QUALITY ON THE JOHANNESBURG STOCK EXCHANGE

By

Christian Bester
1242913

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Master of Commerce (50% Research) in Finance

Supervisor: Dr. Daniel Page

School of Economics and Finance

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ABSTRACT

The quality factor of equity investing has been gaining momentum in recent years. Specifically, recent studies have shown that employing quality investing strategies can deliver superior risk-adjusted returns. This study follows the path paved by Asness, Frazzini and Pedersen (2013) by ranking shares according to a range of proxies used to define and identify quality shares. Asness et al. (2013) focused on shares that are traded solely in developed countries but this study aims to contribute towards the existing body of literature by focusing on shares that are traded on the Johannesburg Stock Exchange. Subsequently, this study aims to determine whether portfolios that are formed on quality proxies deliver superior returns in relation to portfolios that are formed on low quality (junk) proxies.

The shares considered for each portfolio are limited to the top 100 shares on the JSE based on market capitalisation. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each junk portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Quality minus Junk (QMJ) factors are constructed as the intersection of four equally-weighted and market-capitalisation weighted portfolios formed on size and quality in order to establish whether a quality premium exists on the Johannesburg Stock Exchange (JSE).

In line with recent international literature, this study finds that profitability proves to produce higher average returns compared to other quality proxies such as capital structure and capital expenditure. Moreover, this study finds evidence to suggest that quality portfolios dominate their low-quality counterparts in terms of raw average returns and buy-and-hold returns over the period 2000-2020. This study also finds evidence of a quality premium on the JSE over the period 2000-2020 when a quality portfolio follows a market-capitalisation weighting scheme. Lastly, evidence is presented in this study which sheds light on the possible hedging advantages that quality investing has to offer during unstable economic conditions.

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1. INTRODUCTION

1.1 BACKGROUND

There is a growing number of studies that have documented the quality factor of equity investing. Specifically, recent studies have shown that employing quality investing strategies can earn superior risk-adjusted returns. Asness, Frazzini and Pedersen (2013) ranked shares according to a range of proxies that are used to define and identify quality, and found that the high quality shares earned superior risk-adjusted returns in the United States and across 24 other countries. Novy-Marx (2014) explains that exploiting the quality dimension of value has the ability to dramatically improve the performance of traditional value investing strategies.

Research by Schroders QEP (2017) has suggested that the attributes which collectively describe quality shares are the same attributes that value shares often lack. This means that investing in quality shares provides a natural diversification to value shares, as value shares typically exhibit lower profitability, higher cyclicality in growth and a more distressed balance sheet. This indicates that value investing may have some element of targeting a quality factor that has only recently been documented. Investors who have reached stratospheric levels of success such as Warren Buffett who have adopted value-tilted investment strategies have been documented to consider quality measures in stock selection, in order to pin down stocks which are trading at a discount as they have strong financial indicators such as decent operating margins and stable profitability metrics which are undervalued by the market (Rabener, 2017). However, Hsu, Kalesnik and Kose (2019) elucidate that the quality factor and traditional value factors are not one in the same thing owing to their relatively low correlation and as such, the quality factor should be considered independently from other investment factors. One could argue that investors who have adopted a value investing style for decades and have been successful in their own right may be exploiting quality factors unbeknown to them. Hsu et al. (2019) emphasise that the quality factor is different to the value factor as the quality factor has been targeted by indices around the globe, separate from other traditional factors such as size and value. Specifically, Hsu et al. (2019) explain that within the last decade, MSCI, FTSE Russel and Deutsche Bank are a few among others that have implemented a range of indices that target the quality factor.

Recent academic literature identifies a number of factors used to define a quality investment strategy. However, there is no globally accepted definition of quality within the finance universe (Hsu et al., 2019). This proposes a challenge for practitioners who aim to target the quality factor as its interpretation lacks consistency unlike other conventional factors such as value and size. For example, Novy-Marx (2014) uses gross profitability as a measure of profitability which is then used as a proxy to identify high quality financials. According to Novy-Marx (2014) a firm that exhibits high levels of gross profitability indicates that the firm is high quality. On the other hand, Asness et al. (2013) employ a number of metrics along with gross profitability which is then used as a proxy to identify quality. This indicates that portfolios that have been formed using different proxies to identify quality may produce different premiums.

Asness et al. (2013) conclude that the price of quality fluctuates over economic cycles with evidence to suggest that quality was at its cheapest levels during the dotcom bubble when the authors analysed quality measures over the period 1951 - 2012. Furthermore, Hsu et al. (2019) concluded that a low price of quality predicts a higher future return of quality-minus-junk which is a portfolio that goes long quality stocks and short junk (low quality) stocks. This suggests that quality stocks, that are low priced, may produce a reliable source of return.

1.2 PROBLEM STATEMENT

Recent empirical studies document quality investing at a country-level by analysing top quality stock markets. Asness et al. (2013) examine quality in the U.S along with 24 other countries whereas, Zaremba (2014) examines the explanatory power of quality as a determinant of cross-sectional variation in country-level stock returns. Furthermore, Hsu et al. (2019) examine the robustness of different proxies used to identify quality but extensive research leads me to conclude that there is no evidence of empirical studies focusing on quality that is documented in developing capital markets, and more specifically, in South Africa. Under the preliminary review of available seminal papers and empirical studies, there is a research gap for academics to explore the effectiveness of quality investing strategies in South Africa.

1.3 RESEARCH OBJECTIVES

As the quality factor lacks evidence of it being documented in developing markets, this study assesses a range of quality proxies which have been recognised in previous literature to determine which of these factors could be regarded as a consistent source of income when adopting a quality investment strategy in South Africa. The main hypothesis to be tested is whether portfolios which are formed using high quality proxies deliver superior risk-adjusted excess returns in relation to portfolios which are formed using low quality proxies in respect to shares listed on the JSE. The empirical evidence to be presented will allow further sub-hypothesis to be tested which will provide commentary on the robustness of various proxies used to define quality.

1.4 IMPORTANCE AND BENEFITS OF THE PROPOSED STUDY

The proposed study is undertaken with the purpose of appending more knowledge to the existing literature on quality investing, given that academics exploring this discipline have documented limited comprehension within the South African context. The proposed study dives into the financial abyss as it is the first (if not one of the few) South African studies to document the quality factor on the Johannesburg Stock Exchange (JSE). This study further cements its significance as it will provide evidence to investors that may prompt them to exploit quality investing strategies which deviate from the more traditional equity investing strategies.

1.5 LIMITATIONS

Examining the performance of portfolios formed using quality factors and more specifically, quality proxies that have been proposed in previous studies is the main principle of this study therefore, limiting the research scope within this boundary.

1.6 DEFINITION OF KEY TERMS

Table I: Abbreviations used in this document

Abbreviation	**Meaning**
A/E	Assets to Equity
CFA	Chartered Financial Analyst
D/E	Debt to Equity
ETF	Exchange Traded Fund
IPO	Initial Price Offering
JSE	Johannesburg Stock Exchange
QMJ	Quality Minus Junk
ROA	Return on Assets
ROE	Return on Equity
ROIC	Return on Invested Capital
S&P	Standard and Poor's

The section that follows provides a literature review detailing quality under the broader umbrella of factor investing.

2. LITERATURE REVIEW

2.1 DEFINING QUALITY

There is no general consensus amongst authors and practitioners when it comes to defining quality within the financial universe, "Quality as a category, although popular in practitioner circles, lacks a widely accepted definition" (Hsu et al., 2019, p. 57). Novy-Marx (2014) suggests that quality has no universally accepted definition, unlike value. Quality is defined as, "...characteristics that investors should be willing to pay a higher price for, everything else equal" (Asness et al., 2013, p. 2). Quality, as a growing element in the financial universe, is a set of measures that are employed to identify high-quality financial metrics in firms (Hsu et al., 2019). Indeed quality has no universally accepted definition however, there are a number of significant similarities amongst authors when it comes to identifying the characteristics that can be employed as proxies which have been described to capture quality.

Novy-Marx (2014) employs seven quality strategies that are designed to identify quality characteristics and are used to form a single quality factor. Some of these strategies include Sloan's (1996) accruals-based measure of earnings quality, and Piotroski's (2000) F-score measure of financial strength, amongst others. Within each of these seven strategies are a collection of metrics that Novy-Marx (2014) uses to identify quality. For example, Piotroski's (2000) F-score measure of financial strength is composed of four profitability measures, three liquidity measures and two operating efficiency measures. However, Novy-Marx (2014) identifies gross profitability as one of the seven main quality strategies that he employs as a proxy to identify quality. This is consistent with Hsu et al. (2019), as they identify profitability as one of their seven characteristics that are used as proxies to define quality.

Similar to Novy-Marx (2014) and Hsu et al. (2019), Asness et al. (2013) also identify profitability as one of their proxies to identify quality. Asness et al. (2013) identify capital safety as one of the proxies to define quality. Safety is a composite proxy that consists of different measures such as low financial leverage, low idiosyncratic volatility, low bankruptcy risk and low beta. Interestingly, Hsu et al. (2019) share a similar characteristic, namely capital structure which is also a composite proxy that the authors use to identify quality which consists of D/E and A/E.

Oakley (2017) identifies asset growth as a proxy in relation to identifying quality companies. Similar to Oakley (2017), Hsu et al. (2019) identify asset growth as one of their proxies used to define quality. It is clear that there appears to be a trend in recent literature that points towards three proxies that are used to identify quality shares which are profitability, capital structure and asset growth.

2.1.1 PROFITABILITY

Asness et al. (2013) explains that proxies used to identify quality shares need to be measured in advance. This suggests that quality proxies should be persistent and robust. In terms of profitability and its robustness, Hsu et al. (2019) concluded that profitability is robust when used as a proxy to define quality based on their three-step procedure. Fama and French (2006); Hou, Xue and Zhang (2015) and Novy-Marx (2013) all found evidence of a positive premium linked with profitability. Specifically, their results indicate that more profitable companies deliver higher excess returns compared to companies that exhibit lower profitability. Asness et al. (2013) include profitability metrics such as gross profits, margins, earnings accruals and cash flows in constructing a quality portfolio. Lepetit, Cherief, Ly and Sekine (2021) explore the benefits of employing profitability measures amongst institutional investors. Specifically, ROA and ROE are sought-after return metrics, "They show significant advantages such as allowing a cross-sectional comparison of all companies, including financial institutions, or capturing the net profit available to shareholders" (Lepetit et al., 2021, p. 13). This corresponds with the profitability metrics employed by Chipeta and Jardine (2014) in their recent study of IPO performance on the JSE as they use return on assets ROA and return on equity ROE. Hsu et al. (2019) also include ROIC along with ROE and ROA as profitability metrics used to identify quality. This indicates that measuring a firm's profitability across various profitability metrics is key to identifying whether a firm's stock is high quality or not. Specifically, we should expect a firm that exhibits high levels of gross profitability, ROE, ROA and ROIC to be of a higher quality than firms with low levels of ROE, ROA and ROIC.

2.1.2 CAPITAL STRUCTURE

Asness et al. (2013) regard quality firms as firms that have low leverage in their capital structure. Although Fama and French (1992) conclude that their study finds no evidence to suggest that average returns are positively related to beta, the authors did find evidence that firm's with high book leverage (ratio of book assets to book equity) deliver lower average returns. Hsu et al. (2019) find that companies with high D/E are low-quality companies. This indicates that companies with a low A/E ratio and a low D/E ratio are high quality companies compared to companies that exhibit a high A/E ratio and a high D/E ratio.

2.1.3 CAPITAL EXPENDITURE

Titman, Wei and Xie (2004) along with Cooper, Gulen and Schill (2008) found evidence to support the notion that companies with low levels of investment tend to deliver higher returns. Specifically, Cooper, Gulen and Schill (2008) found a negative relationship between asset growth and risk-adjusted returns. Hsu et al. (2019) examined the robustness of low asset growth in relation to identifying quality and concluded that growth in total assets is robust. This suggests that firms that have low levels of asset growth are higher quality firms compared to firms that have high levels of asset growth.

2.3 QUALITY MINUS JUNK FACTOR (QMJ)

Asness et al. (2013) pioneered the quality minus junk factor which goes long high-quality stocks and short low-quality stocks. Specifically, Asness et al. (2013) found that portfolios - based on the quality minus junk factor - earned significant risk-adjusted returns in the United States and across 24 other countries. This provides new evidence to the growing academic literature on quality investing which indicates that it is possible to earn superior risk-adjusted returns by ranking shares according to their quality by means of employing a range of proxies used to identify quality. Opposing the findings of Asness et al. (2013), Fischer (2014) examined the performance of a quality-minus-junk factor, considering the stocks of the Swiss Performance Index and found the factor to be insignificant at a 5% level. Fischer (2014) explains that this is possibly because Swiss companies, on average, are high-quality compared to their foreign counterparts. This suggests that it may be difficult to examine the effects of a quality-minus-junk factor in Switzerland when "junk" Swiss companies may be considered high quality compared to foreign counterparts. In light of these contradictory findings, there is no evidence of any literature that has examined the effectiveness of a quality-minus-junk factor in developing markets, specifically, South Africa.

2.4 FLIGHT TO QUALITY

This study investigates proxies used to identify quality and junk shares on the JSE. This will provide a sophisticated argument which comments on the effectiveness of the quality minus junk factor which has been recently documented. However, quality is not only limited to equities as academics and practitioners have documented quality in bond markets, financial reporting as well bank lending to name a few.

2.4.1 BONDS

O'Hara, Wang, and Zhou (2018) investigate quality in the bond market by analysing quality trades measured by a number of various quality execution factors such as transparency and smaller trading networks. O'Hara et al. (2018) conclude that the quality of a trade execution plays a significant role in the corporate bond market. Therefore, it's clear that quality is not only limited to equities or bonds which is emphasised by Zaremba (2014) who notes that the quality of stock market companies can be interpreted in various ways.

2.4.2 FINANCIAL REPORTING

Biddle, Hilary and Verdi (2009) investigate the correlation between financial reporting quality and investment efficiency. Specifically, the authors found evidence that firms with high levels of reporting quality reduce facets which destroy shareholder value such as moral hazard and adverse selection that impedes efficient investment.

2.4.3 LOANS DURING THE 2007-2008 GLOBAL FINANCIAL CRISES

Bank lending during the recent global financial crisis of 2007-2008 provides a fitting example on how loans were perceived by the market as only high quality loans were viewed favourably by market participants, "The near disappearance of non-investment grade issues was part of an overall flight to quality, an extreme version of what is typically observed in recessions" (Ivashina & Scharfstein, 2010, p. 324). Thus, it would appear that the flight to quality has minimal boundaries in the financial universe but it must be noted that quality may be extremely important to investors during times of economic turmoil and market downturns.

2.5 QUALITY DURING TIMES OF ECONOMIC UNCERTAINTY

The Black Swan: The Impact of the Highly Improbable (Taleb, 2007) is a chilling depiction of the severe widespread damage caused by unpredictable events which cripple financial markets around the world resulting in stock market crashes sending investors into a sell-off frenzy. Martynova and Renneboog (2008) conclude that stock market crashes are the coinciding events associated with the end of the five corporate takeover waves which the authors examined over the period 1890 - 2001. This indicates that stock market crashes, often ignited by black swan events, are devastating to global economies. This may lead investors to searching for investment strategies which may limit their potential loss in market downturns.

Novy-Marx (2014) notes that defensive equity strategies have gained momentum in the years following the 2007-2008 global financial crisis with particular reference to the market's poor performance in the last quarter of 2008. Novy-Marx (2014) indicates that these defensive equity strategies are characterised by low-volatility and low market betas which have generated outperformance during market downturns. The link between quality and these defensive strategies is articulated by Novy-Marx (2014) as the author elaborates that defensive strategies pick stocks which are tilted towards value as they include traits such as low leverage and stable return on equity which are common themes found in quality investing strategies. Lepetit et al. (2021) provide a more recent stance on quality investing and its potential benefits during down markets. The authors state that their quality factor proves to be a good hedging strategy against the market during times of economic turmoil specifically, during the 2007-2008 global financial crisis and the ongoing Covid-19 pandemic. Lepetit et al. (2021) provide empirical evidence which shows that their long-short quality factor outperforms their benchmark which is the MSCI World Developed Market ex-financials and real estate index on a risk adjusted basis during market downturns. Specifically, their long-short quality factor delivers an average risk adjusted return of 1.34% compared to its benchmark which delivers 0.48% over the period 2007 - 2020. Furthermore, Lepetit et al. (2021) note that their long-short quality factor not only outperforms its benchmark during times of economic contraction but remains stable during times of economic expansion. Specifically, the Lepetit et al. (2021) find evidence to suggest that their quality factor delivers a steady and smooth performance over the period which falls between the recent 2007 - 2008 global financial crises and the Covid-19 pandemic. This indicates that a quality strategy may not only be beneficial during market downturns but also during market upturns when investor sentiment appears to be of a more bullish nature.

2.6 DIVERSIFICATION

Adopting a quality investment strategy which may prove advantageous throughout various economic cycles speaks directly to the well recognised benefits of diversification. Despite the mounting evidence in favour of more complex methods for achieving a diversified portfolio, Jacobs, Müller and Weber (2013) present a sophisticated argument which cautions against overcomplicating diversification techniques. Jacobs et al. (2013) propose to investigate the efficiency of realising diversification potential for individual investors who have employed heuristic models as well as more sophisticated optimisation techniques. These objectives are fueled by evidence that individual investors in the United States significantly underperform standard domestic market indices on a risk-adjusted basis which may be due to their convoluted methods for achieving diversification. Markowitz (1952) deserves to be brought into the spotlight at this point as he is regarded as the pioneer behind optimisation models which are still employed and taught around the world today by practitioners and academics respectively. However, Jacobs et al. (2013) state that individual investors may not have the resources nor the knowledge to implement such arduous optimisation techniques stemming from Markowitz (1952) which ultimately proves costly and damaging to their diversified portfolios.

For global equity diversification, Jacobs et al. (2013) compare 11 optimisation models with a broad range of heuristic weighting schemes and find evidence to suggest that none of the optimisation models significantly outperform the much less complex heuristics models. Interestingly, in terms of the heuristic weighting schemes, an equally-weighted strategy is more successful than a market-weighted strategy. Based on the findings from Jacobs et al. (2013) this study proposes to employ an equally-weighted and a market capitalisation heuristic strategy rather than more complex optimisation models for the following two reasons: Firstly, this paper intends to reach beyond the expertise of institutional investors and cater for individual investors who may not have the necessary resources to implement taxing optimisation strategies. Secondly, the findings from Jacobs et al. (2013) indicate that by setting aside the expertise of investors, a less-complicated heuristic approach is not only easier to implement but also proves to perform on par with more complex strategies in terms of reaching desirable levels of diversification.

3. METHODOLOGY

3.1 SAMPLING AND DATA COLLECTION

This study uses data obtained from Bloomberg and focuses on a set of liquid shares on the JSE listed over the period January 2000 - December 2020. This sample period reflects the growing recognition of quality as an investment style which has been gaining momentum over the past two decades. Furthermore, this study aims to present results that reflect the investable universe that is available to the individual investor within the scope of the JSE. Specifically, this study aims at shares that are ranked in the top 100 on the JSE based on market capitalisation as these shares are generally more liquid. This base sample is then rebalanced semi-annually according to market capitalisation and average monthly value traded over the previous six months. Ultimately, this leads to a sample set of shares that are not static but change over time as shares list and delist and as market capitalisations change.

3.1.1. PORTFOLIO SORTS

The initial quality sort involves classifying shares based on a historical sorting period (estimation period), where the sorting period considered takes place prior to the portfolios being formed. Each quality proxy is treated independently and shares are sorted using the following quality factors:

- profitability proxied by ROE and ROA,
- capital structure proxied by D/E,
- capital expenditure proxied by asset growth.

Please refer to Appendix A for the formulas.

At each proxy portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios in respect to each proxy, namely: Quality or Junk. This translates into four quality proxy portfolios and four junk proxy portfolios. Specifically, each quality proxy portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy. On the other hand, each junk portfolio constitutes shares that are ranked in the bottom 25% based on historical performance in relation to each. In order for a share to be considered, each share requires at least four months of historical return prior to the portfolio formation date. Portfolio sorts are conducted on a semi-annual basis where equally weighted quartile monthly portfolio returns are calculated assuming a buy-and-hold strategy.

3.2 DESCRIPTION OF OVERALL RESEARCH DESIGN

3.2.1 RAW RETURNS

An analysis of monthly holding period returns is applied to each portfolio. The purpose of this approach will eventually allow for returns to be bootstrapped together in order to get a single time series representing a single strategy return. Returns are calculated on a buy-and-hold basis. This is used to determine whether a quality premium exists on the sample of shares from the JSE used in this study by simply subtracting the average junk portfolio returns from the average quality portfolio returns which is essentially in line with the quality minus junk factor pioneered by Asness et al. (2013). The buy and hold strategy employed to each portfolio will also validate which quality factor, and more specifically, which proxy produces the highest returns. In this study, the monthly buy-and-hold strategy is similar to those employed by Ritter (1991) and Chipeta and Jardine (2014) and is represented mathematically as:

$$BHR_{i,t} = \Pi_1^n (1 + r_{i,t}) \tag{1}$$

Where: $BHR_{i,t}$ is the annual buy and hold return on portfolio $_i$ at time $_t$.

The benefit of using a buy-and-hold return strategy allows one to “invest” one rand in each of the 25 shares that make up each portfolio. Theoretically, each portfolio at formation date will have a value of 25 rand and subsequently, depending on the performance of each share in each portfolio, the portfolio value will either decrease or increase. In order to measure if a quality premium exists, this study follows a similar methodology employed by Asness et al. (2013) which is to take the average return on the quality portfolios and minus the average return from the junk portfolios:

$$QMJ = \frac{1}{4}\,(\textit{Quality Portfolio Factor}) - \frac{1}{4}\,(\textit{Junk Portfolio Factor}) \tag{2}$$

Where: the *Quality Portfolio Factor* is composed of the aggregate returns attributable to the four independent quality portfolios formed on the sorting procedure which found them to be in the top 25% of historical performance in relation to the four proxies used to define and identify quality shares, the *Junk Portfolio Factor* is composed of the aggregate returns attributable to the four independent junk portfolios formed on the sorting procedure which found them to be in the bottom 25% of historical performance in relation to the four proxies used to define and identify quality shares.

3.2.2 EXCESS RETURNS

The proposed study maintains its research stature by measuring excess returns - that is, returns relative to a suitable benchmark. The purpose of this is to determine whether superior returns could be earned in other investments that are not limited to quality investment strategies. Measuring the performance of a portfolio with that of a financial market benchmark can indicate portfolio quality or lack thereof, "Benchmarks can be used to assess the quality and/or quantity of a company's performance by comparing its performance with that of its peers and competitors" (Clare, 2018, p. 189). Rosen (2020) emphasizes that an appropriate benchmark must align itself with the objectives of the portfolio and one should shy away from choosing benchmarks that are not reflective of a strategy's investment universe. Therefore, it is clear that choosing an appropriate benchmark is instrumental in safely measuring the performance of an investment and failure to do so will likely lead to a skewed perception of the investment's performance.

The CFA Institute highlights key characteristics which should be considered when choosing an appropriate benchmark. This study can report that the JSE All Share Index (J203) meets these characteristics, but more importantly, The JSE All Share Index consists of the largest 164 listed companies on the JSE according to their market cap. This reflects the quality investment strategy of holding 25 shares in each of the quality and junk portfolios and more specifically, aligns itself to the liquid sample of shares based on their market cap. To be thorough, the S&P South African Quality Index meets all seven requirements mentioned above and many may argue that this index is a more suitable benchmark as it aligns itself with the core purpose of this study being quality. However, the S&P South African Quality Index was launched in 2014 which does not allow for an adequate observation period as this study uses data over the period January 2000 - July 2021.[1] As with the raw returns, buy and hold returns will be measured in respect of the JSE All Share Index on a monthly basis. Subsequently, the monthly returns will eventually be bootstrapped in order to arrive at a single time series representing a single return strategy at the end of each calendar year. This study follows a similar methodology used by Chipeta and Jardine (2014) in order to calculate excess returns which is achieved by employing a buy and hold benchmark adjusted strategy which is represented mathematically as:

$$BHAR_{i,t} = BHR_{i,t} - BHR_{m,t} \tag{3}$$

Where: $BHR_{i,t}$ is the annual buy and hold return on portfolio $_i$ at time $_t$, and $BHR_{m,t}$ is the corresponding annual benchmark buy and hold return at time $_{t.}$

3.2.3. RISK-ADJUSTED RETURNS

As previously stated, Asness et al. (2013) concluded that the quality stocks examined in their study managed to earn significant risk-adjusted returns in the U.S. and globally across 24 countries. This study follows in the footprints of Asness et al. (2013) in the sense that it investigates the risk-adjusted returns of the sample of JSE shares relative to the market portfolio, namely, the J203. An effective and statistically robust method of evaluating risk-adjusted returns is achieved by employing a time-series attribution regression which is well known in the financial academic universe. Page and Auret (2018) provide a brief overview of time-series attribution regressions. Specifically, the authors explain that time-series attribution regressions can be traced back to various methods used to test the Capital Asset Pricing Model (CAPM). Subsequently, time-series attribution regressions have been utilised to define risk-adjusted excess returns. Notably, this study does not intend to employ time-series attribution regressions to test tranches embedded deeply across the fields

[1] The S&P South African Quality Index was launched on December 10, 2014. The Satrix Quality South Africa ETF was launched and made available to investors on September 27, 2017 which directly tracks the S&P South African Quality Index. These launch dates are significant as they reiterate that quality has been gaining momentum in recent years and more specifically, quality factor indices along with tracking ETFs are beginning to surface in emerging markets. According to Satrix, the S&P South African Quality Index employs a set of metrics to calculate a quality score for shares traded on the JSE.

of asset pricing, but rather to investigate whether high-quality shares offer excess risk-adjusted returns relative to low-quality shares on the JSE. Formally, the regression model can be represented mathematically as:

$$Y_{i,t} = \alpha_i + \beta_i X_{j,t} + \varepsilon_{i,t} \tag{4}$$

Where $Y_{i,t}$ is the quality portfolio i return at time t, α_i is the time-series alpha representing the excess risk-adjusted return earned by portfolio i, β_i represents an $L \times 1$ vector of time-series coefficients or factor loadings, $X_{j,t}$ represents a $T \times L$ matrix of L excess return premiums and $\varepsilon_{i,t}$ the time-series error term that is assumed to be stationary, homoscedastic and follows a normal distribution:

$$(\varepsilon \sim N(0,\sigma^2)).$$

A simple way to gauge the effective and diverse nature of a time-series regression is to emphasize that this method is diverse and has been applied across various financial studies that range from Chipeta and Jardine's (2014) study on post IPO (initial price offering) performance to Auret and Wolf's (2009) study on the dividends signalling theory in South Africa.

The regression outputs will provide further commentary on the performance of the high quality and low quality (junk) portfolios relative to the J203. Specifically, the results will cement any evidence of the four quality proxies used to identify and define high quality shares earning returns in excess of the market and if so, whether the excess returns are statistically significant. Furthermore, the regression analysis will also focus on the four low quality (junk) proxies used to define and identify low quality (junk) shares with the intent of providing further insight on the performance of the low quality proxies in relation to the high quality proxies as well as providing any evidence of the low quality (junk) proxies earning returns in excess of the market. Lastly, the regression will allow this study to comment on any consistencies that may be in line with the findings from Asness et al. (2013) who provided robust evidence to conclude that the quality shares examined in their study earned statistically significant risk-adjusted returns.

4. EMPIRICAL RESULTS

4.1. PROXY RETURNS

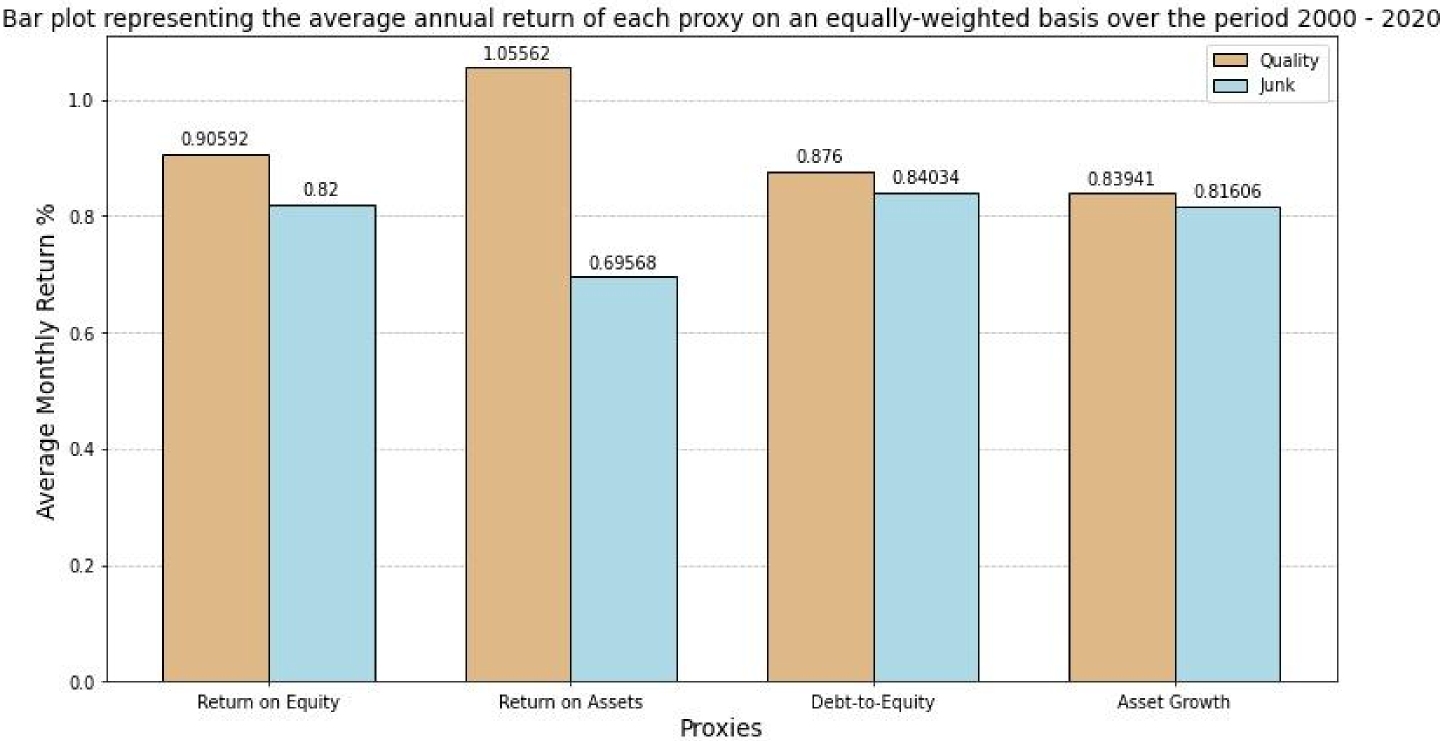
4.1.1. EQUALLY-WEIGHTED PROXY RETURNS

As a starting point, the average monthly returns achieved by the four quality proxies used to identify quality stocks and the four low quality (junk) proxies used to identify low quality (junk) stocks are calculated. This is important as it cements the foundation of this study's central analysis of whether high quality stocks outperform low quality (junk stocks) and subsequently, whether a quality premium exists on the JSE.

Figure I illustrates the average monthly returns achieved by each quality and low quality (junk) proxy over the sample period. Figure I reports that the two proxies used to define high profitability shares (high ROA and high ROE) delivered the highest average monthly returns compared to all the other proxies over the sample period. Specifically, the high ROA equally weighted proxy delivered the highest average return of 1.05% followed by the high ROE equally weighted proxy which delivered 0.91%. These results are consistent with the findings of Hsu et al. (2019) as the authors concluded that high ROA and high ROE are robust factors that can be used to identify quality shares. Fama and French (2008, 2016) and Cooper, Gulen and Schill (2008) concluded that firms with lower levels of capital expenditure (asset growth) appear to deliver higher average returns compared to firms with higher levels of capital expenditure which is congruent with the results shown in Figure 1. Specifically, the low AG equally weighted proxy outperformed the high AG equally weighted proxy albeit by a narrow margin of 0.02%. In terms of D/E, Hsu et al. (2019) concluded that the quality proxy low D/E (capital structure) is non-robust however, the results in Figure 1 suggest that it has some explanatory power of identifying quality shares. Specifically, the low D/E equally weighted proxy delivers an average return of 0.88% which is only 0.003% less than the high ROE equally weighted proxy. On the other hand, it could be argued that the high D/E (junk) equally weighted proxy closely tracks the low D/E (quality) equally weighted proxy as it delivers 0.84% which amounts to a minimal difference of 0.04% which favours the conclusion reached by Hsu et al. (2019).

Overall, emphasis needs to be placed on the results which show that the quality sorts are highly consistent with the international literature as the two quality profitability proxies (ROE and ROA) along with the quality capital structure (DE) and capital expenditure (AG) proxies outperformed their low quality (junk) counterparts on an equally-weighted basis.

Figure I: Equally-Weighted Proxy Returns



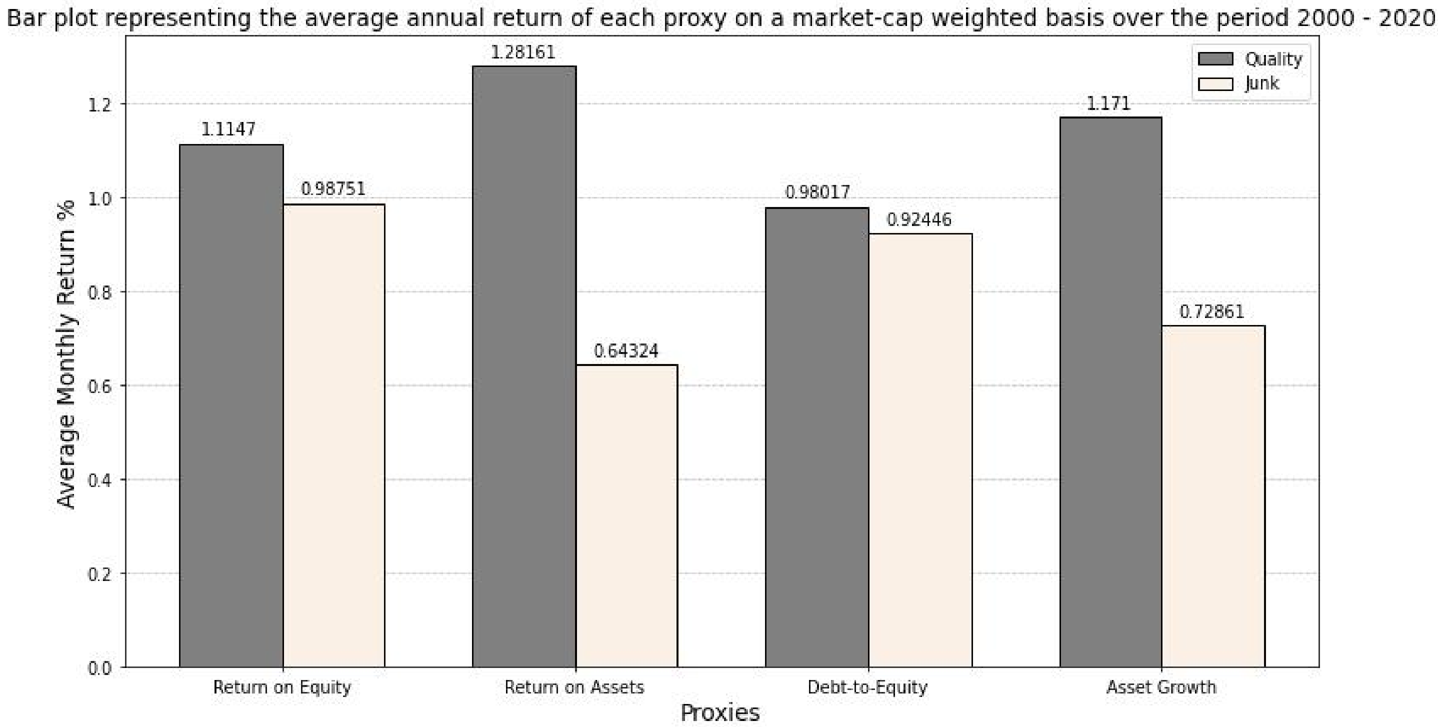
Note: Figure 1 represents the average returns achieved from each of the proxies used to form each of the four quality and low quality (junk) portfolios on an equally-weighted basis. The four quality proxies are low asset growth, low debt-to-equity, high return-on-assets, and high return-on-equity. The four low quality (junk) proxies are high asset growth, high debt-to-equity, low return-on-assets, and low return-on-equity. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalisation as only the top 100 shares on the JSE in terms of their market capitalisation are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalisation. The sample period is run over January 2000 to December 2020.

4.1.2. MARKET-CAP WEIGHTED PROXY RETURNS

Figure II illustrates the average monthly returns achieved by each quality and low quality (junk) proxy over the sample periods. Similar to the equally-weighted proxy returns, the high ROA market-cap weighted proxy delivered the highest average return equivalent to 1.28%. In contrast to the equally-weighted proxy returns, the high ROE market-cap weighted proxy delivered only the third highest average return of 1.11% succumbing to the low AG market-cap weighted proxy which delivered an average return of 1.17%. The strong performance by the low AG market-cap weighted proxy yields a robust argument against the conclusion reached by Hsu et al. (2019). Interestingly, the minimal differences observed between the quality and junk proxies in Figure I appear to become more significant on a market-cap weighted basis. Specifically, as the portfolios shift from equally-weighted to market-cap weighted, the margin between the quality proxy returns and their low quality counterparts appears to increase. For example, the margin between the high ROA and low ROA market-cap weighted proxies is equal to 0.64% which is 0.28% greater than the difference between the high ROA and low ROA equally-weighted proxies. A similar result is observed when comparing the difference between the low AG and high AG market-cap weighted proxies which is equal to 0.44% which is 0.42% greater than the difference between the low AG and high AG equally-weighted proxies. Overall, the results shown in Figure II highlight two main points which demand attention:

- All four of the high quality market-cap weighted proxies delivered superior average monthly returns when compared to the low quality market-cap weighted proxies which is highly consistent with the international literature.
- All four of the high quality market-cap weighted proxies delivered average monthly returns in excess of their respective equally-weighted counterparts. This result contradicts Jacobs et al. (2013) who found that an equally-weighted strategy is more successful than a market-weighted strategy.

Figure II: Market-Cap Weighted Proxy Returns

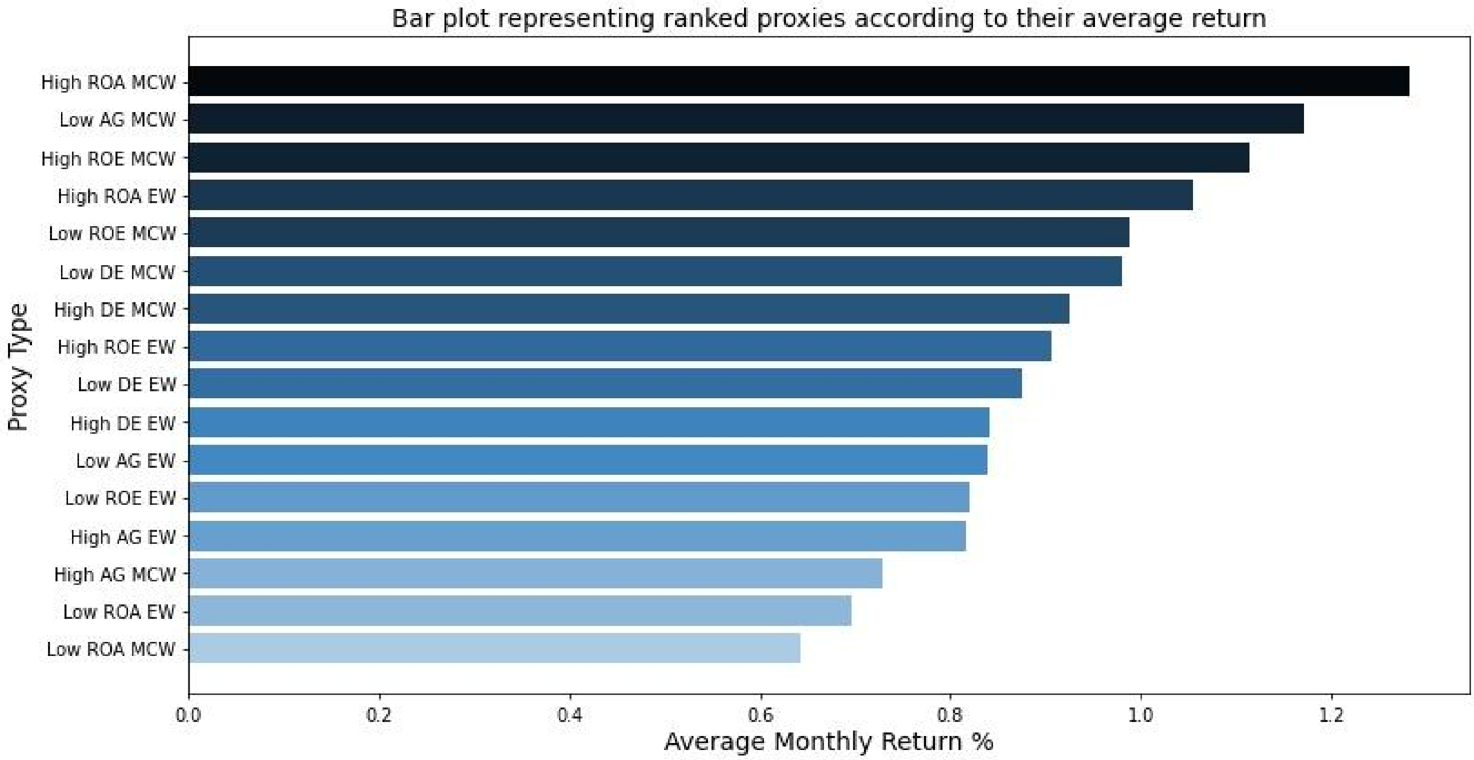


Note: Figure 2 represents the average returns achieved from each of the proxies used to form each of the four quality and low quality (junk) portfolios on a market-cap weighted basis. The four quality proxies are low asset growth, low debt-to-equity, high return-on-assets, and high return-on-equity. The four low quality (junk) proxies are high asset growth, high debt-to-equity, low return-on-assets, and low return-on-equity. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalisation as only the top 100 shares on the JSE in terms of their market capitalisation are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalisation. The sample period is run over January 2000 to December 2020.

4.1.3 RANKED PROXY RETURNS

Figure III illustrates each quality and low quality (junk) proxy which is ranked according to their average monthly return over the sample period on an equally-weighted and market-cap weighted basis. This translates into 16 portfolios which represent each quality and junk proxy. The results show that by ranking the portfolio returns, the top three positions are held by portfolios that are based on a market-cap weighted basis. Specifically, the high ROA market-cap weighted portfolio dominates the remaining 15 portfolios, followed by the low AG and high ROE market-cap weighted portfolios respectively. These results reiterate the concluding comments reached by Lepetit et al. (2021) who state that high ROE and high ROA are sought after profitability metrics. Moreover, these top three performing market-cap weighted portfolios provide further evidence which contradicts the conclusion by Jacobs et al. (2013) who found that an equally-weighted strategy is more successful than a market-weighted strategy. It is worth noting that the weakest performing portfolio is the low ROA market-cap weighted portfolio followed by the low ROA equally-weighted portfolio. These two poorly performing portfolios cement the growing literature on quality as their higher quality counterparts appear to outperform them significantly. This suggests that quality proxies have a more positive effect on portfolio performance compared to lower quality(junk) proxies on both an equally-weighted and market-cap weighted basis.

Figure III: Ranked Proxy Returns



Note: Figure 3 represents the ranked average returns achieved from each of the proxies used to form each of the four quality and low quality (junk) portfolios on an equally-weighted and market-cap weighted basis. The four quality proxies are low asset growth, low debt-to-equity, high return-on-assets, and high return-on-equity. The four low quality (junk) proxies are high asset growth, high debt-to-equity, low return-on-assets, and low return-on-equity. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalisation as only the top 100 shares on the JSE in terms of their market capitalisation are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalisation.

EW and MCW denote proxies that are formed on an equally-weighted and market-cap weighted basis respectively. The sample period is run over January 2000 to December 2020.

This paper expands its commentary on the average monthly returns earned by each quality and junk proxy by implementing a series of paired two sample t-tests. T-tests of this nature have been documented in recent financial literature as Leepsha and Mishra (2012) employed a series of paired t-tests in order to analyse post-merger performance on a select number of manufacturing companies in India. Moving away from post merger performance but still within the realms of finance, Pathak (2016) applied paired t-tests in order to document the operating performance on a range of Nepalese financial institutions. For the purposes of this study, paired t-tests are employed in order to establish whether the average monthly returns achieved by each proxy is statistically significantly different from zero.

Table II shows the results of the t-tests performed on the average raw returns achieved by each respective proxy on an equally-weighted and market-cap weighted basis. The null hypothesis states that the average raw returns are not different from zero. If the p-value > 5%, this study fails to reject the null hypothesis as the average returns are not different from zero at the 95% confidence interval or at the 5% level of significance. The results in Table II indicate that all four of the high quality equally-weighted proxy returns are statistically significant at the 1% level of significance thus, the null hypothesis is rejected at the 99% confidence interval. This is not surprising as all four of these proxies delivered average monthly returns in a range of 0.83% and 1.06%. In terms of the low quality (junk) equally-weighted proxy returns, the high DE and high AG proxy returns are statistically significant at the 1% level of significance whereas the low ROE and low ROA proxy returns are statistically significant at the 5% level of significance. These results are consistent with the average monthly returns achieved by the equally-weighted proxies shown in Figure I. Specifically, as the portfolios shift from quality to junk, there is a noticeable decline in average monthly returns. This decline in performance is reflected in the p-values; shifting from quality to junk sorts, the p-values increase which suggests that their average monthly returns become less statistically significant from zero.

The p-values for the market-cap weighted proxy returns paint a similar picture to those of the equally-weighted proxy returns. Specifically, all four of the high quality proxy returns are statistically significant at the 1% level of significance. Shifting away from the quality sorts and into the junk portfolios, it is evident that the p-values become less statistically significant owing to the decline in monthly average returns. Namely, the low ROA proxy which delivered the lowest average monthly return compared to all the other junk and quality proxies on both an equally-weighted and market-cap weighted basis, shows the highest p-value of 0.05692 which is only statistically significant at the 10% level of significance. This is not surprising as one should expect the p-values to increase in value if their corresponding monthly average returns are closer to zero. Overall, the proxy statistics are largely consistent with the international literature as all eight of the high quality proxy returns are statistically significant at the 1% level of significance suggesting that their monthly average returns are significantly different from zero. Conversly, only four of the eight low-quality proxy returns are significant at the 1% level of significance as the other four proxies are statistically significant at the 5% and 10% level of significance respectively, owing to their monthly average returns ranging between 0.82% and 0.64% which is closer to zero.

Table II: Proxy Statistics

Quality Proxies (Equally-Weighted):	ROE	ROA	DE	AG
Average Monthly Return	0.90592%	1.05562%	0.87600%	0.83941%
P-Value	***0.00149****	***0.00010****	***0.00074****	***0.00342****
Standard Deviation	4.36610%	4.12760%	3.96759%	4.39827%
Junk Proxies (Equally-Weighted):	ROE	ROA	DE	AG
Average Monthly Return	0.82002%	0.69568%	0.84034%	0.81606%
P-Value	***0.01097***	***0.02659***	***0.00420****	***0.00252****
Standard Deviation	4.95495%	4.83004%	4.50342%	4.14097%
Quality Proxies (Market-Cap Weighted):	ROE	ROA	DE	AG
Average Monthly Return	1.11470%	1.28161%	0.98017%	1.17100%
P-Value	***0.00252****	***0.00090****	***0.00280****	***0.00084****
Standard Deviation	5.65516%	5.90271%	5.02798%	5.36623%
Junk Proxies (Market-Cap Weighted):	ROE	ROA	DE	AG
Average Monthly Return	0.98751%	0.64324%	0.92446%	0.72861%
P-Value	***0.00555****	***0.05692****	***0.00624****	***0.02774***
Standard Deviation	5.46581%	5.26522%	5.10955%	5.09709%

Note: Italicised p-values are presented where *, ** and *** denotes statistical significance at the 10%, 5% and 1% levels respectively. The sample period is run over January 2000 to December 2020.

4.2. QUALITY AND JUNK PORTFOLIO RETURNS

4.2.1. EQUALLY-WEIGHTED PORTFOLIO RETURNS

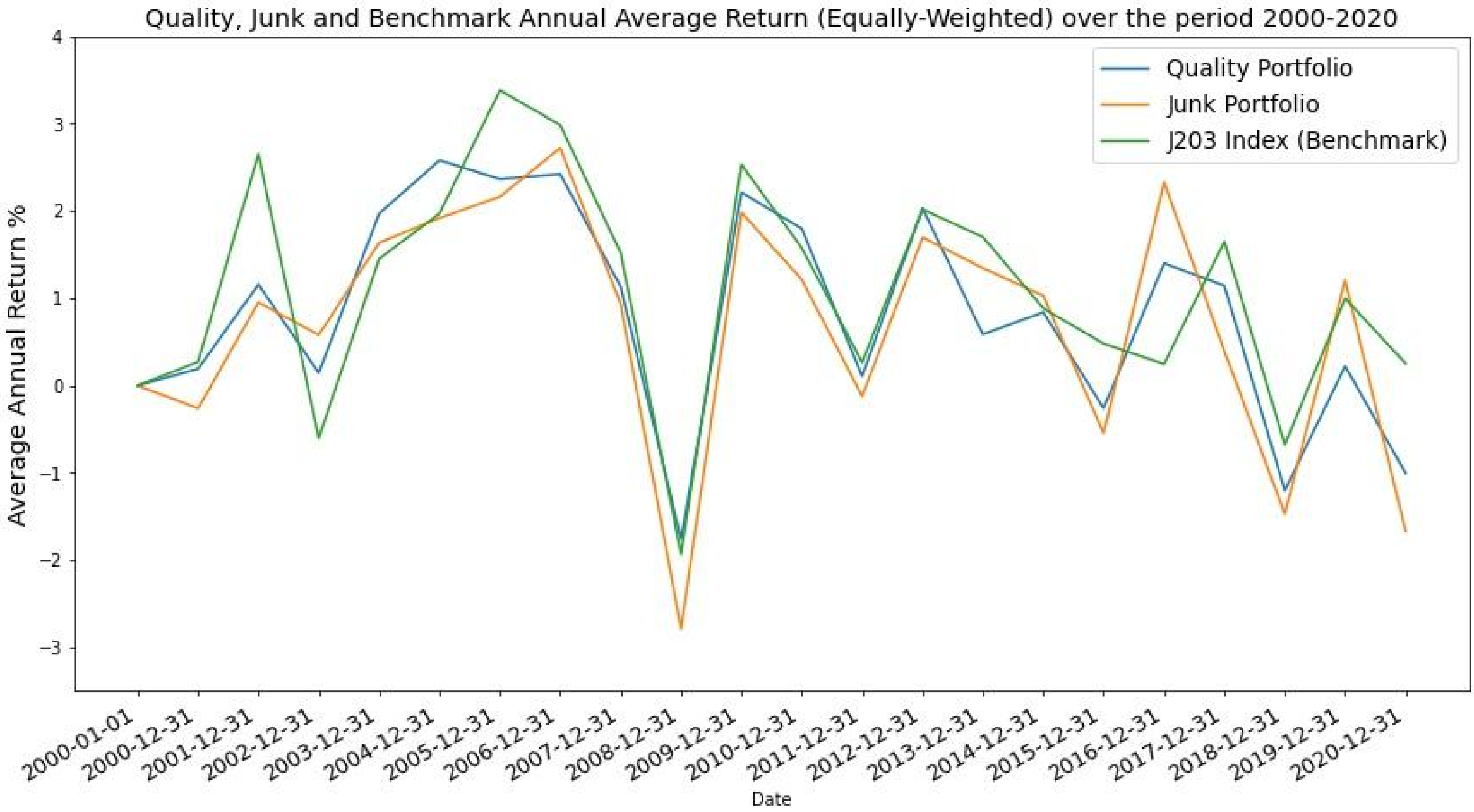
The growing debate surrounding quality stock returns that has been documented in recent academic literature. This study aims to shed light on quality stock returns sampled from a developing market as previous literature has focused on quality stock returns studied in developing markets.

Figure IV illustrates the average annual returns of the equally-weighted quality portfolio and the equally-weighted junk portfolio along with the J203 Index. The annual average returns from the four equally-weighted quality and junk proxies have been bootstrapped in order to form a single time series return which represents a single quality portfolio average return and a single low quality (junk) portfolio average return from portfolio formation date (time t) and the subsequent 21 years (t + 252 months) on an equally-weighted basis. Returns from the JSE All Share Index (J203) are also bootstrapped to form a single time series return that represents an average benchmark return.

Figure IV shows that the quality portfolio outperformed the junk portfolio in 15 of the 21 years within the sample period on an equally-weighted basis. These results support the findings by Novy-Marx (2014) who employed several quality factors in order to form a single quality return that could deliver higher average returns compared to a single low quality return. Moreover, these results indicate that the quality portfolio managed to deliver superior average annual returns relative to the junk portfolio for 71.43% of the sample period. Conversely, the J203 delivered higher average annual returns compared to both the quality and junk portfolio in 13 of the 21 year observation period from 2000 to 2020. The quality portfolio managed to outperform the benchmark in seven of the 21 years within the sample period while the junk portfolio managed to outperform the benchmark in five of the 21 years within the sample period. Although the quality portfolio fails to outperform the benchmark on a consistent basis, the results show that the quality portfolio still manages to outperform its junk counterpart relative to the benchmark.

At this point it is worth noting how the quality portfolio and the junk portfolio appear to closely track the J203 over the sample period. The most striking trough seen in Figure IV is observed at the end of 2008. Specifically, each portfolio along with the benchmark experienced a steep decline in average annual returns in the beginning of 2007 with the most probable explanation owing to the 2007-2008 global financial crises. Although Lepetit et al. (2021) state that their quality factor proves to be a good hedging strategy against the market during times of economic turmoil specifically, during the 2007-2008 global financial crisis, the results in Figure IV contradict Lepetit et al. (2021) statement. Specifically, the quality portfolio experienced a 172.58% decrease in average annual return from the beginning of 2007 to the beginning of 2009. Over the same two years, the junk portfolio experienced a 202.35% decrease in annual average return whereas the J203 experienced a 164.64% decrease in annual average return. Although the quality portfolio experienced less of a decrease in annual average returns compared to the junk portfolio during the 2007-2008 global financial crises, the systematic devastation that spread through the world's financial markets was too overwhelming for the equally-weighted quality portfolio to guard against. More recently, there is early evidence to show how the performance of the portfolios were negatively affected by the COVID-19 pandemic. On the 5th of March 2020, the first COVID-19 patient was confirmed in South Africa. This was followed by the South African national government implementing a national lockdown on the 27th of March 2020. It can be seen in Figure IV that both portfolios along with the benchmark experienced an increase in average return from the end of 2018 until the end of 2019. However, there is a noticeable decrease in the performance of both portfolios along with the benchmark in 2020. This evidence is not robust in the sense that the sample period does not take into account the full impact of the pandemic however, it is reasonable to suggest that the pandemic had a negative impact on both portfolios and the benchmark during the first year of the national lockdown. Lastly, it is worth noting that the highest average annual return over the sample period was achieved by the J203 in 2005 which delivered 3.38%. Conversely, the lowest average annual return over the sample period was achieved by the junk portfolio which delivered -2.78% in 2008.

Figure IV: EQUALLY-WEIGHTED PORTFOLIO RETURNS



Note: Figure IV illustrates calendar-time portfolio returns. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalization as only the top 100 shares on the JSE in terms of their market capitalization are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each junk portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced every six calendar months so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalization. By bootstrapping the returns from the four quality portfolios as shown in Figure I, it is possible to form a single quality portfolio arithmetic average return which represents a single time series return on an equally-weighted basis. This method is replicated throughout the four junk portfolios and the J203 index to form a single junk portfolio arithmetic average return and a single benchmark (J203 Index) arithmetic average return. Returns are in ZAR and do not include currency hedging. Returns are represented as an annual percentage. The sample period is run over January 2000 to December 2020.

4.2.2. MARKET-CAP WEIGHTED PORTFOLIO RETURNS

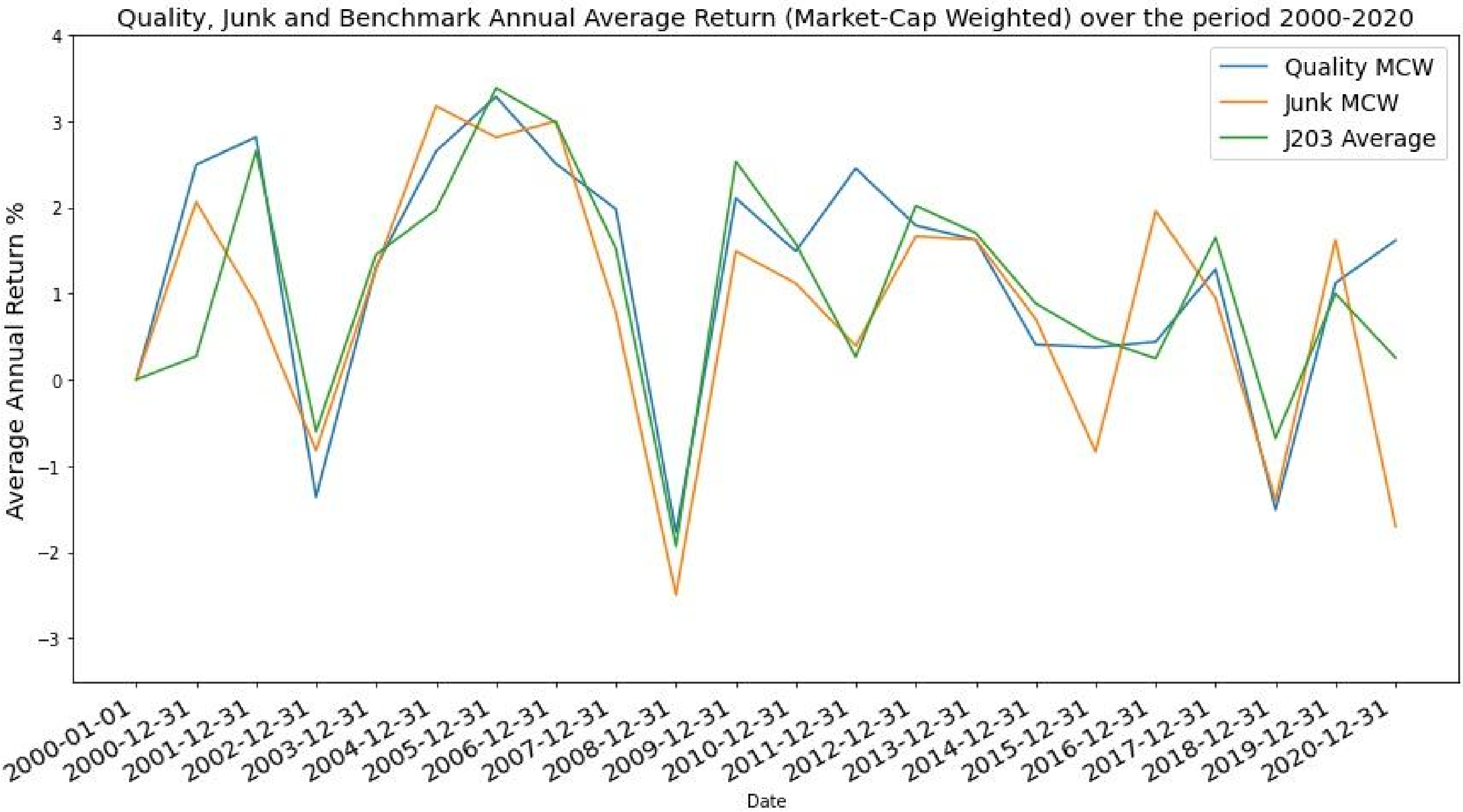
Figure V illustrates the average annual returns of the market-cap weighted quality portfolio and the market-cap weighted junk portfolio along with the J203 Index. The annual average returns from the four market-cap weighted quality and junk proxies have been bootstrapped in order to form a single time series return which represents a single quality portfolio average return and a single low quality (junk) portfolio average return from portfolio formation date (time t) and the subsequent 21 years ($t + 252$ months) on a market-cap weighted basis. Returns from the JSE All Share Index (J203) are also bootstrapped to form a single time series return that represents an average benchmark return.

Figure V shows that the quality portfolio outperformed the junk portfolio in 13 of the 21 years within the sample period on a market-cap weighted basis. Note that the equally-weighted quality portfolio managed to outperform its low-quality equally- weighted counterpart in 15 of the 21 years within the sample period. The quality market-cap portfolio managed to outperform the J203 benchmark in nine of the 21 years within the sample period. Recall that the quality equally-weighted portfolio managed to outperform the J203 benchmark in 7 of the 21 years within the sample period. These results indicate that the market-cap weighted quality portfolio has performed better than the equally-weighted quality portfolio when compared to the benchmark however, when compared to the low-quality market-cap portfolio, it has performed slightly worse. A possible explanation for this result is that the overall average returns achieved by both the quality and junk market-cap weighted portfolios are higher than the equally-weighted portfolios. This explanation is supported by the results in Figure III which illustrate that the top three performing quality proxies are market-cap weighted. Figure VI to follow also supports this explanation as the two market-cap weighted portfolios (quality and junk) outperformed the quality equally-weighted portfolio. Furthermore, the J203 delivered higher average annual returns compared to both the quality and junk market-cap weighted portfolios in 11 of the 21 year observation period from 2000 to 2020. This is two fewer times compared to the quality and junk equally-weighted portfolios. This result further cements the notion that the market-cap weighted portfolios delivered higher returns on average compared to their equally-weighted counterparts.

Similar to the equally-weighted annual average returns, Figure V shows how closely each of the portfolios track the benchmark from the beginning of 2002 until the beginning of 2011 and again from the beginning of 2018 until the beginning of 2020. The impact of the 2007-2008 global financial crises on the market-cap weighted portfolios. Specifically, each portfolio along with the benchmark experienced a dramatic decrease in average returns in the beginning of 2007 with returns rebounding in 2009 to similar levels before the crises. Once again, this result stands in strong contradiction to Lepetit et al. (2021). Specifically, the quality portfolio experienced a 170.63% decrease in average annual return from the beginning of 2007 to the beginning of 2009. Over the same two years, the junk portfolio experienced a 183.13% decrease in annual average return whereas the J203 experienced a 164.64% decrease in annual average return. Although the quality portfolio experienced less of a decrease in annual average returns compared to the junk portfolio during the 2007-2008 global financial crises, the results indicate that even if the portfolios are formed on a market-cap weighted basis, the crises completely crippled their performance. Turning to the performance of each of the portfolios along with the benchmark during the first year of the national lockdown due to the COVID-19 pandemic, Figure V shows that the market-cap weighted quality portfolio appears to experience an increase in annual average return whereas the market-cap weighted junk portfolio along with the benchmark appear to experience a decrease in annual average return in the year 2020. It must be emphasised that this result is not robust enough to conclude on the performance of each portfolio along with the benchmark during the pandemic as the sample period does not take into account the entire lifespan of the pandemic however, there is early evidence to suggest that the market-cap quality portfolio seems be unaffected and more interestingly, improve in performance during the first year of the national lockdown.

Lastly, it is worth noting that the highest average annual return over the sample period was achieved by the J203 in 2005 which delivered 3.38%. Conversely, the lowest average annual return over the sample period was achieved by the junk portfolio which delivered -2.49% in 2008.

Figure V: MARKET-CAP WEIGHTED PORTFOLIO RETURNS

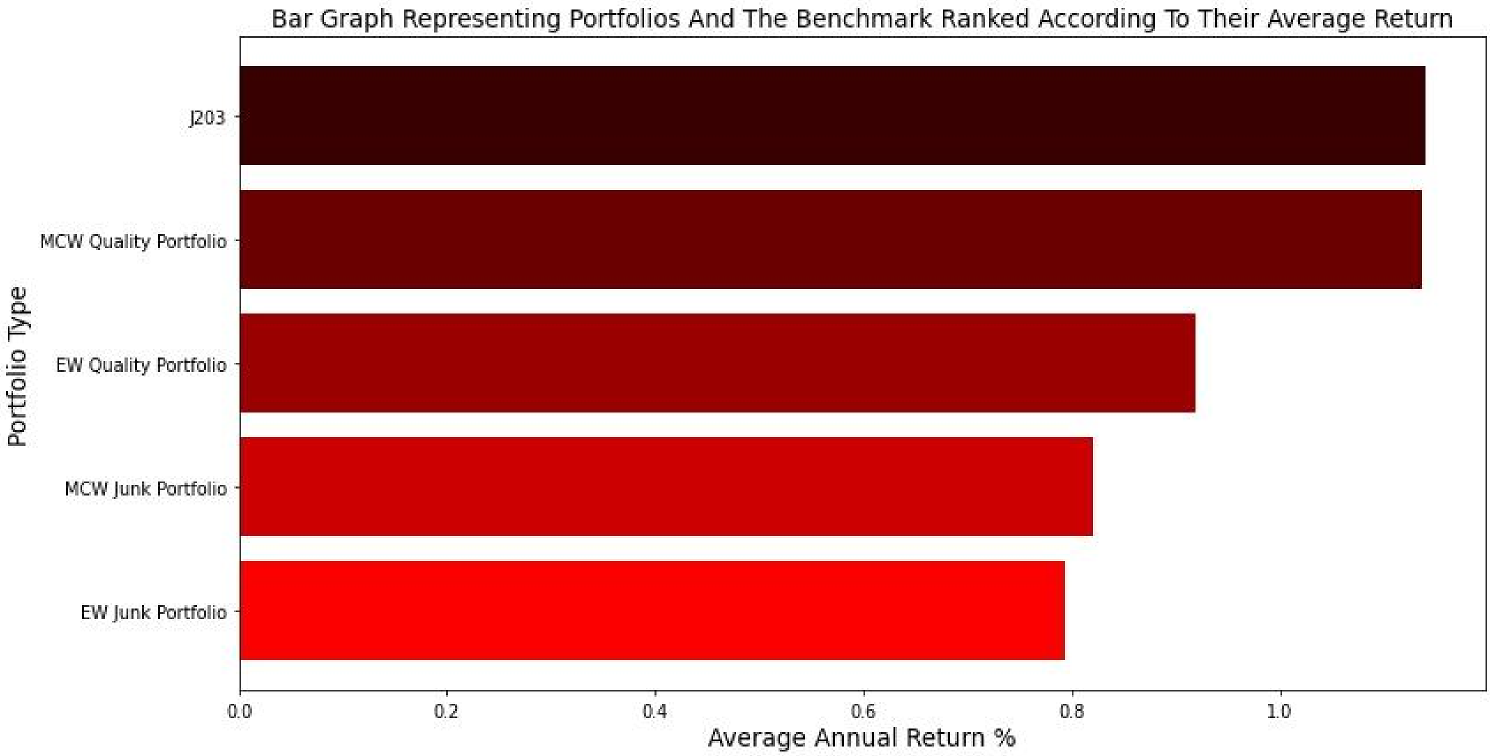


Note: Figure V illustrates calendar-time portfolio returns. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalization as only the top 100 shares on the JSE in terms of their market capitalization are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each junk portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced every six calendar months so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalization. By bootstrapping the returns from the four quality proxies as shown in Figure I, it is possible to form a single quality portfolio arithmetic average return which represents a single time series return on an market-cap weighted basis. This method is replicated throughout the four junk portfolios and the J203 index to form a single junk portfolio arithmetic average return and a single benchmark (J203 Index) arithmetic average return. Returns are in ZAR and do not include currency hedging. Returns are represented as an annual percentage. The sample period is run over January 2000 to December 2020.

4.2.3. RANKED PORTFOLIO RETURNS

Figure VI illustrates the ranked market-cap weighted and equally-weighted quality and junk portfolios respectively, along with the J203 Index. Portfolios are ranked according to their average annual return from the portfolio formation date (time t) and in the subsequent 21 years (t + 252 months). Figure VI illustrates that over the sample period, the J203 delivered the highest average return equal to 1.14%. The market-cap weighted quality portfolio delivered an average return of 1.12%. This translates to the J203 delivering an average return of 0.003% in excess of the market-cap weighted quality portfolio over the sample period. On the other hand, emphasis needs to be placed on the results which show that both quality portfolios (market-cap weighted and equally-weighted) delivered average returns in excess of their low quality counterparts. The lowest average seen in Figure VI is the equally-weighted junk portfolio. Without deviating from this study's central theme of analysing and comparing quality and junk returns, it appears that the weighted scheme applied when sorting portfolios has a major role to play in portfolio performance.

Figure VI: Ranked Proxy Returns



Note: Figure VI represents the ranked average returns achieved by each of the four portfolios as well as the J203 Index. Quality and junk proxies are used to form the two quality and two low quality (junk) portfolios on an equally-weighted and market-cap weighted basis. The four quality proxies are low asset growth, low debt-to-equity, high return-on-assets, and high return-on-equity. The four low quality (junk) proxies are high asset growth, high debt-to-equity, low return-on-assets, and low return-on-equity. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalisation as only the top 100 shares on the JSE in terms of their market capitalisation are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalisation. By bootstrapping the returns from the four quality proxies as shown in Figure I, it is possible to form a single quality portfolio arithmetic average return which represents a single time series return on an market-cap weighted and equally-weighted basis. This method is replicated throughout the four junk portfolios and the J203 index to form a single junk portfolio arithmetic average return and a single benchmark (J203 Index) arithmetic average return. Returns are in ZAR and do not include currency hedging. Returns are represented as 21 year arithmetic average percentage. EW and MCW denote portfolios that are formed on an equally-weighted and market-cap weighted basis respectively. The sample period is run over January 2000 to December 2020.

This paper sheds light on its finding that quality stocks outperform low quality (junk) stocks over the majority of the sample period: is this finding because of limited market efficiency? Fama (1970) explains that the efficient market hypothesis states that share prices reflect all information. On this basis, we expect that shares listed on the JSE should reflect quality according to the efficient market hypothesis however, the quality portfolio consistently outperforms the low quality (junk) portfolio on an equal-weighted and market-cap weighted basis over the majority of the sample period used in this study. Asness et al. (2013) provides a possible explanation for this as the authors explain that high quality stock returns are consistently in excess of low quality stock returns as investors have failed to identify quality and have subsequently underpriced high quality characteristics. However, the J203 delivered higher average annual returns compared to both the equally-weighted quality and equally-weighted junk portfolio in 13 of the 21 year observation period from 2000 to 2020. On a market-cap weighted basis, J203 delivered higher average annual returns compared to both the quality and junk market-cap weighted portfolios in 11 of the 21 year observation period from 2000 to 2020. These findings lend themselves to the conclusion reached by Jenson and Bennigton (1984) that share prices are almost impossible to predict. It is possible that the quality portfolio outperformed the low quality portfolio on both an equally-weighted and market-cap weighted basis as a result of investors underpricing quality shares however, the J203 outperforming both quality portfolios supports the efficient market hypothesis which states that generating consistent alpha is impossible (Fama, 1970). In a universe of high quality and low quality shares, possible profitable opportunities exist as a result of quality under-pricing however, in an investment universe that reflects all possible investment opportunities available to investors, the benchmark (J203) is seen outperforming both the equally-weighted and market-cap weighted quality portfolios. Investors would have earned higher arithmetic average returns by investing in the Satrix ALSI Index Fund which tracks the J203 over the sample period.

4.2.3. PORTFOLIO STATISTICS

This study broadens its coverage on the average raw returns achieved by the quality and junk portfolios respectively by once again, bringing into fruition the use of t-tests. In this instance, the t-tests are designed to provide evidence that the average raw returns earned by each portfolio is statistically significantly different from zero. The null hypothesis remains the same which is that the average raw returns are not different from zero.

Table III shows the results of the t-tests and it is immediately observed that the p-values for each of the equally-weighted and market-cap weighted portfolios are less than 1%. These results indicate that the average raw returns achieved by the equally-weighted and market-cap weighted quality and junk portfolios respectively, are statistically significantly different from zero at the 99% confidence level. Therefore, the null hypothesis is rejected.

Table III: Portfolio Statistics

Equally-Weighted Portfolios:	Quality	Junk
Average Monthly Return	0.91924%	0.79302%
P-Value	***0.00043****	***0.00530****
Standard Deviation	3.98507%	4.36547%
Market-Cap Weighted Portfolios:	Quality	Junk
Average Monthly Return	1.13687%	0.82096%
P-Value	***0.00061****	***0.00797****
Standard Deviation	5.07124%	4.75268%

Note: Italicised p-values are presented where *, ** and *** denotes statistical significance at the 10%, 5% and 1% levels respectively. The sample period is run over January 2000 to December 2020.

4.3. RISK-ADJUSTED RETURNS

Table IV shows the time-series regression that has been employed to examine the excess returns (in excess of the J203) achieved by each of the equally-weighted quality and junk proxy portfolios.

Column [a] presents the time series alpha for each quality portfolio where the high ROA equally-weighted portfolio achieves the highest alpha, equivalent to 0.19% per month (2.3% per annum) and is statistically insignificant at the 10% level. It is important to note that all of the equally-weighted quality portfolios achieve positive alpha's except for the Low AG equally-weighted quality portfolio which has an alpha equal to -0.001% per month (-0.012% per annum). Column [b] presents the factor loadings (beta) for each of the quality portfolios where the High ROA portfolio achieves the highest market loading of 0.72 and is statistically significant at the 1% level.

Column [d] presents the time series alpha for each equally-weighted junk portfolio where the High AG portfolio achieves the highest alpha, equivalent to -0.01% per month (-0.13% per annum) and is statistically significant at the 10% level. It must be noted that all four of the equally-weighted junk proxies exhibit negative alpha's with the Low ROA equally-weighted portfolio achieving the lowest alpha of -0.21% per month (-2.51% per annum). Although the equally-weighted junk portfolios all achieve negative alpha's, none of their p-values are statistically significant at the 10% level of significance. These results suggest that the equally-weighted junk portfolios deliver negative risk-adjusted returns over the sample period albeit statistically insignificant. Column [e] presents the factor loadings for each of the equally-weighted junk portfolios where the Low ROE portfolio achieves the highest market loading of 0.78 and is statistically significant at the 1% level.

Table IV: Regression Outputs on the Risk-Adjusted Returns for each Equally-Weighted Portfolio

	Equally Weighted Quality Proxies				Equally Weighted Junk Proxies		
	[a] α	[b] βJ203	[c] R^2		[d] α	[e] βJ203	[f] R^2
High ROE	0.00045	0.71776	62%	Low ROE	-0.00122	0.78481	58%
	0.80253	*0.00000****			*0.57192*	*0.00000****	
High ROA	0.00192	0.72004	70%	Low ROA	-0.00209	0.75380	56%
	0.204155	*0.00000****			*0.32930*	*0.00000****	
Low DE	0.00083	0.66132	64%	High DE	-0.00073	0.76147	66%
	0.60351	*0.00000****			*0.67702*	*0.00000****	
Low AG	-0.00001	0.70193	59%	High AG	-0.00011	0.68906	64%
	0.98855	*0.00000****			*0.94908*	*0.00000****	

. Note: Regression outputs are presented alongside their italicised p-values where *, ** and *** denotes statistical significance at the 10%, 5% and 1% levels respectively. α represents the portfolio alphas which is the intercept of monthly excess returns, β represents the coefficient or factor loading on the applied regression and R2 represents the adjusted R2 related to the specific time series regression.

Table V shows the time-series regression that has been employed to examine the excess returns (in excess of the J203) achieved by each of the market-cap weighted quality and junk proxy portfolios.

Column [a] presents the time series alpha for each quality portfolio where the LOW AG market-cap weighted portfolio achieves the highest alpha, equivalent to 0.05% per month (0.66% per annum) and is statistically insignificant at the 10% level. In contrast to the equally-weighted quality portfolios, all of the market-cap weighted quality portfolios exhibit negative alpha's except for the Low AG market-cap weighted portfolio. Column [b] presents the factor loadings (beta) for each of the market-cap weighted quality portfolios where the High ROA portfolio achieves the highest market loading of 1.09 and is statistically significant at the 1% level.

Column [d] presents the time series alpha for each market-cap weighted junk portfolio where the Low ROE portfolio achieves the highest alpha, equivalent to -0.12% per month (-1.39% per annum) and is statistically insignificant at the 10% level. All four of the market-cap weighted junk portfolios exhibit negative alpha's with the Low ROA portfolio achieving the lowest alpha of -0.39% per month (-4.66% per annum) and is statistically significant at the 10% level. Column [e] presents the factor loadings for each of the market-cap weighted junk portfolios where the High AG portfolio achieves the highest market loading of 0.92 and is statistically significant at the 1% level.

The results from Table IV and V are arguably contradictory with the results described earlier on the raw returns achieved by each of the equally-weighted and market-cap weighted proxies. Specifically, the average returns delivered by the market-cap weighted proxies dominate the average returns achieved by the equally-weighted portfolio over the sample period. Moreover, the market-cap weighted quality portfolio's average raw return of 1.14% was not only greater than the equally-weighted quality portfolio but was only 0.01% less than the average raw return achieved by the J203. On this basis, one would expect the market-cap weighted risk-adjusted returns to be greater than the equally-weighted risk-adjusted returns but the regression results clearly indicate that the alpha's achieved by the equally-weighted quality portfolios are greater than the market-cap weighted quality portfolios. More interestingly, the betas associated with the market-cap weighted quality portfolios range between 0.896 and 1.089 whereas the betas associated with the equally-weighted quality portfolios range between 0.661 and 0.720. This result somewhat contradicts the Efficient Market Hypothesis (EMH) as Bouchaud, Jean-Philippe, Ciliberti, et al. (2016) explain that excess returns should be related to a risk premium according to the EMH. However, the lower betas are associated with higher alpha's in the equally-weighted quality portfolios compared to the higher betas associated with lower alpha's in the market-cap weighted quality portfolios. This suggests that on a risk-adjusted basis, the equally-weighted quality portfolios deliver superior returns for a lower level of risk compared to the market-cap weighted quality portfolios.

Table V: Regression Outputs on the Risk-Adjusted Returns for each Market-Cap Weighted Portfolio

	Market Cap Weighted Quality Proxies				Market Cap Weighted Junk Proxies		
	[a] α	[b] βJ203	[c] R^2		[d] α	[e] βJ203	[f] R^2
High ROE	-0.00168	1.06878	83%	Low ROE	-0.00116	0.91984	65%
	0.29292	*0.00000****			*0.58989*	*0.00000****	
High ROA	-0.00025	1.08941	78%	Low ROA	-0.00388	0.85948	61%
	0.88974	*0.00000****			*0.07685**	*0.00000****	
Low DE	-0.00096	0.89685	73%	High DE	-0.00160	0.90403	70%
	0.58115	*0.00000****			*0.40042*	*0.00000****	
Low AG	0.00055	0.92986	69%	High AG	-0.00380	0.92369	76%
	0.78069	*0.00000****			*0.02466***	*0.00000****	

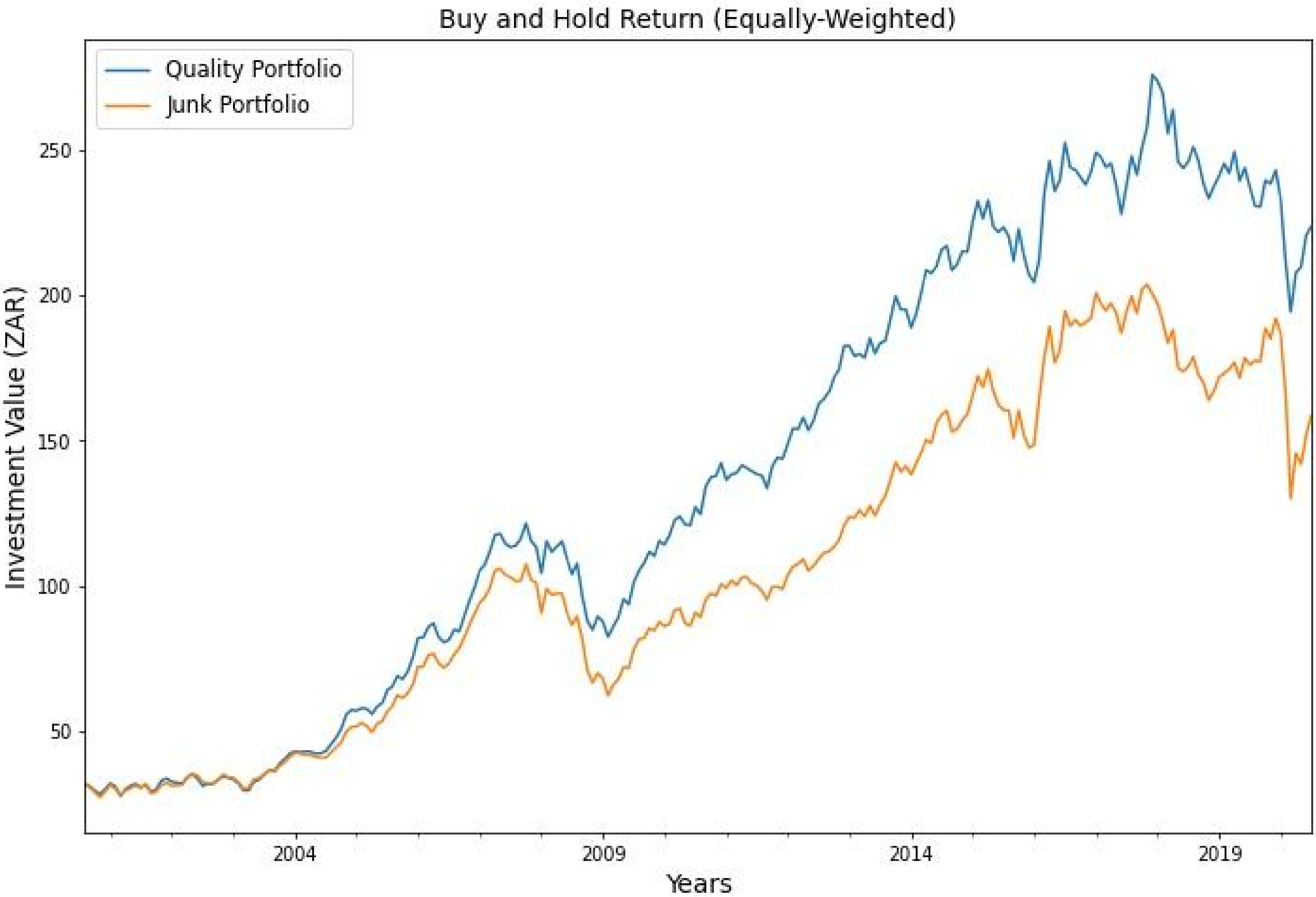
Note: Regression outputs are presented alongside their italicised p-values where *, ** and *** denotes statistical significance at the 10%, 5% and 1% levels respectively. α represents the portfolio alphas which is the intercept of monthly excess returns, β represents the coefficient or factor loading on the applied regression and R2 represents the adjusted R2 related to the specific time series regression.

4.4. BUY AND HOLD RETURNS

4.4.1. EQUALLY-WEIGHTED RETURNS

Figure IV displays the buy-and-hold returns achieved by investing 30 rand (ZAR) in the equally-weighted quality and junk portfolio respectively, over the sample period 1 January 2000 to 31 December 2020. Both portfolios closely track each other in the five year period from 2000 - 2004. In 2005, it is clear that the quality portfolio began to climb above the junk portfolio in 2005 and remained dominating the junk portfolio over the rest of the sample period. Both portfolios exhibit turbulent performance in 2007 before crashing in 2008 - 2009 which is safe to suggest as a result of the 2007-2008 global financial crises. The fact that both portfolios did not drastically decline in value in 2007 but experienced sharp declines in 2008 may suggest a lagged reaction to the crises. In the years following the crises, both portfolios show a gradual increase in value until 2015 where a noticeable decrease in value is observed. Interestingly, both portfolios experience a dramatic decline in value in the year 2020 with the most reasonable explanation being the Covid-19 Pandemic. At the end of the sample period, the quality portfolio has a value of R223.52 and the junk portfolio has a value of R158.61. These findings are consistent to the arithmetic average returns displayed in Figure I.

Figure IV: Equally-Weighted Buy and Hold Returns

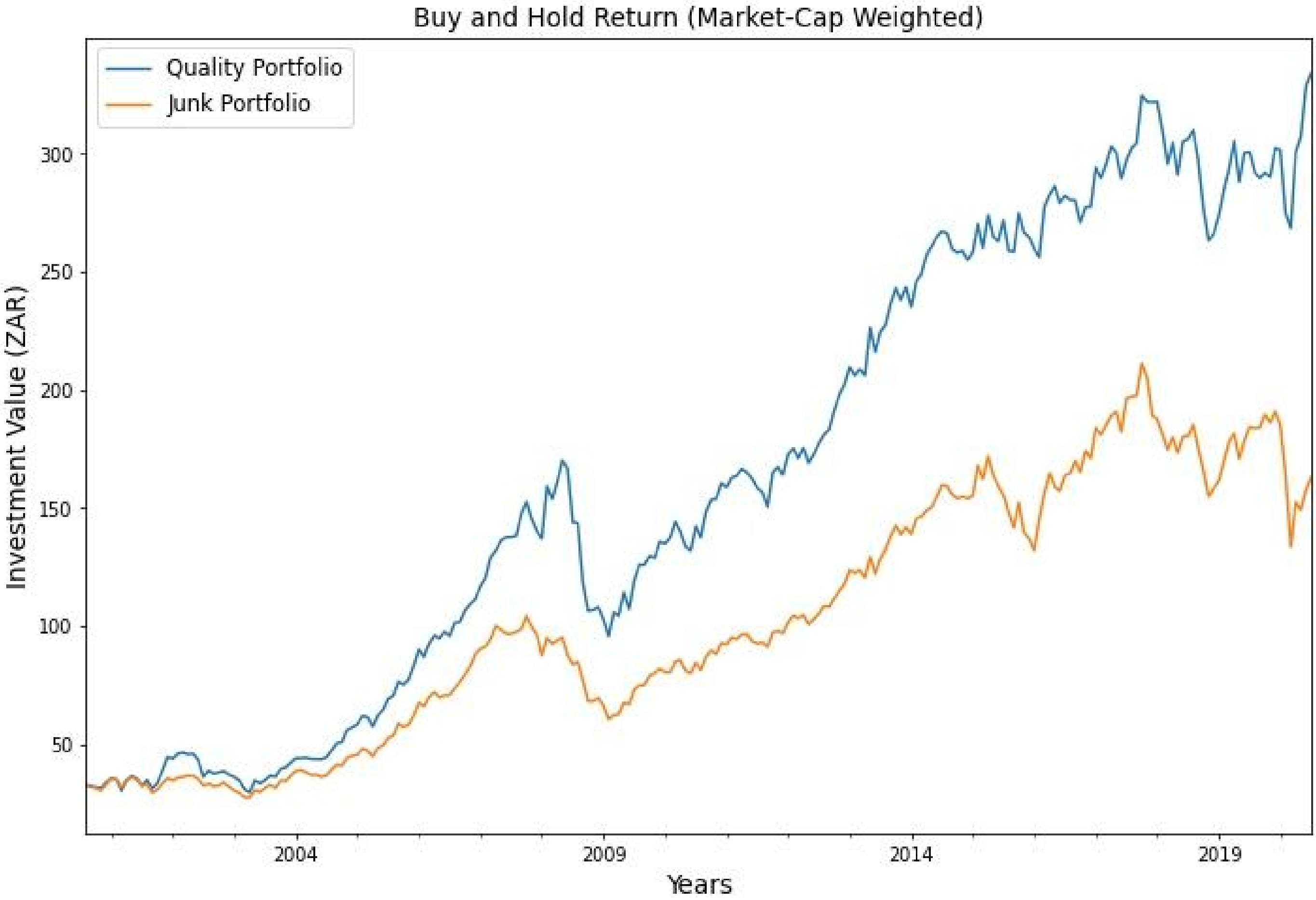


Note: Figure IV illustrates calendar-time portfolio buy-and-hold returns. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalization as only the top 100 shares on the JSE in terms of their market capitalization are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalization. The graph displays the 30 rand (ZAR) investment in long-only equally-weighted quality and long-only equally-weighted junk portfolios. The investment value is the 30 rand (ZAR) buy and hold return based on the cumulative returns on the four quality portfolios and the average return on the four low quality (junk) portfolios. The sample period is from January 2000 to December 2020.

4.4.2. MARKET-CAP WEIGHTED RETURNS

Figure V displays the buy-and-hold returns achieved by investing 30 rand (ZAR) in the market-cap weighted quality and junk portfolio respectively, over the sample period 1 January 2000 to 31 December 2020. In contrast to the equally-weighted buy-and-hold returns, the market-cap weighted quality portfolio separates itself from the market-cap weighted junk portfolio towards the end of 2001 as opposed to 2004. The quality portfolio remains dominant throughout the sample period. Both portfolios also experienced turbulent performance in 2007 before declining in 2008-2009. However, it must be noted that the decrease in gradient appears to be more severe in the quality portfolio than the junk portfolio in 2008. In the years following 2009, both portfolios show a gradual increase in value until 2015 where a noticeable decrease in value is observed in the junk portfolio whereas the quality portfolio experiences far less of an impact. consistent with the equal-weighted portfolios, both market-cap weighted portfolios experience a dramatic decline in value in the year 2020 with the most reasonable explanation being the Covid-19 Pandemic. However, the quality portfolio is seen to rebound in value in the latter months of 2020 whereas the junk portfolio appears to gradually increase in value at a much slower rate. At the end of the sample period, the quality portfolio has a value of R334 and the junk portfolio has a value of R163.06. These findings are consistent to the arithmetic average returns displayed in Figure II.

Figure V: Market-Cap Weighted Buy and Hold Returns



Note: Figure V illustrates calendar-time portfolio buy-and-hold returns. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalization as only the top 100 shares on the JSE in terms of their market capitalization are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalization. The graph displays the 30 rand (ZAR) investment in long-only market-cap weighted quality and long-only market-cap weighted junk portfolios. The investment value is the 30 rand (ZAR) buy and hold return based on the cumulative returns on the four quality portfolios and the average return on the four low quality (junk) portfolios. The sample period is from January 2000 to December 2020.

4.5. BENCHMARK ADJUSTED BUY AND HOLD ABNORMAL RETURNS

Figure VI displays the benchmark-adjusted buy-and-hold returns achieved by investing 30 rand (ZAR) in the equally-weighted and market-cap weighted quality and junk portfolios respectively after accounting for the average return achieved by the market (J203) over the sample period. The purpose of this is to establish whether investing in either quality or junk portfolios produces returns in excess of the market return.

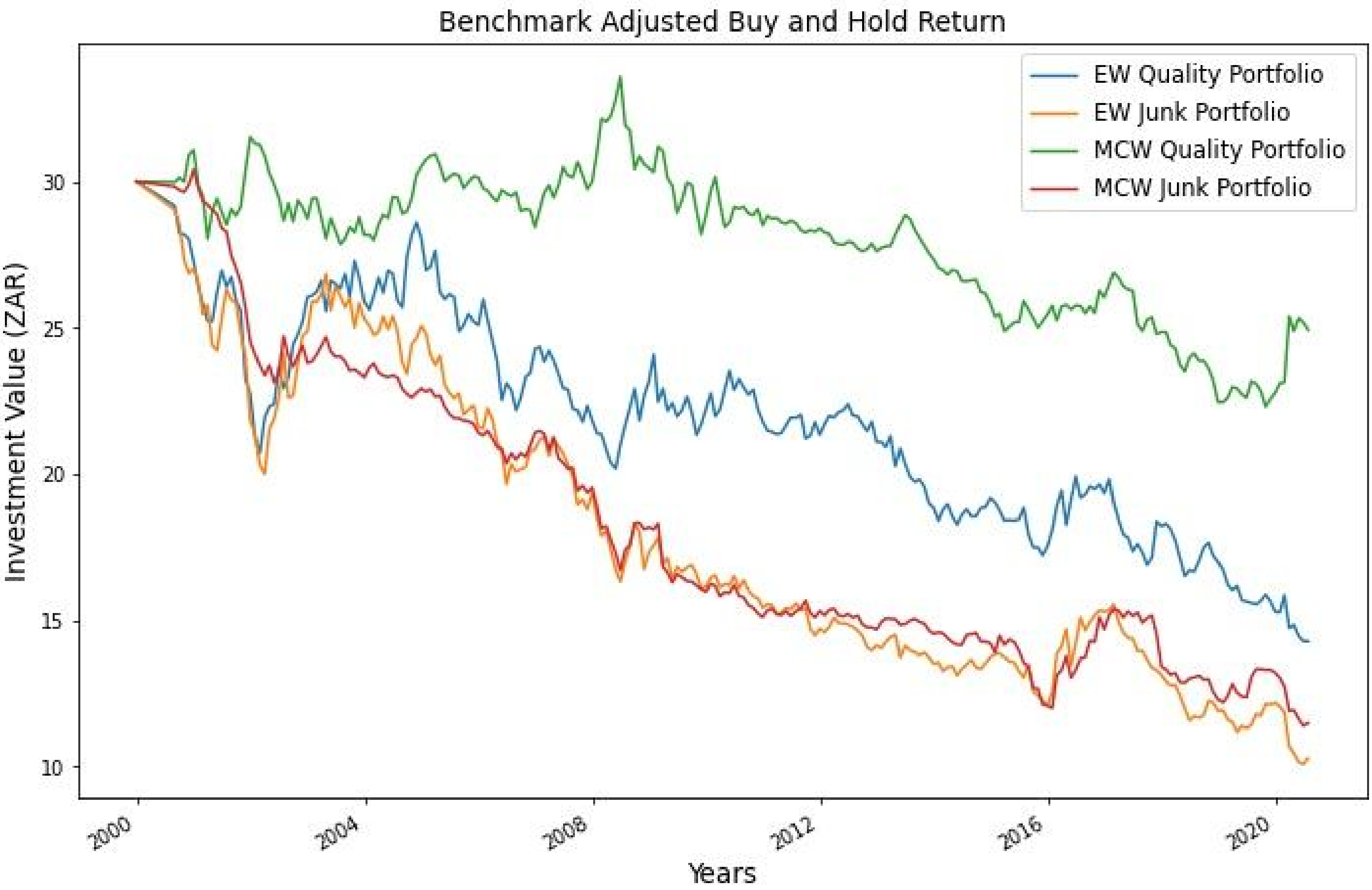
Figure VI shows that both the market-cap weighted quality is the only portfolio to temporally achieve positive abnormal returns in excess of the market. Specifically, the market-cap weighted quality portfolio managed to produce abnormal returns as seen by the peaks above the R30 investment value over the period 2001-2008. As for the equally-weighted quality portfolio, abnormal returns are not evident as the portfolio failed to increase the original investment value of R30 over the sample period. In terms of the market-cap weighted and equally-weighted junk portfolios, both portfolios fail to achieve abnormal returns in excess of the market as both portfolios decrease in value over the sample period.

An interesting result from Figure IV is that the market-cap weighted quality portfolio appears to produce positive abnormal buy-and-hold returns in periods when all three of the other portfolios appear to produce negative abnormal buy and hold returns. Specifically, at the start of 2002, the equally-weighted quality portfolio along with both junk portfolios appear to experience a steep decline in performance in excess of the benchmark however, the market-cap weighted quality portfolio is seen to experience a steep incline in performance in excess of the benchmark. A similar pattern is observed over the period 2007-2009 when the equally-weighted quality portfolio along with the two junk portfolios experience a gradual decline in performance whereas the market-cap weighted quality portfolio experiences a gradual increase in performance over the same period. This pattern is repeated in 2015 and 2020. The periods in which there is an increase in benchmark adjusted buy-and-hold returns achieved by the market-cap weighted quality portfolio may not be a coincidence as these periods are well documented times of financial turmoil. Specifically, the market-cap weighted quality portfolio delivers an increase in benchmark adjusted returns over the periods 2007-2009 and more noticeably in 2020. These periods correspond to the 2007-2008 global financial crisis as well as the systematic devastation in financial markets as a result of the Covid-19 Pandemic in 2020. This finding is consistent with Lepetit et al. (2021) who find evidence to suggest that their quality factor delivers a steady and smooth performance over the period which falls between the recent 2007 - 2008 global financial crises and the Covid-19 pandemic.

It's important to note that despite the possible hedging opportunities displayed by the market-cap weighted quality portfolio during market downturns, both of the equally-weighted portfolios as well as the two market-cap weighted portfolios fail to turn profitable over the sample period. Specifically, at the end of the sample period the value of the market-cap weighted quality and junk portfolios are R24.93 and R11.49 respectively. At the end of the sample period the value of the equally-weighted quality and junk portfolios are R14.29 and R10.28 respectively. These results reiterate the poor performance of the junk portfolios in relation to the market but more importantly, it reiterates the poor performance of the quality portfolios in relation to the market.

The results bring to light the findings from Bender, Hammond and Mok (2014) who authored a seminal paper on capturing alpha (returns in excess of the market). Bender et al. (2014) note that traditionally, investors attributed portfolio returns to a combination of passive market exposure and active portfolio management. Moreover, the authors concluded that investing in passive risk premia indices can account for up to 80% of alpha. Therefore, it can be argued that an investor who has an appetite to capture alpha through active portfolio management such as sorting and picking shares according to factors that have been used to identify and define quality may be left disappointed as the results from Figure VI demonstrate that the quality portfolios fail to consistently capture alpha over the sample period. More importantly, investors who seek to capture alpha through quality investing strategies on the JSE may be persuaded to explore more passive investment strategies in order to achieve returns in excess of the market return.

Figure VI: Benchmark Adjusted Returns



Note: Figure VI illustrates calendar-time portfolio returns. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalization as only the top 100 shares on the JSE in terms of their market capitalization are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalization. The graph displays the 30 rand (ZAR) investment in long-only equally-weighted and market-cap weighted quality portfolios as well as long-only equally-weighted and market-cap weighted junk portfolios. The investment value is the 30 rand (ZAR) benchmark adjusted buy and hold return calculated by taking the cumulative returns on the two quality portfolios and subtracting the cumulative return from the J203 Index. This method is replicated on the two low quality (junk) portfolios. The sample period is from January 2001 to December 2020.

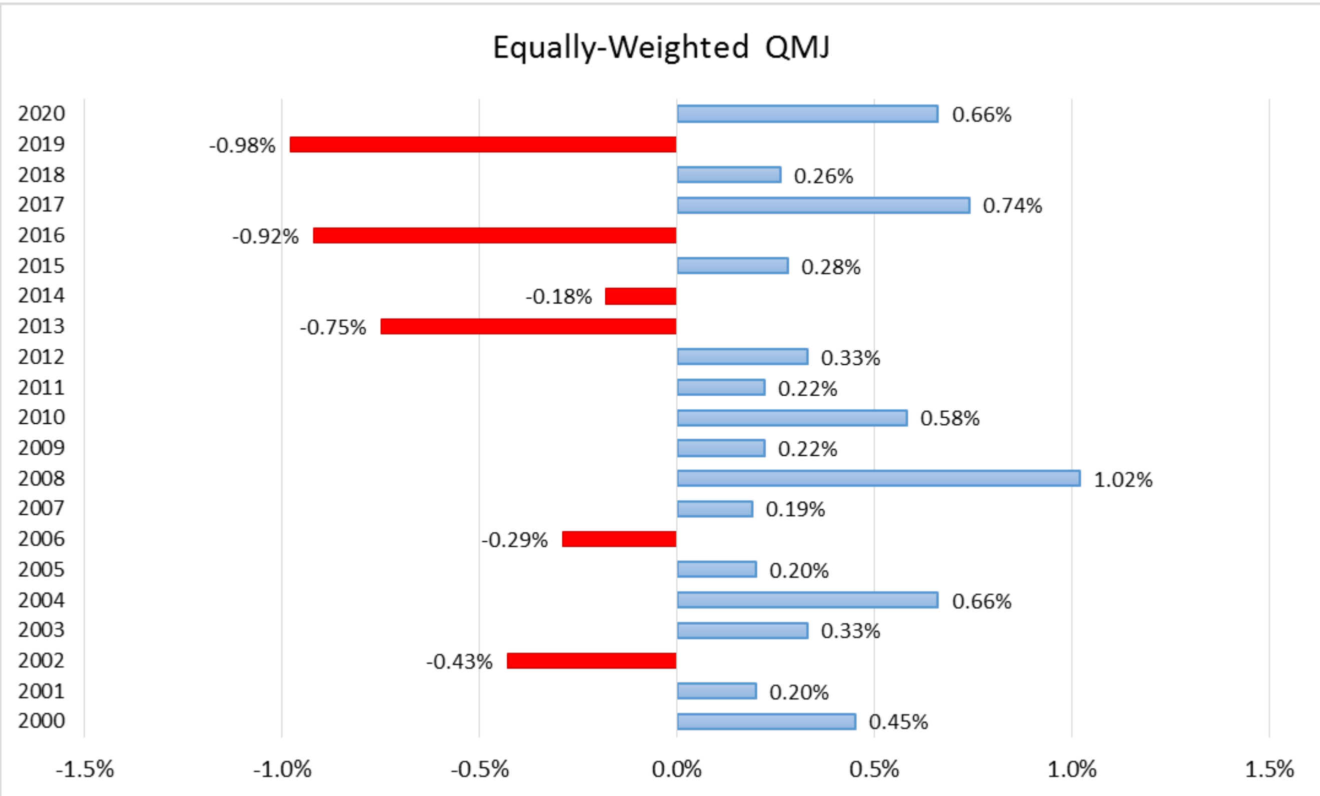
4.5. THE QUALITY PREMIUM

Figures VII and VIII display the quality-minus-junk (QMJ) factor pioneered by Asness et al. (2013). The QMJ factor is designed to investigate whether a quality premium exists by determining whether a quality portfolio achieves returns in excess of a junk portfolio. The

QMJ factor is directly related to the average returns achieved by the quality and junk portfolios over the sample period as seen in Figure IV and Figure V. Specifically, the QMJ factor is calculated by subtracting the junk portfolio's average returns from the quality portfolio's average returns.

Figure VII displays the equally-weighted QMJ returns over the sample period. A quality premium is evident in 15 of the 21 years during the sample period 1 January 2000 to 31 December 2020. Figure VII demonstrates that the equally-weighted quality premium is most pronounced in 2008 equal to 1.02% in the height of the 2007-2008 global financial crises. This result serves as evidence to support the notion that high quality stocks have the ability to produce higher average returns compared to their lower quality counterparts in times of economic turmoil. The second most pronounced quality premium over the sample period is seen in 2017 which is equal to 0.74%.

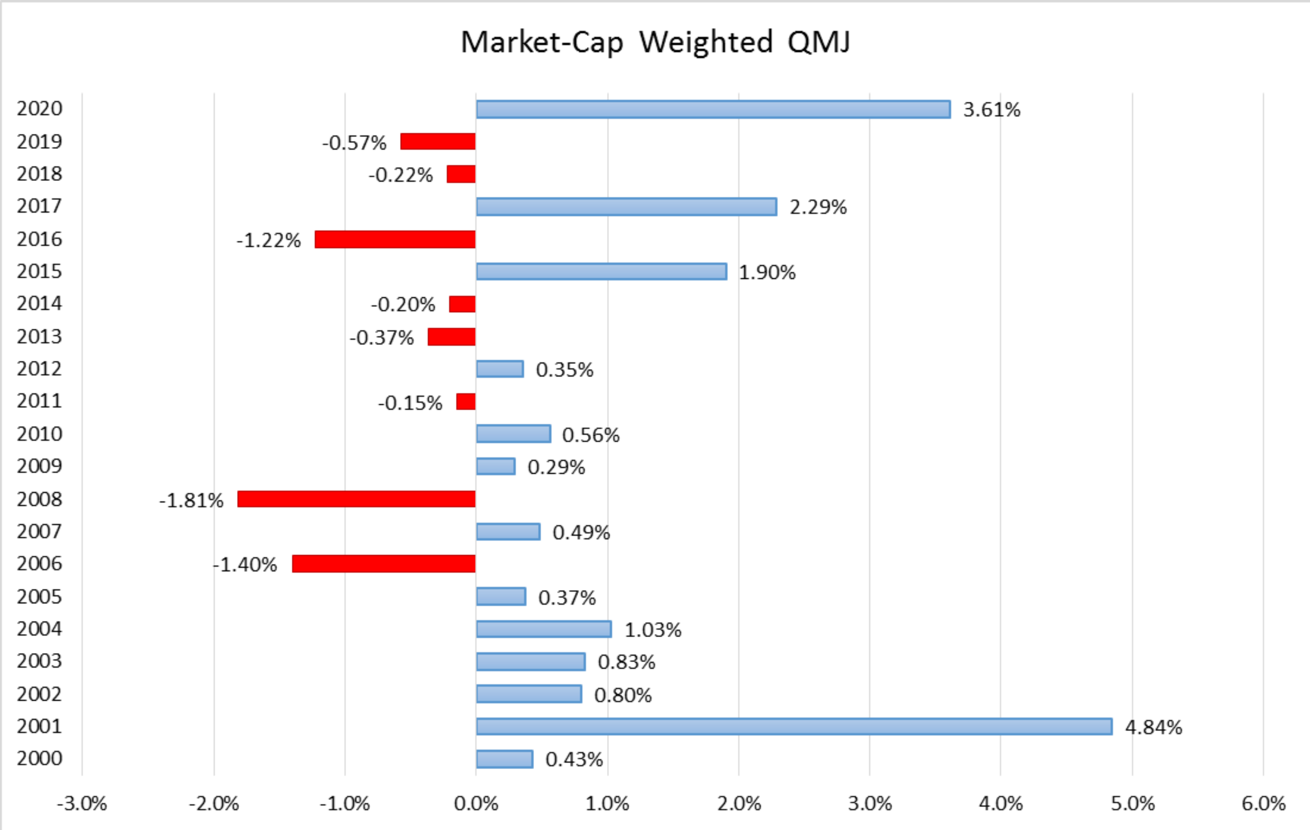
Figure VII: Equally-Weighted Quality-Minus-Junk Returns



Note: Figure VII illustrates calendar-time portfolio returns. Quality minus Junk (QMJ) factors are constructed as the intersection of four equally-weighted proxy portfolios formed on size and quality. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalization as only the top 100 shares on the JSE in terms of their market capitalization are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalization. The QMJ factor return is the average return on the four quality portfolio's minus the average return on the four low-quality (junk) portfolios and is expressed as an annual percentage. The sample period runs from January 2000 to December 2020.

Figure VIII displays the market-cap weighted QMJ returns over the sample period. A quality premium is evident in 13 of the 21 years during the sample period 1 January 2000 to 31 December 2020. Figure VIII shows that the market-cap weighted quality premium is most pronounced in 2001 equal to 4.84%. This result is 3.82% greater than the highest QMJ return achieved over the sample period on an equally-weighted basis. Contrary to the strong performance of the equally-weighted QMJ return in 2008, the market-cap weighted QMJ achieves a dismal -1.81% which proves to be the worst performing year for the market-cap weighted QMJ factor. However, this result does not rule out the evidence provided above on the notion that quality stocks may have the ability to outperform their junk counterparts but rather, this result sheds light on the impact on portfolio performance based on different weighting schemes.

Figure VIII: Market-Cap Weighted Quality-Minus-Junk Returns



Note: Figure VIII illustrates calendar-time portfolio returns. Quality minus Junk (QMJ) factors are constructed as the intersection of four market-cap weighted portfolios formed on size and quality. Every six calendar months, stocks are sorted and assigned to form a size portfolio based on their market capitalization as only the top 100 shares on the JSE in terms of their market capitalization are considered for each portfolio. At each portfolio formation date, quartile breakpoints are inserted and shares are classified into one of two portfolios, namely: Quality and Junk. Each quality portfolio constitutes shares that are ranked in the top 25% in relation to each quality proxy and each low quality (junk) portfolio constitutes shares that are ranked in the bottom 25% in relation to each quality proxy. Portfolios are refreshed and rebalanced on a semi-annual basis so that each portfolio maintains shares that are ranked in the top 100 shares on the JSE according to their market capitalization. The QMJ factor return is the average return on the four quality portfolio's minus the average return on the four low-quality (junk) portfolios and is expressed as an annual percentage. The sample period runs from January 2000 to December 2020.

Although an equally-weighted and market-cap weighted quality premium is observed over the majority of the sample period, these findings lack evidence to support whether the quality premium is significant or not. This study broadens its coverage on the QMJ returns achieved on an equally-weighted and market-cap weighted basis respectively by once again, bringing into fruition the use of t-tests. The t-tests are designed to provide evidence that the QMJ returns are statistically significantly different from zero. The null hypothesis remains the same, which is that the QMJ returns are not different from zero.

Table IV shows the results of the t-tests and it is immediately observed that the market-cap weighted QMJ returns are statistically significant at the 10% level of significance. This result indicates that the null hypothesis is rejected as the returns are significantly different from zero at a 90% confidence level. On the other hand, the equally-weighted QMJ returns are not statistically significant thus, this study fails to reject the null hypothesis as the returns are significantly different from zero at a 90% confidence level. Asness et al. (2013) found a significant quality premium in their study that focused on a sample of stocks in the United States and 24 other countries. However, Fischer (2014) concluded that there is no evidence to support a quality premium on the Swiss Performance Index as the author explained that most Swiss companies listed on the Swiss Performance Index are high quality stocks making it difficult to differentiate between quality stocks and junk stocks.

Considering the findings of Asness et al. (2013) and Fischer (2014), it can be argued that the market-cap weighted quality premium on the JSE observed in this study is consistent with the findings from Asness et al. (2013). On the other hand, it could be argued that the lack of significance related to the equally-weighted quality premium on the JSE observed in this study is consistent with the findings of Fischer (2014) as the shares sampled in this study are all possibly high quality shares. This suggests that the quality premium observed is insignificant as it is difficult to distinguish between quality JSE shares and junk JSE shares even though these shares have been ranked according proxies used to identify and define quality.

Table VI: QMJ Factor Statistics

QMJ Factor	Market-Cap Weighted QMJ	Equally-Weighted QMJ
Average Monthly Return	0.32%	0.14%
P-Value	***0.08210****	***0.23381***
Standard Deviation	2.80307%	1.80961%

Note: Italicised p-values are presented where *, ** and *** denotes statistical significance at the 10%, 5% and 1% levels respectively. The sample period is run over January 2000 to December 2020.

5. CONCLUSION

The majority of academic literature that has documented quality investing focuses on shares that are traded on stock markets in developed countries. This paper adds to the existing body of literature by focusing on shares on the JSE in order to determine whether a quality premium exists. This study maintains that it is one of the first studies to document quality investing on shares that are traded on the JSE.

This study defines quality characteristics based on the works of previous researchers who have identified capital structure, capital expenditure and profitability as proxies for identifying and defining quality. The results in this study indicate that the profitability proxy has more explanatory power in identifying and defining quality shares compared to the other two proxies, namely capital structure and capital expenditure. Furthermore, the results indicate that the quality portfolio manages to consistently outperform the low quality (junk) portfolio on both an equally-weighted and market-cap weighted basis over the sample period used in this study. However, the J203 benchmark manages to consistently outperform the quality and junk portfolios based on equal and market-cap weighting procedures thus, supporting the efficient market hypothesis that generating alpha is impossible.

T-tests were employed to provide coverage on the level of significance relating to the average raw returns achieved by each quality and junk proxy used to identify and define quality shares. The t-tests revealed that the average raw returns for each quality proxy portfolio are statistically significant at the 1% level and that the returns for each quality proxy portfolio were statistically significantly different from zero. A time-series regression analysis was then employed to provide commentary on the risk-adjusted returns achieved by each quality and junk portfolio respectively. The regression results indicated that the equally-weighted quality proxy portfolios delivered superior alphas compared to the junk portfolios as all the quality proxies delivered positive alphas barring the Low AG proxy. On the other hand, the market-cap weighted quality proxies delivered a less impressive performance as all of the alphas were negative barring the Low AG proxy. All four of the low-quality market-cap proxy portfolios delivered negative alphas. In terms of the equally-weighted buy and hold returns, the quality portfolio dominated the junk portfolio over the sample period however, both portfolios remain profitable. Consistent with the equally-weighted buy and hold returns, the market-cap weighted portfolios also remained profitable over the sample period with the market-cap weighted quality portfolio dominating its junk counterpart as well as the equally-weighted quality portfolio. However, the benchmark-adjusted buy and hold returns in respect of both the market-cap weighted and equally-weighted quality and junk portfolios remained fruitless over the sample period.

This study finds evidence of an equally-weighted quality premium on the JSE in 15 of the 21 years over the sample period however, the t-statistics revealed that the quality premium is not statistically different from zero. On the other hand, this study finds evidence of a market-cap weighted quality premium on the JSE in 13 of the 21 years over the sample period. Moreover, the t-statistics revealed that the market-cap quality premium is statistically significantly different from zero, albeit at the 10% level. This study also finds inconclusive evidence to suggest that a quality investment strategy may yield a possible hedge against downside market conditions. However, future studies could add to the growing literature on quality investing by examining the significance of a quality premium on the JSE during bullish and bearish market conditions.

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7. APPENDIX A

Table II: Financial Ratio Formulas

Financial Ratio	**Formula**
Assets to Equity (A/E)	$\frac{Assets}{Equity}$
Asset Growth	$\frac{P2-P1}{P2}$ x 100 Where P1 = Prior year's total asset value Where P2 = Current year's total asset value
Debt to Equity (D/E)	$\frac{Debt}{Equity}$
Return on Assets (ROA)	$\frac{Net\ Income}{Average\ Total\ Assets}$
Return on Equity (ROE)	$\frac{Net\ Income}{Shareholders\ Equity}$
Return on Invested Capital (ROIC)	$\frac{Net\ Income - Dividends}{Total\ Capital\ Invested}$