10, the INDI Top 25, the FINI Top 15, and the MRP move in the same pattern. They start with a difference and take a huge difference during the 2008 financial crisis. After establishing that all the variables are integrating in the same order (1) at the first differencing, it is crucial to find if there are long-run associations between the explanatory and dependent variables. The log-return series appear similar but are not identical, but they seem to share similar shocks or disturbances. We used cointegration to determine this procedure. Cointegration shows the presence of a long-run association amongst variables. It means they are integrating in the same order, but in the presence of a linear combination of at least one or more variables, they are integrating in order I(0). The first criterion to be met when using the Johansen cointegration test is to indicate an optimal lag to be used. The Johansen test finds the deterministic trend assumption in the VAR model and removes the serial correlation on the residuals. The optimal lag is therefore obtained from the information criteria approach, as per how many lags should be included in the model. The null hypothesis of no cointegrating vectors for *FF3FM*, *CH4FM*, and *FF5FM* is rejected since the trace test statistic is more than critical at the 5% level of significance for our variables.

### *4.2. Descriptive Statistics of the Variables*

Table 3 summarizes the descriptive statistics for all sectors. The descriptive statistics are crucial to the analysis since they help determine if each sector and market are linked, as well as how closely the return distribution resembles the normal distribution. This is done for all sectors' market returns, and for 6-month and 12-month momentum variables. The evaluation begins with a comparison of factor-imitating arithmetic mean returns based on the highest and lowest percentiles. This is done for the key sectors, with the resources, industrial, and financial sectors receiving special attention.

**Table 3.** Descriptive statistics of sectors used in research (January 2000 to December 2016).

| | **Mean** | **Standard Deviation** | **Kurtosis** | **Skewness** | **Minimum** | **Maximum** | **Confidence Level (95.0%)** |
|---|---|---|---|---|---|---|---|
| ***All Share*** | 0.0365 | 0.0476 | 0.7557 | −0.2825 | −0.1255 | 0.1616 | 0.0066 |
| ***Top 40*** | 0.0349 | 0.0507 | 0.8257 | −0.2969 | −0.1404 | 0.1656 | 0.0070 |
| ***Resources 10*** | 0.0326 | 0.0763 | 1.1538 | −0.4953 | −0.2563 | 0.2035 | 0.0105 |
| ***Industrial 25*** | 0.0307 | 0.0505 | 1.2984 | −0.8543 | −0.1510 | 0.1428 | 0.0070 |
| ***Financial 15*** | 0.0437 | 0.0499 | 0.2726 | −0.0906 | −0.0989 | 0.1775 | 0.0069 |

Source: Own estimates.

As can be seen in Table 3, the mean value for the market return where the All-Share index was used as a proxy for the market is 0.0365, while the standard deviation for the market return is 0.0476. This indicates that the market returns did not deviate much from the mean, implying that the deviations from returns of the overall market are centred on zero. However, the distribution is skewed negatively, indicated by the skewness value of −0.2825. This is supported by the kurtosis value of 0.7557, which suggests a platykurtic distribution. A platykurtic distribution has a thinner tail than a normal distribution. The maximum and minimum returns of the sample period were 0.1616 and −0.1255, respectively. The JSE Top 40 index's returns have a mean of 0.0349 and a standard deviation of 0.0507. This sector's returns are in line with the All-Share, but the deviation is slightly higher. The JSE Top 40's skewness is −0.2969, and the kurtosis is 0.8257. The maximum value is 0.1656, and the minimum value is −0.2969. The returns of all the sectors analyzed in this study indicate that most of the returns are in tandem with the All-Share index, except technology.

The financial sector's returns are greater than the market's, with a mean of 0.0437 and a standard deviation of 0.0499, respectively. As a result, their returns in this area are less erratic. The financial sector has the lowest high kurtosis of 0.2726 and the lowest skewness of −0.0906, implying that the returns are greater than zero. Asset pricing tests should ideally be performed on individual securities; however, with over 170 actively traded equities on the JSE, statistical considerations require stock grouping into portfolios). When asset pricing tests are run on portfolios, the influence of firm-specific risk on mean estimation and other descriptive statistics is dramatically reduced. As a result, grouping allows for a reduction in the number of test assets while minimizing data loss. As a result, the analysis was centered on sectors, with the three most notable being the resources, industrial, and financial sectors. The measure of their risk (i.e., volatility on return) is analyzed, as these three moves in lockstep with the ALSI. For this study, the best technique of factor construction was to analyze the JSE's segmentation into resources, financial, and industrial shares. For each of these sectors, distinct SMB, HML, WML, RMW, and RMW factors were created. Note that these factors are referred to as SMB Factor (mmall minus large cap); HML Factor (value minus growth); WML factor (winner minus loser), RMW factor (robust minus weak operating profitability), as well as CMA factor (conservative minus aggressive investing).

Table 4 depicts the descriptive statistics of the basic overview, distribution, and volatility of the return for the factors in all the asset pricing models. Furthermore, for this study, the information on whether stock returns, MRP, SMB, HML, WML, RMW, and CMA are volatile or not is provided.

**Table 4.** Descriptive statistics of the asset pricing factor model constituents.

| | Mean | Standard Deviation | Kurtosis | Skewness | Minimum | Maximum | Confidence Level (95.0%) |
|---|---|---|---|---|---|---|---|
| MRP | 0.0060 | 0.0528 | 0.4700 | −0.0968 | −0.1546 | 0.1537 | 0.0073 |
| SMB | 0.0045 | 0.0303 | 0.2504 | 0.2260 | −0.0818 | 0.0874 | 0.0042 |
| HML | −0.0044 | 0.0430 | 2.3186 | 0.8381 | −0.0896 | 0.1904 | 0.0059 |
| WML | 0.0460 | 0.0390 | 1.8692 | 0.6033 | −0.0838 | 0.1947 | 0.0054 |
| RMW | −0.0006 | 0.0322 | 1.9132 | 0.2649 | −0.1067 | 0.1271 | 0.0044 |
| CMA | −0.0079 | 0.0351 | 0.7517 | 0.2828 | −0.0959 | 0.1198 | 0.0049 |

Source: Own estimates.

The mean value of stock market benchmark returns is 0.0104, with a standard deviation of 0.0522, indicating that stock returns are volatile and centered on zero. Furthermore, the distribution is negatively skewed, with a skewness value of −0.0380 and a kurtosis value of 0.3818, indicating asymmetrical skewness. This indicates that most of the returns are on the left side of the distribution. Outliers are also present in the distribution, as seen by the maximum of 0.1491 and the minimum of −0.1491. The SMB and HML are added to the single-factor model in the Fama and French three-factor model. The SMB factor has a standard deviation of 0.0303 and a mean of 0.0045. This factor has a positive skewness of 0.2260 and kurtosis of 0.2504, indicative of a slight left-hand-sided distribution of the return. The SMB factor has a minimum value of −0.0818 and a maximum value of 0.0874. On the other hand, the value factor, HML, has a negative mean of −0.0044 and a standard deviation of 0.0430. The HML has the highest skewness of all the factors at 0.8381, and its kurtosis is 2.3186. Lastly, the minimum value of the HML is −0.0896, and the maximum value is 0.1904. The Carhart four-factor model adds the momentum factor component, thus, the WML. This has a mean value of 0.0460 and a standard deviation value of 0.0390 over 6-month period returns. This indicates that the returns are above zero; however, most of the returns are located on the right side of the distribution, as indicated by the skewness value of 0.6033 and the kurtosis value of 1.8692, which suggests the distribution is sharper than the normal distribution. The maximum value of 0.1947 and the minimum value of -0.0838 indicate that outliers are present in the distribution. The RMW and CMA variables have mean values of −0.0006 and −0.0079, respectively, in the Fama and French five-factor model. They had negative standard deviations as well. The RMW's kurtosis is slightly higher than the CMA's, at 1.9132. (0.7517). The HML and CMA numbers show that they are in tandem and similarly volatile. As can be seen from the descriptive statistics above, the

JSE has a high level of volatility, meaning that investors and practitioners would demand compensation for the risk they have inherited in the market.

### 4.3. Fama and French Three-Factor Model

The results show that the model has superior predictive capacity when the risk-free rate is contained—that is, when the risk-free rate is included as the regression intercept. Details of results are presented in Table 5. Table 6 shows the summary of styles present in the sectors when using FF3FM.

Despite the fact that much study has been done and continues to be done on this subject, there seems to be no unanimity on the influence of market anomalies on predicted returns. Table 6 outlines Fama and French's (1992, 1993) three-factor model, as well as the market anomalies discovered in each of the three sectors. The small-cap bias is present fully in the industrial and financial sectors. Value bias is only present in the financial sector. The mild growth bias and the mild small-cap bias indicate some presence but were not statistically significant. Graham and Uliana (2001) examined the JSE industrial sector and found the existence of the value growth effect in the South African market. In our analysis, the industrial sector over the study period does not display the same result. This could be due to the differing time period of research, as Graham and Uliana's study covered the period 1987 to 1992, and a different methodology was implemented. In a study conducted by Bhana (2014), value portfolios consistently beat growth portfolios on a risk-adjusted basis from January 1997 to December 2012. The financial industries are affected by the value anomaly, meaning a positive link between security returns and the ratio of accounting-based estimates of value to the security's market price.

**Table 5.** Fama and French three-factor model results.

| | | | | |
|---|---|---|---|---|
| *RESI TOP 10 Fama and French Three-Factor Model* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 804 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | −0.419790 | 0.213331 | −1.967787 | 0.0495 |
| C(3) | 0.009291 | 0.181479 | 0.051194 | 0.9592 |
| C(4) | −0.120180 | 0.215150 | −0.558587 | 0.5766 |
| C(5) | −0.377221 | 0.216475 | −1.742557 | 0.0818 |
| C(6) | 0.631443 | 0.241740 | 2.612072 | 0.0092 |
| C(7) | 0.333555 | 0.201126 | 1.658432 | 0.0976 |
| C(8) | −0.600044 | 0.260230 | −2.305826 | 0.0214 |
| C(9) | −0.177546 | 0.195436 | −0.908462 | 0.3639 |
| C(10) | 0.000822 | 0.006011 | 0.136798 | 0.8912 |
| Determinant residual covariance | | $4.68 \times 10^{-12}$ | | |
| Equation: D(RESI_TOP_10) = C(2) × D(RESI_TOP_10(−1)) + C(3) × D(RESI_TOP_10(−2)) + C(4) × D(MRP(−1)) + C(5) × D(MRP(−2)) + C(6) × D(SMB(−1)) + C(7) × D(SMB(−2)) + C(8) × D(HML(−1)) + C(9) × D(HML(−2)) + C(10) | | | | |
| Observations: 201 | | | | |
| R-squared | 0.463504 | Mean dependent var | | −0.000136 |
| Adjusted R-squared | 0.438224 | S.D. dependent var | | 0.113666 |
| S.E. of regression | 0.085195 | Sum squared resid | | 1.386310 |
| Durbin–Watson stat | 2.141373 | | | |

**Table 5.** *Cont.*

| | | | | |
|---|---|---|---|---|
| *INDI Top 25 Fama and French Three-Factor Model* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 804 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | −0.476398 | 0.202300 | −2.354914 | 0.0188 |
| C(3) | −0.300116 | 0.160030 | −1.875370 | 0.0611 |
| C(4) | −0.187412 | 0.238300 | −0.786453 | 0.4318 |
| C(5) | −0.100292 | 0.176648 | −0.567747 | 0.5704 |
| C(6) | −0.054728 | 0.155501 | −0.351949 | 0.7250 |
| C(7) | 0.131462 | 0.120284 | 1.092931 | 0.2748 |
| C(8) | 0.133551 | 0.138094 | 0.967099 | 0.3338 |
| C(9) | 0.244832 | 0.123893 | 1.976156 | 0.0485 |
| C(10) | 0.000174 | 0.003980 | 0.043650 | 0.9652 |
| Determinant residual covariance | | $2.78 \times 10^{-12}$ | | |
| Equation: D(INDI_TOP25) = C(2) × D(INDI_TOP25(−1)) + C(3) × D(INDI_TOP25(−2)) + C(4) × D(MRP(−1)) + C(5) × D(MRP(−2)) + C(6) × D(HML(−1)) + C(7) × D(HML(−2)) + C(8) × D(SMB(−1)) + C(9) × D(SMB(−2)) + C(10) | | | | |
| Observations: 201 | | | | |
| R-squared | 0.382072 | Mean dependent var | | 0.000127 |
| Adjusted R-squared | 0.352955 | S.D. dependent var | | 0.070118 |
| S.E. of regression | 0.056402 | Sum squared resid | | 0.607610 |
| Durbin–Watson stat | 2.242138 | | | |
| *FINI Top 15 Fama and French Three-Factor Model* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 804 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | 0.347764 | 0.148402 | 2.343396 | 0.0194 |
| C(3) | 0.309416 | 0.106256 | 2.911977 | 0.0037 |
| C(4) | 0.484425 | 0.101629 | 4.766585 | 0.0000 |
| C(5) | 0.394994 | 0.090459 | 4.366546 | 0.0000 |
| C(6) | −0.637192 | 0.108830 | −5.854906 | 0.0000 |
| C(7) | −0.475310 | 0.095203 | −4.992589 | 0.0000 |
| C(8) | 0.258083 | 0.111920 | 2.305951 | 0.0214 |
| C(9) | 0.249751 | 0.109377 | 2.283389 | 0.0227 |
| C(10) | 0.000109 | 0.003742 | 0.029224 | 0.9767 |
| Determinant residual covariance | | $5.90 \times 10^{-12}$ | | |
| Equation: D(FINI_TOP_15) = C(2) × D(FINI_TOP_15(−1)) + C(3) × D(FINI_TOP_15(−2)) + C(4) × D(HML(−1)) + C(5) × D(HML(−2)) + C(6) × D(MRP(−1)) + C(7) × D(MRP(−2)) + C(8) × D(SMB(−1)) + C(9) × D(SMB(−2)) + C(10) | | | | |
| Observations: 201 | | | | |
| R-squared | 0.480708 | Mean dependent var | | $-8.87 \times 10^{-5}$ |
| Adjusted R-squared | 0.456239 | S.D. dependent var | | 0.071923 |
| S.E. of regression | 0.053036 | Sum squared resid | | 0.537249 |
| Durbin–Watson stat | 2.145314 | | | |

**Table 6.** Summary of styles present in sectors using FF3FM.

| | RESI Top 10 | INDI Top 25 | FINI Top 15 |
|---|---|---|---|
| MRP | N/A | N/A | Market risk neg |
| HML | Mild growth bias | N/A | Value bias |
| SMB | Small-cap bias | Mild small-cap bias | Small-cap bias |

Source: Compiled by the authors.

The persistence of size and value (proxied by the price–earnings effects) in the cross-section of returns on the JSE was observed by Strugnell et al. (2011) when they looked at the period January 1994 to October 2007. Small companies outperformed large capitalization firms in the JSE resources, industrial, and financial sectors, according to this analysis. The value and size effect anomaly on the JSE was not supported by Auret and Cline (2011), who used all ALSI constituents from 1988 to December 2006. As a result, the JSE appears to have size (small-cap) and value anomalies. The Fama and French three-factor model, on the other hand, appears to only explain a portion of the value anomaly, and there is some evidence of an increase.

### *4.4. Carhart Four-Factor Model Using a Six-Month Holding Period*

The Carhart four-factor model is a variation of the three-factor model in that it incorporates a fourth important variable known as momentum. Due to a lack of data before 2000, we only looked at the six-month momentum variables. The effect of the six-month momentum variable will be used in the short term. Below is a cross-sector analysis of the CH4FM both with and without the CAPM premise for six-month momentum returns. Table 7 below shows the results of the Carhart foru-factor model.

**Table 7.** Carhart four-factor model.

| | | | | |
|---|---|---|---|---|
| *CH4FM RESI Top 10 2000–2016* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 1005 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | −0.492149 | 0.182606 | −2.695143 | 0.0072 |
| C(3) | −0.054355 | 0.173275 | −0.313692 | 0.7538 |
| C(4) | −0.160054 | 0.212021 | −0.754894 | 0.4505 |
| C(5) | −0.382013 | 0.213626 | −1.788230 | 0.0741 |
| C(6) | −0.631375 | 0.209096 | −3.019538 | 0.0026 |
| C(7) | −0.204740 | 0.177979 | −1.150362 | 0.2503 |
| C(8) | 0.946710 | 0.253052 | 3.741168 | 0.0002 |
| C(9) | 0.494147 | 0.204593 | 2.415267 | 0.0159 |
| C(10) | −0.614879 | 0.212952 | −2.887406 | 0.0040 |
| C(11) | −0.389580 | 0.171222 | −2.275295 | 0.0231 |
| C(12) | 0.000787 | 0.005909 | 0.133160 | 0.8941 |
| Determinant residual covariance | | $5.39 \times 10^{-15}$ | | |
| Equation: D(RESI_TOP_10) = C(2) × D(RESI_TOP_10(−1)) + C(3) × D(RESI_TOP_10(−2)) + C(4) × D(MRP(−1)) + C(5) × D(MRP(−2)) + C(6) × D(HML(−1)) + C(7) × D(HML(−2)) + C(8) × D(SMB(−1)) + C(9) × D(SMB(−2)) + C(10) × D(WML(−1)) + C(11) × D(WML(−2)) + C(12) | | | | |
| Observations: 201 | | | | |
| R-squared | 0.487019 | Mean dependent var | | −0.000136 |
| Adjusted R-squared | 0.457163 | S.D. dependent var | | 0.113666 |
| S.E. of regression | 0.083746 | Sum squared resid | | 1.325546 |

**Table 7.** *Cont.*

| | | | | |
|---|---|---|---|---|
| Durbin–Watson stat | 2.159925 | | | |
| *CH4FM INDI Top 25 2000–2016* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 1005 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | −0.584665 | 0.156487 | −3.736184 | 0.0002 |
| C(3) | −0.334869 | 0.148147 | −2.260387 | 0.0240 |
| C(4) | −0.200625 | 0.130749 | −1.534430 | 0.1253 |
| C(5) | 0.057178 | 0.114542 | 0.499186 | 0.6178 |
| C(6) | −0.067257 | 0.175051 | −0.384217 | 0.7009 |
| C(7) | −0.065614 | 0.162813 | −0.403005 | 0.6870 |
| C(8) | 0.334341 | 0.162009 | 2.063722 | 0.0393 |
| C(9) | 0.346002 | 0.133257 | 2.596505 | 0.0096 |
| C(10) | −0.224332 | 0.146206 | −1.534356 | 0.1253 |
| C(11) | −0.130332 | 0.115307 | −1.130303 | 0.2586 |
| C(12) | 0.000129 | 0.003973 | 0.032570 | 0.9740 |
| Determinant residual covariance | | $3.33 \times 10^{-15}$ | | |
| Equation: D(INDI_TOP25) = C(2) × D(INDI_TOP25(−1)) + C(3) × D(INDI_TOP25(−2)) + C(4) × D(HML(−1)) + C(5) × D(HML(−2)) + C(6) × D(MRP(−1)) + C(7) × D(MRP(−2)) + C(8) × D(SMB(−1)) + C(9) × D(SMB(−2)) + C(10) × D(WML(−1)) + C(11) × D(WML(−2)) + C(12) | | | | |
| Observations: 201 | | | | |
| R-squared | 0.390664 | Mean dependent var | | 0.000127 |
| Adjusted R-squared | 0.355200 | S.D. dependent var | | 0.070118 |
| S.E. of regression | 0.056304 | Sum squared resid | | 0.599162 |
| Durbin–Watson stat | 2.238280 | | | |
| *CH4FM FINI Top 15 2000–2016* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 1005 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | 0.212627 | 0.139494 | 1.524272 | 0.1278 |
| C(3) | 0.237988 | 0.103702 | 2.294910 | 0.0220 |
| C(4) | 0.374455 | 0.098056 | 3.818796 | 0.0001 |
| C(5) | 0.340608 | 0.092080 | 3.699038 | 0.0002 |
| C(6) | −0.622687 | 0.113411 | −5.490524 | 0.0000 |
| C(7) | −0.472293 | 0.101217 | −4.666153 | 0.0000 |
| C(8) | 0.407520 | 0.125275 | 3.253007 | 0.0012 |
| C(9) | 0.333726 | 0.116650 | 2.860909 | 0.0043 |
| C(10) | −0.292242 | 0.109742 | −2.662988 | 0.0079 |
| C(11) | −0.156472 | 0.101551 | −1.540830 | 0.1237 |
| C(12) | 0.000107 | 0.003808 | 0.028105 | 0.9776 |
| Determinant residual covariance | | $7.35 \times 10^{-15}$ | | |
| Equation: D(FINI_TOP_15) = C(2) × D(FINI_TOP_15(−1)) + C(3) × D(FINI_TOP_15(−2)) + C(4) × D(HML(−1)) +C(5) × D(HML(−2)) + C(6) × D(MRP(−1)) + C(7) × D(MRP(−2)) +C(8) × D(SMB(−1)) + C(9) × D(SMB(−2)) + C(10) × D(WML(−1)) + C(11) × D(WML(−2)) + C(12) | | | | |

**Table 7.** *Cont.*

| | | | |
|---|---|---|---|
| Observations: 201 | | | |
| R-squared | 0.467965 | Mean dependent var | $-8.87 \times 10^{-5}$ |
| Adjusted R-squared | 0.437000 | S.D. dependent var | 0.071923 |
| S.E. of regression | 0.053966 | Sum squared resid | 0.550433 |
| Durbin–Watson stat | 2.157940 | | |

As seen in the statistics above for the full sample period, the R-squared for the RESI Top 10 index is the highest at 0.4870. The FINI Top 15 index comes in second at 0.4679, followed by the INDI Top 25 index at 0.3906. The regression findings in the Carhart four-factor model for the whole sample period for the RESI Top 10 index show that the MRP's lag 1 and lag 2 are both negatively insignificant and the HML has a statistically significant lag 1 of −0.6314. On the other hand, the value factor has a lag 2 that is negative and insignificant. The HML has a statistically significant lag 1 of −0.6314. The value factor, on the other hand, has a Lag 2 that is negatively negligible. The SMB lag 1 and lag 2 are also statistically significant at 0.9467 and 0.4941, respectively. WML lag 1 and lag 2 have statistically significant coefficients of −0.6149 and −0.3896, respectively. The monthly value of the speed of adjustment is 0.000787. Any structural changes in the parameters would result in a 0.944 percent shift away from equilibrium within a year. Table 8 below shows the summary of market anomalies in the four-factor model.

**Table 8.** Summary of market anomalies present in the four-factor model.

| | **RESI Top 10** | | | **INDI Top 25** | | | **FINI Top 15** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **2000–2016** | **2000–2008** | **2009–2016** | **2000–2016** | **2000–2008** | **2009–2016** | **2000–2016** | **2000–2008** | **2009–2016** |
| MRP | N/A | N/A | N/A | N/A | N/A | N/A | Neg market risk | Neg market risk | N/A |
| HML | Mild growth bias | Growth | Mild value bias | N/A | Moderate growth bias | Mild value bias | Value bias | Value bias | value bias |
| SMB | Small cap bias | Small cap bias | Mild large cap bias | Small cap bias | Small cap bias | Large cap bias | Small cap bias | Small cap bias | Large cap bias |
| WML | Contrarian bias | Contrarian bias | N/A | Mild contrarian bias | Moderate contrarian bias | Momentum | Contrarian bias | Contrarian bias | Momentum bias |

Source: Compiled by the authors.

The three-factor model, according to Basiewicz and Auret (2010), may be used to illustrate the value and size effects, and they observe that they persist after correcting for liquidity. There was no indication of a small size effect; however, there was proof that shares with bigger market capitalization underperformed, according to Muller and Ward (2013). The existence of a tiny size effect in contradiction was discovered in this analysis, but only from 2000 to 2008 in bullish conditions. Large market capitalization only existed under negative conditions from 2009 to 2016. Muller and Ward (2013) recognized momentum as crucial because they discovered that the momentum approach outperformed with a 3-month and 12-month holding duration. Furthermore, although this study found only evidence of momentum, not size, van Rensburg and Robertson (2003) conclude that beta coefficient as a single risk factor adequately explains security returns on the JSE. Another article discusses the existence of a momentum impact on securities traded on the JSE. Bolton and Von Boetticher (2015) studied the ALSI top 40 effect and the reaction after the 2008 financial crisis from 2009 to 2014. They found no indication of the momentum impact on the ALSI top 40 effect or the reaction after the 2008 financial crisis. Nonetheless, some empirical results show that size, value, and momentum abnormalities existed in the South African equities market. It may therefore be deduced that the CH4FM catches some momentum effects that the Fama and French three-factor model misses. The CH4FM might be said to only capture a portion of the value in the industrial and resources sectors. From 2009 to 2016, this study found that equities that underperformed in the previous six months tended to continue losing in the next six months. From 2009 to 2015, there is evidence that stocks in the industrial and financial sectors that have outperformed in the previous six months tend to consistently win for the next six months.

### *4.5. Fama and French Five-Factor Model*

Because all style-based risk variables that predict returns are not captured, a single-component model is unable to adequately explain them. As a result, several researchers and asset pricing managers have found that variations in multifactor models are effective. Fama and French developed a more complicated asset pricing model that takes profit and investment effects into account. This model has been challenged by some academics for failing to account for the momentum effect, which has been demonstrated to play an important role in explaining returns. The FF5FM is a step up from the FF3FM, which is well-known around the world (1993). Monthly price data, annual balance sheet, and income statement returns are used to compute the variables' size, value, operating profitability, and investment considerations. Table 9 below shows results using the Fama and French five-factor model.

**Table 9.** Fama and French five-factor model.

| | | | | |
|---|---|---|---|---|
| *FF5FM RESI TOP 10 2000–2016* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 1206 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | −0.766040 | 0.201865 | −3.794804 | 0.0002 |
| C(3) | −0.230066 | 0.189451 | −1.214383 | 0.2249 |
| C(4) | 0.386444 | 0.443720 | 0.870919 | 0.3840 |
| C(5) | 0.376808 | 0.335256 | 1.123942 | 0.2613 |
| C(6) | −0.593968 | 0.358663 | −1.656059 | 0.0980 |
| C(7) | −0.152366 | 0.333405 | −0.457000 | 0.6478 |
| C(8) | 0.112049 | 0.279216 | 0.401297 | 0.6883 |
| C(9) | −0.183835 | 0.252674 | −0.727558 | 0.4670 |
| C(10) | 0.221277 | 0.192590 | 1.148955 | 0.2508 |
| C(11) | 0.180357 | 0.192082 | 0.938962 | 0.3480 |
| C(12) | −0.114134 | 0.371435 | −0.307280 | 0.7587 |
| C(13) | −0.286745 | 0.275632 | −1.040318 | 0.2984 |
| C(14) | 0.000898 | 0.006076 | 0.147748 | 0.8826 |
| Determinant residual covariance | | $6.60 \times 10^{-19}$ | | |
| Equation: D(RESI_TOP_10) = C(2) × D(RESI_TOP_10(−1)) + C(3) × D(RESI_TOP_10(−2)) + C(4) × D(HML(−1)) + C(5) × D(HML(−2)) + C(6) × D(CMA(−1)) + C(7) × D(CMA(−2)) + C(8) × D(MRP(−1)) + C(9) × D(MRP(−2)) + C(10) × D(SMB(−1)) +C(11) × D(SMB(−2)) + C(12) × D(RMW(−1)) + C(13) × D(RMW(−2)) + C(14) | | | | |

**Table 9.** *Cont.*

| | | | | |
|---|---|---|---|---|
| Observations: 201 | | | | |
| R-squared | 0.463636 | Mean dependent var | | −0.000136 |
| Adjusted R-squared | 0.426348 | S.D. dependent var | | 0.113666 |
| S.E. of regression | 0.086091 | Sum squared resid | | 1.385969 |
| Durbin–Watson stat | 2.198772 | | | |
| *FF5FM INDI TOP 25 2000–2016* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 1206 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | −0.432410 | 0.179892 | −2.403717 | 0.0164 |
| C(3) | −0.293774 | 0.159374 | −1.843297 | 0.0655 |
| C(4) | −0.143747 | 0.170669 | −0.842257 | 0.3998 |
| C(5) | −0.075960 | 0.161009 | −0.471772 | 0.6372 |
| C(6) | 0.254707 | 0.268197 | 0.949701 | 0.3425 |
| C(7) | 0.203726 | 0.206179 | 0.988103 | 0.3233 |
| C(8) | −0.250130 | 0.233805 | −1.069822 | 0.2849 |
| C(9) | −0.003206 | 0.218586 | −0.014667 | 0.9883 |
| C(10) | −0.294198 | 0.225696 | −1.303513 | 0.1927 |
| C(11) | −0.150248 | 0.173442 | −0.866272 | 0.3865 |
| C(12) | 0.184366 | 0.121637 | 1.515710 | 0.1299 |
| **C(13)** | **0.261075** | **0.122764** | **2.126646** | **0.0337** |
| **C(14)** | **0.000250** | **0.003986** | **0.062806** | **0.9499** |
| Determinant residual covariance | | $4.07 \times 10^{-19}$ | | |
| Equation: D(INDI_TOP25) = C(2) × D(INDI_TOP25(−1)) + C(3) × D(INDI_TOP25(−2)) + C(4) × D(MRP(−1)) + C(5) × D(MRP(−2)) + C(6) × D(HML(−1)) + C(7) × D(HML(−2)) + C(8) × D(CMA(−1)) + C(9) × D(CMA(−2)) + C(10) × D(RMW(−1)) +C(11) × D(RMW(−2)) + C(12) × D(SMB(−1)) + C(13) × D(SMB(−2)) + C(14) | | | | |
| Observations: 201 | | | | |
| R-squared | 0.393441 | Mean dependent var | | 0.000127 |
| Adjusted R-squared | 0.351274 | S.D. dependent var | 0.070118 | |
| S.E. of regression | 0.056475 | Sum squared resid | | 0.596430 |
| Durbin–Watson stat | 2.250789 | | | |
| *FF5FM FINI TOP 15 2000–2016* | | | | |
| Estimation Method: Least Squares | | | | |
| Sample: 2000M04 2016M12 | | | | |
| Included observations: 201 | | | | |
| Total system (balanced) observations 1206 | | | | |
| | Coefficient | Std. Error | t-Statistic | Prob. |
| C(2) | 0.280526 | 0.151555 | 1.850990 | 0.0644 |
| C(3) | 0.291090 | 0.110659 | 2.630522 | 0.0086 |
| C(4) | −0.518087 | 0.110326 | −4.695972 | 0.0000 |

**Table 9.** *Cont.*

| | | | | |
|---|---|---|---|---|
| C(5) | −0.413413 | 0.099926 | −4.137183 | 0.0000 |
| C(6) | 0.226883 | 0.119732 | 1.894924 | 0.0584 |
| C(7) | 0.265883 | 0.118716 | 2.239657 | 0.0253 |
| C(8) | 1.005884 | 0.196467 | 5.119852 | 0.0000 |
| C(9) | 0.728248 | 0.172157 | 4.230132 | 0.0000 |
| C(10) | −0.236544 | 0.150660 | −1.570050 | 0.1167 |
| C(11) | −0.181162 | 0.148837 | −1.217189 | 0.2238 |
| C(12) | −0.596331 | 0.216568 | −2.753549 | 0.0060 |
| C(13) | −0.352238 | 0.209979 | −1.677494 | 0.0937 |
| C(14) | 0.000153 | 0.003815 | 0.040236 | 0.9679 |
| Determinant residual covariance | | $8.67 \times 10^{-19}$ | | |
| Equation: D(FINI_TOP_15) = C(2) × D(FINI_TOP_15(−1)) + C(3) × D(FINI_TOP_15(−2)) + C(4) × D(MRP(−1)) + C(5) × D(MRP(−2)) + C(6) × D(SMB(−1)) + C(7) × D(SMB(−2)) + C(8) × D(HML(−1)) + C(9) × D(HML(−2)) + C(10) × D(RMW(−1)) + C(11) × D(RMW(−2)) + C(12) × D(CMA(−1)) + C(13) × D(CMA(−2)) + C(14) | | | | |
| Observations: 201 | | | | |
| R-squared | 0.471701 | Mean dependent var | | $-8.87 \times 10^{-5}$ |
| Adjusted R-squared | 0.434974 | S.D. dependent var | | 0.071923 |
| S.E. of regression | 0.054063 | Sum squared resid | | 0.546568 |
| Durbin–Watson stat | 2.201211 | | | |

Table 5 results in the RESI Top 10 index from 2000 to 2016, which is insufficient to establish that the FF5FM fully explains the cross-section variation of expected returns for size, value, profitability, and investment portfolios. According to Du Pisanie, the five-factor model provided the best description of share behavior on the JSE of all the models studied (JSE 2019). The CAPM does not perform well as an explanatory model, although additional variables in an asset pricing model frequently give better results and the outcomes from models with the same number of elements are very comparable. The study made use of the Excel VBA code with differing requirements of each factor and portfolio sorts, thus differing from this study.

Table 10 shows that value bias is statistically significant in the financial sector and that it is moderately present in the other sectors throughout the periods. This suggests that the addition of operating profitability and investing components does not make value obsolete in this study. The operating profitability's results are all statistically negatively insignificant, despite the results alluding to a weak operating profitability bias in all the sectors through the three periods. The financial sector in both the full sample period and from 2009 to 2016 displays an aggressive investing bias. This is the only sector in which it is significant. The small-cap bias is apparent in the industrial sector throughout the data period, from 2000 to 2008, and in the financial sector throughout the sample period. The industrial and financial sectors have a moderately large-cap tilt from 2009 to 2016. Mahlophe (2015) found that the Fama and French five-factor model can account for predicted returns on the JSE in a research study. This also indicated that when profitability and investment factors are added in the model, the value anomaly loses its predictive effectiveness. The five-factor model has not yet been demonstrated to be superior to prior models. It has, however, left space for better models to be developed from it in the future. As shown in Table 4, there are signs of partial existence of weak operating profitability stocks, while there are mild aggressive stocks in all sectors except the financial sectors. According to the research study (Mahlophe 2015), RMW and CMA premiums are not significant at the 10% significance level, implying that these premiums do not assist explain JSE returns. Except for the banking sector, these findings are consistent with this study. Firms in the financial industry that are actively allocating profit toward large expansion projects are more likely to incur stock market losses.

**Table 10.** Summary of market anomalies present in the five-factor model.

| | RESI Top 10 | | | INDI Top 25 | | | FINI Top 15 | | |
|---|---|---|---|---|---|---|---|---|---|
| | **2000–2016** | **2000–2008** | **2009–2016** | **2000–2016** | **2000–2008** | **2009–2016** | **2000–2016** | **2000–2008** | **2009–2016** |
| MRP | N/A | N/A | N/A | N/A | N/A | N/A | Neg market risk | Neg market risk | Neg market risk |
| HML | Mild value bias | Mild value bias | Mild value bias | Mild value bias | Mild Value bias | Mild value bias | Mild value bias | Value bias | Value bias |
| SMB | Mild small cap bias | Mild small cap bias | N/A | Small cap bias | Small cap bias | Mild large cap bias | Small cap bias | Mild small cap bias | Mild large cap bias |
| RMW | Mild weak operating profitability | Mild weak operating profitability | Mild weak operating profitability | Mild weak operating profitability | Mild weak operating profitability | N/A | Mild weak operating profitability | Mild weak operating profitability | Mild weak operating profitability |
| CMA | Mild aggressive investing | Mild aggressive investing | N/A | Mild aggressive investing | Mild aggressive investing | Mild aggressive investing | Aggressive investing | Mild aggressive investing | Aggressive investing |

Source: Compiled by the author.

Our results when comparing the multifactor asset pricing models together over the study period show that the financial sector has most of the style risk factors prevailing as more variables are input. When using the FF3FM, the HML is negatively significant for the resources sector and HML is positively significant at 1% in the financial sector. The resources sector shows some presence of growth anomalies, while the financial sector has a value style risk factor. Furthermore, using the FF3FM, there is positive statistical significance in all three sectors for the SMB; however, this is at different degrees of significance. When the CH4FM is implemented, the resources sector shows significance levels are present on the HML (negative at 1%), the SMB (positive at 5%), and the WML (negative at a 5% level), whereas using the same model for the industrial sectors is only significant at 5% for the size style risk factor. At a 5% level of significance, all variables in the financial industry are statistically significant. Lastly, when the FF5FM is implemented, there is statistical significance at the 10% level for the CMA in the resources sector as the value factor disappears. The FF5FM results in the industrial sector show a significance level at 5% in the SMB. The financial sector seems to have the majority of the style-based risk factors, as the SMB is positively significant at the 5% level, the HML is significant at the 1% level, and the CMA is negatively significant at the 10% level of significance.

The Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and Fama and French (2014) five-factor model capture sector returns in slightly different ways, with the FINI Top 15 index and the RESI Top 10 index having the highest R-squared, respectively. Both CH4FM and FF5FM regressions from 2009 to 2019 appear to match the sector return better than in the prior period. When the CAPM was examined alone, the MRP risk component substantiated statistically high likelihood values for each sector index. The significant levels are dropped as more components are included. It becomes negatively significant in the financial sector for multifactor models. When the excess returns of resources, industrial, and financial indices are regressed against the risk factors, the results demonstrate that the regression coefficients for the bulk of the style risk factors are statistically negligible. Despite the coefficients' statistical insignificance, the magnitude of the probability value results could be used to get some information. Even though the regression results for the three-sector indices have negative coefficients and poor sensitivity to the RMW risk component, the findings suggest that the sector performance has a weak operating profitability bias to some extent. The CMA risk factor on the RESI Top 10 and the INDI Top 25 came to imply the same thing: a degree of aggressive investing bias in both sectors. The CMA risk factor has a high sensitivity in the financial sector. For the most part, the WML risk factor gives modest sensitivity to each of the sectors. For all three sectors and time periods, the majority of WML coefficients show a contrarian bias. The WML coefficients from 2009 to 2016 for the FINI Top 10 suggest this sector has momentum bias, while the INDI Top 25 shows to some degree the presence of mild momentum bias. When using the FF3FM, the negative and significant coefficient suggests that growth bias exists in the JSE sector returns for the full sample period. When the CH4FM and FF5FM regression results are observed, it is noted that value bias exists especially on the FINI Top 10 index. Lastly, the three-sector returns have positive coefficients and show substantial sensitivities to the SMB risk factor, implying that sector performance for all sectors has a small-cap bias to some extent. From 2009 to 2016, the industrial and financial sectors showed a large-cap skew.

When additional criteria such as value and scale are introduced via the FF3FM, however, the financial industry's predictive capacity over the CAPM is demonstrated to be superior to that of the resources and industrial sectors. The value and size (small cap) effects are present in the financial sector, whereas the growth and size (small cap) effects are present in the resources sector. Only a minor degree of moderate size impacts (small cap) can be deduced from the industrial sector. The financial sectors outperform with values that may be inferred in the other sectors, and the presence of a momentum impact is faintly obvious in the industrials and not obvious in the resources sectors. These data demonstrate that the outcomes are consistent, with results changing per JSE industry and impacted by the asset-pricing model used. When the FF3FM and CH4FM are not limited, they are more likely to notice market irregularities in the resources and financial sectors. The financial sector, in particular, has a strong value influence both before and after 2008. Industrial sector returns tend to imply that it is the most efficient sector because the presence of market anomalies is most inferred as a result of statistical insignificance, implying that it is the most efficient of the three sectors on the JSE and that investors can only get market returns in this sector. The FF3FM and the CH4FM are the financial and sector models that can capture the repercussions of market anomalies, with the CH4FM producing a stronger model by including momentum. On top of the value and size effect, the FF5FM adds operating profitability and investment effect. The RMW risk factor indicates the presence of mildly poor operating profitability over a three-year period, with no sector having statistical significance below 5%. The CMA risk factor is the same, but there is evidence of aggressive investing in the financial industries. The FF5FM only outperforms the FINI Top 15 from 2000 to 2016, whereas the CH4FM is the better model for the RESI Top 10 index and the INDI Top 25 index. The FF5FM is a better model for describing the industrial index and the financial sector from 2000 to 2008, whereas the CH4FM is better for the resources sector. Finally, between 2009 and 2016, the CH4FM captures the effects of style-based anomalies better than the other two indices for the INDI Top 25, while the FF5FM performs better for the RESI Top 10 and the FINI Top 15, respectively. Overall, the results of the FF5FM's deployment on the JSE suggest that the FF5FM does a better job than the FF3FM at capturing the effects of market anomalies on the JSE. These findings suggest that while the FF5FM beats the CH4FM, it is unable to effectively explain anomaly effects like operating profitability and investment variables. Another finding that needs to be discussed further is the pace of adjustment, which was modest for most of the estimated models but showed signals of returning to equilibrium when the model was changed. This could be due to the data set we used or the economy's underlying structure in South Africa.

## 5. Conclusions

This study aimed at establishing the effects of market anomalies (style-based risks) on the performance of securities in the resources, industrial, and financial sectors of the JSE. The study compared the performance of the different asset pricing models and their ability to account for market anomalies of the resources, industrial, and financial sectors of the JSE, including the applicability of the FF5FM. According to the data, the CH4FM outperforms the FF5FM in the resources and industrial sectors when held for six months. Both models appear to be tolerated by the financial industry, with the FF5FM performing better. When it comes to capturing the consequences of market anomalies, the CH4FM surpasses the other two asset pricing models in this study. Furthermore, the value anomaly loses its predictive effectiveness in all sectors except the banking industry when RMW and CMA variables are included in the model. To summarize, the data reveal that there is currently no consensus on the best asset pricing model for pricing assets and evaluating risk and returns on the JSE. Market anomalies vary between industries and historical periods, as well as with changes in asset pricing models and their specifications, according to the research. In addition, the findings mean that the JSE's industrial sector is by far the most efficient, making it difficult for investors to produce above-average returns. Furthermore, the results showed that the FF5FM model was applicable to the JSE beginning in 2009; however, when profitability and investment are factored into the model, the value anomaly's forecasting power may be compromised. The most important discovery statistically, educationally, and practically appears to be that investing style risk factors are the best indicator of how risk and return are related in the South African market. The CAPM appears to be obsolete as the South African market grows and becomes more integrated with the rest of the world. Furthermore, due to various study data samples, there is no unanimity on the conclusions offered; some have discovered evidence, while others have not. A clear, comprehensive, and accurate model and understanding of the stock market does not exist. Therefore, this research adds value to the continual development of understanding stock return and risk relationships. The results presented suggest practical ways for investors to identify which investment risk factors give abnormal returns in bearish and bullish market environments. These investment-style risks could help their portfolios have better returns in any market condition. It is certainly important for investors to consider more factors in asset pricing in portfolio management. For future research, there is a need to investigate in-depth stock selection on the JSE stock selection and its performance effects on market segmentation. This will test for the effects of segmentation on the performances of securities in portfolios and identify any sources of segmentation that are evident. This would make a good base for exploring the style-based risks that are prevalent in the South African market.

In a world with an expanding number of factors, it is important to routinely examine and distinguish essential and redundant factors in asset pricing models. This will keep models parsimonious and robust for more policy decisions. For future research, extending the current study using different recently developed state-of-the-art LHS and RHS asset pricing metrics may provide more useful insights into this seminal work. Nonetheless, asset prices express investors' beliefs about the future. Our understanding of how investors form these beliefs, how they evolve over time, and how we can measure them is still limited. Empirical research on investor beliefs that promises to unlock some of the mysteries of asset pricing is needed. Thus, further research focus should be on motivating, building, calibrating, and estimating models with non-RE beliefs

**Author Contributions:** Conceptualization, L.M., and K.K.O.; Methodology, K.K.O., and L.M.; software, K.K.O.; validation, L.M.; Formal analysis, L.M. and K.K.O.; Investigation, L.M.; Writing—original draft preparation, L.M.; writing—review and editing, K.K.O. and L.M.; supervision, K.K.O. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding. The APC was funded by [University of the Western Cape].

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

Ali, Fahad, and Numan Ülkü. 2021. Quest for a parsimonious factor model in the wake of qualityminus-junk, misvaluation and Fama-French-six factors. *Finance Research Letters* 41: 101847. [CrossRef]

Asness, Clifford, Moskowitz Tobias, and Pedersen Lasse. 2013. Value and Momentum Everywhere. *The Journal of Finance* 68: 929–85. [CrossRef]

Auret, Christo, and Rael Cline. 2011. Do the Value, Size and January Effects Exist on the JSE? *Investment Analysts Journal* 74: 29–37. [CrossRef]

Banz, Rolf W. 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* 9: 3–18. Available online: https://www.sciencedirect.com/science/article/pii/0304405X81900180 (accessed on 15 March 2022). [CrossRef]

Basiewicz, Patryk, and Christo Auret. 2010. Feasibility of the Fama and French three-factor model in explain returns on the JSE. *Investment Analysts Journal* 71: 13–25. [CrossRef]

Basu, S. 1977. Investment performance of common stocks in relation to their price earnings ratios: A test of Efficient Market Hypothesis. *Journal of Finance* 32: 663–82. [CrossRef]

Bhana, Narendera. 2010. The stock market reaction to criticism of corporate governance practices of companies listed on the JSE. *Investment Analysts Journal* 72: 1–12. Available online: http://www.scopus.com/inward/record.url?eid=2-s2.0-78649801872&partnerID=tZOtx3y1 (accessed on 15 March 2022). [CrossRef]

Bhana, Narendera. 2014. Value versus growth share returns: The case for companies listed on the Johannesburg Stock Exchange. *International Journal of Finance & Policy Analysis* 6: 36–48.

Bolton, Jordy, and Sven T. Von Boetticher. 2015. Momentum Trading on the Johannesburg Stock Exchange after the Global Financial Crisis. *Procedia Economics and Finance* 24: 83–92. [CrossRef]

Carhart, Mark. 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance* 52: 57–82. [CrossRef]

Chinzara, Zivanemoyo, and Tinashe Harry Kambadza. 2014. Evidence of segmentation among African equity markets. *African Finance Journal* 16: 19–38.

Cox, Shaun, and James Britten. 2019. The Fama-French five-factor model: Evidence from the Johannesburg Stock Exchange. *Investment Analysts Journal* 48: 240–61. [CrossRef]

De Bondt, Werner F. M., and Richard Thaler. 1985. Does the Stock Market Overreact? *The Journal of Finance* 40: 793–805. [CrossRef]

Dickey, David, and Wayne Fuller. 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *JASA Journal of the American Statistical Association* 74. [CrossRef]

Dirkx, Philipp, and Franziska Peter. 2018. Implementing the Fama-French Five-Factor Model for the German Stock Market. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3300642 (accessed on 15 March 2022).

Fama, Eugene. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance* 25: 838–417. [CrossRef]

Fama, Eugene, and Kenneth French. 1992. The cross-section of expected stock returns. *The Journal of Finance* 47: 427–65. [CrossRef]

Fama, Eugene, and Kenneth French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33: 3–56. [CrossRef]

Fama, Eugene, and Kenneth French. 1996. Profitability, investment, and average returns. *Journal of Financial Economics* 82: 491–518. [CrossRef]

Fama, Eugene, and Kenneth French. 2014. Dissecting Anomalies with a Five-Factor Model. Fama-Miller Working Paper. pp. 1–49. Available online: https://ssrn.com/abstract=2503174 (accessed on 15 March 2022).

Fama, Eugene, and Kenneth French. 2015. A Five-factor Asset Pricing Model. *Journal of Financial Economics* 116: 1–22. [CrossRef]

Graham, Mark, and E. Uliana. 2001. Evidence of a value-growth phenomenon on the Johannesburg Stock Exchange. *Investment Analysts Journal* 53: 7–18. [CrossRef]

Gustafsson, Lars, and Joakim Lundqvist. 2010. *Momentum under Different Market Climates: Evidence from the South African Market*. Stockholm: Stockholm School of Economics.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48: 65–91. [CrossRef]

JSE. 2019. Monthly JSE Index Values. Available online: https://www.jse.co.za/content/JSEIndexClassificationandCodesItems/Monthly%20ALSI%20Values.xlsx (accessed on 15 March 2022).

Kruger, Ryan, and Francois Toerien. 2014. The Consistency Of Equity Style Anomalies On The JSE During A Period Of Market Crisis. *The African Finance Journal* 16: 1–18.

La Grange, P. L., and John Krige. 2015. Profitability of Momentum Strategies on the JSE. *Studies in Economics and Econometrics, Taylor & Francis Journals* 39: 49–66.

Mahlophe, Mpho. 2015. Effect of Market Anomalies on Expected Returns on the JSE: A Cross-Sector Analysis. Master's thesis, North-West University, Vanderbijlpark, South Africa.

McKane, Graeme, and James Britten. 2018. Liquidity and size effects on the Johannesburg Stock Exchange (JSE). *Investment Analysts Journal* 47: 229–42. [CrossRef]

Mosoeu, S. 2017. Testing the Fama-French Five-Factor Model in Selected Emerging and Developed Markets. *WITS*. Available online: https://hdl.handle.net/10539/26264 (accessed on 15 January 2022).

Muller, Chris, and Michael Ward. 2013. Style-based effects on the Johannesburg Stock Exchange: A graphical time-series approach. *Investment Analysts Journal* 77: 1–16. [CrossRef]

Musarurwa, Rujeko. 2019. Fama French 5 Factor Model and Its Applications. *Quants Portal.* Available online: https://blog.quantinsti.com/fama-french-five-factor-asset-pricing-model/ (accessed on 20 April 2022).

Ozkan, Nesrin. 2018. Fama-French Five-Factor Model and The Necessity of Value Factor: Evidence From Istanbul Stock Exchange. *PressAcademia Procedia (PAP)* 8: 14–17. [CrossRef]

Page, Daniel, and Christo Auret. 2019. A panel-data analysis of the explanatory power of factor premiums on the Johannesburg Stock Exchange (JSE). *Investment Analysts Journal* 48: 102–13. [CrossRef]

Page, Michael, and Christian Way. 1992. Stock market overreaction: The South Africa evidence. *Investment Analysts Journal* 36: 35–49. [CrossRef]

Philpott, Michael, and C. Firer. 1994. Share price anomalies and the efficiency of the JSE. *Investment Analysts Journal* 23: 39–51. [CrossRef]

Strugnell, Dave, Evan Gilbert, and Ryan Kruger. 2011. Beta, size, and value effect on the JSE. 1994–2007. *Investment Analysts Journal* 40: 1–17. [CrossRef]

van Rensburg, Paul. 2001. A Decomposition of Style-Based Risk on the JSE. *Investment Analysts Journal* 54: 45–60. [CrossRef]

van Rensburg, Paul, and M. Robertson. 2003. Size, price-to-earnings and beta on the JSE Securities Exchange. *Investment Analysts Journal* 32: 7–16. [CrossRef]

Vardharaj, Raman, and Frank Fabozzi. 2007. Sector, Style, Region: Explaining Stock Allocation Performance. *Financial Analysts Journal* 63: 59–70. [CrossRef]

Zaremba, Adam, Huaigang Long, and Andreas Karathanasopoulos. 2019. Short-Term Momentum (Almost) Everywhere. *Journal of International Financial Markets, Institutions and Money* 63: 101140. [CrossRef]