UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
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PERFORMANCE PERSISTENCE OF SOUTH AFRICAN UNIT TRUST FUNDS

Dissertation by

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Submitted in fulfilment of the requirements for the degree

Magister Philosophiae in Financial Management Sciences

in the

Faculty of Economic and Management Sciences

at the

University of Pretoria

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October 2021

DECLARATION

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ACKNOWLEDGEMENTS

First and foremost, I thank the Lord for granting me the opportunity to pursue this journey and for guiding me throughout.

I would also like to express my sincere gratitude to the following entity and individuals who contributed towards making the completion of this study possible:

- Prof Henco van Schalkwyk and Dr Elbie Louw for their patience, guidance, and insight throughout this journey;
- My father, mother, and sister for their love and support;
- My friend Michael for his continuous encouragement, statistical insight, and teachings;
- My friends and loved ones for their encouragement and support – particularly Danie, Jesse, Werner, and Anneze.
- Finally, I would like to thank everyone at the Mastercard Scholarship Foundation – your guidance and support throughout my studies have been invaluable.

ABSTRACT

The optimality of active or passively managed investment fund alternatives is a contentious topic in the field of investment management. The efficient market hypothesis states that active funds should not be able to derive net-of-fee risk-adjusted returns in excess of their benchmarks on a persistent basis. However, emerging market economies such as South Africa that have less efficient markets, present active managers with greater opportunities to persistently outperform after fees have been accounted for. This study evaluates the performance persistency of actively managed South African equity, interest-bearing, multi-asset, and real estate unit trust funds relative to investable passive alternatives. The rolling holding period performance of actively managed unit trusts relative to investable passive alternatives are assessed by making use of notched boxplots. Active funds are classified as persistent out- or underperformers if the median of their rolling period excess return distributions relative to their respective passive alternatives is significantly different from zero at a 5% level of significance.

This study finds that a greater proportion (83.969%) of active funds persistently out- or underperform their comparable passive alternatives. More evidence of persistently outperforming funds is found amongst interest-bearing and real estate funds. Conversely, a greater number of persistently underperforming funds are found amongst equity and multi-asset funds. Furthermore, this study concludes that other determinants of unit trust fund performance persistence such as the degree of competition, sector- and fund-level diseconomies of scale, and investment charges should supplement the analysis of a fund's performance history when making future investment decisions.

Keywords: Performance persistence, unit trusts, active management, passive management, Association of Savings and Investment South Africa, rolling holding periods, notched boxplots

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
AMH	Adaptive market hypothesis
ASISA	Association for Savings and Investment South Africa
CI	Confidence interval
CIS	Collective investment scheme
CISCA	Collective Investment Schemes Control Act 45 of 2002
CPI	Consumer price index
DME	Developed market economy
EME	Emerging market economy
EMH	Efficient market hypothesis
ETF	Exchange traded fund
GBM	Geometric Brownian motion
IQR	Inter-quartile range
IR	Information ratio
JSE	Johannesburg Stock Exchange
MDD	Minimum disclosure document
NAV	Net asset value
SA	South Africa
TIC	Total investment charge
UK	United Kingdom
US	United States of America
ZAR	South African Rand

LIST OF DEFINITIONS

Term	Meaning
Fund	Unit trust, mutual fund, exchange traded fund, or similar investment vehicle.
Active fund	Fund whose managers employ an active management strategy in managing the fund.
Passive fund	Fund whose managers employ a passive management strategy in managing the fund.
Collective investment scheme	The legal structure that South African unit trusts and exchange traded funds are registered as per the Collective Investment Schemes Act 45 of 2002.
ASISA category	The category under which a particular fund is categorised per the Association of Savings and Investment South Africa classification standard.

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

“The principal role of the mutual fund is to serve its investors” – John C. Bogle

At the end of 2000, the South African unit trust industry had R128 billion under management and consisted of 334 funds. These figures grew significantly to 1686 funds and R2 730 billion under management as at 31 December 2020, approximately 3.8 times South Africa’s 2020 gross nominal savings (ASISA, 2021; SARB, 2021). Of the total funds under management, R999 billion (36.6%) was attributable to investments by retail investors (ASISA, 2021). One can therefore conclude that unit trusts play a significant role in facilitating consumer savings in South Africa.

Unit trusts are popular investments in many countries, but they vary in naming conventions. For example, in the United States of America (US) and the United Kingdom (UK), they are called open-end mutual funds and open-ended investment companies, respectively (Harris, 2019). The growth of these instruments, both internationally and in South Africa specifically, has been attributed to increased demand for different investment products and the convenience of accessing a diversified set of assets in a cost-effective manner (Arifin & Mulyati, 2017; Oldert, 2018). Unit trusts, mutual funds, and other similar investment structures can broadly be classified into two groups based on how they are managed, namely active or passive funds.

Fund managers decide whether to manage unit trusts as active or passive funds (Grinblatt & Titman, 1989). Active funds invest capital in a manner that is expected to provide a risk-adjusted return in excess of their benchmarks. In contrast, passive funds invest capital to mimic the risk-adjusted returns of their benchmarks (Sharpe, 1991). Greater research and trading fees raise the total management fees of active funds, which active managers justify with the prospect of greater risk-adjusted returns (Clearly, Atkinson, & Drake, 2019; Harris, 2019). Whether investments in active funds enhance investor wealth more than investments in passive funds is debatable, as active funds have demonstrated inconsistent evidence of superior after-fee, risk-adjusted returns relative to their benchmarks (Malkiel, 2005). This active versus passive debate draws on three predominant matters - market efficiency, performance, and performance persistence (Stein, 2003).

Market efficiency pertains to the efficient market hypothesis (EMH), which states that markets are informationally efficient and that security prices reflect market information as soon as it becomes available (Farmer & Lo, 1999). This implies that active managers cannot make use of available market information in order to derive risk-adjusted returns in excess of their benchmarks (Malkiel, 2005). However, Clearly et al. (2019) states that markets, as well as asset classes, may fall on a continuum between complete efficiency and complete inefficiency. Ozdemir (2008) argues that prices of securities in emerging market economies (EME), such as South Africa, are much less efficient than those in developed market economies (DME). Phiri (2015) provides evidence of this by showing that the South African equity market does have inefficiencies that can be exploited by active fund managers to derive risk-adjusted returns in excess of their respective benchmarks.

The concept of value-adding performance assumes that market inefficiencies exist and that it is possible for active funds to derive risk-adjusted returns in excess of their benchmarks (Stein, 2003). However, this concept seeks to understand whether active managers have the skill to exploit these inefficiencies to generate abnormal returns (Reilly & Brown, 2015). Furthermore, it considers whether abnormal returns (if any) are sufficient to overcome the expenses charged by the fund (Carhart, 1997; Droms & Walker, 2001). Lo (2004) states that infrequent market inefficiencies of sufficient size that allow skilful active fund managers to derive risk-adjusted returns in excess of their benchmarks and costs may occur even if markets are deemed to be relatively efficient. These inefficiencies have been shown to occur more frequently in EMEs (Aktan, Sahin, & Kucukkaplan, 2018).

The last matter, namely persistence, investigates whether funds that have generated a certain level of performance can continue to do so for a sustained period of time (Scher & Muller, 2005). Goetzmann and Ibbotson (1994) assert that the evaluation of the persistence in actively managed funds' performance aids in identifying skilful active fund managers, which will guide investors on which active funds to invest in to increase their wealth. Findings that actively managed funds can persistently earn risk-adjusted returns in excess of systematic benchmark returns (and fees) would produce evidence that active funds can consistently add value, as well as evidence against market efficiency (Clearly et al., 2019). This would justify the selection of an active fund over a passive fund since this would increase investors' wealth and standard of living both before and after retirement (Arifin & Mulyati, 2017). It has been suggested that it is possible to observe persistent performance, particularly in EMEs (Chen & Li, 2006; Mobarek, Mollah, & Bhuyan, 2008; Phiri, 2015).

Most prior analyses of persistence focus on equity mutual funds or unit trusts (Cremers, Fulkerson, & Riley, 2019). This suggests that a need exists for further analysis of the persistence of active fund performance. Given that South Africa is an EME that has demonstrated market inefficiencies and the possibility exists for actively managed South African funds to create value for investors. Therefore, investigating the matter of persistence further to infer whether actively managed South African funds are optimal investments compared to similar passive alternatives would add value. Finally, since passive funds are the alternative to actively managed unit trusts in the active versus passive debate, active fund performance is compared to passive alternatives' instead of their respective benchmarks.

1.2 PROBLEM STATEMENT

The sparse analyses of the persistence of unit trust performance result in a limited evaluation of South African funds' performance that guides investors in their decisions between active or passively managed unit trusts. This may lead investors to make suboptimal investment choices that may be detrimental to their levels of wealth and standard of living both before and after retirement.

1.3 PURPOSE STATEMENT

A more comprehensive evaluation of the performance persistence of South African unit trusts would be valuable. Hence, the purpose of this study is to investigate whether actively managed unit trusts demonstrate the ability to persistently outperform comparable passive unit trusts or exchange traded funds (ETF). This will be done from the perspective of South African investors and addresses the limitations of prior studies on persistence within an emerging market context.

1.4 RESEARCH OBJECTIVE

The objective of the study is to investigate whether actively managed South African unit trusts display persistent performance relative to passive alternatives by considering funds from the following ASISA categories:

- Equity;
- Interest-bearing;
- Multi-asset; and
- Real estate.

1.5 IMPORTANCE AND BENEFITS OF THE PROPOSED STUDY

This study assists in informing South African retail investors on whether to invest their capital with actively or passively managed South African unit trusts within the ASISA categories considered. This may enhance their wealth derived from investments, and their overall standard of living both before and after retirement. Past research on the persistence of unit trust performance is expanded on by evaluating persistence of actively managed unit trusts from several ASISA categories.

1.6 DELIMITATIONS AND ASSUMPTIONS

This study will only consider South African unit trusts and exchange traded funds that are registered as CISs. The performance will be measured based on the specific performance measures that consider return and risk characteristics of investments. The persistence of performance is considered only in terms of South African Rand. Only retail funds are considered. This study does not seek to explain the source of returns derived from the evaluated unit trusts based on the utilised performance measures, nor does it seek to describe the skill of unit trust managers. Furthermore, neither CISs that are constructed as funds of funds nor exchange traded notes are considered. Finally, this study assumes that the passive alternatives to which an active fund is compared is an appropriate representation of an alternative passive fund investment.

1.7 CHAPTER LAYOUT

This study is structured as follows: Chapter two presents a review that discusses pertinent literature that has contributed to the active versus passive debate and positions this work in accordance with it. Chapter three describes the methodology and data that will be utilised to address the identified problems. Chapter four reports and analyses the results, and chapter five concludes the study.

CHAPTER 2: LITERATURE REVIEW

This chapter begins by providing a brief history and overview of the South African unit trust industry. This is followed by a discussion on market efficiency in terms of the Efficient Market Hypothesis (EMH), the Adaptive Market Hypothesis (AMH), and active and passive fund management as the two broad resultant alternatives provided to the investor. It then addresses fund performance with respect to measurement, benchmarking, performance in aggregate, and the associated evidence. A discussion on the persistence of fund performance follows, including local evidence found on the matter. The final section concludes the literature review.

2.1 THE SOUTH AFRICAN UNIT TRUST INDUSTRY

The first South African unit trust was launched on the 14th of June 1965 by Sage (Oldert, 2018). This was done to provide the layman access to the South African securities market, which at the time was seen as only for those with specialist financial knowledge. The industry grew from an initial R600 000 assets under management (AUM) to R562 million between June 1965 and May 1969, when growth was stinted for nearly ten years after the South African stock market crashed in the second half of 1969 (Oldert, 2018). However, the stock market's resurgence in the latter part of the 1980s led to a rapid expansion of the unit trust industry once again (Meyer-Pretorius & Wolmarans, 2006). By the end of 2000, 265 registered unit trusts were in existence with R127 billion AUM – despite the stock market crash that occurred in 1987 (Meyer-Pretorius & Wolmarans, 2006). These figures grew to 943 funds with R927 billion AUM at the end of 2010, despite the market crash of 2008, and 1 686 funds with R2 730 billion AUM at the end of 2020 (ASISA, 2021). Meyer-Pretorius and Wolmarans (2006) attribute the growth of the industry to the ease of access that unit trusts provide to a diversified pool of assets. Figure 1 shows the growth that the South African unit trust industry has experienced between 1965 and 2020.

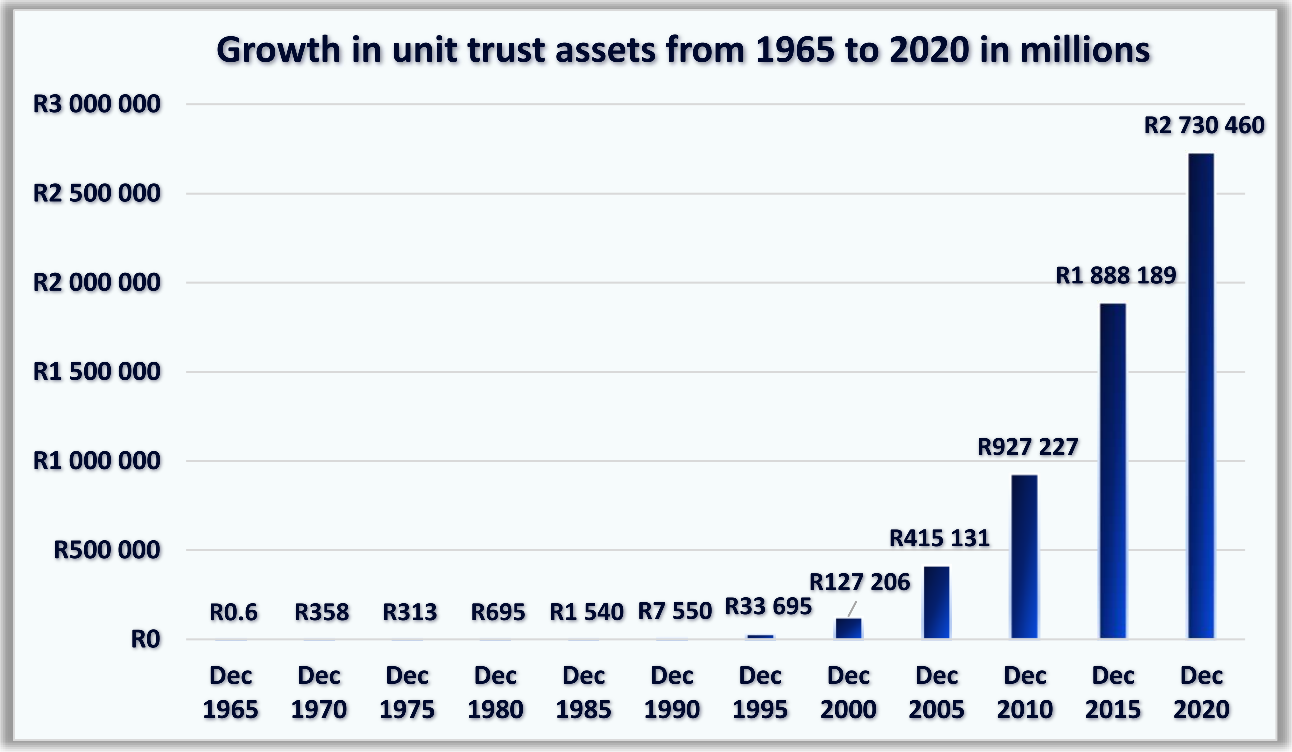


Figure 1: Growth in SA unit trust industry AUM

Source: Adapted from ASISA (2021)

2.1.1 The structure of collective investment schemes

A unit trust is a type of collective investment scheme (CIS) that divides a pooled set of funds into identical units, which represent proportional ownership of the assets purchased (Oldert, 2018). All CIS vehicles in South Africa are governed by the Collective Investment Schemes Control Act 45 of 2002 (CISCA), with unit trusts being the most common type (Oldert, 2018). According to Section 1(d) of the Collective Investment Scheme Control Act 45 of 2002 (CISCA), a CIS is a scheme that invites or permits members of the public to invest money in a portfolio (a pool of securities and/or funds) whereby at least two or more investors partake and hold participatory interests in the portfolio. The investors share the risks and benefits of their investment in proportion to their participatory interests in the portfolio.

CISs are regulated investment vehicles that are required to hold the portfolio of funds and assets in trust (Oldert, 2020). The trustee (typically banks or insurance companies) of a CIS acts as legal custodian of portfolio assets on behalf of the investors. The duties of trustees are set out in Section 70 of the CISCA; however, one of their primary functions is to ensure that the management of the portfolio assets is aligned with the deed of the CIS and CISCA (Section 70(1)(a)). CISCA defines the deed as an agreement between the manager and the trustee which sets out the general policies of the CIS that the manager must comply with. The manager, or management company, is the authorised entity that administers the CIS and is responsible for appointing trustees in terms of Section 68(1) of CISCA.

According to Section 4 of CISCA, the manager (or management company) of the CIS is responsible for the appointment of asset managers (Section 4(4)(c)). The asset managers of a CIS must manage the portfolio in accordance with the CIS's mandate, which describes the objectives, investment parameters, and constraints of the CIS (ASISA, 2018). The parameters in the mandate of a CIS is more specific than the policies of the CIS (as set out in the deed), while the constraints that limit the investment universe of the CIS to specific assets determines within which ASISA category the particular CIS falls (ASISA, 2018). Unit trusts are grouped by the Association for Savings and Investment South Africa (ASISA) into categories in terms of maximum allowable exposure to local and offshore asset classes. ASISA represents the interests, promotes the growth, and is the licensed body that administers the self-regulation of the South African CIS industry (ASISA, 2018).

According to Board Notice 90 of 2014 of CISCA, South African ETFs also fall under the regulation of CISCA. However, ETFs and unit trusts differ to some degree. The primary difference is that ETFs are traded on an exchange whilst the participatory interests of a unit trust are traded directly between the management company and the investor (known as an over-the-counter transaction) (Andhee, 2013). Furthermore, since ETFs are exchange traded, they can be traded at any time that the exchange is open, whereas the units of a unit trust can only be traded once a day (Charteris, 2013). Additionally, ETFs allow for the in-kind exchange of the underlying securities as redemption of participatory interest; and can be sold short – neither of which is possible with unit trust investments (Deville, 2008). Finally, unit trusts may be managed either actively or passively in contrast to ETFs, which are generally managed passively (Charteris, 2013). Table 1 summarises the differences between unit trusts and ETFs.

Table 1: Differences between unit trusts and ETFs

CIS	Unit trust	ETF
Method of exchange	Traded over the counter	Exchange traded
Frequency of exchange	Once a day	Any time that the exchange is open
Redemption	Cash	Cash or in-kind
Allowable positions	Long only	Long and short
Management	Active or passive	Mostly passive

2.1.2 Classification of South African collective investment schemes

Most of the unit trusts before the 1990s only invested in equities (Oldert, 2018). Today, however, an array of unit trusts and ETFs that invest in different asset classes and geographic regions are available to the South African investor (Oldert, 2018). ASISA categorises these CISs according to a three-tier structure (ASISA, 2018):

- First-tier: classification based on geographic focus – South African, worldwide, global, and regional.
- Second-tier: broad asset allocation classes – equity, multi-asset, interest-bearing, and real estate.
- Third-tier: based on aspects such as sector, time horizon, and specific prudent limits.

The category under which each CIS is registered constrains the allowable exposure to certain assets in terms of geographic focus and asset class (ASISA, 2018). Currently, funds registered with ASISA as South African CISs must invest at least 60 percent of their assets in South African markets. Moreover, a maximum of 30 percent of assets may be invested outside South Africa, and 10 percent of South African CISs' assets may be invested specifically in Africa (excluding South Africa) (ASISA, 2018). In addition to the investment options provided under the second- and third-tier categories, CISs may vary according to the broad management strategy employed – namely, active and passive management.

The growth in the South African CIS industry has led to an increased variety of investment options in terms of exposure to different asset classes compared to products prior to the 1990s (Oldert, 2020). Passive and active investment alternatives have expanded the option-set even further. However, uncertainty exists among researchers and practitioners regarding which of the two management strategies benefits the investor most. Stein (2003) suggests three elements that must be considered to make an optimal decision between the two alternatives: market efficiency, performance, and performance persistence.

2.2 MARKET EFFICIENCY

The ASISA classification of funds will affect the investable universe and security-specific characteristics that may influence fund performance – these are ergonomic elements of fund performance (Brown, 2008). Further ergonomic elements that influence fund performance, such as economic changes and market quality, are determined by the efficiency of the respective markets that funds invest in (Brown, 2008). The extent of a particular market's efficiency influences the price behaviour of securities within it (Fama, 1970). Therefore, since funds are portfolios of securities, market efficiency has a bearing on the decisions of fund investors. Two predominant hypotheses have been proposed in the attempt to describe the efficiency of markets – the Efficient Market Hypothesis (EMH) and the Adaptive Market Hypothesis (AMH). This section discusses these two hypotheses and their influence on investment decisions relating to active and passive funds.

2.2.1 The Efficient Market Hypothesis

The EMH states that markets are efficient and that security prices fully reflect all available information within the market (Fama, 1970). This means that new information that becomes available in the market spreads quickly and is incorporated into security prices immediately (Malkiel, 2003). This definition of market efficiency was first proposed by Fama (1965), stating that stock prices follow a random walk, which according to Samuelson (1965), meant that correctly priced securities would fluctuate randomly. This implies that the price movements of securities from one period to the next are independent of each other, and therefore approximate a random walk pattern (Malkiel, 2003). This random walk pattern suggests that security prices cannot be predicted apart from their long-run upward trend (Malkiel, 2003).

The original definition of market efficiency as defined by the EMH was deemed to be restrictive, which led many authors to reject it (Ball & Brown, 1968; Fama, Fisher, Jensen, & Roll, 1969). This led Fama (1970) to expand on his prior work by proposing a framework that describes the degree of market efficiency in terms of three forms – weak, semi-strong, and strong.

- The weak form of market efficiency stipulates that security prices reflect all past market data and that investors cannot obtain superior risk-adjusted returns relative to the market by extrapolating patterns from past price information (known as technical analysis).
- The semi-strong form of market efficiency stipulates that security prices reflect all publicly available information and that investors cannot obtain superior risk-adjusted returns relative to the market from performing technical analysis or from analysing financial data to predict future security prices (known as fundamental analysis).
- The strong form of market efficiency stipulates that security prices fully reflect all public and private information, which means investors cannot make use of technical analysis, fundamental analysis, or private information to derive excess risk-adjusted returns relative to the market.

The degree of market efficiency varies among different geographical markets as well as markets for various asset classes (Clearly et al., 2019; Duhon, Spentzos, & Stewart, 2019). Clearly et al. (2019) states that the three predominant factors that drive the degree of efficiency are the number of market participants, information availability, and impediments to trading. When many participants partake in a particular market, the mispricing of securities is corrected faster as a greater degree of competition exists among the participants to correctly incorporate information to extract abnormal profits before other participants can. Additionally, limiting impediments on trading that inhibit participants from utilising available information in their trading activity enhances their ability to incorporate relevant information into security prices correctly.

Developed market economies (DMEs) have a greater number of market participants, greater availability of information, and fewer impediments to trading (Clearly et al., 2019). In contrast, emerging market economies (EMEs) have fewer market participants, less availability of information, and greater impediments to trading (Clearly et al., 2019). As a result, financial markets in EMEs tend to be less efficient than those in DMEs (Aktan et al., 2018; Fountas & Segredakis, 2002; Kearney, 2012; Ozdemir, 2008). However, evidence of anomalies has been found – particularly relating to the strong and semi-strong forms of market efficiency (Gabriela ğiĠan, 2015; Lee, Lee, & Lee, 2010; Phiri, 2015). Chowdhury, Howe, and Lin (1993) and Long and Rao (1995) found evidence that trading based on private information delivers abnormal returns in both DMEs and EMEs, suggesting that the strong-form of the EMH does not hold. Gan, Lee, Hwa, and Zhang (2005) and Raja, Sudhahar, and Selvam (2009) provide evidence that shows that the semi-strong form of the EMH does not hold in DMEs or EMEs either.

Weak-form market efficiency attracts the most attention in the empirical literature (Gabriela ğiĠan, 2015). This form draws strongly on the random walk process, as it states that security prices change over time based on a pattern that follows a linear drift (i.e. a non-random trend) and a random shock component (Fama, 1970). When time-series data (such as security price changes over time) follows such a pattern, it is said to display a unit root or that it follows Geometric Brownian motion (GBM) (Lee et al., 2010). Therefore, to test if markets are weak-form efficient, researchers test the time-series data of security price changes for the presence of a unit root (Aktan et al., 2018). Most literature on this subject tested for the presence of a unit root by making use of statistical methods that implicitly assume that no non-linearities exist in the drift component and that the data considered contains no structural breaks (i.e., a change in the governing set of relationships within the time-series data considered) (Aktan et al., 2018). However, these assumptions have been criticised by more recent literature (Gabriela ğiĠan, 2015; Lee et al., 2010; Phiri, 2015).

Studies that have tested for weak-form market efficiency without considering the effects of non-linearities and structural breaks have been inconclusive for both DMEs and EMEs (Chaudhuri & Wu, 2003a, 2003b; Narayan & Narayan, 2007). According to Lim and Brooks (2011) as well as Phiri (2015), studies that utilise tests that ignore the influence of these factors produce trivial results as both EMEs and DMEs are susceptible to social, economic, and political shocks, which may cause non-linearities and structural breaks to arise within the data under consideration. More recent literature utilises statistical models that account for these factors and have produced more conclusive evidence. It demonstrates that the financial markets of both DMEs and EMEs fluctuate through periods of weak-form efficiency and inefficiency (i.e., not weak-form efficient). However, DMEs tend towards weak-form efficiency, whilst EMEs tend toward weak-form inefficiency (Lee et al., 2010; Narayan, 2006, 2008; Narayan & Smyth, 2007; Ozdemir, 2008). Appiah-Kusi and Menyah (2003) and Phiri (2015) demonstrate that the latter is the case for the South African stock market by showing that the market tends to be weak-form inefficient.

The evidence that demonstrated that markets fluctuate in terms of their degree of efficiency over time does not fully conform to the original definitions of market efficiency as proposed by Fama (1970). Instead, they assume that the level of market efficiency is constant over time (Urquhart & McGroarty, 2016). Therefore, the evidence suggests that the extent of a particular market's efficiency can be altered over time by structural changes that occur due to market shocks. This concept of time-varying market efficiency was accounted for by the AMH, a hypothesis that was built on the theory provided by the EMH.

2.2.2 The Adaptive Market Hypothesis

The EMH assumes that market participants act rationally when incorporating market information into security prices (Lo, 2004). However, evidence suggests that participants can make large errors in the pricing of securities due to the biases inherent in human behaviour (De Bondt & Thaler, 1990; Huberman & Regev, 2001; Malkiel, 2003). Behavioural finance – the study of human behaviour in financial decisions – asserts that market participants are not fully rational and may occasionally be driven by emotion (Lo, 2004; Shefrin, 2001). Behaviourists argue that market participants behave similarly, which may result in information being erroneously translated into security prices (Akerlof & Shiller, 2010; Shiller, 2000; Sine & Strong, 2019). Behavioural finance and the EMH are at odds with each other; however, both disciplines have attained traction in the empirical literature (Verheyden, De Moor, & Vanpée, 2016). In response to this debate, Lo (2004) provided an alternative point of view where both schools of thought may work in tandem. This theory has been termed the Adaptive Market Hypothesis (AMH). The AMH provides a framework that reconciles the EMH with the evidence of behavioural biases inherent in individuals' decisions (Lo, 2005), as depicted in Figure 2.

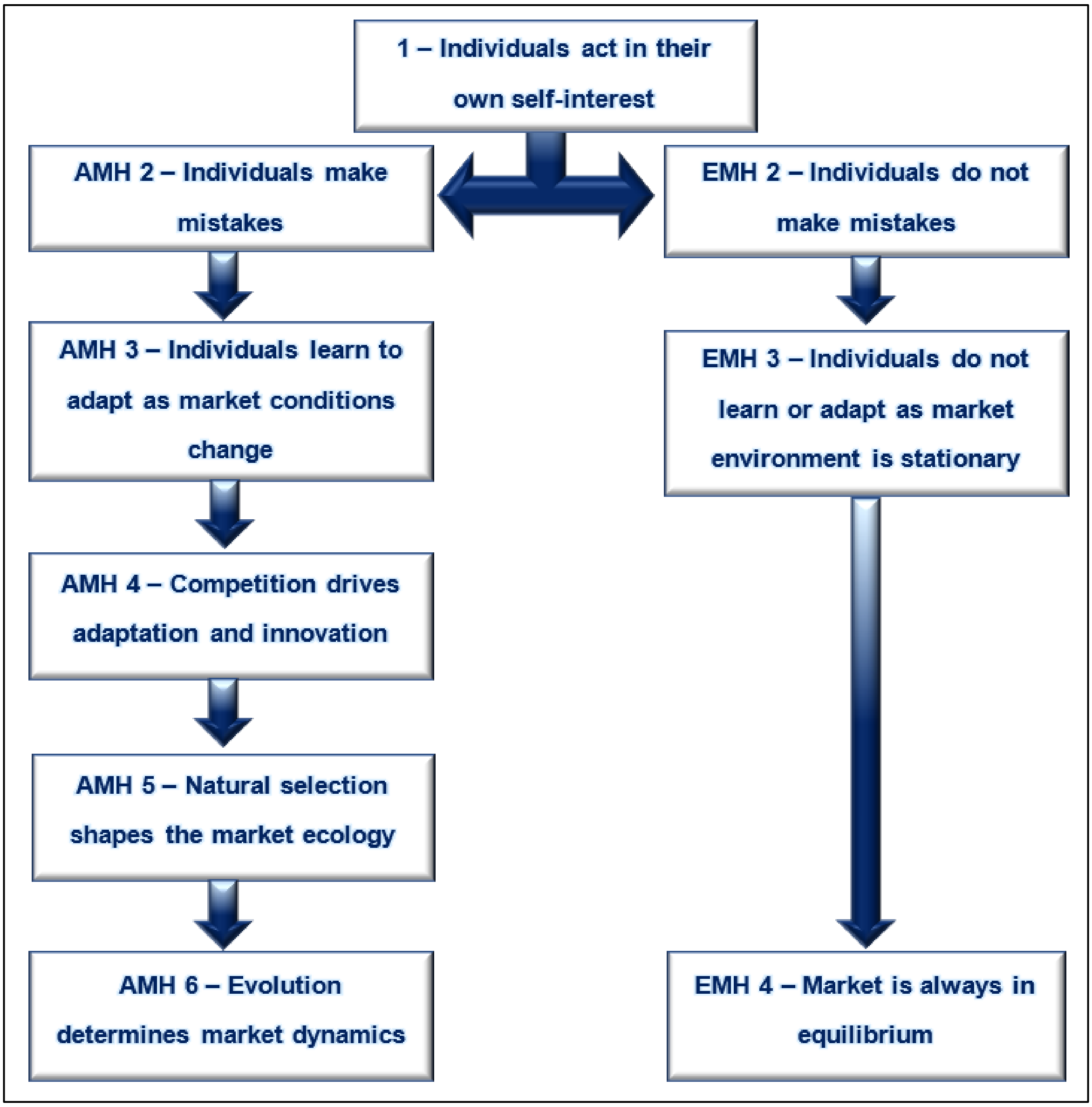


Figure 2: Framework of market efficiency as described by the AMH

Source: Adapted from (Lo, 2004, 2005)

The AMH asserts that the financial market is a "coevolving ecology" (Farmer & Lo, 1999). Within this "ecology", participants hold rational expectations to maximise expected utility (i.e., they act in their own self-interest) (Lo, 2005). This is consistent with the EMH (block 1 of Figure 2). However, changes to this "ecology" can occur by means of endogenous or exogenous shocks, as suggested by Lim and Brooks (2011) and Phiri (2015). The AMH departs from the EMH in its description of market efficiency in the event of such shocks. When shocks occur, the AMH states that participants will make decisions based on their best guess of what is optimal – which is guided by behavioural biases. This causes individuals to make mistakes (or behave irrationally) (Lo, 2005). Participants learn from these mistakes to adapt to the changes in the functionality of the market (Lo, 2005) (blocks AMH 2 and 3 of Figure 2). This contrasts with the EMH, which suggests that individuals do not make mistakes since the market environment is considered stationary, and always in equilibrium – or steady-state (Lo, 2004, 2005) (blocks EMH 2 to 4 of Figure 2).

Competition amongst participants drives the adaptation process as they seek to “survive” (profit from) the pricing aberrations caused by shocks through the innovation of new trading strategies (Lo, 2004) (block AMH 4 of Figure 2). Throughout this period of “stress on the ecology”, participants are influenced by behavioural traits such as fear and greed that affect their decision-making process and the formation of new strategies (Lo & Repin, 2002). “Survivors” of the adaptation process trade away inefficiencies in prices with their new trading strategies at the cost of those who are unable to adapt sufficiently – or those on the opposing side of the new and innovative trades (Lo, 2004, 2005). Lo (2004) described this as a process of natural selection that alters the market’s dynamics and efficiency (block AMH 5 of Figure 2). The occurrence of the natural selection process in response to periodic shocks to the market “ecology” facilitates a continual evolution of market dynamics and efficiency over time (Lo, 2004, 2005) (block AMH 6 of Figure 2).

The functionality of the market, as described by the EMH, applies when the market is in a steady-state – when no structural changes to the market environment are occurring (Lo, 2004, 2005). The AMH implies that markets will continually experience periods of efficiency and inefficiency as disturbances to the market environment occurs (Lo, 2004, 2005). Empirically, this would result in the market displaying a pattern of time-varying efficiency whereby the market would follow a pattern that approximates GBM in some periods whilst displaying significant structural breaks during times of stress (or volatility) (Lo, 2004, 2005). The AMH also provides a rationale for the fluctuation between weak-form efficiency and weak-form inefficiency observed within DMEs and EMEs (Lee et al., 2010; Lim & Brooks, 2011).

Since the advent of the AMH, several studies have tested its explanatory power of market behaviour in both DMEs and EMEs. DMEs tend to experience less frequent shocks; however, significant time-varying efficiency is observed when these shocks occur (Ito & Sugiyama, 2009; Kim, Shamsuddin, & Lim, 2011; Lim, Luo, & Kim, 2013; Urquhart &

McGroarty, 2016). In contrast, EMEs tend to experience a more significant number of shocks and have also been demonstrated to display a considerable amount of time-varying efficiency (Lim, Brooks, & Kim, 2008; Smith, 2012; Todea, Ulici, & Silaghi, 2009). Urquhart and Hudson (2013) also find evidence of time-varying efficiency and contend that the AMH may better describe market behaviour than the EMH.

The recent evidence in favour of the AMH's description of market efficiency, as well as the evidence against the weak form of the EMH (especially in EMEs), has challenged the conventional view that passive funds were superior alternatives compared to active funds (Cremers et al., 2019). In particular, recent findings suggest that both alternatives may be viable options, depending on the nature and dynamics of the markets invested in (Cremers et al., 2019).

2.2.3 Active and passive fund management

Active and passive funds are a manifestation of views on market efficiency in how funds are managed. Accepting the EMH would suggest that the investor should favour passive funds, whilst rejection thereof would suggest that active funds may be optimal. In contrast, the AMH suggests that the favourability of each alternative varies over time. Asset managers may apply active or passive investment strategies to various forms of portfolios. However, the interests of fund-investors are focused on the performance of active- or passively managed funds.

The fundamental objectives of active and passive funds differ, which results in differences in the way that they invest their capital (Ambachtsheer, 1994). Passive funds seek to mimic the performance of a benchmark (typically a market index) and to minimise the cost of investing (Waldeck, 2012). Conversely, active funds strive to outperform a particular benchmark on a risk-adjusted, net-of-fee basis (Cremers et al., 2019). To achieve their objective, active fund managers attempt to identify and invest in assets that they think will perform well whilst avoiding investments in assets that are expected to perform poorly. Active funds invest in assets that may or may not form part of its benchmark's constituents. Passive fund managers, in contrast, generally buy and hold the benchmark assets in exact proportion to the overall market value of the benchmark index – a method known as pure indexing (Blocher & Whaley, 2015). Passive fund managers may also make use of optimisation or sampling methods of indexing. These indexing methods attempt to identify and purchase assets that exhibit the primary characteristics of benchmark assets to capture their return driving factors (Gastineau, Olma, & Zielinski, 2007).

Active management assumes that there are enough inefficiencies within the market to achieve its fundamental objective. Active funds can achieve this objective when they are able to extract and use information superior to that communicated by the market, correct the mispricing of assets due to trades based on inferior information, and provide liquidity to forced asset sales to earn liquidity premiums (Barras, Gagliardini, & Scaillet, 2020). On the other hand, passive management assumes that markets are mostly efficient and that a fund cannot consistently outperform its benchmark after adjusting for investment risk and fees (Waldeck, 2012). Passive funds, therefore, attempt to transfer as much of the benchmark's performance as possible to the investor. Researchers and practitioners acknowledge that active management is worth pursuing in some markets whilst not in others (Ambachtsheer, 1994). The increased frequency of shocks and the greater amount of inefficiencies in EMEs, as found in the empirical literature on the EMH and AMH, may suggest that these markets are more suited to active management (Wood, 2012).

The AMH suggests that the ability of a particular active manager to achieve their objective can only be done provided that the manager can adapt, innovate, and derive sufficient returns to overcome investment fees in changing market conditions (Campbell et al., 1997; Grossman & Stiglitz, 1980; Verheyden et al., 2016). Verheyden et al. (2016) demonstrated that inefficiencies coincide with times of stress in the market and that some active managers can achieve their objectives during these periods. Active managers who demonstrated the ability to learn from structural changes and manage downside risk during periods of stress were successful in outperforming their market benchmarks (Verheyden et al., 2016).

Globally (South Africa included), active managers charge higher fees than passive managers (Coetzee, de Villiers, & Nel, 2018; Novara, McGee, & Rice, 2019). Greater research and trading fees raise the investment costs of active funds (Grinblatt & Titman, 1989). Passive fund managers use optimisation and sampling methods of indexing to reduce the rebalancing and transaction costs incurred by the fund (Blocher & Whaley, 2015). Another technique used to reduce investment costs is scrip lending. This is where a fund borrows assets that it owns to short-sellers for a fee to enhance returns (Blocher & Whaley, 2015). Scrip lending is predominantly utilised by passive funds as they do not intend to sell overvalued securities like active funds (Blocher & Whaley, 2015). Honkanen (2020) shows that the use of scrip lending significantly reduces the investment fees charged by passive funds. According to Section 85(2) of CISCA, all CISs are permitted to make use of scrip lending; but the mandates of active funds generally limit the use thereof (Honkanen, 2020).

In South Africa, passively managed unit trusts and ETFs are two types of funds that provide exposure to passive management; whilst actively managed unit trusts provide exposure to active management (Andhee, 2013; Charteris, 2013; Strydom, Charteris, & McCullough, 2015). ETFs have been demonstrated to track their benchmark indices more effectively and at a lower cost compared to their comparable passive unit trusts (Andhee, 2013; Strydom et al., 2015). However, the price at which ETFs trade may depart from the underlying portfolio's net asset value (NAV) (Charteris, 2013; Steyn, 2019). Both passive unit trusts and ETFs are regarded as reliable forms of passively managed funds (Andhee, 2013; Strydom et al., 2015). Smart beta ETF funds, which attempt to provide concurrent exposure to both strategies, exist as well (Malkiel, 2014). Table 2 summarises the differences between active and passive management.

Table 2: Differences between active and passive management

	Active Management	Passive Management
Fundamental objective	To outperform benchmark on a risk-adjusted, net-of-fee basis.	To mimic benchmark performance and to minimise investment costs.
Investment methods	Invests in assets that are expected to perform well. Avoids assets expected to perform poorly. Limited use of scrip lending.	Pure, optimised, and sampling methods of indexing. Greater use of scrip lending.
Theoretical assumptions	Markets are mostly inefficient.	Markets are mostly efficient.
Investment costs	More costly than passive management.	Less costly than active management.

2.2.4 Arguments for passive funds

The most frequently cited reason why passive funds may be superior investments is that active funds are, on average, unable to outperform their benchmarks on a net-of-fee basis

(Fortin & Michelson, 2002). This has been demonstrated in both DMEs and EMEs (Choi & Zhao, 2020; Janse van Rensburg & Krige, 2018; Wermers, 2000; Wessels & Krige, 2005a). In addition, most DMEs and some EMEs have been demonstrated to be relatively efficient – which validates the assumption of passive management (Gabriela ğiĠan, 2015). It is also argued that passive funds tend to be less risky compared to active funds since they do not take on the risk of incorrectly forecasting asset prices (Malkiel, 2003), and they hold widely diversified portfolios that mimic the market index (Andhee, 2013). Finally, passive funds earn more from scrip lending since short-sellers prefer to lend from them as active funds are more likely to recall their assets in market downturns (Engelberg, Reed, & Ringgenberg, 2018; Honkanen, 2020; Johnson & Weitzner, 2018).

These aspects have led to a proliferation in the number of passively managed funds in DMEs (Cremers, Ferreira, Matos, & Starks, 2016). However, the number of passively managed funds in EMEs has increased at a slower rate (Bhattacharya & Galpin, 2011; Waldeck, 2012). Figure 3 demonstrates this by comparing the AUM proportions of active funds to passive funds in the South African General Equity ASISA category. Funds of funds and smart beta ETFs have been excluded for this comparison.

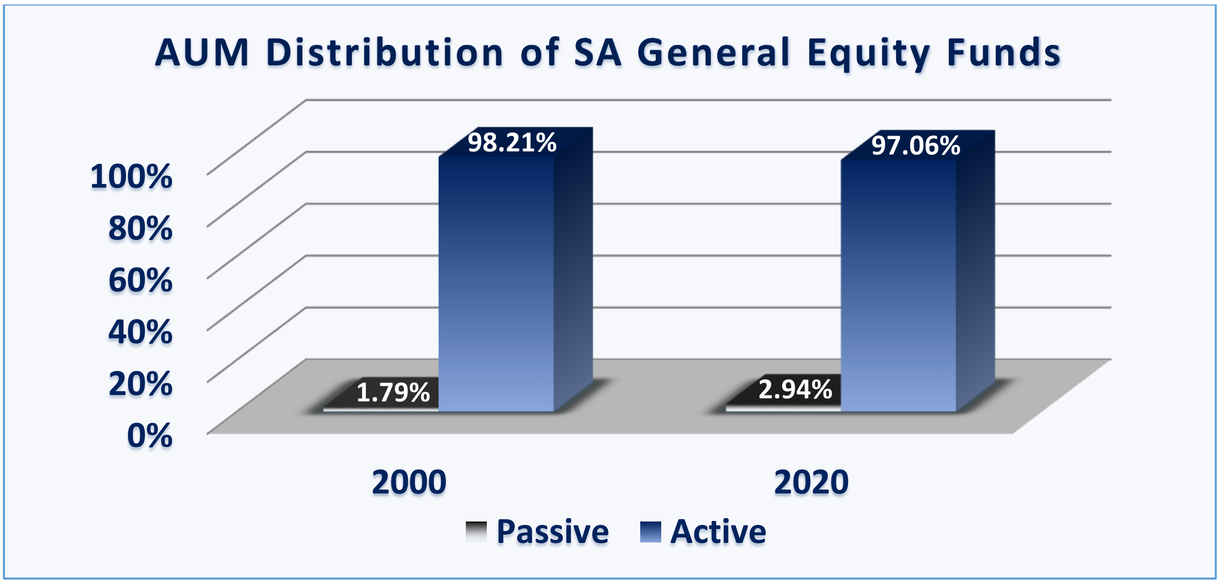


Figure 3: Distribution of assets under management (AUM) of SA General Equity Funds

Source: Adapted and calculated from ASISA (2000), ASISA (2021), and Morningstar Direct

Masters (1998) argues that passive management in EMEs is counterintuitive as these markets are generally less efficient. Therefore, the case for active management in EMEs is much stronger since the fundamental assumption of passive management does not fully hold in these markets (Gabriela ğiĠan, 2015; Masters, 1998).

2.2.5 Arguments for active funds

If active funds derive superior net-of-fee performance compared to passive alternatives, active funds are valuable investments, even if their performance does not beat that of the index against which their performance is measured (Coetzee et al., 2018). Furthermore, active funds tend to outperform passive alternatives in times of market stress (Aktan et al., 2018; Peng, Chen, Shyu, & Wei, 2011). It is thus reasoned that active funds are more likely to outperform passive alternatives in EMEs as their markets are more volatile and prone to more frequent periods of market stress (Wood, 2012). Furthermore, benchmark indices in EMEs tend to experience greater asset turnover and are more concentrated (Masters, 1998) – both matters that are evident in South African indices (Raubenheimer, 2010, 2012; Rickens, 2020). It is thus argued that passive funds in EMEs would expose investors to concentrated asset positions and incur greater rebalancing costs. This would expose passive investors to greater investment risk and higher trading fees (Lambridis, 2017) – factors that are inconsistent with passive funds' fundamental objective. Additionally, Pedersen (2018) contends that more frequent reconstitutions of benchmark indices provide active funds with greater opportunities to achieve their objective. Finally, Honkanen (2020) demonstrate that active funds which engage in a limited degree of scrip lending can gain information from short-sellers about which assets to avoid, which can be used to derive performance in excess of passive funds that will retain their positions in these assets.

To date, limited evidence suggests that active funds can achieve their fundamental objective has been found (Malkiel, 2005; Muller & Ward, 2011). Therefore, to determine which of the two alternatives – active or passive funds – are superior, an evaluation of how they perform would be valuable.

2.3 PERFORMANCE

Fund performance entails an evaluation to determine how much better off the investor was from investing in a particular fund relative to other alternatives over a certain period (Berk & Van Binsbergen, 2015, 2017). Since the returns obtained by the investor is net of fees, investors are typically concerned with net-of-fee performance analyses (Allen, Brailsford, Bird, & Faff, 2003; Berk & van Binsbergen, 2017). Evaluation tools are employed to infer which funds out- and underperformed relative to some desired standard. The tools used for this evaluation are referred to as performance measures and benchmarks. From the perspective of active and passive funds, performance analyses may be utilised to distinguish which set of funds were superior over a certain evaluation period. Therefore, this section will discuss the matters pertaining to performance measurement and benchmarking as background to the theory and evidence of fund performance analyses discussed thereafter.

2.3.1 Performance measurement

The risk and return of an investment are positively correlated (Allen et al., 2003); therefore, a fund manager may potentially increase a fund's returns by investing in more risky assets (Grinold & Kahn, 2000b). However, investors tend to prefer less risk (Sharpe, 1966); hence, a suitable measure of fund performance must incorporate both the return and risk (Sharpe, 1966). Brown, Goetzmann, Ibbotson, and Ross (1992) stress the importance of this, as they show that a failure in doing so can result in misinterpretations of fund performance. The appropriate adjustment for risk is subject to debate; hence, risk-adjusted performance measures are a matter of continuing research. Different measures may lead to different inferences of fund performance (Brown, 2008; Ferson & Schadt, 1996); however, some of the most recognised risk-adjusted measures include the Sharpe ratio, Jensen's alpha, and the information ratio (Allen et al., 2003; Waldeck, 2012). Additionally, the Fama-French three-factor model and the Fama-French-Carhart four-factor model are recognised risk-adjusted performance measures that attribute returns to an identified set of risk factors (Carhart, 1997; Fama & French, 1993; Waldeck, 2012).

The Sharpe ratio calculates a fund's return above the risk-free rate relative to the total amount of risk taken on by the fund (measured by the standard deviation of returns) (Sharpe, 1994). Jensen's alpha is an intercept of a regression equation that explains a particular fund's returns (in excess of the risk-free rate) relative to the returns above the risk-free rate derived by a proxy of the market portfolio (referred to as the single-factor model) (Jensen, 1968). Finally, the information ratio is a ratio of returns above or below a fund's benchmark (typically a proxy of the market portfolio) relative to the excess risk taken on compared to the benchmark (measured by the standard deviation of excess returns) (Grinold, 1989).

Fama and French (1993) and Carhart (1997) expanded Jensen's original single-factor model. Fama and French introduced a three-factor model which added the equity size and book-to-market values as risk factors in addition to the original market proxy risk factor. Carhart introduced an additional risk factor that accounts for equity price momentum - the tendency for rising equity prices to continue rising in the short-term (Jegadeesh & Titman, 1993). Collectively, this produced the Fama-French-Carhart four-factor model. This measure adjusts for an equity fund's performance for aggregate market risk, the risk associated with equity market capitalisation, equity value or growth style characteristics, and equity price momentum. The four-factor model exhibited superior explanatory power of US equity mutual fund performance compared to the single- and three-factor models (Carhart, 1997). Since most research on fund performance centred around equity mutual funds in the US, this model gained the most traction in the empirical literature since its inception (Cremers et al., 2019). However, adaptations of these equity factor models that benchmark fund performance to alternative risk-factors have also been used.

In addition to the described, a more simplistic risk-adjusted performance measure is a fund's excess performance relative to a benchmark (excess returns). In this context, the term alpha also refers to how much better off the investor is for investing in a particular fund. For this measure to be appropriate, and since active funds seek to outperform a benchmark on a risk-adjusted, net-of-fee, basis; a fund must have a benchmark that mimics the risks that a fund will take on (Allen et al., 2003).

2.3.2 Performance benchmarking

The benchmark acts as a risk-return performance combination that funds seek to match or outperform and is often represented by a proxy of the market that a fund invests in (Grinold & Kahn, 2000a). A fund's performance can be evaluated on an absolute basis – which is its performance compared to its benchmark; and a relative basis – which is its performance relative to a peer group of funds (Allen et al., 2003). These forms of evaluation provide different standards to which fund performance can be compared. Absolute performance is the primary evaluation used to infer whether a fund added value to the investor (active funds) or whether it tracked the benchmark effectively (passive funds) (Berk & Van Binsbergen, 2015). Active managers add value to investors if they deliver greater net-of-fee, risk-adjusted return than an appropriate benchmark (Cremers et al., 2019). Hence, the conclusions drawn about the value that an active fund creates for an investor only has merit if an appropriate benchmark is used in its performance evaluation. The inconclusive research on risk-adjustment (for performance measurement) and the requirement that appropriate risk must be reflected in benchmarks means that the allocation of suitable fund benchmarks is a subject of continuing research as well (Grinold & Kahn, 2000a).

Conventional benchmarks include market or style indices representing the market or investment style that a particular manager seeks to mimic or outperform (Cremers & Petajisto, 2009). Some active funds employ an absolute rate of return as a benchmark – which is a stated numerical return objective (for example, 7 percent). Passive funds do not use absolute return objectives as they cannot employ indexing techniques on such a benchmark. Passive funds do not use holdings-based benchmarks either since these benchmarks are used to evaluate active fund managers' security selection and market timing abilities (Daniel, Grinblatt, Titman, & Wermers, 1997; Wermers, 2000).

In terms of the respective performance measures, a Sharpe ratio greater than that of its benchmark, as well as positive information ratios or excess return measures, signal that a fund outperformed on a risk-adjusted basis. If this outperformance held on a net-of-fee basis, the fund would have added value to the investor (Cremers et al., 2019). The single-, three-, or four-factor models implicitly benchmark their performance to the risk factors in the models (Cremers, Petajisto, & Zitzewitz, 2012; Huij & Verbeek, 2009; Jensen, 1968). Thus, a fund would demonstrate risk-adjusted outperformance if the alpha is positive and value addition if the alpha is positive and returns were measured on a net-of-fee basis (or positive net-alphas). Market indices, and by extension, the passive funds that mimic them should theoretically deliver alphas of zero when evaluated with factor models on a gross-of-fee basis (or gross-alphas) and negative net-alphas (Cremers et al., 2012). All the above measures may also be calculated for a peer group of funds to rank them in terms of relative performance. This informs the investor which funds were top and bottom performers within a particular subset of funds. Hence, the described measures may be used to determine both absolute and relative performance amongst a group of funds.

The ability of an active fund to add value describes whether an investor is better-off for investing in it and not its benchmark (Berk & Van Binsbergen, 2015, 2017). The literature on fund performance tends to focus on active funds' ability to add value - or to achieve their fundamental objective. Evidence of the inability to do so is generally viewed as evidence in favour of passive funds since it is assumed that they can readily mimic the risk factors inherent to most benchmarks (Berk & Van Binsbergen, 2015, 2017). Performance studies that investigate the optimality of active and passive funds apply the described measures and benchmarks to derive this evidence. Accordingly, Sharpe (1991) proposed a theory that describes what should theoretically be observed in such evaluations.

2.3.3 Performance in aggregate

Sharpe (1991) introduced a concept that attempts to describe active funds' ability to add value to investors, known as the arithmetic of active management. The market return is the weighted average of all securities within it (Sharpe, 1991), and passive investors hold the market portfolio through replication. Thus, the gross-of-fee return on the average passively managed dollar must equate to the market return. Active investors within the same market who seek the outperformance thereof are constrained by the same investable universe. Therefore, successful active trades within the same market must come at the cost of unsuccessful active trades. Thus, the population of active investors within a particular market must be made up of a group of simultaneously out- and underperforming active investors whose collective gross-of-fee performance aggregate to that of the overall market. The gross-of-fee return on the average actively managed dollar, therefore, must also equate to the return of the market. However, since active investors bear greater costs than passive investors, the net-of-fee return on the average actively managed dollar must be less than that of the average passively managed dollar (Sharpe, 1991). It is thus reasoned that the aggregate net-of-fee performance of active managers must be inferior compared to the aggregate net-of-fee performance of passive managers.

Fama and French (2008) produce evidence in favour of this concept, except they refer to this idea as equilibrium accounting. They argue that the aggregate net-of-fee performance of active management is a negative-sum game equal to the average cost imposed by active managers on investors. Fama and French (2009) expand this argument by contending that equilibrium accounting should hold regardless of what a certain set of investors define their investable universe as (for example, as only value or growth stocks). Additionally, in their study on market efficiency and fund performance, Verheyden et al. (2016) presented evidence that some active funds' outperformance was at the cost of underperforming active funds. Finally, the AMH also suggests that "survivors" profit at the expense of those who are unable to adapt and innovate sufficiently (Lo, 2004, 2005).

According to Sharpe (1991), this does not negate the practice of active management. The researcher states that it is "perfectly possible" for some active funds to outperform passive funds on a net-of-fee basis, as only a majority share of all actively managed dollars is bound to underperform. Furthermore, active funds do not make up the entire population of active investors, as individual investors and other actively managed investment products form part of the active investor population. Lastly, not all passive investors utilise a pure indexing approach. Some passive investors use optimisation or sampling-based approaches that may be more or less successful than the market over some evaluation periods. Therefore, Sharpe (1991) states that the best way to determine whether a particular active fund is a valuable investment is to compare its performance to that of a comparable passive alternative.

Pedersen (2018) revised the arithmetic of active management by presenting evidence that shows that it is possible for active investors, particularly active funds, to beat passive funds on aggregate on a net-of-fee basis. Pedersen (2018) argues that the continual reconstitution of various investment universes, and the addition and subtraction of securities from these universes, create the opportunity for active investors to add value on aggregate. Pedersen (2018) states that the introduction or deletion of securities to and from an investable universe (through initial public offerings, seasoned offerings, bankruptcy, and the inclusion or removal of securities from an index – depending on the investable universe) routinely result in a large amount of mispriced assets. This provides active investors with an opportunity to find undervalued assets and avoid overvalued assets, whilst passive investors would accept the market determined price.

Additionally, indices that represent a particular investment universe must be rebalanced over time, which will force passive managers to rebalance and incur transaction costs (Pedersen, 2018). These uniform and relatively concurrent trades may then inflate or depress security prices (Pedersen, 2018), which can increase the transaction costs charged by brokers providing the opportunity for active managers to take advantage of liquidity premiums or discounts as suggested by Barras et al. (2020). In aggregate, the more frequently reconstitution and asset removal or addition occur, the more opportunity there will theoretically be for active managers to add value (Pedersen, 2018). Both Sharpe and Pederson's arguments are well-grounded in theory; however, they must be reconciled with empirical evidence to evaluate their merit.

2.3.4 Evidence

Most academic literature on fund performance is biased towards equity mutual funds in the US (Cremers et al., 2019). Therefore, most of the evidence on this subject focussed on active equity funds' ability to outperform their benchmarks after fees in the US market. Jensen (1968) was one of the first authors to investigate whether active funds can add value to investors. He found that, on average, active funds are unable to do so. Ippolito (1989) revisited Jensen's work and found that active funds can add value, but not once load fees (sales charges for purchasing fund shares/units) are considered. Both Jensen (1968) and Ippolito (1989) made use of the single-factor model. Gruber (1996) and Choi and Zhao (2020) subsequently confirmed Ippolito's findings using four-factor models, also presenting strong evidence supporting Sharpe's theory. These works agree that, on aggregate, active funds in the US are unable to add value to the investor.

Hendricks, Patel, and Zeckhauser (1993) and Fama and French (2010) show that the underperformance of poorly performing active funds exceeds the superior performance of well-performing active funds in most periods. As a result of this, estimates in aggregate are biased downwards, which thus ignores the ability of top-performing active funds to add value (Hendricks et al., 1993). This, as well as the four-factor model's superior explanatory power of US mutual fund performance (Carhart, 1997), spurred a subset of research that revisited the topic using enhanced versions of the model.

Kosowski, Timmermann, Wermers, and White (2006) used an adaptation of the four-factor model and found significant evidence of value addition among the top 10 percent of funds. The researchers concluded that most active funds could not add value to their investors; however, a subgroup of top-performing active funds are consistently able to do so. Fama and French (2010) conducted a study that made use of a similar adaptation of the four-factor used by Kosowski et al. (2006). However, they found that less than two percent of active funds can add value. Fama and French (2010) attributed the difference in their results to the differences in time periods studied. Additionally, the researchers only required a fund to have eight months of return history to be included in the sample of funds evaluated, compared to Kosowski et al. (2006), who required a fund to have at least five years of return history. Huij and Verbeek (2007) made use of an alternative modification of the four-factor model and produced evidence of value addition amongst the top decile of active funds. Similarly, Barras et al. (2020) also investigated US active funds by making use of a modified four-factor model and showed that 38.2 percent of active funds could produce positive net-alphas.

Barras, Scaillet, and Wermers (2010) used a technique termed the false discovery rate approach to estimate whether active managers can add value. This technique sought to remove false indications of value addition. They showed that active funds that add value have decreased from 14.4 percent in 1990 to only 0.6 percent in 2006. In contrast, Berk and Van Binsbergen (2015) defined alpha as the returns of a particular active fund in excess of an optimal set of comparable passive funds. Using this measure, they found that the average active fund in the US generates a net-alpha of 0.36 percent per year, which calls prior findings in favour of Sharpe's arithmetic of active management in the US into question. The differences in observed evidence between the studies mentioned above and relative to prior literature were attributed to novelties in the performance measurement models employed (Barras et al., 2020; Barras et al., 2010; Berk & Van Binsbergen, 2015; Fama & French, 2008; Huij & Verbeek, 2007; Kosowski et al., 2006).

Outside of the US, more evidence of value addition in aggregate could be observed. Dyck, Lins, and Pomorski (2013) state that the limited evidence of value-adding performance amongst active US equity funds may be attributed to the notion that the US equity market is arguably the most efficient in the world. Otten and Bams (2002) provided evidence against the suggestion that active funds do not add value. Active equity funds in the Netherlands, UK, Italy, and France could add value in aggregate, whilst active funds in Germany failed to do so. Active funds in these nations were evaluated with factor models as well as an adapted four-factor model that adjusts for expected economic changes (termed conditional-alpha models). However, Ferreira, Keswani, Miguel, and Ramos (2013) subsequently produced a study that evaluated the aggregate active fund performance across 27 countries with the four-factor model (including Germany, France, the Netherlands, the UK, and Italy). They found that the average performance of equity funds aggregated across all 27 nations considered was unable to add value; however, active funds in 13 out of the 27 nations were able to add value in aggregate within their own markets. The UK was the only nation in which this could be observed amongst the nations that Otten and Bams (2002) also evaluated.

Evidence from EMEs provides the most evidence of value addition in aggregate. Of the 27 countries that were evaluated by Ferreira et al. (2013), five were EMEs. All five of these nations (India, Indonesia, Malaysia, Poland, and Thailand) were included in the 13 nations in which active equity funds demonstrated value addition in aggregate. Koutsokostas, Papathanasiou, and Balios (2019) evaluated Greek equity funds with factor models. They found that only top-performing active funds could add value to investors, but not in aggregate.

In South Africa, Wessels and Krige (2005a) show that before fees, active funds on aggregate beat passive funds – which is inconsistent with Sharpe's theory. However, this superior performance in aggregate compared to benchmarks does not hold on an after-fee basis. Using the information ratio, Wessels and Krige (2005a) also show that between 31 percent and 41 percent of active equity funds add value compared to the South African All Share Index – depending on the length of the evaluation period studied. Bertolis and Hayes (2014) demonstrated that funds in the South African general equity category could add value during times of economic growth, but not when the economy is experiencing a downturn. The researchers used a single-factor model for their analysis.

The evidence suggests that active funds in DMEs are generally unable to add value in aggregate. In contrast, actively managed funds in EMEs provide more evidence of value addition in aggregate. The evidence corresponds with the theories on market efficiency as active funds proved to be more valuable in less efficient EMEs. Berk and van Binsbergen (2017) state that most of the prior research suggesting that active funds in DMEs cannot add value in aggregate may be flawed for two reasons. The first being that active funds were not compared to the performance of comparable passive alternatives. This is argued to be a superior performance measure as it considers practical investable alternatives available to the investor (Berk & van Binsbergen, 2017; Berk, van Binsbergen, & Miller, 2020). The second is that most literature only focussed on active funds that invest only in US markets. Since active funds' ability to add value depends on a market's level of efficiency (Byrne & Smudde, 2019), one may expect to observe more evidence of value addition in EMEs when measuring active fund performance by comparing it to comparable passive funds.

Regardless of the market in question, evidence of active funds that added value was prevalent among top-performing funds. Matallín-Sáez, Soler-Domínguez, and Tortosa-Ausina (2016) state that active funds may be valuable investments even if they do not add value in aggregate, and their value to the investor would depend on whether they can identify a value-adding active fund. To aid this identification process, investors commonly make use of past performance to inform their expectations of future performance (Gruber, 1996; Matallín-Sáez et al., 2016).

2.4 PERFORMANCE PERSISTENCE

Persistence in fund performance evaluates whether funds that have produced a certain level of performance can continue to do so for a sustained period of time (Scher & Muller, 2005). Research on performance persistence typically considers whether the information obtained from a performance evaluation over some historical period, referred to as the formation period, can be used to inform investors' future decisions to enhance their wealth (Carpenter & Lynch, 1999). This is done by considering if evaluations of past performance inform investors in their attempt to invest in (or avoid) a value-adding/outperforming (or underperforming) active fund over some future holding period (Matallín-Sáez et al., 2016). Demiralp and Fernando (2016) showed that a failure to consider performance persistence might result in suboptimal investment decisions as not all funds perform persistently.

Like performance evaluations, performance persistence can be analysed on an absolute or relative basis. Absolute performance persistence considers if funds consistently out- or underperform compared to a benchmark or add value if the analysis is net-of-fees, over a set of formation and holding period intervals (Wermers, 1997). Thus, absolute analyses of persistence only distinguish between groups of funds that out- or underperformed their benchmarks; or funds that added value or not if the analyses were net-of-fees. In contrast, relative performance persistence evaluates how funds perform relative to their cohort over set formation-holding period intervals. Top and bottom performers are typically identified by splitting ranked funds at the median (Goetzmann & Ibbotson, 1994). However, most analyses of persistence split ranked funds into quantiles of the group's performance to determine top- and bottom-performers and make use of factor models that implicitly benchmark fund performance to risk factors (Allen et al., 2003). This informs researchers whether specific quantiles of funds identified in a formation period persist their performance in subsequent holding period/s. The factor models then communicate out- or underperformance, or added value, after performance persistence has been established.

As is the case with performance, the literature on the matter of performance persistence seems to be biased towards actively managed equity mutual funds in the US, a market that has been shown to be relatively efficient (Malkiel, 2005). This section discusses the pertinent developments and evidence of performance persistence and considers the findings of South African studies.

2.4.1 Early evidence

Early investigations of US equity mutual funds provided limited evidence of persistent outperformance; however, strong evidence was found that persistent underperformance exists (Grinblatt & Titman, 1988, 1989, 1992, 1993). The evidence was concentrated amongst growth- and income-orientated funds. The studies by Grinblatt & Titman evaluated fund performance with a factor-model (which they termed as the "P8 benchmark") that accounted for equity size and dividend-yield as risk factors. Evidence of performance persistence was found among the top decile (outperformed) and bottom quartile (underperformed) of funds over successive one- and five-year periods. The researchers contended that the performance of the top decile of funds would not have been able to add value if their analyses considered fees. Additionally, their sample did not account for the effect of survivorship bias as the authors argued that its effect was negligible, an assertion that was subsequently criticised by Brown et al. (1992). It was demonstrated that survivorship bias could significantly impact the result of performance and persistence studies as it creates an upward bias in the performance figures of a group of funds due to the exclusion of defunct funds' performance (Brown et al., 1992).

Brown and Goetzmann (1995) evaluated persistence on an absolute basis over successive annual periods using excess return measures and a sample relatively free of survivorship bias and found evidence of persistence among underperformers. Hendricks et al. (1993) analysed the net-of-fee performance persistence of growth-orientated equity funds using several factor models (including Grinblatt & Titman's "P8 benchmark" – but not the Fama-French-Carhart models). It was demonstrated that performance persistence could be observed over annual periods among the top octile of value-adding funds (the "hot-hands" effect) and the bottom three octiles of underperformers (the "icy-hands" effect). Several quarterly holding and formation periods were considered. It was found that value-adding performance persistence is primarily a short-term phenomenon among US funds and that it dissipates over periods beyond a year. Conversely, persistent underperformers continued for longer than a year. Additionally, it was shown that a strategy of moving one's capital to funds in the top octile of active funds every quarter, based on annual formation periods, would add between 3 to 6 percent in value to investors. This study was limited by the fact that it did not account for survivorship bias either.

Hendricks et al. (1993) conjectured five possible rationales for empirical evidence of short-term, value-adding persistence. Four conjectures were subsequently found to affect a fund's persistence. Firstly, strategies employed by a particular fund manager may be influenced by changing market conditions. Secondly, fund fees may rise in response to the recent successes. Thirdly, security identification of superior managers may get "bid away" (i.e., similar competing trades from competitors for securities that managers attempt to purchase for their fund/s). Finally, excessive capital inflows due to superior past performance may "bloat" the fund, resulting in fewer successful investment ideas per actively managed dollar.

2.4.2 Price momentum

Kaminsky, Lyons, and Schmukler (2004) subsequently found that the success of certain investment strategies, such as momentum-based styles, are affected by changing market conditions supporting the first conjecture of Hendricks et al. (1993). Carhart (1997) contended that prior evidence of persistent value-addition and outperformance is attributed to the equity price momentum effect identified by Jegadeesh and Titman (1993) – particularly since momentum style characteristics are associated with growth-orientated equity investing. Thus, it was added as an additional risk factor in the Fama-French three-factor model to evaluate fund performance (producing the four-factor model). The researcher showed that annual, value-adding, performance persistence among the top-decile of active funds was mostly explained by equity price momentum. Additionally, Carhart (1997) found that the diminished evidence of persistent value addition was partly attributed to increased management fees subsequent to periods of outperformance. This supported the second conjecture proposed by Hendricks et al. (1993).

The findings made by Carhart (1997) were notable since the sample used was free of survivorship bias and because it was demonstrated that the four-factor model had superior explanatory power of US fund returns. Accounting for survivorship bias in performance data became common in most subsequent performance and persistence studies (Cremers et al., 2019). Wermers (1997) augmented Carhart's study by using the four-factor model and the "lagged-zero-measure" – which shows the effect of active momentum investing decisions. The researcher's findings concurred with Carhart's by showing that equity price momentum predominantly explains persistent outperformance among the top decile of funds. However, he showed that momentum-based returns earned by active funds were due to active investment decisions and not due to passive equity-based risk factors, as suggested by Carhart. Carhart (1997) and Wermers (1997) considered several period combinations and observed persistent underperformance amongst the bottom two deciles of funds that lasted longer than a year, despite price momentum's effect on top performers.

The four-factor model was subsequently critiqued as a measure of fund performance (Cremers et al., 2012; Huij & Verbeek, 2007, 2009; Stein, 2014). Horst and Verbeek (2000) demonstrated that the original version of the four-factor model used by Carhart (1997) could bias analyses to show persistent underperformance. Statistically optimised versions of this model provided some evidence of persistent out- and underperformance. Using a bootstrapped version, Kosowski et al. (2006) demonstrated significant evidence of persistent value addition among the top decile of funds using three- and one-year formation and holding periods. A Bayesian alpha version used by Huij and Verbeek (2007) provided evidence of persistent value addition among the top decile of funds over three- and one-year formation and holding periods. Finally, the version that controlled for false discovery rates, as used by Barras et al. (2010), demonstrated persistent value addition for annual holding periods based on one-, three-, and five-year formation periods among the top 14.4 percent to 0.6 percent of funds. These studies all observed persistent underperformance amongst the bottom two to three deciles of funds.

Analyses outside the US were influenced less by the identification of the equity price momentum effect, as most studies on equity funds in DMEs and EMEs outside the US still found evidence of persistence amongst top-performers after accounting for momentum. Otten and Bams (2002) used the four-factor model to measure annual performance and observed value-adding persistence among the top six deciles of funds in the UK. No evidence of performance persistency could be observed among French, German, or Italian funds. Ferreira, Keswani, Miguel, and Ramos (2019), however, also made use of the four-factor model and annual periods to demonstrate that persistent value addition could be observed among the top quintile of funds in the UK, France, Italy, Netherlands, Denmark, Belgium, as well as Germany. Additionally, Ferreira et al. (2019) provide evidence of persistent value addition among the top two quintiles of Indian funds and the top two quantiles of Thai and Indonesian funds. Persistent underperformance among the bottom quintiles of funds in all nations was observed. Finally, Koutsokostas et al. (2019) observed persistent underperformance amongst the worst five Greek funds using the four-factor model and annual periods.

In South African markets, Page and Auret (2019) showed that the equity momentum effect is evident and that its effect lasts between three to nine months. Nana (2012) evaluated South African general equity unit trusts with the four-factor model on a gross-of-fee basis and demonstrated that 22 to 25 percent of these funds could persistently outperform, whilst between 25 to 31 percent persistently underperformed for successive one- to five-year periods.

From the perspective of the EMH, Jegadeesh and Titman (2001) state that active investors who trade based on equity momentum and earn abnormal profits present evidence against weak-form market efficiency - a matter which Wermers (1997) argued to be possible. From the perspective of the AMH, Daniel, Hirshleifer, and Subrahmanyam (1998) state that the equity momentum effect is due to biases in investor behaviour that active fund managers can exploit to earn abnormal profits. Kaminsky et al. (2004) supported this as they demonstrated that active fund managers make use of momentum investment strategies during market contractions – a strategy that the four-factor model would explain away and not credit to active fund performance.

Regardless of whether equity momentum-based investing is viewed as an active or passive investment strategy, it does not seem to remove all evidence of persistence in value addition/outperformance as originally suggested by Carhart (1997). However, its effect seems to be greater amongst equity funds in the US, as evidence of persistence among funds that outperformed or added value could be observed amongst active equity funds in other DMEs and EMEs. Furthermore, the exploitation thereof seems to contradict the weak-form of the EMH and coincide with the AMH and the first conjecture proposed by Hendricks et al. (1993). Accordingly, Keswani and Stolin (2006) proposed that the differences in evidence may be attributed to the degree of competition among various markets.

2.4.3 Competition

Keswani and Stolin (2006) stated that active funds in more competitive environments compete more aggressively to attain abnormal profits, which closes the performance gap on top performers. This coincides with the EMH, since Clearly et al. (2019) states that competition is one of the determinants of market efficiency, as it drives participants to incorporate information into prices to extract abnormal returns before competitors can. In terms of the AMH, increased competition results in more resources being devoted to identifying “innovative” investment strategies, or to learn and imitate successful managers’ strategies. This supports the third conjecture of Hendricks et al. (1993) which stated that security identification of superior managers may get “bid away”. Concurrently, Ambachtsheer (1994) stated that the identification of a successful active fund depends on the manager’s ability to understand all of its adversaries (passive funds and other active funds) well enough to consistently fashion trades to systematically beat competitors.

The degree of competition faced by funds varies across different markets, sectors of a market, and investment styles (Ferreira et al., 2019; Hoberg, Kumar, & Prabhala, 2018; Keswani & Stolin, 2006). Competition relates to the two other determinants of market efficiency described by Clearly et al. (2019) - informational efficiency and impediments on trading. Within a less competitive environment, fewer active managers can optimally monitor and mimic other successful active funds’ strategies (Hoberg et al., 2018). Furthermore, fewer skilled analysts would analyse a particular set of securities (Cremers, Pareek, & Sautner, 2017). This creates informational friction among fund managers regarding optimal investment decisions (Cremers et al., 2017; Hoberg et al., 2018). Additionally, fund mandates constrain investments to certain markets, styles, or sectors – which impedes trading by preventing investments in assets in less competitive environments (Hoberg et al., 2018). Collectively, this results in suboptimal capital flows to mispriced assets and a slower correction of asset prices - which creates more opportunities for profitable trades that generates persistent value addition (Clearly et al., 2019; Cremers et al., 2017; Hoberg et al., 2018).

Using the four-factor model and annual periods, Ferreira et al. (2019) studied the performance persistence of equity funds across 27 countries (or markets). It was demonstrated that persistent value addition was present in most countries, even after accounting for momentum. Additionally, the degree of competitiveness within the sample of countries was evaluated as a determinant of the observed persistence. It was found that markets with fewer competing active funds and more concentrated fund industries produce more evidence of persistent value addition amongst outperformers. In contrast, markets that had more competing funds and less concentrated fund industries produced more evidence of persistence among underperformers.

Keswani and Stolin (2006) evaluated the influence of the degree of competition on performance persistence across different sectors. Like in South Africa, funds in the UK are categorised into clearly defined unit trust sectors, whose membership is enforced and monitored by the industry trade body (Keswani & Stolin, 2006). Four unit trust sectors in the UK namely domestic equity, global equity, domestic non-equity, and global non-equity sectors were considered. Gross-of-fee returns were used to measure fund performance, and the median sector performance was used to distinguish between top and bottom performers. Annual periods were used, and the degree of observed persistence was contrasted to proxies for competitiveness to evaluate their relationship. The average of a specific sector's returns was included in their model to control for a sector's asset-specific effects. More persistence among bottom-performers was observed in more competitive sectors that are less concentrated and that contain a greater number of funds. Conversely, persistence among top performers was evident in less competitive sectors. This study was limited by the fact that it did not correct for the risk associated with fund performance.

Hoberg et al. (2018) assessed how the performance persistence of US equity funds is influenced by the degree of competition faced within a particular equity-style cluster using annual periods. The researchers created clusters based on risk factors of size, value or growth attributes, momentum, and dividend-yield. Clusters were used to group funds based on the "style packages", a selection of exposures to risk factors, that funds offer to their investors. Groupings were updated quarterly to monitor the change in a cluster's competitiveness and style. Fund performance was evaluated based on gross-of-fee, excess returns; where the benchmark was the average return generated by the funds within a particular style cluster. Persistent outperformance among the top two to three quintiles was observed in clusters where fewer funds were present, and where style similarity was lower. Conversely, only evidence of persistent underperformance was found in clusters where the number of funds and style similarity was greater. Furthermore, a greater number of underperformers were shown to make up more competitive clusters (the bottom three to four quintiles depending on the degree of competition faced). Finally, the findings were tested for robustness by making use of the Fama-French-Carhart four-factor model and were shown to hold regardless of the performance measure used.

Additionally, Hoberg et al. (2018) arranged funds into groups to evaluate style-specific effects. Single style-focussed groupings were formed based on small or large capitalisation focus, value or growth focus, and momentum or contrarian (equity price reversion) focus. It was demonstrated that the effect of style-specific factors was transitory and insignificant compared to the degree of competition faced by a particular set of funds. Finally, the researchers contended that funds in less competitive style clusters have less competitors that mimic good investment strategies, and that they benefit from entry barriers against funds in other clusters who are constrained by their mandates to follow a particular "style package".

Hunter, Kandel, Kandel, and Wermers (2014) and Mateus, Mateus, and Todorovic (2019) tested a similar concept by adapting the traditional four-factor model to include a fifth factor termed the "active peer benchmark". This factor is the sum of the alpha and error terms of a four-factor model's output derived from one of nine US or UK Morningstar equity fund sector's returns. The fifth factor standardises the performance of a sector, aiding the identification of superior active funds amongst a cohort that focuses on a similar investment universe. Over annual periods, the top quartile of funds in eight out of the nine US sectors persistently added value, whilst evidence of persistent underperformance among the bottom quartile was observed for seven out of the nine sectors (Hunter et al., 2014). For funds in the UK, Mateus et al. (2019) demonstrated that approximately 30 percent persistently outperformed across all sectors, whilst approximately 27 percent persistently underperformed. In contrast to the annual periods used by Hunter et al. (2014), Mateus et al. (2019) used three- and one-year formation and holding period combinations.

It should be noted that neither Keswani and Stolin (2006) nor Hoberg et al. (2018) considered performance persistence on a net-of-fee basis in their studies; hence, active funds' ability to add value to investors could not be observed. Competition alone, however, does not preclude other factors from influencing the persistence of fund performance (Hoberg et al., 2018). Hoberg et al. (2018) state that competition and diseconomies of scale can coexist since both are distinct forces that influence the industrial organisation.

2.4.4 Diseconomies of scale

The term "diseconomies of scale" was introduced by Berk and Green (2004) to refer to the effect that fund size may have on performance. It states that as a fund's AUM increases, its performance will decrease. Berk (2005) states that investors within a certain market are aware of who the superior fund managers are and that investors will shift capital to their funds. Additionally, it is contended that managerial ability cannot be optimally utilised to generate outperformance when excessive capital is under management (Berk, 2005). Therefore, the fund becomes "bloated" relative to the number of investment ideas per actively managed dollar, as suggested by the fourth conjecture of Hendricks et al. (1993).

Berk (2005) argues that informed investors would allocate so much capital to the fund that generates the best returns that it will drive down its expected return until it is equal to that of the second-best fund's expected return. Informed investors would then allocate capital to both funds until their expected returns are equivalent to the third-best fund's expected return. This process would repeat until all active funds' expected returns are equal to that of an investable passive alternative of comparable risk. Conversely, poor performers will experience fund outflows which will lift their expected return until it is equivalent to that of the passive alternative. Due to this effect, Berk (2005) suggested that active funds cannot persistently add value as capital would be shifted until gross-of-fee performance equates to that of the passive alternative. Hence, over time, all funds should tend towards underperformance equivalent to the fee charged by the fund (Berk, 2005; Berk & Green, 2004; Berk & van Binsbergen, 2017).

The rationale for the imposition of fund size on managerial ability is that as the AUM of a fund increases, the absolute amount of capital that has to be attributed to an optimal investment position also increases (Perold & Salomon Jr, 1991). This increases the number of staggered and unfilled purchase orders for optimal assets, resulting in purchases of the "next-best" security (Perold & Salomon Jr, 1991; Pollet & Wilson, 2008). In terms of the EMH and AMH, larger trades inhibit fund managers' ability to scale up "innovative" strategies optimally and have a greater price impact that enhances informational and market efficiency (Barras et al., 2020; Pástor, Stambaugh, & Taylor, 2015).

Evaluations on the effect of diseconomies of scale tend to consider its influence on fund performance more than its effect on performance persistence. Among US equity funds, Berk and Green (2004) showed that fund size and performance are inversely related. Barras et al. (2020) showed that fund performance is highly sensitive to fund size as the average gross-alpha decreases by approximately 1.5 percent when the fund size increases by one standard deviation of average fund size. Hoberg et al. (2018) considered the combined effect of fund size and style-level competition on performance persistence. They found that the top three quintiles of funds in clusters of smaller funds that faced less competition persistently outperformed. Conversely, in clusters made up of larger funds that faced greater competition, only persistent underperformance among the bottom two quintiles of funds was evident. However, clusters of larger funds that faced less competition demonstrated persistent outperformance among the top quintile of funds; whilst smaller funds facing more competition demonstrated persistent outperformance among the top quintile of funds.

Using their sample of 27 countries, Ferreira et al. (2013) found that the inverse relationship between fund size and performance only held in the US, as funds in the other countries all experienced increasing returns to scale (i.e., performance improves as fund size increases). Comparably, Deb (2019) provided evidence showing that larger Indian funds are more likely to add value persistently, whilst smaller funds are more likely to underperform persistently.

In South Africa, the effect of fund size has only been evaluated with respect to fund performance. Pardoe (2018) argues that smaller equity unit trusts tend to outperform larger equity unit trusts. Pillay, Muller, and Ward (2010) show that equity unit trust performance becomes negatively affected by increasing fund size when fund sizes exceed R5 billion as they become forced to hold the market capitalisation weighting of the JSE All Share Index. This leads large funds to engage in benchmark-hugging, which is when active funds hold positions similar to a benchmark index - like passive indexing (Petajisto, 2013). This increases the likelihood of an active fund to underperform a passive alternative on a net-of-fee basis since active funds generally charge higher fees (Cremers & Petajisto, 2009).

The concept proposed by Berk and Green (2004) assumes that funds immediately experience diseconomies of scale as they grow and that no informational frictions exist within a market, thus allowing investors to allocate capital to superior funds competitively. These assumptions have been criticised by Pástor and Stambaugh (2012) as it has been shown that even the most developed markets experience informational frictions and that investors learn of optimal investments over time. Furthermore, it is argued that fund growth due to past performance experiences transition dynamics before diseconomies of scale take effect (Hoberg et al., 2018). Within less competitive markets, less aggressive fund marketing keeps investors misinformed for longer, which slows the movement of capital to optimal funds, and by extension, optimal asset positions (Roussanov, Ruan, & Wei, 2018). Hoberg et al. (2018) observed that funds that face less competition, which may be proxied by the sector size (Ferreira et al., 2019; Pástor et al., 2015), have greater ability to establish optimal investment positions. Additionally, Ferreira et al. (2013) argued that larger foreign funds, in fund sectors smaller than those of the US, may be experiencing increasing returns to scale due to an enhanced ability to establish optimal positions. Therefore, Pástor et al. (2015) proposed that diseconomies of scale may take effect at the sector level as well as at the fund level. The researchers reasoned that funds that follow the same strategy compete to purchase similar assets. Hence, the collective value and movement of their capital would act to correct a particular universe of asset prices, which would also limit the scalability of active fund strategies (Pástor et al., 2015).

Pástor et al. (2015) evaluated this preposition by considering fund performance in the US and found stronger evidence of sector-level diseconomies of scale compared to that found at the fund-level. Hoberg et al. (2018) expanded on their findings by considering how clusters (or “style-industries”) of different sizes, with different levels of competition, vary with respect to their performance persistence. Persistent outperformance was reported for the top three quintiles of funds in smaller clusters that faced less competition (in terms of style similarity and the number of competing peer funds). Funds in larger and more competitive clusters only demonstrated persistent underperformance among the bottom quintile of funds. Larger and less competitive clusters showed persistent outperformance among the top two quintiles of funds, whilst smaller and more competitive clusters demonstrated no persistence in fund performance. The impact of sector-level diseconomies of scale on performance persistence outside the US remains largely unexplored.

2.4.5 Prominent South African evidence

Meyer (1998) produced one of the first prominent studies on the performance persistence of South African funds. Funds were grouped together and split at the median in terms of their single-factor alpha to evaluate fund performance after management fees but before investor transaction costs. Investor transaction costs vary depending on the type of investor and the nature of the transaction (Oldert, 2020); hence, South African studies generally exclude it to facilitate comparability. Meyer (1998) found evidence of persistence amongst bottom performers over successive one-, three-, and four-year periods and evidence of persistence amongst top performers over successive two-year periods.

Firer, Beale, Edwards, Hendrie, and Scheppening (2001) evaluated the performance persistence of equity and fixed-income funds. Raw returns (unadjusted for risk) were used to measure the performance of fixed-income funds, and the Sharpe ratio was used to measure the performance of equity funds. The funds were ranked and split at the median to assess performance persistency, and the researchers considered three-month, six-month, annual, and two-yearly formation and holding period combinations. Top and bottom performing equity funds persisted in their performance for all period combinations considered. Performance persistence was evident for all formation period lengths associated with two-yearly holding periods amongst the fixed income funds. Most of the evidence of performance persistency amongst the fixed-income funds were attributed to bottom performers.

Collinet and Firer (2003) evaluated the performance persistency of South African equity funds by using the Sharpe ratio and by splitting funds at the median. Several formation and holding period combinations were considered. Evidence of persistence over successive six-month periods was found for top and bottom performers. Evidence from longer periods showed little to no evidence of persistence. Collinet and Firer (2003) suggested that their findings were relatively inconclusive and that the results of an analysis of performance persistence may be sensitive to the holding period length and the time period studied.

Wessels and Krige (2005b) investigated the relative persistency of active South African general equity funds by making use of net returns (unadjusted for risk) and rolling three-year performance windows. Of the top and bottom third of funds, 37 and 21 percent, respectively, demonstrated persistent performance when the evaluation window was rolled forward by one year. However, when the evaluation window was rolled forward by three years, only six and five percent of the top and bottom performers, respectively, demonstrated performance persistency.

Brown (2008) and Thobejane, Simo-Kengne, and Mwamba (2017) also evaluated South African equity fund performance. Nine different performance measures were used between the two studies, and both studies considered annual periods. Brown (2008) found evidence of annual performance persistence among the top and bottom quartile of performers (performance measures specifying out-/underperformance were not used). Thobejane et al. (2017) tested for the persistence of their entire sample's performance and did not distinguish between top-and-bottom- or out-/underperformers. No evidence of performance persistence was found. Thobejane et al. (2017) attributed this to the poor economic conditions that prevailed in South Africa over their sample period, as they stated that annual value-adding performance persistence was observed by studies in other EMEs over the same sample period.

Hoch (2015) evaluated the absolute performance persistence of equity funds over six-month, one-, two-, and three-year periods using a single-factor model and found evidence of persistence among underperformers. Malefo, Hsieh, and Hodnett (2016) provided evidence that was similar to the performance analysis of Bertolis and Hayes (2014). The researchers evaluated the gross-of-fee performance of 20 South African general equity funds with four different performance measures. Sixteen funds were able to outperform during expansionary periods, whilst only six of these 16 were able to do so during contractionary periods. The six funds that persistently outperformed through expansionary and contractionary periods were also found to outperform over the entire evaluation period.

South African studies present mixed evidence of performance persistence. A large amount of evidence amongst bottom performers has been observed, which is consistent with the findings in other DMEs and EMEs. The effect of various evaluation period lengths has been considered to a greater extent compared to international literature. Furthermore, as is the case with most studies around the world, South African studies generally focus on equity fund performance, which may limit the existing evidence on performance persistence as equity markets are generally more efficient than markets for other assets (Clearly et al., 2019).

2.5 CONCLUSION

The literature suggests that DMEs exhibit greater market efficiency, whilst EMEs tend to be less efficient and that the AMH may provide a better explanation of asset price behaviour than the EMH. Options between active and passive funds are provided to investors, and the decision between them is influenced by market efficiency. Performance evaluations make use of performance measures and benchmarks to evaluate how much better-off an investor would have been if they invested in a particular fund. Limited evidence of value-adding active funds has been found in the US; however, more evidence could be observed in other DMEs and EMEs.

Performance persistence among equity funds seems to be concentrated among funds in the extremities of fund rankings and is more prevalent among bottom-/underperformers compared to top-/outperformers. Momentum-based investment does not seem to explain the performance persistence of funds fully, and some authors argue it is an active investment style. Finally, competition, fund- and industry/sector-level diseconomies of scale appear to be related determinants of persistence in fund performance. The findings of performance and persistence analyses are influenced by the performance measure used. The persistence of active fund performance, as measured by its performance relative to a passive alternative, has not been considered in South African literature.

CHAPTER 3: RESEARCH DESIGN AND METHOD

The previous chapter described market efficiency, the concept of performance, and the study of performance persistence as the three predominant topics in the active versus passive debate. This chapter describes the research paradigm, inquiry strategy, sampling, data collection, and statistical analysis that will be used in this study. It concludes with a description of the procedure to comply with ethical research standards, followed by the delimitations, limitations, and assumptions of this research.

3.1 RESEARCH PARADIGM

A positivist research paradigm is employed to analyse the performance persistence of South African unit trust funds. Positivism assumes that reality exists independently of the observer and is governed by fixed laws that withhold values from the reasoning process (Douglas, 2004; Rehman & Alharthi, 2016).

3.2 DESCRIPTION OF INQUIRY STRATEGY AND BROAD RESEARCH DESIGN

A quantitative research design and a deductive research approach are utilised in this study. Quantitative research designs analyse data by using quantitative strategies and/or statistical techniques to propose an answer to the research question under investigation (Soiferman, 2010). A deductive approach seeks to see if a theory or generalisation applies to a specific instance (Spens & Kovács, 2006). This study is descriptive in nature, meaning it delineates an existing set of phenomena to gain a better understanding thereof (Lynn, 2002). Additionally, it may inform the adoption of practices that are influenced by the phenomena investigated (Lynn, 2002). Finally, secondary data is utilised, which is defined as data that other researchers or institutions collect for research and/or record-keeping purposes (Hox & Boeije, 2005). The research design and strategy proposed is consistent with prior research on the persistence of fund performance (Carhart, 1997; Collinet & Firer, 2003; Grinblatt & Titman, 1992; Hendricks et al., 1993; Kahn & Rudd, 1995; Nana, 2012; Wermers, 1997).

3.3 SAMPLING

Samples of active and passive funds are obtained for this study. Active funds are analysed for the presence of performance persistence, whilst passive funds are used as passive alternatives for performance measurement. Only retail funds classified as South African unit trusts or exchange traded funds (ETFs) are considered. The filings of each fund are manually inspected to ensure that their objectives comply with that of an active or passive fund. Purposive sampling is used, which is a technique that relies on the judgement of the researcher to construct a sample to optimally answer the research objectives (Etikan & Bala, 2017). This technique may be subject to researcher bias; however, it is deemed optimal when a restricted number of units in a population owns the qualities required to address specific research objectives (Sharma, 2017).

3.4 DATA

This study makes use of time-series data, which is a collection of observations of a particular variable at different time intervals (Palma, 2016). South African unit trusts and ETFs are the units of analysis considered in this study. The return data for these funds are considered. The sample data is sourced from the Morningstar Direct database, which is made available by the University of Pretoria. This database contains the information of all surviving and obsolete funds and has been used as a data source in prior prominent research on performance persistence, both locally and internationally (Hoch, 2015; Mateus et al., 2019).

3.4.1 Return data

Monthly return data is utilised for the samples of active and passive funds. The collected return data of the unit trusts under investigation will serve as input to the performance measures calculated in the Morningstar Direct database and R (R Core Team, 2021). The extracted information on fund performance will then be analysed for performance persistence by using relevant statistical data tests.

The variables that are evaluated are the unit trust and ETF return data in South African Rand (ZAR). Returns are calculated by making use of the time-weighted return methodology, which is the compound rate of growth over a period for a single unit of currency invested at the beginning of a period (Clarfeld, 1998; Morningstar, 2021). The calculation considers the effect of fund fees and assumes that distributed gains are reinvested. For South African funds, fees are recovered directly from the fund and are described as the fund's total investment charge (TIC) (Oldert, 2020). The fees charged to retail investor unit classes are higher than those charged to institutional investor unit classes, both locally (Oldert, 2020) and internationally (Dyck et al., 2013). This study only considers retail unit classes; therefore, the returns calculated reflect the net-of-TIC returns obtainable by the retail investor. Investor transaction costs vary depending on the type of investor and the nature of the transaction (Meyer, 1998; Oldert, 2020) and are thus excluded from returns to facilitate comparability.

A filtering process is followed to determine the Association of Savings and Investment South Africa (ASISA) categories from which fund return data is collected. Firstly, all ASISA categories containing passively managed unit trusts and ETFs are identified. Secondly, the history of return data is considered to determine data sufficiency. ASISA categories containing passive funds that have insufficient historical data to meet the minimum required data points are excluded from the analysis.

3.4.2 Minimum required data points

To ensure sufficient observations to calculate the risk-adjusted performance measures, a minimum number of continuous monthly observations for each respective fund must exist before it is included in the sample. Matallín-Sáez et al. (2016) state that the inclusion of funds with limited performance data has the following effects – firstly, it limits the measurement of persistence robustness. Secondly, it may introduce a bias on the observed results if a fund's performance is correlated with the effect within the limited period for which data is available. Finally, comparing funds with limited periods of existence may add noise to performance estimates. For an ASISA category to be included in the sample, it must contain passive funds with a minimum of 36 continuous monthly observations in addition to the number of months within the holding period used for its third-tier ASISA category. Therefore, the minimum number of continuous monthly observations required for a particular fund is dependent on the holding period used for funds in its ASISA category.

3.4.3 Category holding period

The holding periods used for analysis are assigned to funds by approximating a minimum recommended holding period for the funds within a particular ASISA category. The approximations of the minimum recommended holding periods are based on the information obtained from leading practitioners in the South African CIS industry. Table 3 displays the responses obtained from three of the largest asset managers in South Africa.

Table 3: Minimum recommended holding periods

	Asset manager 1	Asset manager 2	Asset manager 3	Approximated minimum recommended holding period	Minimum required data points
SA Equity Categories	10+ years (120+ months)	7+ years (84+ months)	5+ years (60+ months)	7 years (84 months)	10 years (120 months)
SA Interest-Bearing Variable Term	3+ years (36+ months)	No comment	1-3 years (12-36 months)	3 years (36 months)	6 years (72 months)
SA Multi-Asset High Equity	5+ years (60+ months)	5+ years (60+ months)	5+ years (60+ months)	5 years (60 months)	8 years (96 months)
SA Multi-Asset Low Equity	3+ years (36+ months)	3+ years (36+ months)	3+ years (36+ months)	3 years (36 months)	6 years (72 months)
SA Real Estate General	10+ years (120+ months)	5+ years (60+ months)	5+ years (60+ months)	5 years (60 months)	8 years (96 months)

Source: Communications with industry practitioners

The minimum recommended holding periods used are approximated based on consistency in the guidance provided by the industry practitioners. All South African equity funds, both general and thematic, are assigned holding periods of seven years as proposed by asset manager 2 since it is a mid-point between the most aggressive (asset manager 3) and the most conservative (asset manager 1) advised holding periods. Equity funds other than those categorised as general equity funds are referred to as thematic equity funds. The managers of these funds are mandated to invest in equities of a particular economic sector or theme (Oldert, 2020). Five- and three-year holding periods are used for South African Multi-Asset High and Low Equity categories, whilst three- and five-year holding periods are used for South African Interest-Bearing Variable Term and Real Estate categories.

The minimum number of monthly data points required for funds from a particular ASISA category to be included in the sample is specified in the last column of Table 3. This period is a summation of the relevant category's holding period and the 36 minimum continuous monthly observations required. For example, the minimum required data points for SA equity categories are 10 years (or 120 months). This is made up of the approximated minimum recommended holding period of 7 years (84 months) plus an additional 3 years (36 months).

3.4.4 Analysis start date

Once the ASISA categories have been identified, the analysis start date for each ASISA category is determined. Second-tier ASISA categories classify funds based on broad asset allocations. A uniform date is selected for all ASISA categories belonging to a particular second-tier classification. This keeps common cross-sectional risk-return characteristics of broad asset classes constant over an evaluation period (Matallín-Sáez et al., 2016). For each ASISA category included, a time period equal to the category holding period plus 36 months ending 31 December 2020 is rolled back annually. This is done until the inclusion of a full year of additional return data for the passive alternative (described in section 3.5) within the relevant category is no longer possible. The category starting date is set as the first of January for the final year included. A particular group's most recent starting date under a second-tier ASISA category is then selected as the analysis start date for all categories within the respective second-tier ASISA category. The analysis start date until 31 December 2020 makes up the full analysis period for the category considered. Return data for all actively managed unit trusts and passive alternatives that were in existence from the beginning of the analysis start date for their respective categories until the end of December 2020 is collected. One actively managed interest-bearing variable term fund was removed from the sample due to its anomalous investment objective.

3.5 PASSIVE ALTERNATIVES

Accepted performance evaluation methods such as raw returns, the Sharpe ratio, and factor models have been argued to be of limited use for evaluating fund performance (Berk et al., 2020; Blake & Timmermann, 2003; Van Heerden, 2015). This has led researchers to opt for the use of a set of passive investment fund opportunities to adjust for risk (Berk & Van Binsbergen, 2015). Ambachtsheer (1994) states that investors must evaluate an active fund based on a model that contrasts its performance to a homogenous group of funds with whom it competes to attract capital. In terms of the active versus passive fund investment decision, a homogenous group entails passive funds that mimic the investment objective of the active fund in question (Ambachtsheer, 1994). This is consistent with the assertion of Sharpe (1991), who stated that the optimal manner to evaluate the performance of an active fund is to contrast its performance with that of a passive alternative. Furthermore, as the study of performance persistence forms part of the active versus passive debate, contrasting the performance of an active fund to a passive alternative is intuitively appealing and theoretically supported.

This practice is credible from a practical perspective since investors may be presented with passive and active fund options. Berk and Van Binsbergen (2015) state that one of the primary advantages of following this approach is that it ensures the avoidance of look-ahead bias in performance measurement. Look-ahead bias is to rely on information that was not available at the initiation of the investment period studied (Ter Horst, Nijman, & Verbeek, 2001). Hence, active fund performance would not be penalised for using successful trading strategies before they become known to the market (Berk & Van Binsbergen, 2015, 2017; Berk et al., 2020). Furthermore, it ensures that active fund performance is compared directly to alternative investable opportunities that were available over the investment period studied (Berk & Van Binsbergen, 2015, 2017; Berk et al., 2020).

Berk and Van Binsbergen (2015) recommend the use of a linear projection to determine the optimal construction of passive alternatives prior to the analysis period. However, the limited return data available for passive South African funds prevent the use of this method. Therefore, a passive fund (passive unit trust or ETF) that was in existence at the analysis starting date for its category until 31 December 2020 is allocated as the passive alternative for all active funds within the same category. This ensures that the passive alternative was accessible by investors from the beginning of the analysis period and that sufficient return history is available for the analysis.

To ensure that the allocated passive fund's performance is representative of its category's risk-return attributes, it is required to track its ASISA category index (ASISA, 2018). If more than one passive fund meets this requirement, the fund with the lowest tracking error (described in section 3.6.1.2) to the index from the analysis start date until 31 December 2020 is selected as the passive alternative. If none of the available passive funds tracks the category index, passive funds that track an index whose universe is the ASISA category index are considered (JSE, 2021). Passive funds incepted after the analysis starting dates are not considered as information regarding their tracking error would not be available to the investor at the time of their inception. Additionally, the substitution of passive funds as the allocated passive alternative with subsequently incepted funds would require the investor to actively monitor and reinvest in available passive funds. South African multi-asset categories do not have category indices (ASISA, 2018). Hence, the passive funds that were in existence at the analysis starting date with available return data until 31 December 2020 are used as the passive alternatives for these categories. If more than one fund meets this requirement, the passive fund with the lowest average TIC is selected.

Allocating passive alternatives in this manner is appropriate as it optimally utilises the limited data of South African passive funds. Cremers et al. (2019) argued that the regulatory constraints faced by active funds might inhibit their ability to outperform. Hence, comparing funds in the described manner ensures that active funds are compared to passive funds that are constrained to the same investable universe and regulatory requirements imposed by ASISA. Finally, this approach facilitates the avoidance of survivorship bias in the performance figures as surviving active funds are compared to surviving passive funds over the period studied (Goetzmann & Ibbotson, 1994). Survivorship bias creates an upward bias in the performance figures of a grouping of funds due to the exclusion of obsolete funds' performance figures (Brown et al., 1992).

3.6 DATA ANALYSIS

Prior to performing the data analysis, the descriptive statistics of fund returns are presented to provide insight into their distributional characteristics. To analyse the persistence of fund performance, the performance of each active unit trust is first determined according to the performance measures described in section 3.6.2. The performance measures indicate whether the fund performance is superior, or inferior when compared to a passive alternative for a particular period. Fund performance is measured again over subsequent periods to determine how it has changed over time. This information serves as input to the statistical test procedures described in section 3.6.3 to draw inference about whether a fund demonstrates persistence in terms of its performance over time. All data analyses are conducted using Excel and R.

3.6.1 Descriptive statistics

The descriptive statistics presented include measures of central tendency, dispersion, and correlation.

3.6.1.1 *Measures of central tendency*

The measures used to describe the central values of a data set are the mean and the median. The value for the arithmetic mean is presented, which is the sum of all observations divided by the total number of observations in the data set (Anderson, Sweeney, Williams, Camm, & Cochran, 2016). The median is the value of the middle observation when data points are arranged in ascending order (Anderson et al., 2016).

3.6.1.2 *Measures of dispersion*

Measures of dispersion describe the variability of the observed data (Anderson et al., 2016). Sample standard deviation is presented to describe the degree to which the observations differ from their mean value and is calculated as follows (Anderson et al., 2016):

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{1}$$

Where *n* is the total number of observations, x_i is the *i*th observation of return, and $\bar{x}$ is the mean return. To supplement standard deviation, tracking error is also presented. The tracking error is used to quantify the divergence between the returns of an active fund and its passive alternative, or a passive fund and the index that it tracks (Goodwin, 1998). Tracking error is defined as follows (Goodwin, 1998):

$$\widehat{\sigma_\alpha} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\alpha_i - \bar{\alpha})^2} \tag{2}$$

Where α_i is the *i*th observation of excess return (described further in section 3.6.2.1), and $\bar{\alpha}$ is the mean excess return.

3.6.1.3 *Correlation*

The Pearson correlation coefficient (correlation for brevity) is presented to describe the relationship between the returns of the active funds and their assigned passive alternatives. Correlation (denoted by ρ) is defined as follows (Khamis, 2008):

$$\rho = \frac{Cov_{(x,y)}}{\hat{\sigma}_x . \hat{\sigma}_y} \tag{3}$$

Where the numerator is the covariance between two variables and the denominator is the product of their standard deviations. The value of ρ is bounded between negative one and one. A value for ρ that is close to zero indicates a weak- or no relationship. Values for ρ that are closer to one (negative one) indicate a stronger positive (negative) linear relationship between the variables considered.

3.6.2 Performance measurement

The literature study identified seven frequently-used performance measures: raw returns, the Sharpe ratio, three variations of factor models, the information ratio, and excess return measures. This study compares the performance of active funds to comparable passive alternatives by making use of the excess returns, omega ratio, and the information ratio. Table 4 describes the limitations of the performance measures not used in this study.

Table 4: Limitations of common performance measures

Performance Measure	Limitations	Implications	Applicable studies
Raw returns	Does not adjust for risk.	May induce investors to take more risk without potential reward of additional return.	Atanasov, Pirinsky, and Wang (2018); Blake, Elton, and Gruber (1993); Blake and Timmermann (2003); Brown et al. (1992); Gruber (1996).
Sharpe ratio	Assumes normally distributed returns, can be manipulated to favour predetermined outcomes, and fails to consider diversification benefits of imperfectly correlated assets.	May bias performance evaluations upwards or downwards.	Amenc and Giraud (2004); Brooks and Kat (2002); Spurgin (2001); Van Heerden (2015); Yau, Schneeweis, Robinson, and Weiss (2007).
Factor models	Assumes that hypothetical factor portfolios can effectively be replicated by passive funds. Fails to consider the effect of transaction costs, market trade impact, and trading constraints faced by funds.	May bias performance evaluations downward.	Berk and Van Binsbergen (2015); Berk and van Binsbergen (2017); Berk et al. (2020); Cremers et al. (2019); Fama and French (2010); Huij and Verbeek (2009); Stein (2014).

3.6.2.1 *Excess returns*

Recent studies contend that active funds' performance should be measured as excess returns, where the benchmark is a similar passive fund (or set of passive funds) (Barras et al., 2020; Berk & Van Binsbergen, 2015, 2017; Berk et al., 2020; Demiralp & Fernando, 2016; Pástor et al., 2015). Both active and passive funds provide a service to the investor by providing a well-diversified portfolio (Berk & van Binsbergen, 2017). The negative net-alpha expected from passive funds represents the compensation for the diversification services provided by the fund manager (Berk et al., 2020). Yet active funds provide an additional service by conducting research to take positions in optimal securities which raises the required compensation (Grinblatt & Titman, 1989). Hence, the value of the additional service provided must be reflected in the net-alpha of the return difference between similar active and passive funds (Berk & van Binsbergen, 2017). To measure performance in this manner ensures that market trade impact, transaction costs, and trading constraints that impede fund managers' trading activity are accounted for (Cremers et al., 2012; Huij & Verbeek, 2009). Finally, passive and active funds face similar constraints when considering statutory requirements – a factor that most performance measures do not account for (Busse, Goyal, & Wahal, 2010; Cremers et al., 2019). As such, this study makes use of the alpha derived from excess returns as defined in equation 4 (Berk & Van Binsbergen, 2015):

$$\alpha_{ex} = R_a - R_p \tag{4}$$

Where R_a is the return derived by an active fund and R_p is the return derived by the passive alternative over the same time interval. To supplement the analysis, returns in excess of inflation are also considered. Equation 4 is modified for this purpose and is calculated as per equation 5:

$$\alpha_{exi} = R - \pi \tag{5}$$

Where R is the return derived by the active fund or passive alternative considered, π represents inflation as inferred from the South African headline consumer price index (CPI). If excess return as defined in equation 4 is positive (negative), then the active fund considered delivered superior (inferior) returns relative to the passive alternative. If inflation-adjusted returns in terms of equation 5 is positive then the relevant active fund or passive alternative derived positive real returns. If not, then the relevant investable option failed to do so.

3.6.2.2 *Omega ratio*

The omega ratio was introduced by Keating and Shandwick in 2002 and is the most recently developed risk-adjusted performance measure compared to frequently-used performance measures such as the Sharpe ratio, factor models, the information ratio, and excess returns. De Wet, Krige, and Smit (2008) showed that the omega ratio is a superior measure compared to the Sharpe ratio when evaluating South African unit trusts. This is due to the Sharpe ratio's inability to account for a return distribution's skewness and kurtosis appropriately. The omega ratio makes no distributional assumptions about a fund's returns, and it fully accounts for all variability (or risk) of a fund's returns. This measure captures the first two moments of a fund's return distribution (mean and variance) as well as the higher moments of skewness and kurtosis which makes it a relevant measure of performance to make investment decisions (Brown, 2008). Skewness refers to the degree of asymmetry of a distribution, and kurtosis refers to the degree to which a distribution contains observations in its tails (DeCarlo, 1997). Omega is a ratio of gains relative to losses as it indicates the probability of value-weighted gains and losses for returns above and below a threshold (Keating & Shadwick, 2002a). It is calculated with the following equation (Keating & Shadwick, 2002b):

$$\Omega(L) = \frac{\int_L^b [1 - F(x)]dx}{\int_a^L F(x)dx} \tag{6}$$

Where $F(x)$ is the cumulative density function of fund returns (x) over the interval (a, b) and L is the hurdle rate. This ratio is used to calculate the performance of an active fund with the hurdle rate set to the return of the assigned passive alternative. A value for $\Omega(L)$ that is greater than one suggests that the active fund outperformed its passive alternative and a value of less than one suggests that it underperformed. To supplement the analysis, the information ratio is presented as a third performance measure.

3.6.2.3 *Information ratio*

The information ratio (IR) is a risk-adjusted performance measure that adjusts the excess returns of a fund compared to a benchmark by the variability (tracking error) of the excess return (Grinold, 1989). Since this study allocates a passive alternative as a benchmark, a fund's excess return is contrasted to the tracking error between the active fund and its passive alternative. The IR is provided as it is argued to reduce the noise to variability ratio compared to the excess return measure (Kosowski, Naik, & Teo, 2007). This measure is calculated with the following equation (Goodwin, 1998):

$$IR = \frac{\alpha_{ex}}{\widehat{\sigma_\alpha}} \tag{7}$$

Where α_{ex} is the excess return as defined in equation 4, and $\widehat{\sigma_\alpha}$ is the tracking error as defined in equation 2. If the IR is positive, the fund delivered superior performance compared to the passive alternative. If not, the fund delivered inferior performance compared to the passive alternative. Active fund performance relative to other active funds in its peer group can also be inferred by ranking their performance in descending order. Therefore, an active fund will outperform if it produces an IR that is greater than that of another active fund in its peer group (i.e., relative outperformance). However, an active fund would outperform the passive alternative (i.e., absolute outperformance) if it derives a positive IR. This study focuses on analysing the value of past performance in deciding between active and passive investment options. Therefore, the primary focus of this research will be on the absolute out- or underperformance of a fund.

3.6.3 Testing procedure

Prior studies predominantly evaluate active funds based on how persistently they maintain their performance ranking within a peer group of active funds, which are relative tests of performance persistence (Anderson & Schnusenberg, 2005; Blake & Timmermann, 2003). Testing for performance persistence compared to stated performance standards, or absolute performance persistence, is less common (Brown & Goetzmann, 1995; Hoch, 2015). Since this study evaluates how persistently an active fund performs relative to a passive alternative, it tests for the presence of absolute performance persistence. Relative tests of performance persistence are limited in their ability to inform investors faced with the active or passive fund investment decisions (Brown & Goetzmann, 1995; Hoch, 2015). Absolute tests of performance persistence contribute in a practical sense to investors' decision-making process. It may advise the investor whether active funds that demonstrated superior (inferior) performance in the past can be expected to continue to do so in the future, which informs investors about the optimality of active or passive investment fund options (Brown & Goetzmann, 1995; Hoch, 2015).

The most frequently used statistical testing procedures are applied to an entire group or sub-groups of funds within the sample studied. These procedures evaluate whether a particular grouping of funds demonstrated persistent performance over several formation and holding period intervals. The rationale for this is that a grouping procedure allows for the aggregation of performance results over the analysed periods, which may increase the power of a statistical test (Brown & Goetzmann, 1995; DeFusco, McLeavey, Pinto, & Runkle, 2019). Fewer tests of performance persistence of individual funds exist. Table 6 provides a description of these procedures, their limitations, and the applicable studies that utilise and describe them.

From the perspective of this research, an assessment of individual funds' performance persistence is deemed optimal. The statistical rationale for this is that it enhances the granularity of the investigation (Bellahsène & Léonard, 2008). Additionally, it aids the avoidance of survivorship bias as inferences about individual funds' performance figures are not aggregated with a grouping of other funds' performance figures. The economic rationale is that it considers whether a particular fund in isolation displays performance persistence (Collinet & Firer, 2003; Hoch, 2015). To analyse the performance persistency of individual active funds, this study evaluates the rolling holding period performance observations of the analysed funds.

Table 5: Common tests for performance persistence

Test applied	Description	Limitations	Applicable studies
Rank Correlation	Tests whether fund ranks over the respective formation and holding periods are correlated. Evidence of positively (negatively) correlated ranks is viewed as evidence in favour of performance persistence (reversal).	Grouped test – constrained in terms of ability to identify individual funds that perform persistently. Fails to identify persistence amongst the top- and bottom-most groupings of funds within the sample of funds.	Brown (2008); Carpenter and Lynch (1999); Deb (2019); Keswani and Stolin (2006); Thobejane et al. (2017); Carhart (1997).
Cross-sectional regressions	Simple ordinary least squares procedure that regresses the performance rankings or performance measures of funds over successive formation and holding periods. Evidence of performance persistence (reversal) is indicated by a positive (negative) and statistically significant slope coefficient of the estimated regression equation.	Grouped test – constrained in terms of ability to identify individual funds that perform persistently. Fails to identify persistence amongst the top- and bottom-most groupings of funds within the sample of funds. Furthermore, this model may be limited by its failure to meet the assumptions of ordinary least squares procedures, resulting in inefficient hypothesis tests.	Carpenter and Lynch (1999); Collinet and Firer (2003); Deb (2019); Firer et al. (2001); Meyer (1998); Grinblatt and Titman (1988); Grinblatt and Titman (1989); Grinblatt and Titman (1992).

Table 5: Common tests for performance persistence *(continued)*

Test applied	Description	Limitations	Applicable studies
Recursive portfolios	Tests for the performance persistency of equally- or value-weighted quantile portfolios formed on a recursive basis over formation and holding periods. Applies statistical tests to performance measure utilised or uses the statistical significance of a performance measure to make inferences about performance persistence (reversal).	Grouped test – constrained in terms of ability to identify individual funds that perform persistently.	Barras et al. (2010); Carhart (1997); Carpenter and Lynch (1999); Ferreira et al. (2019); Grinblatt and Titman (1993); Hendricks et al. (1993); Hoberg et al. (2018); Huij and Verbeek (2007); Hunter et al. (2014); Kosowski et al. (2006); Matallín-Sáez et al. (2016); Otten and Bams (2002); Wermers (1997).
Contingency tables or transition matrices	Successively categorise funds as top or bottom performers relative to a median or average performance, or as out- or underperformers compared to a benchmark, over several formation and holding periods. Utilises statistical tests for independence or association to make inferences about performance persistence or reversal.	Can be applied to groups of funds or individual funds. Creates a binary classification of performance preventing the assessment of the quantum of out-/underperformance associated with a fund's performance persistence.	Brown (2008); Brown and Goetzmann (1995); Carpenter and Lynch (1999); Deb (2019); Fagerland, Lydersen, and Laake (2017); Hoch (2015); Keswani and Stolin (2006); Matallín-Sáez et al. (2016); Mateus et al. (2019); Meyer (1998); Nana (2012).
Runs test	Assesses whether a sequence of holding period performance observations is random or not. A finding that the sequence of observations is non-random suggests that the performance of a particular fund displayed persistence.	Applied to individual funds. Creates a binary classification of performance preventing the assessment of the quantum of out-/underperformance associated with a fund's performance persistence.	Collinet and Firer (2003); Siegel (1956); Jensen (1969).

3.6.3.1 *Mean rolling holding period performance*

A reliable manner in which to assess a fund's performance persistency is to evaluate its performance over rolling time periods (Pancheka, 2021). The average omega ratio, information ratio, excess returns, and inflation-adjusted returns for rolling holding periods are reported to evaluate active fund performance over time. Active funds' omega ratio for the full analysis period is reported as well. This is done to assess the out- or underperformance over time and the full analysis period. The percentage of rolling periods that the fund outperformed over time in terms of the omega ratio is presented to assess the tendency of the active fund to persistently outperform its passive alternative.

The funds' holding periods (as specified in section 3.4.3) are rolled forward on a monthly basis. Therefore, the first holding period for a fund stretches from the analysis starting date used for the category to which the fund belongs and spans the length of one approximated minimum recommended holding period. The following holding period then starts one month after the analysis starting date of the relevant category. This procedure is repeated until a full approximated holding period can no longer be formed. This is similar to the method used by Wessels and Krige (2005b).

3.6.3.2 *Distribution of rolling holding period performance*

To statistically evaluate performance persistency, all active funds' rolling holding period excess returns relative to the passive alternative are plotted onto a distribution. Notched boxplots of the distributions are constructed to perform the analysis (McGill, Tukey, & Larsen, 1978). To assess the statistical significance, a 95 percent two-sided confidence interval around the median of each active fund's rolling holding period excess returns is constructed. The median of the rolling holding period excess returns is used as it is less likely to be distorted by outliers within the produced distribution (Hippel, 2005). The confidence interval is depicted by the notches on the notched boxplot shown in Figure 4.

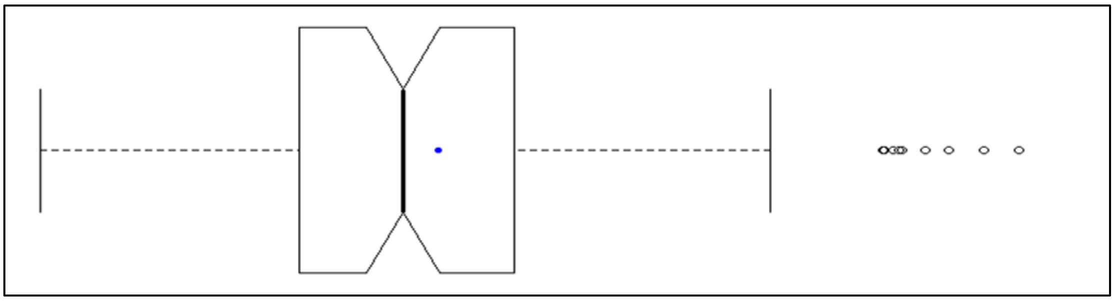


Figure 4: Notched boxplot

Source: Constructed by author

The notches (or confidence interval) are represented by the V-like indentation, and the solid black line between the notches represents the median rolling holding period excess returns. The solid blue dot represents the mean of the fund's distribution of rolling holding period excess returns. The box represents the inter-quartile range (IQR), which is the difference between the third and first quartile (Li, Chen, Chang, & Chen, 2012). The dashed black lines that extend from the ends of the box are the whiskers of the boxplot (Babura, 2017). The solid black lines at the ends of the whiskers mark the boxplot's upper and lower fences (Babura, 2017). The lower fence extends 1.5 times the IQR below the value for the first quartile, whilst the upper fence extends 1.5 times the IQR above the value for the third quartile (Li et al., 2012). The hollow points represent outlier values that fall outside of the upper and lower fences of the boxplot. The confidence interval tests the following hypothesis:

H_0: *Active fund i does not provide median excess returns that are different from zero over time;*

and

H_a: *Active fund i does provide median excess returns that are different from zero over time.*

If the confidence interval about the median does not overlap with the value of zero, then the median is significantly different from zero at a 95 percent confidence level (Reimann, Filzmoser, Garret, & Dutter, 2008). Therefore, if the confidence interval (notches) indicated on a particular active fund's boxplot does not overlap with zero, then the null hypothesis is rejected. If the lower (upper) bound for a particular active fund's confidence interval falls above (below) zero, then it is deemed as a persistent outperformer (underperformer). However, if the confidence interval about the median does overlap with zero then a failure to reject the null hypothesis occurs (Reimann et al., 2008), indicating that the active fund's performance is not persistent. Table 6 summarises the decision-making criteria relevant to whether the null hypothesis can (or fails to) be rejected in favour of the alternative hypothesis.

Table 6: Decision-making criteria relevant to hypothesis

Decision-making criteria	Confidence interval
Persistent outperformer	Reject null hypothesis: lower bound > 0
Performance not persistent	Fail to reject null hypothesis: 0 falls within confidence interval
Persistent underperformer	Reject null hypothesis: upper bound < 0

Figure 5 shows a boxplots of a persistent outperformer, a fund whose performance is not persistent, and a persistent underperformer. The dotted red line indicates excess returns of zero (the performance of the passive alternative).

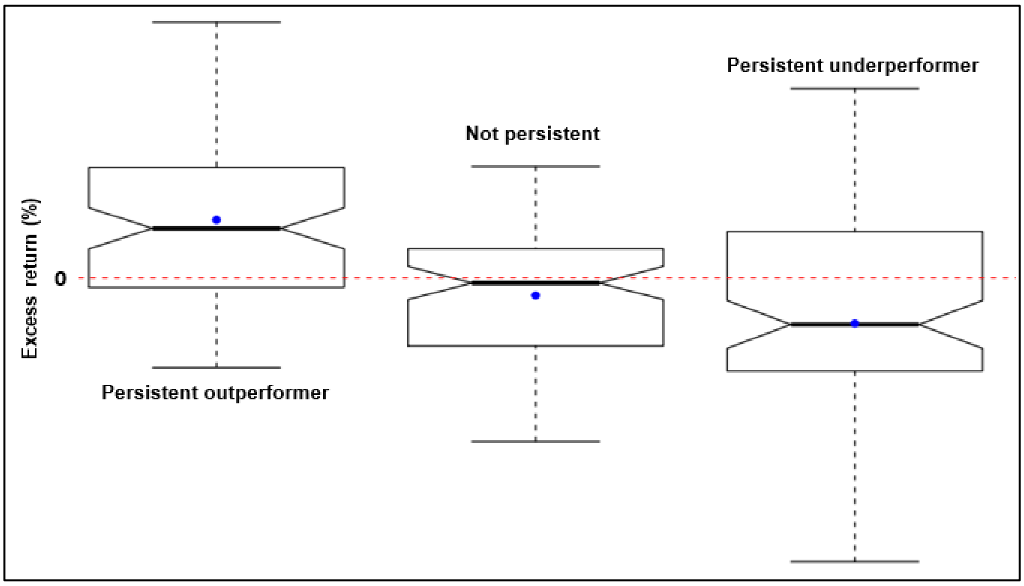


Figure 5: Notched boxplots of a persistent outperformer, a fund whose performance is not persistent, and a persistent underperformer
Source: Constructed by author

Note that this test considers the distribution of the time-series excess returns and not the sequence of excess returns relative to a passive alternative that would be observed by considering adjacent formation and holding period performances. Therefore, funds that are able to outperform the passive alternative more frequently are more likely to be regarded as persistent outperformers. The 95 percent confidence interval is calculated using equation 8 (Babura, 2017; Crawley, 2013; Reimann et al., 2008):

$$M \pm 1.58\left(\frac{IQR}{\sqrt{N}}\right) \tag{8}$$

Where M is the median, IQR is the inter-quartile range, and N is the number of observations within the sample. The confidence interval (notches) about the median is relatively insensitive to the underlying distribution of the sample (Babura, 2017; Crawley, 2013).

In addition to the limitations of the tests described in Table 5, the evidence of persistence for a particular fund may be derived from a sample extracted from the tail of a distribution of observed performance measures. Furthermore, if performance persistence exists, a fund's performance for a given month will be associated with the performance displayed in other months within its return history (Vidal-García, 2013). Therefore, the use of formation and holding periods that split performance assessments may create a bias in the statistical tests applied (Vidal-García, 2013).

Assessing performance persistence with the described procedure addresses these concerns. The use of rolling holding period performances may reduce the sampling error of estimated performance measures for the adjacent formation and holding periods whilst maintaining the dependency structure of performance observations (Lahiri, 2006; Pancheka, 2021; Radovanov & Marcikić, 2014). Furthermore, by setting the holding period lengths equal to the approximated minimum recommended holding period for funds within a particular ASISA category, it assesses the performance persistency in a manner that is commensurate with a practical investment situation.

3.7 ASSESSING AND DEMONSTRATING THE QUALITY AND RIGOUR OF THE PROPOSED RESEARCH DESIGN

Brown (2008) identifies eight prominent aspects of variation in South African research on performance persistence. Two of these aspects are the statistical methods used and the conclusions drawn. The rationale for the chosen statistical tests has been discussed throughout; however, the remaining six aspects relate to methodological decisions which are utilised as a checklist to demonstrate the quality and rigour of the chosen methodology of this study.

3.7.1 The number of unit trusts considered

The number of unit trusts considered has a bearing on the potential of incurring small sample bias, which is when insufficient observations exist for a variable under consideration that may bias the estimates of a parameter in a statistical evaluation (Hayakawa, 2007). This is addressed in two ways. Firstly, the requirement imposed for a fund to have a minimum number of observations for it to be included in the sample ensures that available data for each fund is sufficient to derive unbiased estimates of performance measures. Additionally, it ensures that a sufficient number of observations are available for the rolling holding periods to provide an unbiased representation of a fund's performance distribution over time. Secondly, the inclusion of funds from multiple ASISA categories expands the sample of funds considered. The sample of funds considered in this study (131 funds) is greater than that of multiple prior prominent studies on the performance persistence of South African funds such as Meyer (1998) (13 funds), Firer et al. (2001) (76 funds), Collinet and Firer (2003) (43 funds), Wessels and Krige (2005b) (32 funds), Malefo et al. (2016) (20 funds), and Hoch (2015) (98 funds).

3.7.2 Category of unit trusts considered

Prior South African studies primarily focus on the performance persistence of equity unit trusts. This study expands on the current knowledge by considering unit trusts from categories under each of the second-tier ASISA classes grouped under the first-tier category South African unit trusts.

3.7.3 Period over which data extends

The time horizons selected ensure that fund performance and persistence analyses extend over several periods to consider the effect of changing market conditions that may influence market functionality and fund performance (Fama, 1998; Ferson & Schadt, 1996; Novara et al., 2019). All horizons include times in which the market experienced both periods of shock and steady states – which allows for the consideration of both the effects of the efficient and adaptive market hypotheses.

3.7.4 Data type and frequency

The use of rolling monthly time periods resembles the practical situation faced by an investor who can invest at any point in time (Hoch, 2015). The secondary data obtained from

Morningstar is of the necessary quality for this study as it is a respected provider of data in the industry and academia (Mateus et al., 2019; Morningstar, 2017).

3.7.5 Performance measure used

Excess returns and the omega ratio do not make any distributional assumptions that may subject the analysis to biases associated with relying on these assumptions. The allocation of the passive funds as the benchmarks against which active fund performance is measured ensures that active funds are evaluated relative to an investable alternative and facilitates the avoidance of look-ahead bias.

3.7.6 Horizon for persistence evaluation

Collinet and Firer (2003) state that the evidence of performance persistence may depend on the length of the holding periods analysed. This concern is addressed by the consideration of holding periods that approximate the minimum recommended holding period for a fund in a particular ASISA category. This allows for an analysis that provides practical guidance to investors as it coincides with the investment horizon that most retail investors would be advised to commit their capital for.

3.8 RESEARCH ETHICS

The data will be prepared for analysis as described in the data analysis section and will not be manipulated in any manner. The necessary ethical clearance has been obtained from the Ethics Committee of the Faculty of Economic and Management Sciences at the University of Pretoria prior to the commencement of assessments.

3.9 DELIMITATIONS

The delimitations applicable to this research are listed in this section.

The research is limited to the following ASISA categories:

- SA Equity Financial
- SA Equity General
- SA Equity Industrial
- SA Equity Large cap
- SA Equity Resource
- SA Multi-Asset High Equity
- SA Multi-Asset Low Equity
- SA Interest-Bearing Variable term
- SA Real Estate General

- This research is limited to retail funds.
- This study will not expand on the potential determinants of performance persistence.
- Funds of funds are excluded as they create two layers of fees (Yau et al., 2007), and smart beta funds are excluded as they attempt to provide exposure to a blend of active and passive investment strategies (Malkiel, 2014).
- This study does not account for investor transaction costs.
- Although this study considers individual funds' performances, any inferences regarding the aggregate value of active management may be subject to a degree of survivorship bias.

3.10 LIMITATIONS

This study is subject to the following limitations:

- The use of rolling periods may overrepresent elements of fund performance in the statistical assessments applied to individual funds.
- The requirement for longer return histories may bias the analysis to consider the performance persistence of more mature funds.
- The use of passive alternatives that track their respective ASISA category indices may be suboptimal for instances where certain active funds' performance tends towards more focussed active investment styles and/or objectives.
- Passive funds incepted after the analysis starting dates are not considered.

3.11 ASSUMPTIONS

This research is based on the following set of assumptions:

- The passive alternative to which an active fund is being compared is an appropriate representation of an alternative passive fund investment.
- The holding periods applied to the ASISA categories under investigation are deemed appropriate based on consultation with industry professionals as well as constraints pertaining to the available data.
- The results and analysis assumes the perspective of a South African retail investor.
- This study assumes that the definition of performance persistence pertains to the distribution and frequency of performance, and not necessarily the sequence of observed performance.

3.12 SUMMARY

This study makes use of a positivist research paradigm and follows a quantitative and deductive research approach. Secondary time-series data is sourced from the Morningstar Direct database. The data is analysed using Excel, and R. Active funds are sampled from the ASISA categories considered, and comparable passive funds are used as passive investment alternatives for the evaluation.

This study uses four performance measures - excess returns compared to a passive alternative, inflation-adjusted returns, the omega ratio, and the information ratio. The rolling holding period performance (with a one-month moving step) of the funds is evaluated to assess active fund performance over time. The rolling holding periods within the full analysis period for a particular category of funds is used for this purpose. In addition, the active funds' full analysis period omega ratio is reported. The full analysis period for a specific category of funds commences from its ASISA category's analysis starting date until 31 December 2020.

Notched boxplots are used to evaluate active funds' performance persistence statistically. Confidence intervals about the median of active funds' rolling holding period returns are used to evaluate the statistical significance of their performance persistency relative to a passive alternative.

CHAPTER 4: RESULTS AND DISCUSSION

The previous chapter described the research method utilised in this study. This chapter presents the results and analysis thereof by commencing with a summary of the data used and its associated descriptive statistics. Funds' rolling holding period performances are presented thereafter. The descriptive statistics and test results are presented separately for equity, interest-bearing, multi-asset, and real estate Association of Savings and Investment South Africa (ASISA) categories. A discussion follows the presentation of results for each of these categories.

4.1 ACTIVE FUND DATA

Table 7 summarises the sample data for all active funds considered. All active funds have been assigned codes and are listed in appendix A.

Table 7: Sample data of active funds considered

ASISA Category	Analysis start date	Number of funds in sample	Active fund codes	Data points in full sample period ending 31/12/2020	Data points per holding period	Number of rolling holding periods (1 month moving step)
SA Equity	01/01/2007	51 funds (Financial – 4 funds) (General – 38 funds) (Industrial – 3 funds) (Large Cap – 1 fund) (Resource – 5 funds)	Financial: F1 - F4 General: G1 – G38 Industrial: I1 – I3 Large Cap: L1 Resource: R1 – R5	168 months	All equity categories – 84 months	All equity categories – 85 periods
SA Interest-Bearing - Variable Term	01/01/2015	16 funds	B1 – B16	72 months	36 months	37 periods
SA Multi-Asset	01/01/2011	48 funds (High Equity – 30 funds) (Low Equity – 18 funds)	High Equity: M1 – M30 Low Equity: N1 – N18	120 months	High Equity - 60 months Low Equity - 36 months	High Equity - 61 periods Low Equity - 85 periods
SA Real Estate - General	01/01/2013	16 funds	P1 – P16	96 months	60 months	37 periods

Active funds with return data available from the analysis start date for its ASISA category to 31 December 2020 are included in the sample. The full analysis period for a particular ASISA category stretches from its analysis start date to 31 December 2020. The different analysis starting dates and the varying lengths of the relevant categories' holding periods create differences in the number of data points considered per fund category.

4.2 PASSIVE ALTERNATIVE DATA

For each ASISA category, a passively managed unit trust or exchange traded fund (ETF) is allocated as a passive alternative for all active funds within the category. The passive fund is required to have available return data from the analysis starting date for its category until 31 December 2020 and is required to track its category index. If more than one passive fund option is available, the fund with the lowest tracking error to the index over the full analysis period is selected. If none of the available passive funds tracks their category index, passive funds that track an index whose universe is the ASISA category index is used. South African multi-asset categories do not have category indices. Hence, the passive funds that were in existence at the analysis starting date, with available return data until 31 December 2020, are used as the passive alternatives for these categories. If more than one passive fund meets this criterion, the passive fund with the lowest average total investment charge (TIC) is selected.

Table 8 displays the funds that are allocated as passive alternatives for the respective categories. All passive alternatives have been assigned codes. South African (SA) general equity, interest-bearing variable term, and general real estate categories have one available passive fund that tracks their respective category indices at their analysis start dates until 31 December 2020. These funds are therefore allocated as the categories' passive alternatives. The SA thematic equity categories only have available passive funds that track indices falling within the universe of their ASISA category indices. Apart from the SA large cap equity category, thematic equity categories only have one passive fund available per category. These funds are therefore allocated as the respective categories' passive alternatives. The passive alternative for the SA large cap equity category is the passive fund (PL), with the lowest annualised tracking error over the analysis period (0.34%). PM and PN are allocated as passive alternatives as they are the only passive funds available at the analysis starting date for the SA multi-asset categories.

Table 8: Sample of passive funds considered

Third-tier ASISA Categories	ASISA category index	Passive alternative fund name	Passive alternative code	Index tracked	Passive unit trust/Passive ETF	Passive alternative annualised return over full analysis period	Passive alternative annualised median rolling period return	Passive alternative annualised mean rolling period return in excess of inflation
SA Equity – Financial	FTSE/JSE Financials Index	Satrix FINI ETF	PF	FTSE/JSE Financial 15 Index	Passive ETF	6.329%	14.203%	6.905%
SA Equity – General	FTSE/JSE All Share Index	Gryphon All Share Tracker	PG	FTSE/JSE All Share Index	Passive unit trust	9.170%	11.423%	5.636%
SA Equity – Industrial	FTSE/JSE All Share Industrials Index	Satrix Capped INDI ETF	PI	FTSE/JSE Capped Industrial 25 Index (FTSE/JSE Industrial 25 Index prior to 1 January 2018)	Passive ETF	12.810%	18.933%	11.303%
SA Equity – Large Cap	FTSE/JSE Large Cap Index	Satrix 40 ETF	PL	FTSE/JSE Top 40 Index	Passive ETF	9.128%	10.953%	5.189%
SA Equity – Resources	FTSE/JSE Resources Index	Satrix RESI ETF	PR	FTSE/JSE Capped Resources 10 Index (FTSE/JSE Resources 10 Index prior to 1 July 2015)	Passive ETF	4.541%	-0.923%	-5.605%
SA Interest-Bearing – Variable Term	FTSE/JSE All Bond Index	Satrix Bond Index A1	PB	FTSE/JSE All Bond Index	Passive unit trust	7.270%	7.985%	3.082%
SA Multi-Asset High Equity	NA	Nedgoup Investments Core Diversified C	PM	Proprietary Index	Passive unit trust	9.333%	9.472%	3.536%
SA Multi-Asset Low Equity	NA	Nedgoup Investments Core Guarded C	PN	Proprietary Index	Passive unit trust	8.732%	7.708%	3.234%
SA Real Estate General	FTSE/JSE SA Listed Property Index	Satrix Property Index A1	PP	FTSE/JSE SA Listed Property Index	Passive unit trust	-1.060%	5.162%	-4.303%

Source: Calculated by the author with R and Morningstar Direct

4.3 DESCRIPTIVE STATISTICS

The descriptive statistics of the total monthly return data for active and passive funds for each category are presented and discussed in this section. The detail of each active fund's descriptive statistics is found in appendix B. Scatterplots of annualised total returns, and the annualised standard deviation for each fund is included in appendix C.

4.3.1 Equity funds

Fifty-one active equity funds are included in the sample between 1 January 2007 and 31 December 2020. Of the 51 funds, 38 are general equity funds, whilst 13 are thematic equity funds. The descriptive statistics of funds in the general and thematic equity categories are presented and discussed separately.

4.3.1.1 *General equity funds*

Table 9 shows the descriptive statistics for the passive alternative (PG). Table 10 presents comparative summaries of the descriptive statistics for the sample of active funds (G1 – G38) relative to the passive alternative.

Table 9: Descriptive statistics of monthly and annualised total return data for the passive alternative of the general equity category (1 Jan 2007 to 31 Dec 2020)

	Monthly	Annualised
Mean total return	0.825%	10.36%
Median total return	1.118%	14.272%
Standard deviation	4.278%	14.820%

Source: Calculated by author with Excel

The passive alternative generates a mean monthly total return of 0.825%, which is greater than 30 of the 38 active funds' mean monthly total returns. Additionally, only three active funds show a median monthly total return greater than that of the passive alternative. However, the passive alternative's monthly standard deviation of 4.278% is greater than 28 of the 38 active funds.

Table 10: Comparative summary of descriptive statistics for active general equity funds relative to the passive alternative (1 Jan 2007 to 31 Dec 2020)

	Number	Percent
Active funds in sample	38	100%
Active funds with mean annualised total return > passive alternative	8	21.053%
Active funds with median annualised total return > passive alternative	3	7.895%
Active funds with annualised standard deviation < passive alternative	28	73.684%
Active funds with correlation > 0.8 to passive alternative	34	89.474%
Range of active funds' annualised tracking error to passive alternative	4.239% - 17.684%	

Source: Calculated by author with Excel

The active funds' annualised tracking errors to the passive alternative range from 4.239% (G1) to 17.684% (G25). Of the 38 active funds, 34 have correlations between 0.8 and 1 relative to the passive alternative. This suggests that the passive alternative's returns have a strong positive linear relationship to most active fund returns in the sample.

4.3.1.2 *Thematic equity funds*

Table 11 presents the descriptive statistics for each respective thematic equity category's passive alternative. Table 12 presents comparative summaries of the descriptive statistics for the sample of active thematic equity funds relative to their respective passive alternatives.

Table 11: Descriptive statistics of monthly and annualised total return data for the passive alternatives of the thematic equity categories (1 Jan 2007 to 31 Dec 2020)

Thematic equity category	Mean total return		Median total return		Standard deviation	
	Monthly	Annualised	Monthly	Annualised	Monthly	Annualised
Financial (PF)	0.679%	8.461%	1.059%	13.47%	5.678%	19.669%
Industrial (PI)	1.101%	14.038%	1.18%	15.111%	4.289%	14.857%
Large Cap (PL)	0.839%	10.55%	0.871%	10.971%	4.689%	16.243%
Resource (PR)	0.641%	7.969%	0.322%	3.934%	7.334%	25.405%

Source: Calculated by author with Excel

The mean monthly total returns for three active financial equity funds are greater than that of the category's passive alternative (PF). None of the active financial equity funds have median monthly total returns that are greater than PF. All four active financial equity funds have lower standard deviations than PF. The active financial funds' total returns are strongly related to that of their passive alternative, as suggested by the active funds' correlations which are all in excess of 0.95. The annualised tracking error for the active financial equity funds ranges between 4.424% (F1) to 6.232% (F3).

Table 12: Comparative summary of descriptive statistics for active thematic equity funds relative to the passive alternatives (1 Jan 2007 to 31 Dec 2020)

Thematic equity category	Financial (F1 – F4)		Industrial (I1 – I3)		Large Cap (L1)		Resource (R1 – R5)	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Active funds in sample	4	100%	3	100%	1	100%	5	100%
Active funds with mean annualised total return > passive alternative	3	75%	0	0%	1	100%	5	100%
Active funds with median annualised total return > passive alternative	0	0%	2	66.67%	0	0%	3	60%
Active funds with annualised standard deviation < passive alternative	4	100%	3	100%	1	100%	4	80%
Active funds with correlation > 0.8 to passive alternative	4	100%	3	100%	1	100%	4	80%
Range of active funds' annualised tracking error to passive alternative	4.424% - 6.232%		5.82% - 7.049%		1.717%		8.269% - 30.385%	

Source: Calculated by author with Excel

All three of the active industrial funds have mean monthly total returns that are less than their passive alternative's whilst two active funds have median monthly total returns greater than the passive alternative (PI). PI demonstrates a greater standard deviation than all three active industrial funds. The active funds' correlations to PI are all in excess of 0.883, whilst their annualised tracking errors range between 5.82% (I1) to 7.049% (I3).

The active large cap equity fund's mean monthly total returns exceed its passive alternative's, whilst its median monthly total returns and standard deviation are less than the passive alternative's. The active fund's total returns are very strongly correlated with its passive alternative's, as shown by the correlation of 0.994. The active large cap fund has an annualised tracking error of 1.717%.

All five active resource funds' mean monthly total returns are greater than their passive alternative's, whilst only three have median monthly total returns exceeding that of their passive alternative (PR). Additionally, four out of the five funds appear to have a standard deviation less than that of PR. With the exception of R5, the active funds are strongly correlated to PR as respective pairwise correlations all exceed 0.925. R5 stands out in terms of its return behaviour as it is the only active resource fund that demonstrates a greater standard deviation of return compared to PR. Additionally, it is the only active resource fund with a pairwise correlation to PR of less than 0.8. This may be attributed to its focus on trading gold-related equities and not general resource-related equities. The active resource equity funds have annual tracking errors relative to the passive alternative which range from 8.269% (R4) to 30.385% (R5).

4.3.2 Interest-bearing funds

Sixteen active interest-bearing funds are included in the sample between 1 January 2015 to 31 December 2020. All 16 of the interest-bearing funds are categorised under the variable term category. Table 13 presents the descriptive statistics for the passive alternative (PB). Table 14 presents comparative summaries of the descriptive statistics for the sample of active funds (B1 – B16) relative to the passive alternative.

Table 13: Descriptive statistics of monthly and annualised total return data for the passive alternative of the interest-bearing variable term category (1 Jan 2015 to 31 Dec 2020)

	Monthly	Annualised
Mean total return	0.618%	7.673%
Median total return	0.612%	7.598%
Standard deviation	2.513%	8.705%

Source: Calculated by author with Excel

Ten of the 16 active funds in the sample generate a mean monthly total return greater than that of the passive alternative (PB), whilst 14 active funds generate a median monthly total return greater than PB. Eleven of the active funds have monthly standard deviations that are less than that of PB.

Table 14: Comparative summary of descriptive statistics for active interest-bearing variable term funds relative to the passive alternative (1 Jan 2015 to 31 Dec 2020)

	Number	Percent
Active funds in sample	16	100%
Active funds with mean annualised total return > passive alternative	10	62.5%
Active funds with median annualised total return > passive alternative	14	87.5%
Active funds with annualised standard deviation < passive alternative	11	68.75%
Active funds with correlation > 0.8 to passive alternative	16	100%
Range of active funds' annualised tracking error to passive alternative	0.422% - 5.273%	

Source: Calculated by author with Excel

Most of the active funds' returns are strongly correlated the returns of PB since all 16 active funds have correlations above 0.8. The tracking error for the active funds relative to PB ranges from 0.422% (B10) to 5.273% (B2).

4.3.3 Multi-asset funds

The sample consists of 48 active funds from two multi-asset categories from 1 January 2011 to 31 December 2020. Of the 48 active funds, 30 are from the multi-asset high equity category, and 18 are from the multi-asset low equity category. The descriptive statistics are presented and discussed separately for each category.

4.3.3.1 *Multi-asset high equity funds*

Table 15 shows the descriptive statistics for the passive alternative (PM). Table 16 presents comparative summaries of the descriptive statistics for the sample of active funds (M1 – M30) relative to the passive alternative.

Table 15: Descriptive statistics of monthly and annualised total return data for the passive alternative of the multi-asset high equity category (1 Jan 2011 to 31 Dec 2020)

	Monthly	Annualised
Mean total return	0.779%	9.757%
Median total return	0.891%	11.229%
Standard deviation	2.56%	8.869%

Source: Calculated by author with Excel

Most of the active funds have mean and median monthly total returns less than that of the passive alternative. Thirteen active funds appear to display less return variability compared to the passive alternative (PM), as shown in Table 16.

Table 16: Comparative summary of descriptive statistics for active multi-asset high equity funds relative to the passive alternative (1 Jan 2011 to 31 Dec 2020)

	Number	Percent
Active funds in sample	30	100%
Active funds with mean annualised total return > passive alternative	7	23.333%
Active funds with median annualised total return > passive alternative	8	26.667%
Active funds with annualised standard deviation < passive alternative	13	43.333%
Active funds with correlation > 0.8 to passive alternative	24	80%
Range of active funds' annualised tracking error to passive alternative	2.06% - 7.305%	

Source: Calculated by author with Excel

The annual tracking error for the active funds ranges between 2.06% (M30) and 7.305% (M23), and 24 of the 30 active funds have correlations greater than 0.8 relative to PM.

4.3.3.2 *Multi-asset low equity funds*

Table 17 shows the descriptive statistics for the passive alternative (PN). Table 18 presents comparative summaries of the descriptive statistics for the sample of active funds (N1 – N18) relative to the passive alternative.

Table 17: Descriptive statistics of monthly and annualised total return data for the passive alternative of the multi-asset low equity category (1 Jan 2011 to 31 Dec 2020)

	Monthly	Annualised
Mean total return	0.712%	8.884%
Median total return	0.823%	10.332%
Standard deviation	1.534%	5.314%

Source: Calculated by author with Excel

Of the 18 active funds, three have mean and median monthly returns greater than that of the passive alternative (PN), respectively. Twelve of the active funds have standard deviations that are less than that of PN.

Table 18: Comparative summary of descriptive statistics for active multi-asset low equity funds relative to the passive alternative (1 Jan 2011 to 31 Dec 2020)

	Number	Percent
Active funds in sample	18	100%
Active funds with mean annualised total return > passive alternative	3	16.667%
Active funds with median annualised total return > passive alternative	3	16.667%
Active funds with annualised standard deviation < passive alternative	12	66.667%
Active funds with correlation > 0.8 to passive alternative	11	61.111%
Range of active funds' annualised tracking error to passive alternative	1.762% - 6.721%	

Source: Calculated by author with Excel

The active funds have annual tracking errors to PN ranging from 1.762% (N13) to 6.721% (N3). Eleven of the 18 active funds have correlations above 0.8.

4.3.4 Real estate funds

Sixteen active general real estate funds are included in the sample between 1 January 2013 to 31 December 2020. Table 19 presents the descriptive statistics for the passive alternative (PP). Table 20 presents comparative summaries of the descriptive statistics for the sample of active funds (P1 – P16) relative to the passive alternative.

Table 19: Descriptive statistics of monthly and annualised total return data for the passive alternative of the general real estate category (1 Jan 2013 to 31 Dec 2020)

	Monthly	Annualised
Mean total return	0.132%	1.597%
Median total return	0.734%	9.167%
Standard deviation	6.34%	21.963%

Source: Calculated by author with Excel

The passive alternative has a mean and median monthly total return less than nine and five of the active funds, respectively. Ten of the active funds have standard deviations that are less than that of the passive alternative.

Table 20: Comparative summary of descriptive statistics for active general real estate funds relative to the passive alternative (1 Jan 2013 to 31 Dec 2020)

	Number	Percent
Active funds in sample	16	100%
Active funds with mean annualised total return > passive alternative	9	56.25%
Active funds with median annualised total return > passive alternative	5	31.25%
Active funds with annualised standard deviation < passive alternative	10	62.5%
Active funds with correlation > 0.8 to passive alternative	16	100%
Range of active funds' annualised tracking error to passive alternative	1.56% - 12.871%	

Source: Calculated by author with Excel

The annual tracking error of the active funds ranges from 1.56% (P13) to 12.871% (P10). The passive alternative captures the return profile of the active funds well, as all respective pairwise correlations are more than 0.828.

4.3.5 Conclusion: descriptive statistics

Most of the active funds have similar distributional characteristics and return profiles relative to their passive alternatives. R5 (active resource fund) has a return profile that differs from its category's passive alternative. In addition, the active funds in the multi-asset low equity sectors seem to be less correlated to their respective passive alternative as only 61.111% of the active funds have correlations greater than 0.8. Finally, apart from the active funds in the multi-asset high equity sector, a greater proportion of active funds in each sector have lower standard deviations than their respective passive alternatives; hence, active funds appear to be successful at reducing investment risk.

4.4 TEST RESULTS

Active funds' rolling holding period performances relative to their respective passive alternatives are presented in this section. The results are presented in the tables that are ordered by the percentage of rolling holding periods that the active funds outperformed in terms of the omega ratio (Ω). All active funds considered are referred to by their assigned codes. The figures for all performance measures and the bounds for the confidence intervals (CI) are presented on an annualised basis.

4.4.1 Equity funds

The results for 51 active equity funds across five ASISA categories are presented in this section. The output for general equity funds is presented first, and the output for thematic equity funds follows. The analysis of the results concludes this section. The active equity funds are examined over the period 1 January 2007 to 31 December 2020. The number of data points per holding period is 84 months, which results in 85 rolling holding periods over the 14-year analysis period.

4.4.1.1 *General equity funds*

Thirty-eight active general equity funds are examined. The active funds are compared to the passive alternative PG. Table 21 reports the results for the active funds, and Figure 6 presents the active funds' notched boxplots.

The results from the rolling holding period excess returns shown in Table 21 suggest that 33 of the 38 funds demonstrate persistent performance. Of the active funds classified as persistent performers, ten persistently outperformed whilst 23 persistently underperformed the passive alternative. The mean rolling holding period omega ratio, mean excess returns, and mean information ratios of these funds corroborate this finding.

Table 21: Test results for active general equity funds

Figures for the performance measures are presented on an annualised basis. Ω = Omega ratio. The full analysis period omega is calculated from 1 Jan 2007 to 31 Dec 2020. α_{ex}= Returns in excess of the passive alternative, IR = Information ratio, and α_{exi} = Returns in excess of inflation. CI = Confidence interval. PO = a persistently outperforming fund, PU = a persistently underperforming fund, and NP suggests that the fund's performance is not persistent. ** Signifies statistical significance at a 5% level.

Fund Code	Percent Rolling holding periods Ω > 1	Full analysis period Ω	Mean rolling Ω	Mean rolling α_{ex}	Mean rolling IR	Mean rolling α_{exi}	Median rolling α_{ex}	95% CI Lower bound	95% CI Upper bound	PO/PU/NP
G36	94%	1.236	1.220	1.050%	0.204	6.892%	0.902%	0.744%	1.060%	PO**
G1	88%	1.320	1.198	0.773%	0.213	6.454%	0.591%	0.450%	0.731%	PO**
G7	88%	1.308	1.323	1.273%	0.297	7.143%	1.095%	0.795%	1.395%	PO**
G4	86%	1.126	1.148	0.621%	0.090	6.942%	0.531%	0.311%	0.751%	PO**
G24	80%	0.988	1.081	0.210%	0.043	6.048%	0.425%	0.290%	0.559%	PO**
G33	78%	0.846	1.132	0.492%	0.059	6.543%	0.955%	0.602%	1.309%	PO**
G32	76%	1.156	1.147	0.460%	0.108	6.400%	0.325%	0.145%	0.506%	PO**
G21	75%	0.935	1.361	1.295%	0.260	7.148%	1.848%	1.357%	2.340%	PO**
G3	64%	0.944	1.023	-0.188%	-0.032	5.849%	-0.054%	-0.233%	0.124%	NP
G8	61%	1.234	1.190	0.859%	0.142	6.637%	0.371%	0.037%	0.705%	PO**
G15	61%	0.780	1.089	-0.227%	-0.042	5.777%	0.370%	-0.526%	1.266%	NP
G19	61%	0.951	1.104	0.456%	0.046	6.971%	-0.017%	-0.395%	0.360%	NP
G14	56%	0.883	1.134	0.236%	0.044	6.232%	1.331%	0.489%	2.174%	PO**
G35	53%	1.026	1.050	0.033%	0.008	5.853%	-0.020%	-0.269%	0.230%	NP
G31	52%	1.051	1.068	0.109%	0.025	6.069%	-0.162%	-0.363%	0.039%	NP
G29	46%	0.720	0.963	-0.487%	-0.115	5.290%	-0.498%	-0.754%	-0.242%	PU**
G34	40%	0.898	0.991	-0.644%	-0.083	5.455%	-0.904%	-1.313%	-0.495%	PU**
G37	33%	0.854	0.958	-0.640%	-0.125	5.277%	-0.784%	-0.990%	-0.578%	PU**
G2	26%	0.933	0.795	-1.797%	-0.339	4.105%	-2.474%	-2.908%	-2.039%	PU**
G9	25%	0.835	0.790	-2.317%	-0.357	3.588%	-2.914%	-3.475%	-2.352%	PU**
G23	25%	0.793	0.818	-2.136%	-0.327	3.877%	-2.295%	-2.820%	-1.770%	PU**
G12	21%	0.606	0.800	-2.136%	-0.370	3.648%	-1.617%	-2.216%	-1.019%	PU**
G30	15%	0.791	0.817	-1.666%	-0.313	4.098%	-1.591%	-1.947%	-1.234%	PU**
G22	9%	0.681	0.746	-1.905%	-0.391	3.916%	-1.719%	-1.998%	-1.441%	PU**
G25	7%	0.892	0.845	-3.690%	-0.209	2.271%	-3.762%	-4.443%	-3.081%	PU**
G28	5%	0.718	0.803	-2.333%	-0.342	3.662%	-2.337%	-2.555%	-2.119%	PU**
G20	2%	0.594	0.702	-3.338%	-0.520	2.613%	-3.202%	-3.367%	-3.036%	PU**
G13	1%	0.640	0.740	-2.287%	-0.426	3.532%	-2.353%	-2.657%	-2.049%	PU**
G17	1%	0.795	0.811	-2.484%	-0.316	3.473%	-2.342%	-2.594%	-2.089%	PU**
G5	0%	0.712	0.659	-4.023%	-0.528	1.722%	-4.274%	-4.477%	-4.072%	PU**
G6	0%	0.741	0.680	-2.022%	-0.486	3.672%	-2.237%	-2.452%	-2.023%	PU**
G10	0%	0.612	0.541	-7.659%	-0.813	-1.901%	-7.565%	-7.895%	-7.234%	PU**
G11	0%	0.729	0.572	-6.958%	-0.774	-1.179%	-7.497%	-7.932%	-7.062%	PU**
G16	0%	0.517	0.485	-3.856%	-0.897	1.754%	-3.913%	-4.210%	-3.617%	PU**
G18	0%	0.704	0.681	-3.249%	-0.514	2.547%	-3.043%	-3.346%	-2.739%	PU**
G26	0%	0.748	0.667	-4.114%	-0.576	1.846%	-4.215%	-4.400%	-4.029%	PU**
G27	0%	0.732	0.705	-3.113%	-0.496	2.787%	-3.313%	-3.548%	-3.077%	PU**
G38	0%	0.464	0.556	-3.549%	-0.736	2.047%	-3.624%	-3.902%	-3.346%	PU**

Source: Calculated by the author with R and Excel

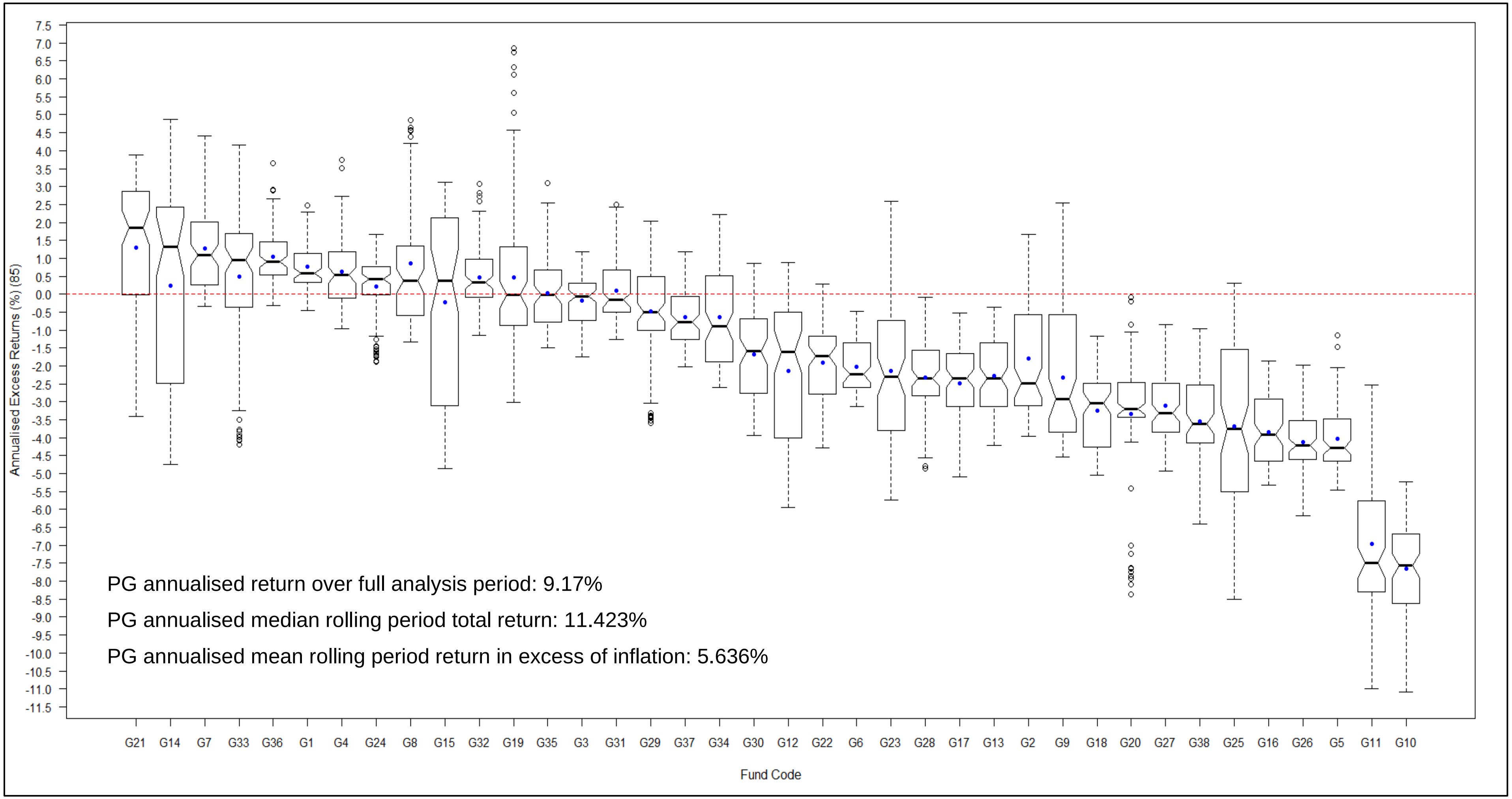


Figure 6: Active general equity funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2007 to 31 Dec 2020)
Source: Constructed by the author with R

As an example, Figure 7 shows the rolling holding period excess return distributions (including median and confidence intervals) of a persistently underperforming and outperforming fund (G22 and G36). The dashed blue and red lines mark the medians and confidence intervals, whilst the solid black line indicates the value of zero.

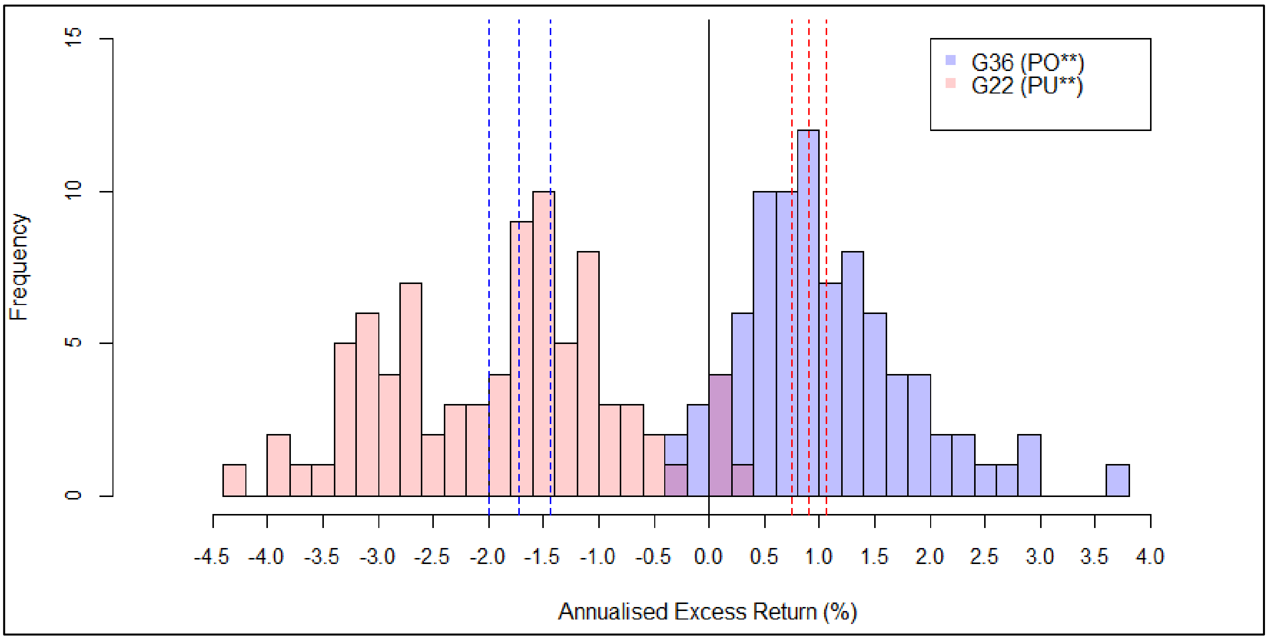


Figure 7: Distributions of rolling holding period excess returns for G36 and G22 (1 Jan 2007 to 31 Dec 2020)
Source: Constructed by the author with R

Figure 7 provides an alternative representation of the rolling holding period excess return distributions displayed by the notched boxplots for G22 and G36 in Figure 6. The left- and rightmost dashed lines (blue for G22 and red for G36) are equivalent to the notches shown on the boxplots for G22 and G36 in Figure 6. The centremost blue and red dashed lines represent the median rolling period excess returns of G22 (-1.719%) and G36 (0.902%), respectively. The evidence in Table 21 suggests that all funds except for G10 and G11 were able to enhance the real wealth of the investor (see Mean rolling α_{exi} and notched boxplots in Figure 6). Additionally, the passive alternative (PG) derived positive inflation-adjusted returns of 5.636%, as reported in Figure 6. This may be attributed to the fact that the funds considered primarily invest in equities.

Notably, the full analysis period omega ratios (Ω) for four of the ten persistently outperforming funds are less than one (as shown in Table 21). This indicates that these funds (G14, G21, G33, G24) could not provide outperformance from 1 January 2007 to 31

December 2020. Figure 6 shows that the excess return distributions of two of these funds, namely G33 and G24, show many negative outliers (ranging between -3.4% and -4.4% for G33 and between -1.2% and -1.9% for G24). The lower whisker fences of G21 and G14 extend well below zero (-3.5% and -4.8%, respectively) compared to their median excess returns that are positive for both funds (1.848% for G21 and 1.331% for G14). Additionally, G14 only outperformed in 56% of its holding periods, as suggested by its rolling holding period omega ratio. This means that the periods in which these funds (G14, G21, G33, and G24) underperformed eliminated the value of outperformance achieved in most of their rolling holding periods. Furthermore, this shows that even though these funds are classified as persistent outperformers, their excess return distributions demonstrate more noisy information.

In contrast, six persistently outperforming funds (G36, G1, G7, G4, G32, and G8) also outperformed over the full analysis period. G4, G7, G1, and G36 outperform the passive alternative in more than 80% of their rolling periods. The boxplots in Figure 6 show that these funds (G4, G7, G1, and G36) have narrower excess return distributions above zero. On the other hand, G8 and G32 outperform in only 61% and 76% of their rolling periods, respectively. The boxplots of G8 and G32 (Figure 6) show that these funds also have relatively narrow excess return distributions with mean and median excess returns closer to zero. However, the outliers above the upper whiskers of G8 and G32 show that these funds are prone to periods of sharp outperformance. The consistency between the full and rolling period performance measures and the narrower excess return distributions suggest that these funds' (G36, G1, G7, G4, G32, and G8) performance histories contain less noisy information.

The test for performance persistency suggests that five of the active funds (G3, G15, G19, G35, and G31) do not persistently out- or underperform the passive alternative as the null hypothesis cannot be rejected. This is shown in Figure 6 with the red line (zero), which falls between the notches on these funds' boxplots (or the value of zero that falls within the confidence intervals in Table 21).

Table 21 reports that 23 of the 38 active funds have negative upper bounds, suggesting that these funds are persistent underperformers. This is in accordance with prior studies, which showed that most of the active general equity funds in the samples considered demonstrated persistent underperformance. The mean rolling period omega ratios of below one, negative information ratios, and negative excess returns for these funds as reported in Table 21 confirm this observation. Apart from G10 and G11, all of these funds were able to provide returns in excess of inflation. However, their persistent underperformance suggests that investors would have been better off if they had invested in the passive alternative.

4.4.1.2 *Thematic equity funds*

Four financial funds, three industrial funds, one large cap fund, and five resource funds make up the sample of active thematic equity funds. The codes for the passive alternatives are shown in Table 22. Table 23 reports the results for the active funds, and Figures 8 – 11 presents the active funds' notched boxplots.

Table 22: Passive alternative codes for thematic equity categories

Fund category	Passive alternative code
Financial	PF
Industrial	PI
Large Cap	PL
Resource	PR

Amongst the 13 active thematic equity funds, seven funds persistently outperform, and five persistently underperform their respective passive alternatives. The boxplot for F1 in Figure 8 shows that this active financial equity fund does not display persistent performance as its notches are intersected by the value of zero. All persistent outperformers produce real returns that are greater than that derived by their respective passive alternatives, as indicated in Table 23 (Mean rolling α_{exi}) and Figures 8 - 11. The converse is observable for persistent underperformers.

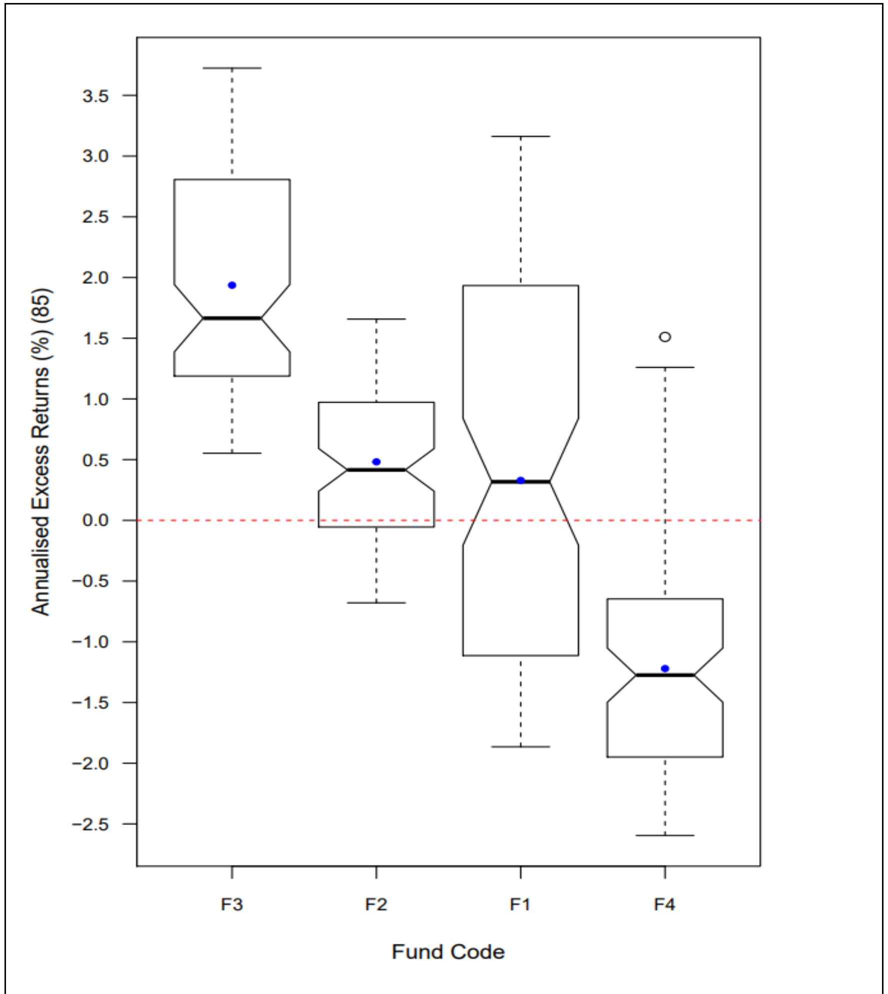
Persistently outperforming thematic funds deliver superior performance relative to their passive alternative in 80% to 100% of their rolling periods, as shown in Table 23. The mean rolling period omega ratios, information ratios, and excess returns confirm the evidence that funds F3, R1, R2, R3, R4, F2, and L1 outperform persistently. Additionally, these funds (F3, R1, R2, R3, R4, F2, and L1) provide superior performance compared to their passive alternatives over the full analysis period, as shown by their omega ratios in Table 23. Of the persistently outperforming funds, two are financial funds, four are resource funds, and one is a large cap fund.

Table 23: Test results for active thematic equity funds

Figures for the performance measures are presented on an annualised basis. Ω = Omega ratio. The full analysis period omega is calculated from 1 Jan 2007 to 31 Dec 2020. α_{ex}= Returns in excess of the passive alternative, IR = Information ratio, and α_{exi} = Returns in excess of inflation. CI = Confidence interval. PO = a persistently outperforming fund, PU = a persistently underperforming fund, and NP suggests that the fund's performance is not persistent. ** Signifies statistical significance at a 5% level.

Fund Code	Fund category	Percent Rolling holding periods Ω > 1	Full analysis period Ω	Mean rolling Ω	Mean rolling α_{ex}	Mean rolling IR	Mean rolling α_{exi}	Median rolling α_{ex}	95% CI Lower bound	95% CI Upper bound	PO/PU/ NP
F3	Financial	100%	1.395	1.401	1.936%	0.341	9.435%	1.665%	1.387%	1.942%	PO**
R1	Resource	100%	1.548	1.593	4.587%	0.523	-0.388%	5.263%	4.624%	5.901%	PO**
R2	Resource	100%	1.197	1.346	1.997%	0.249	-2.754%	1.714%	1.173%	2.256%	PO**
R3	Resource	100%	1.651	1.869	4.824%	0.684	-0.076%	5.109%	4.834%	5.383%	PO**
R4	Resource	100%	1.763	1.866	5.660%	0.710	0.632%	6.276%	5.520%	7.032%	PO**
F2	Financial	85%	1.177	1.146	0.482%	0.122	7.606%	0.415%	0.239%	0.591%	PO**
L1	Large Cap	80%	1.102	1.057	0.078%	0.042	5.322%	0.042%	0.009%	0.075%	PO**
F1	Financial	55%	1.201	1.203	0.329%	0.089	7.529%	0.318%	-0.205%	0.840%	NP
R5	Resource	40%	0.986	0.996	-1.627%	-0.058	-5.806%	-2.649%	-3.850%	-1.447%	PU**
I1	Industrial	29%	0.909	0.979	-0.559%	-0.103	11.112%	-0.657%	-0.788%	-0.526%	PU**
F4	Financial	19%	1.028	0.858	-1.221%	-0.254	5.948%	-1.275%	-1.498%	-1.052%	PU**
I3	Industrial	19%	0.992	0.912	-1.022%	-0.167	10.492%	-1.133%	-1.356%	-0.909%	PU**
I2	Industrial	0%	0.628	0.535	-4.592%	-0.764	6.665%	-4.744%	-4.876%	-4.613%	PU**

Source: Calculated by the author with R and Excel



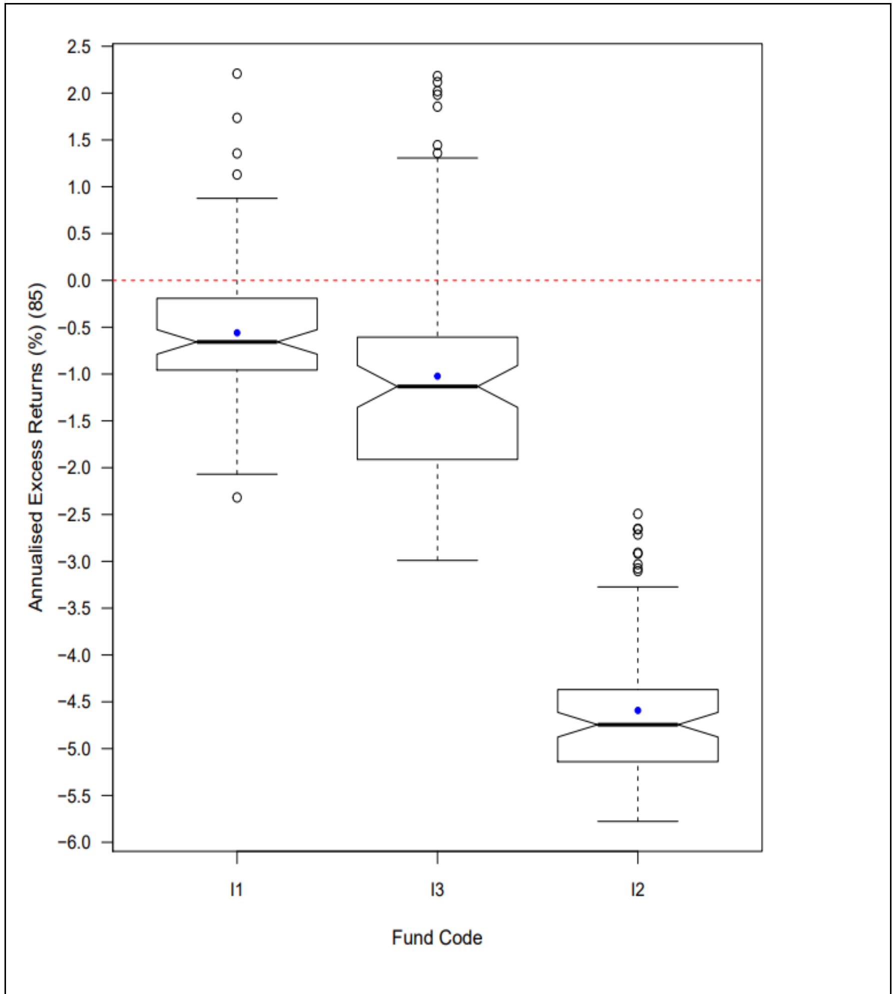
PF annualised return over full analysis period: 6.329%

PF annualised median rolling period total return: 14.203%

PF annualised mean rolling period return in excess of inflation: 6.905%

Figure 8: Active financial equity funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2007 to 31 Dec 2020)

Source: Constructed by the author with R



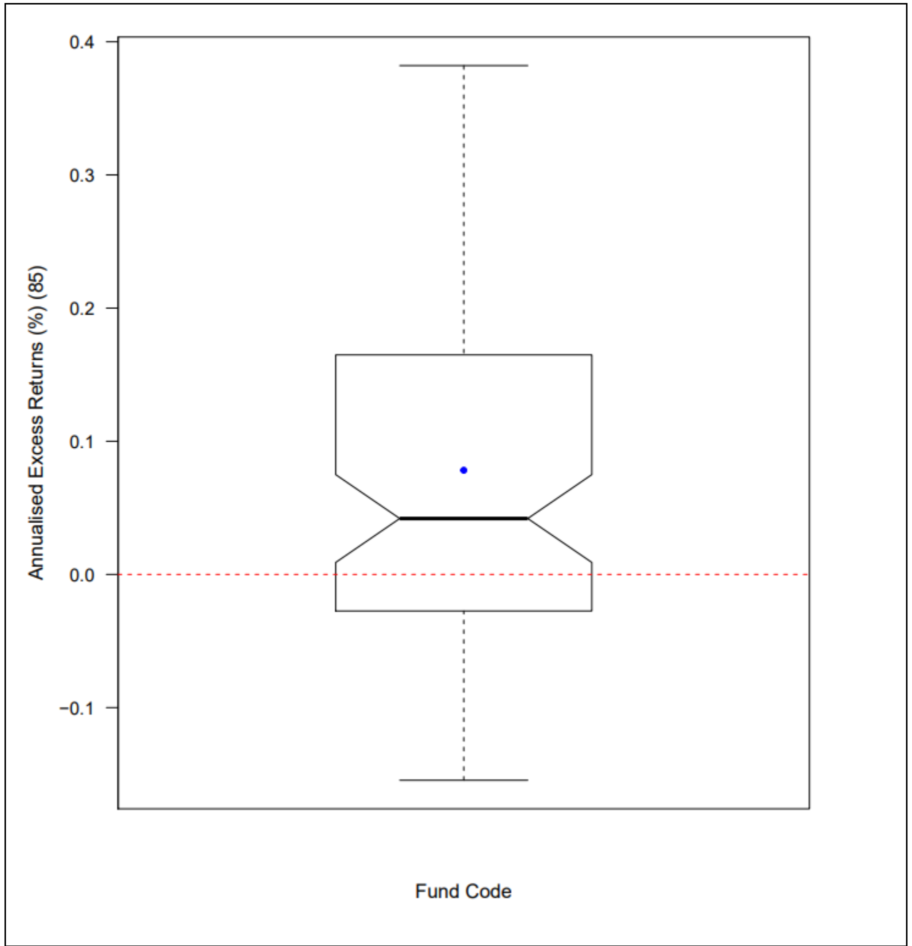
PI annualised return over full analysis period: 12.81%

PI annualised median rolling period total return: 18.933%

PI annualised mean rolling period return in excess of inflation: 11.303%

Figure 9: Active industrial equity funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2007 to 31 Dec 2020)

Source: Constructed by the author with R



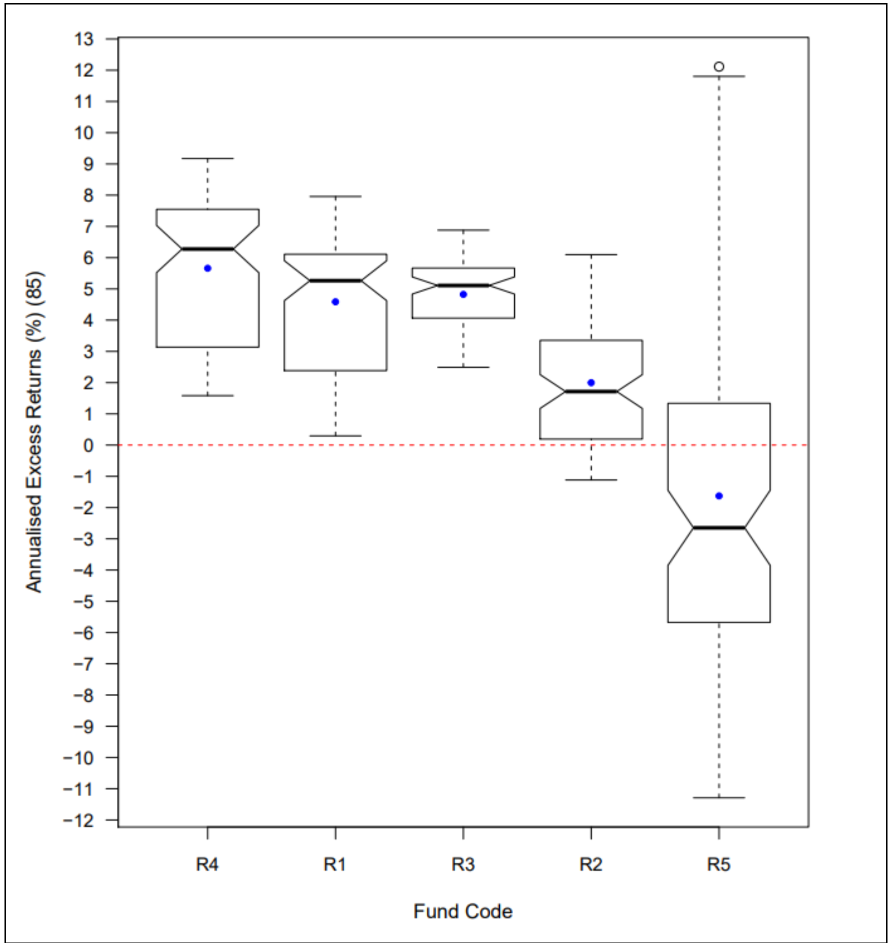
PL annualised return over full analysis period: 9.128%

PL annualised median rolling period total return: 10.953%

PL annualised mean rolling period return in excess of inflation: 5.189%

Figure 10: Active large cap equity fund – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2007 to 31 Dec 2020)

Source: Constructed by the author with R



PR annualised return over full analysis period: 4.541%

PR annualised median rolling period total return: -0.923%

PR annualised mean rolling period return in excess of inflation: -5.605%

Figure 11: Active resource equity funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2007 to 31 Dec 2020)

Source: Constructed by the author with R

Apart from R4, the evidence in Table 23 and Figure 11 show that all resource funds (including the passive alternative) produced negative inflation-adjusted returns. Three of the four persistently outperforming active resource funds (R1, R2, and R3) derived negative inflation-adjusted returns. Therefore, R1 to R3 did not enhance the real wealth of their investors despite their ability to outperform their passive alternative persistently. The persistently underperforming R5 also derived negative inflation-adjusted returns. Resource equity funds' inability to enhance the real wealth of their investors (apart from R4) may be attributed to factors associated with the determinants of South African resource and/or commodity prices for 1 January 2007 to 31 December 2020.

The boxplot for L1 in Figure 10 shows that the persistently outperforming active large cap fund's excess returns are very narrowly distributed around zero (lower and upper whisker fences of approximately -0.18% and 0.39%). This may be attributed to L1 and its passive alternative having a narrow self-reported investment universe that is limited to only the 40 shares that make up the FTSE/JSE Top 40 Index. In contrast, the boxplot of the persistently underperforming active resource fund R5 in Figure 11 has a wide excess return distribution (lower and upper whisker fences of approximately -11.5% and 12%). This may be attributed to R5's focussed investment approach to gold-related equity investments. Hence, the passive alternative's (PR) performance may be too general compared to R5's risk-return profile.

The negative upper bounds of the 95% confidence intervals in Table 23 show that all three active industrial funds persistently underperformed their passive alternative, whilst one financial fund demonstrated persistent underperformance. Once again, the mean rolling period omegas, information ratios, and excess returns of these funds confirm this observation. However, the persistently underperforming F4 incrementally outperformed its passive alternative over the full analysis period, as shown by its omega ratio of 1.028 in Table 23. This stands in contrast with the performance of the industrial funds, which all have full analysis period omega ratios that are less than one.

The consistency between the full analysis period omega ratios and the rolling holding period performance measures (excluding F4) suggest that active thematic equity funds' performance histories contain less noisy information. This may be attributed to the relatively limited investment universes to which these funds are constrained. However, if persistent performance contains information that aids investors' decision between active and passive funds, then the use of active thematic funds' performance history may be of value to investors.

4.4.1.3 *Analysis: equity funds*

Amongst the active general equity funds, more funds underperformed compared to those that outperformed, which is consistent with the findings of Wessels and Krige (2005a) and Bertolis and Hayes (2014). In contrast, more actively managed thematic equity funds outperformed compared to those that underperformed. Inferences about the aggregate value of active management are avoided as the performance of obsolete funds has been excluded. However, given the set of investable passive funds to which the active equity funds are contrasted, evidence of persistently out- and underperforming active funds is observed.

The evidence contrasts with the findings of Meyer (1998), Firer et al. (2001), Collinet and Firer (2003), Hoch (2015), and Thobejane et al. (2017), who found limited evidence of persistent outperformance amongst active equity funds. However, despite the differences in evidence, several linkages and consistencies can be observed. Collectively, 28 of the 51 (54.9%) active equity funds are classified as persistent underperformers. This is consistent with prior South African evidence which suggests that performance persistency is largely concentrated amongst underperformers (Collinet & Firer, 2003; Firer et al., 2001; Hoch, 2015; Meyer, 1998). Seventeen of the 51 (33.333%) active equity funds are classified as persistent outperformers. This is similar to the findings of Malefo et al. (2016) and Brown (2008), who showed that a smaller fraction of outperforming active South African equity funds demonstrated performance persistency (30% and 25% of active funds, respectively).

Hoberg et al. (2018) showed that the forces of sector-level diseconomies of scale and competition co-exist. Contrasting the evidence observed in the general equity category with that of the thematic equity categories suggests that this may be the case amongst South African equity funds as well. The greater number of funds in the general equity category compared to thematic equity categories suggests that it may be subject to a greater degree of competition. Although, the narrower investment universes to which thematic equity funds are constrained compared to general equity funds make thematic equity funds more susceptible to sector-level diseconomies of scale. On a proportionate basis, more thematic equity funds persistently outperform (53.846%) compared to general equity funds (26.316%). Therefore, if these determinants influence the observed degree of persistent outperformance, then fewer competing funds may be slightly more beneficial than smaller investable universes.

Differences in evidence compared to that of prior South African research can be attributed to several factors:

- Performance persistence is measured on an absolute basis relative to that of a passive alternative.
- Performance persistence is evaluated in terms of the observed distribution of performance and not the sequence of performance observations.
- Individual funds that performed persistently can be identified more accurately as the test results for the full sample of funds are not presented on an aggregated basis.

South African equity funds are suitable for investors with a long-term (seven years or more) investment horizon who seek capital appreciation. Hence, these funds are more appropriate for investors with the objective of growing their wealth prior to retirement. The evidence suggests that, in most instances, passive investment alternatives are optimal compared to active funds in achieving this objective.

4.4.2 Interest-bearing funds

This section presents the results and analysis for 16 active interest-bearing variable term funds. The funds are examined over the period 1 January 2015 to 31 December 2020. The number of data points per holding period is 36 months, resulting in 37 rolling holding periods over the six-year analysis period. In addition, the active funds are compared to the passive alternative PB. Table 24 reports the results for the active funds, and Figure 12 presents the active funds' notched boxplots.

The confidence intervals (CI) and notched boxplots in Table 24 and Figure 12 show that nine active funds persistently outperformed (positive 95% CI lower bounds) the passive alternative (PB), whilst four persistently underperformed PB (negative 95% CI upper) bounds). Additionally, the evidence suggests that three active funds do not have median excess returns significantly different from zero over time (zero falls between upper and lower 95% CI). PB and all of the active funds derive positive inflation-adjusted returns, as shown in Table 24 (Mean rolling α_{exi}) and Figure 12. All persistently outperforming funds produce real inflation-adjusted returns greater than that of PB (3.082% as reported in Figure 12), whilst the converse is evident for persistent underperformers.

Table 24: Test results for active interest-bearing variable term funds

Figures for the performance measures are presented on an annualised basis. Ω = Omega ratio. The full analysis period omega is calculated from 1 Jan 2015 to 31 Dec 2020. α_{ex}= Returns in excess of the passive alternative, IR = Information ratio, and α_{exi} = Returns in excess of inflation. CI = Confidence interval. PO = a persistently outperforming fund, PU = a persistently underperforming fund, and NP suggests that the fund's performance is not persistent. ** Signifies statistical significance at a 5% level.

Fund Code	Percent Rolling holding periods Ω > 1	Full analysis period Ω	Mean rolling Ω	Mean rolling α_{ex}	Mean rolling IR	Mean rolling α_{exi}	Median rolling α_{ex}	95% CI Lower bound	95% CI Upper bound	PO/PU/NP
B1	100%	2.468	2.222	1.455%	0.966	4.622%	1.448%	1.331%	1.564%	PO**
B3	100%	1.626	1.786	1.390%	0.673	4.633%	1.445%	1.337%	1.553%	PO**
B9	100%	1.641	1.588	0.679%	0.491	3.859%	0.632%	0.559%	0.706%	PO**
B10	100%	2.472	2.117	0.335%	0.909	3.424%	0.336%	0.307%	0.365%	PO**
B16	100%	2.227	2.210	0.863%	0.957	3.983%	0.762%	0.613%	0.912%	PO**
B11	89%	1.222	1.192	0.306%	0.142	3.543%	0.146%	-0.029%	0.320%	NP
B8	84%	1.093	1.234	0.138%	0.211	3.231%	0.155%	0.099%	0.210%	PO**
B6	76%	1.076	1.180	0.089%	0.066	3.248%	0.246%	0.174%	0.319%	PO**
B5	73%	1.353	1.797	0.649%	0.503	3.781%	0.557%	0.079%	1.035%	PO**
B15	70%	1.015	1.120	0.113%	0.101	3.191%	0.156%	0.086%	0.226%	PO**
B4	68%	0.911	1.096	0.013%	0.013	3.127%	0.123%	-0.001%	0.247%	NP
B2	41%	1.041	0.969	-0.578%	-0.110	2.852%	-0.745%	-1.066%	-0.424%	PU**
B14	35%	0.527	0.764	-0.293%	-0.492	2.760%	-0.024%	-0.116%	0.069%	NP
B12	32%	0.874	0.921	-0.148%	-0.154	2.952%	-0.094%	-0.156%	-0.032%	PU**
B7	30%	0.915	0.894	-0.165%	-0.199	2.919%	-0.214%	-0.321%	-0.107%	PU**
B13	0%	0.515	0.584	-1.667%	-0.732	1.485%	-1.452%	-1.795%	-1.109%	PU**

Source: Calculated by the author with R and Excel

The mean rolling period omega ratios, information ratios, and excess returns in Table 24 support the evidence that nine of the 16 active funds persistently outperform PB (as shown by the positive 95% CI lower bounds). Additionally, all persistent outperformers (B1, B3, B9, B10, B16, B8, B6, B5, and B15) have full analysis period omega ratios greater than one. Apart from B5, the boxplots in Figure 12 show that the persistently outperforming funds have narrow excess return distributions above zero. The consistency between the rolling period performance measures, the full analysis period omega ratio, and the relatively narrow excess return distributions suggest that the persistently outperforming interest-bearing variable term funds' performance histories contain less noisy information.

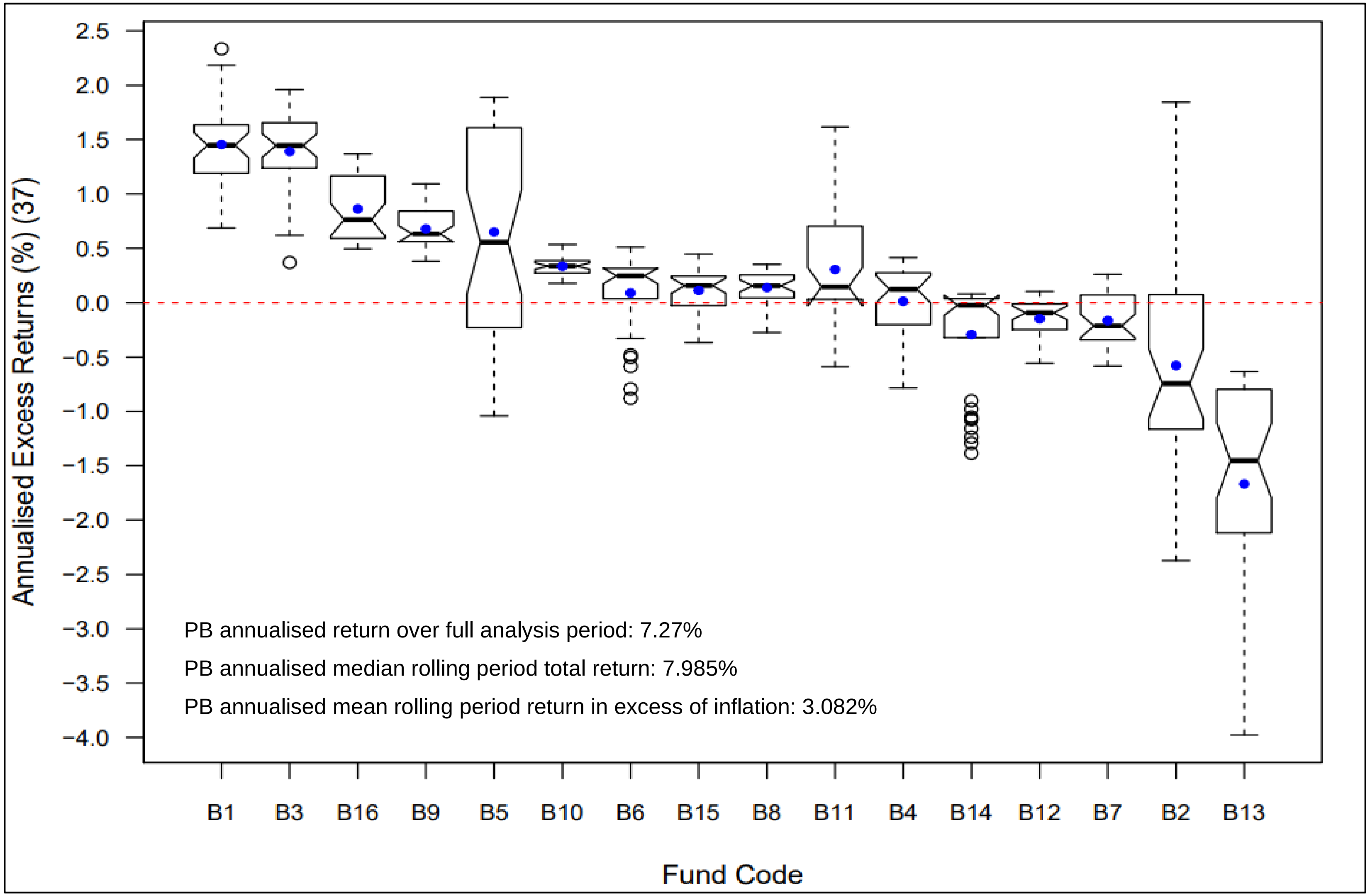


Figure 12: Active interest-bearing variable term funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2015 to 31 Dec 2020)
Source: Constructed by the author with R

The active funds that are classified as persistent underperformers (B2, B12, B7, and B13) have negative mean rolling period excess returns and information ratios as well as mean rolling period omega ratios that are less than one (see Table 24). Apart from B2, all persistent underperformers (B12, B7, and B13) have full analysis period omega ratios that are less than one. B2's full analysis period omega ratio of 1.041 may be attributed to periods of sharp, infrequent outperformance (as shown by the upper whisker fence of 1.93% in Figure 12). Figure 12 shows B7 and B12 have narrowly distributed excess returns below zero, whilst the rolling holding period omega ratio for B13 (Table 24) shows that it does not outperform in any of the holding periods considered. Therefore, the evidence suggests that the performance histories of the persistently underperforming active funds from 1 January 2015 to 31 December 2020 contain less noisy information.

4.4.2.1 *Analysis: interest-bearing funds*

The evidence presented in section 4.4.2 shows that more (56.25%) active interest-bearing variable term funds persistently outperformed than active funds that persistently underperformed (25%). This contrasts with the findings of Firer et al. (2001), who showed that performance persistency was mainly explained by bottom performers (funds ranked below the median of their cohort). Collinet and Firer (2003) stated that the evidence of performance persistency might depend on the period studied, whilst Urquhart and McGroarty (2016) suggested that periods of market stress provide active fund managers with opportunities to outperform.

From 1 January 2015 to 31 December 2020, the South African economy experienced several shocks. First, in December 2015, the South African president changed the nation's finance minister twice within three days (an event called Nenegate) (Magoane, 2020). Second, Fitch and S&P Global downgraded South African credit ratings to sub-investment grade in April 2017, whilst Moody's Investors Service downgraded South African credit ratings to sub-investment status in March 2020 (Ackerman, 2020; Magoane, 2020). Finally, the coronavirus disease 2019 (COVID-19) was declared a pandemic in March 2020, which resulted in frequent fiscal and monetary policy changes in South Africa throughout 2020 (de Villiers, Cerbone, & Van Zijl, 2020). Although these events influenced the South African market as a whole, the severity of their effect on the South African fixed-income (interest-bearing) market is particularly notable. The aforementioned events created sharp increases in nominal yields, resulting in deteriorating prices for interest-bearing assets. This may have benefitted the performance of active funds, which have been shown to outperform passive funds in periods characterised by market stress (Aktan et al., 2018; Peng et al., 2011).

The economic shocks mentioned above likely caused the South African market for interest-bearing securities to experience time-varying efficiency, as suggested by the Adaptive Markets Hypothesis (AMH). In addition, the shocks would have forced passive funds that track investment-grade fixed-income indices to undergo forced asset sales. Therefore, active South African fixed-income (interest-bearing) funds would have been presented with the opportunity to benefit from resultant liquidity premiums (as suggested by Barras et al. (2020)). Hence, the economic shocks and structural changes encountered in the South African market over the full analysis period may have provided active fixed-income fund managers with the opportunity to persistently outperform passive alternatives over the period studied.

The difference in findings compared to Firer et al. (2001) may be attributed to the difference in time periods studied, difference in performance measurement, and/or the difference in the testing procedure. Firer et al. (2001) considered the performance of fixed-income funds between January 1989 and December 1999 and did not consider the risk-adjusted performance of these funds. Furthermore, Firer et al. (2001) evaluated the persistency in performance rankings of fixed-income funds, whereas this study considers persistency in terms of the distribution and frequency of an active funds performance relative to a passive alternative. However, both studies find evidence of performance persistency amongst fixed-income funds despite the difference in the attribution thereof (outperformers versus bottom performers).

Funds categorised under the interest-bearing variable term ASISA category predominantly aim to serve investors with a medium to long-term (three years or more) investment horizon with an objective earning income and potentially earing some capital growth. Moreover, these funds offer diversification potential from equity exposure in investors' portfolios (Fong & Guin, 2007). The evidence suggests that persistently outperforming active interest-bearing funds may enhance investors' wealth compared to passive alternatives if these funds can be identified prior to the investment period.

4.4.3 Multi-asset funds

This section presents the results for 48 active multi-asset funds across two ASISA categories. The results for multi-asset high equity funds are given first, and the results for multi-asset low equity funds follow. The active multi-asset funds are examined over the period 1 January 2011 to 31 December 2020.

4.4.3.1 *Multi-asset high equity funds*

Thirty active multi-asset high equity funds are examined and compared to the passive alternative PM. Table 25 reports the results for the active funds, and Figure 13 presents the active funds' notched boxplots. The number of data points per holding period is 60 months, resulting in 61 rolling holding periods over the ten-year analysis period.

The 95% confidence intervals in Table 25 show that five of the active funds persistently outperformed, 22 persistently underperformed, and three are classified as funds that do not perform persistently. One persistently underperforming active fund (M10) derived negative inflation-adjusted returns (as shown by the Mean rolling α_{exi} in Table 25). The passive alternative (PM) produces mean rolling returns in excess of inflation of 3.536% as reported in Figure 13.

Table 25 shows that three of the five persistent outperformers (M14, M7, and M18) have full analysis period omega ratios greater than one, whilst M3's is precisely one. These four funds' (M14, M7, M18, and M3) mean rolling excess returns and information ratios are all positive, and their mean rolling omega ratios all exceed one. This supports the evidence which suggests that these funds are persistent outperformers (positive 95% CI Lower bound as shown in Table 25). M14, M3, M7, and M18 outperform 70% or more of their rolling holding periods. The frequency of their outperformance, the consistency between their full and rolling period performance measures, and their relatively narrow excess return distributions above zero (apart from M14, which demonstrates volatility above zero - Figure 13) suggest that the performance histories of these funds contain less noisy information.

Table 25: Test results for active multi-asset high equity funds

Figures for the performance measures are presented on an annualised basis. Ω = Omega ratio. The full analysis period omega is calculated from 1 Jan 2011 to 31 Dec 2020. α_{ex}= Returns in excess of the passive alternative, IR = Information ratio, and α_{exi} = Returns in excess of inflation. CI = Confidence interval. PO = a persistently outperforming fund, PU = a persistently underperforming fund, and NP suggests that the fund's performance is not persistent. ** Signifies statistical significance at a 5% level.

Fund Code	Percent Rolling holding periods Ω > 1	Full analysis period Ω	Mean rolling Ω	Mean rolling α_{ex}	Mean rolling IR	Mean rolling α_{exi}	Median rolling α_{ex}	95% CI Lower bound	95% CI Upper bound	PO/PU/NP
M14	89%	1.151	1.267	1.146%	0.249	4.858%	0.772%	0.463%	1.082%	PO**
M3	85%	1.000	1.103	0.381%	0.097	3.987%	0.316%	0.192%	0.440%	PO**
M21	74%	0.969	1.075	0.145%	0.063	3.686%	0.279%	0.164%	0.394%	PO**
M7	70%	1.008	1.066	0.179%	0.061	3.728%	0.197%	0.084%	0.310%	PO**
M18	70%	1.095	1.104	0.285%	0.087	3.930%	0.219%	0.074%	0.363%	PO**
M23	51%	1.136	1.036	-0.073%	-0.012	3.616%	-0.039%	-0.452%	0.375%	NP
M22	48%	0.828	0.974	-0.520%	-0.098	3.135%	-0.438%	-0.800%	-0.076%	PU**
M24	46%	1.241	1.074	0.075%	0.013	3.810%	-0.258%	-0.767%	0.251%	NP
M19	41%	0.571	0.905	-0.914%	-0.234	2.687%	-0.160%	-0.367%	0.048%	NP
M15	36%	0.977	0.953	-0.489%	-0.108	3.159%	-1.202%	-1.780%	-0.624%	PU**
M4	33%	0.958	0.925	-0.686%	-0.143	2.828%	-0.916%	-1.234%	-0.599%	PU**
M2	28%	0.791	0.888	-0.407%	-0.179	3.124%	-0.346%	-0.513%	-0.180%	PU**
M6	28%	1.077	0.929	-0.271%	-0.083	3.214%	-0.224%	-0.352%	-0.095%	PU**
M8	28%	0.666	0.783	-2.270%	-0.278	1.304%	-2.547%	-3.302%	-1.792%	PU**
M30	28%	0.808	0.800	-0.689%	-0.337	2.811%	-0.852%	-1.149%	-0.554%	PU**
M9	25%	0.660	0.784	-2.931%	-0.432	0.606%	-3.185%	-4.232%	-2.138%	PU**
M13	23%	1.073	0.919	-0.375%	-0.124	3.165%	-0.471%	-0.611%	-0.332%	PU**
M11	15%	1.002	0.868	-0.561%	-0.223	3.046%	-0.654%	-0.780%	-0.529%	PU**
M12	15%	0.962	0.830	-0.973%	-0.262	2.576%	-0.942%	-1.204%	-0.679%	PU**
M29	11%	0.910	0.704	-1.517%	-0.474	2.057%	-1.721%	-2.018%	-1.424%	PU**
M1	0%	0.548	0.566	-2.112%	-0.714	1.404%	-2.112%	-2.244%	-1.981%	PU**
M5	0%	0.529	0.566	-3.020%	-0.679	0.449%	-3.315%	-3.691%	-2.939%	PU**
M10	0%	0.618	0.540	-3.883%	-0.744	-0.577%	-4.014%	-4.257%	-3.770%	PU**
M16	0%	0.566	0.506	-2.961%	-0.830	0.574%	-3.135%	-3.274%	-2.997%	PU**
M17	0%	0.621	0.627	-1.364%	-0.602	2.131%	-1.293%	-1.510%	-1.077%	PU**
M20	0%	0.477	0.479	-3.297%	-1.004	0.154%	-3.029%	-3.523%	-2.536%	PU**
M25	0%	0.826	0.865	-0.641%	-0.206	2.920%	-0.547%	-0.630%	-0.464%	PU**
M26	0%	0.669	0.568	-2.265%	-0.694	1.240%	-2.472%	-2.773%	-2.172%	PU**
M27	0%	0.545	0.676	-2.093%	-0.471	1.443%	-2.002%	-2.201%	-1.802%	PU**
M28	0%	0.585	0.636	-1.251%	-0.585	2.232%	-1.258%	-1.378%	-1.138%	PU**

Source: Calculated by the author with R and Excel

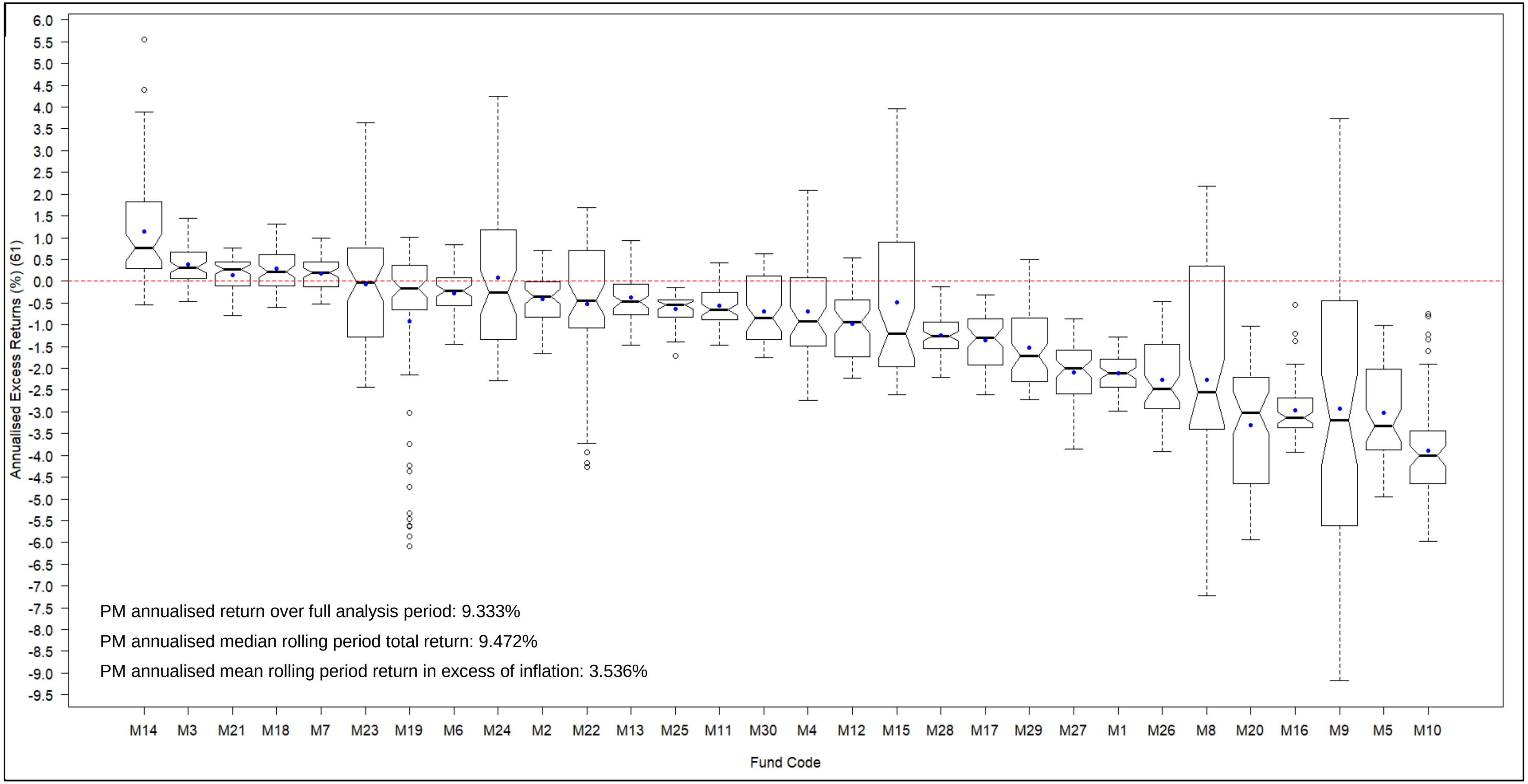


Figure 13: Active multi-asset high equity funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2011 to 31 Dec 2020)
Source: Constructed by the author with R

M21 outperforms in 74% of its rolling holding periods, has a full analysis period omega ratio of 0.969 (Table 25). This may be attributed to periods of sharp underperformance in contrast to its overall performance, as shown by the lower fence of M21's boxplot in Figure 13. The periods of stronger underperformance eliminate M21's persistent and incremental outperformance over the full analysis period. Consistent with their mean rolling period performance measures, 19 of the 22 persistent underperformers have full analysis period omega ratios less than one. Despite this consistency, M4, M15, M8, M9 have comparatively wide excess return distributions (mostly below zero). However, M11, M13, and M6 have comparatively narrow excess return distributions (Figure 13) but have full analysis period omega ratios in excess of one, which contrasts with their mean rolling period performance measures. This suggests that the noisiness of information within the performance histories of persistent underperformers varies.

4.4.3.2 *Multi-asset low equity funds*

Eighteen multi-asset low equity funds are examined and compared to the passive alternative PN. Table 26 reports the results for the active funds, and Figure 14 presents the active funds' notched boxplots. The number of data points per holding period is 36 months, resulting in 85 rolling holding periods over the ten-year analysis period.

A large proportion of the active multi-asset low equity funds are classified as persistent underperformers (72.22%). Table 26 and Figure 14 shows that 13 of the 18 active funds persistently underperform, whilst four funds demonstrate performance that is not persistent, and only one fund is regarded as a persistent outperformer. In addition, all of the funds considered from this category, including the passive alternative (PN), produce positive inflation-adjusted returns. Apart from N15, the evidence in Table 26 shows that the mean rolling period omega ratios, excess returns, and information ratios support the conclusions regarding the persistent out- and underperformance of the active funds considered (Mean rolling Ω > 1, and positive mean rolling α_{ex} and IRs for persistent outperformers; and mean rolling Ω < 1, and negative mean rolling α_{ex} and IRs for persistent underperformers).

Table 26: Test results for active multi-asset low equity funds

Figures for the performance measures are presented on an annualised basis. Ω = Omega ratio. The full analysis period omega is calculated from 1 Jan 2011 to 31 Dec 2020. α_{ex}= Returns in excess of the passive alternative, IR = Information ratio, and α_{exi} = Returns in excess of inflation. CI = Confidence interval. PO = a persistently outperforming fund, PU = a persistently underperforming fund, and NP suggests that the fund's performance is not persistent. ** Signifies statistical significance at a 5% level.

Fund Code	Percent Rolling holding periods Ω > 1	Full analysis period Ω	Mean rolling Ω	Mean rolling α_{ex}	Mean rolling IR	Mean rolling α_{exi}	Median rolling α_{ex}	95% CI Lower bound	95% CI Upper bound	PO/PU/NP
N17	55%	0.980	1.092	0.156%	0.070	3.435%	0.283%	0.114%	0.452%	PO**
N4	48%	0.921	1.140	-0.155%	-0.036	3.091%	-0.053%	-0.424%	0.319%	NP
N16	48%	0.755	1.265	-0.545%	-0.254	2.671%	-0.053%	-0.684%	0.579%	NP
N15	46%	0.521	1.162	-0.951%	-0.321	2.273%	-0.926%	-1.638%	-0.214%	PU**
N14	42%	1.036	1.118	0.142%	0.051	3.394%	-0.076%	-0.355%	0.203%	NP
N7	34%	0.709	0.849	-1.232%	-0.336	1.983%	-1.395%	-2.095%	-0.694%	PU**
N5	29%	0.935	0.974	-0.371%	-0.115	2.869%	-0.346%	-0.736%	0.044%	NP
N3	28%	0.662	0.820	-2.001%	-0.327	1.318%	-1.057%	-1.840%	-0.275%	PU**
N6	27%	1.028	0.939	-0.242%	-0.134	3.003%	-0.324%	-0.442%	-0.206%	PU**
N12	22%	0.741	0.690	-1.216%	-0.405	2.062%	-0.997%	-1.498%	-0.495%	PU**
N2	21%	0.785	0.624	-1.386%	-0.436	1.880%	-1.730%	-2.780%	-0.680%	PU**
N13	16%	0.612	0.718	-0.976%	-0.598	2.239%	-1.274%	-1.500%	-1.047%	PU**
N11	15%	0.967	0.835	-0.373%	-0.121	2.883%	-0.579%	-0.776%	-0.383%	PU**
N9	13%	1.044	0.829	-0.467%	-0.148	2.775%	-0.683%	-0.881%	-0.484%	PU**
N8	9%	0.746	0.781	-0.529%	-0.251	2.720%	-0.518%	-0.674%	-0.362%	PU**
N10	1%	0.727	0.696	-1.438%	-0.497	1.791%	-1.309%	-1.506%	-1.112%	PU**
N1	0%	0.520	0.419	-2.009%	-0.913	1.234%	-2.008%	-2.076%	-1.940%	PU**
N18	0%	0.881	0.611	-1.001%	-0.478	2.239%	-1.140%	-1.246%	-1.033%	PU**

Source: Calculated by the author with R and Excel

Table 26 shows that the persistently outperforming fund (N17) has a full analysis period omega ratio that is less than one, which is inconsistent with the performance indicated by their rolling period performance measures (Mean rolling Ω > 1, and positive mean rolling α_{ex} and IR). This suggests that the performance history of this active fund contains more noisy information. Additionally, two of the persistently underperforming active funds' (N6 and N9) performance histories appear to communicate noisy information as their full analysis period omega ratios (which are greater than one) are not consistent with the performance observations of their rolling period performance measures (Mean rolling Ω < 1, and negative mean rolling α_{ex} and IRs). This inconsistency can be attributed to periods of sharp, infrequent, outperformance as shown by the outliers above the upper fence of N6 and N9's boxplots (Figure 14).

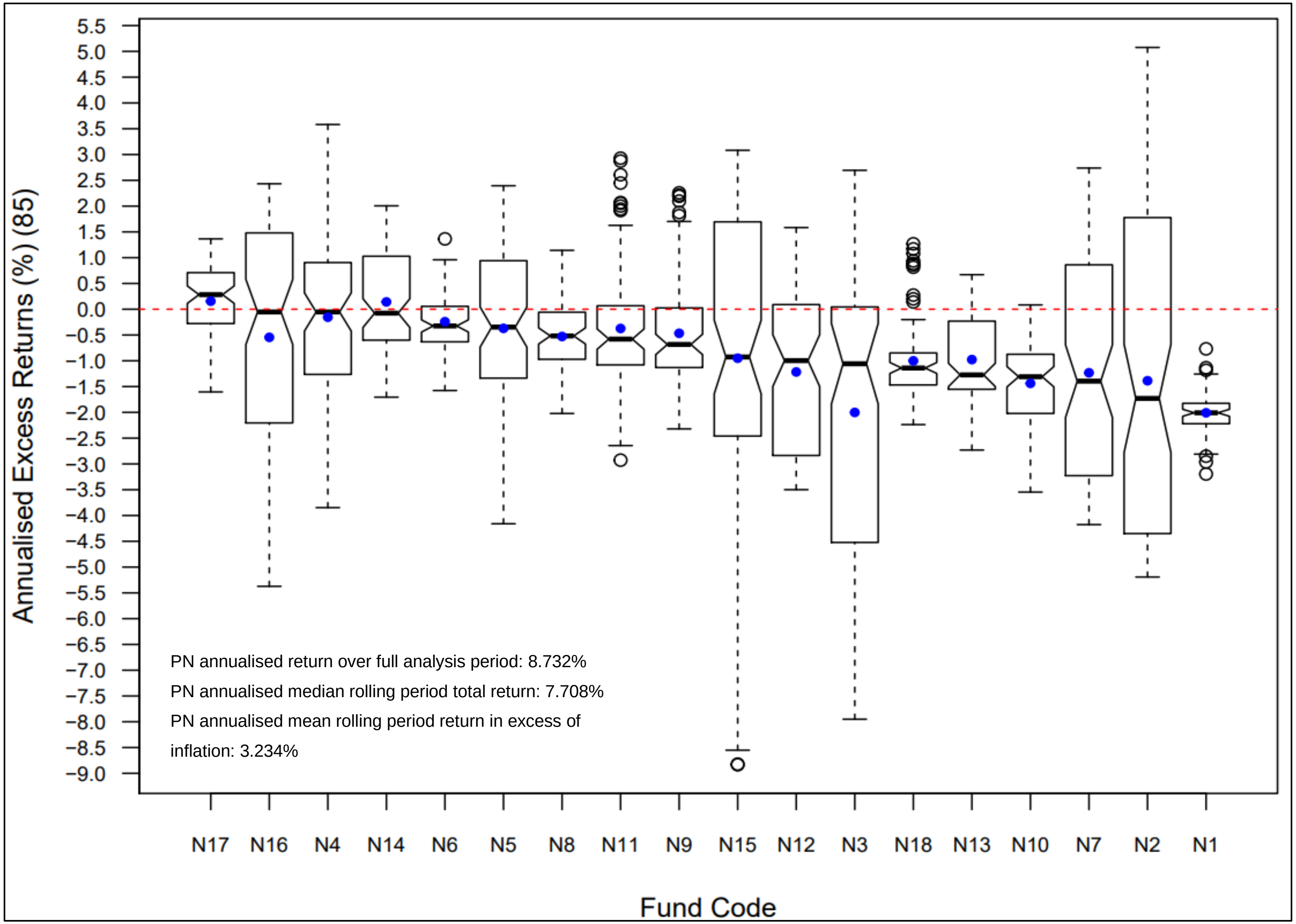


Figure 14: Active multi-asset low equity funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2011 to 31 Dec 2020)

Source: Constructed by the author with R

N15 displays anomalous performance relative to the passive alternative as its mean rolling period omega ratio of 1.162 (indicating mean outperformance) does not coincide with the performance of its negative mean rolling excess returns and information ratio. Figure 14 shows that it has the widest excess return distribution of all the active multi-asset low equity funds studied, suggesting that its risk-return profile may have been markedly different from that of PN.

Table 26 shows consistency in the full analysis period omega ratio and the rolling period performance measures for the persistently underperforming N7, N3, N12, N2, N13, N11, N8, N10, N1, and N18. However, the boxplots in Figure 14 show that some active funds' excess returns are relatively widely distributed (such as N15, N3, N7, and N2). This is consistent with the observation in section 4.3.3.2 (Table 18) that only 11 of the 18 active funds had correlations in excess of 0.8 relative to PN. This is potentially attributed to active multi-asset fund managers who altered their funds' asset allocations in response to changing market conditions. In addition, the active funds may be following strategic asset allocations that are distinctly different from that of PN. Therefore, a notable degree of noise may be inherent to active multi-asset low equity funds' performance histories.

4.4.3.3 *Analysis: multi-asset funds*

For several reasons, active multi-asset fund managers may be in an advantageous position relative to the managers of similar passive funds. Firstly, managers of active multi-asset funds are less constrained in their ability to move capital amongst various asset classes compared to their passive counterparts (Cremers et al., 2019). Secondly, the degree of efficiency varies across markets for different asset classes (Clearly et al., 2019; Duhon et al., 2019). Finally, EMEs such as South Africa have been susceptible to more frequent shocks compared to DMEs (Lim et al., 2008; Phiri, 2015; Smith, 2012; Todea et al., 2009). Therefore, the benefits mentioned above allow active multi-asset fund managers a greater opportunity to time markets for different asset classes than passive funds.

However, despite the advantages afforded to active multi-asset fund managers, the evidence suggests that only 16.67% of the multi-asset high equity funds and 5.56% of the low equity funds persistently outperform. Moreover, persistently underperforming active funds make up 73.33% of the multi-asset high equity funds sample and 72.22% of the multi-asset low equity funds sample. This suggests that persistent outperformance was concentrated amongst a small group of active funds whilst most of the actively managed multi-asset funds persistently underperformed passive investment alternatives. Furthermore, the increased flexibility afforded active multi-asset funds to alter their asset allocations compared to passive alternatives may provide a rationale for the fewer number of active funds with correlations above 0.8 as shown in section 4.3.3 (80% of multi-asset high equity funds and 61.111% of multi-asset low equity funds showed correlations above 0.8 compared to their respective passive alternatives). Alternatively, this may also be attributed to active funds that follow different strategic asset allocations compared to that of their respective passive alternatives.

According to Regulation 28 of the Pension Funds Act of 1956, South African multi-asset high and low equity unit trust categories have asset allocation limits that allow for funds within these categories to be used as investments to save for retirement (ASISA, 2018). The evidence in sections 4.4.3.1 and 4.4.3.2 shows that, in most instances, passive multi-asset investment alternatives are preferable to active options for investors seeking to maximise their wealth level and standard of living both before and after retirement.

4.4.4 Real estate funds

The results and analysis for 16 active general real estate funds are presented in this section. The active real estate funds are examined over the period 1 January 2013 to 31 December 2020. The number of data points per holding period is 60 months, resulting in 37 rolling holding periods over the eight-year analysis period. The fund code for the passive alternative for this category of funds is PP. Table 27 and Figure 15 presents the results and notched boxplots for the active funds.

The 95% confidence intervals (CI) in Table 27 classify seven active property funds as persistent outperformers and four as persistent underperformers. Conversely, the CIs suggest that five of the 16 active funds do not show performance persistency. The passive alternative (PP) and 15 of the 16 active funds derived negative inflation-adjusted returns (see Figure 15 and Mean rolling α_{exi} in Table 27). The only fund that derived positive returns above inflation is P1. However, the persistent outperformers minimised the loss of real wealth in contrast to the performance of PP, as all of these funds (P1, P5, P14, P11, P13, P2, and P7) produce inflation-adjusted returns that are greater than -4.303%.

Table 27: Test results for active general real estate funds

Figures for the performance measures are presented on an annualised basis. Ω = Omega ratio. The full analysis period omega is calculated from 1 Jan 2013 to 31 Dec 2020. α_{ex}= Returns in excess of the passive alternative, IR = Information ratio, and α_{exi} = Returns in excess of inflation. CI = Confidence interval. PO = a persistently outperforming fund, PU = a persistently underperforming fund, and NP suggests that the fund's performance is not persistent. ** Signifies statistical significance at a 5% level.

Fund Code	Percent Rolling holding periods Ω > 1	Full analysis period Ω	Mean rolling Ω	Mean rolling α_{ex}	Mean rolling IR	Mean rolling α_{exi}	Median rolling α_{ex}	95% CI Lower bound	95% CI Upper bound	PO/PU/NP
P1	**100%**	**1.734**	**1.746**	**4.913%**	**0.620**	**0.376%**	**4.993%**	**4.602%**	**5.384%**	**PO****
P5	**100%**	**1.364**	**1.490**	**0.851%**	**0.372**	**-3.236%**	**0.810%**	**0.705%**	**0.915%**	**PO****
P14	**100%**	**2.241**	**2.525**	**3.418%**	**0.942**	**-0.661%**	**3.419%**	**3.212%**	**3.625%**	**PO****
P11	**97%**	**1.302**	**1.193**	**0.681%**	**0.141**	**-3.209%**	**0.866%**	**0.708%**	**1.024%**	**PO****
P13	**97%**	**1.245**	**1.340**	**0.435%**	**0.287**	**-3.870%**	**0.393%**	**0.326%**	**0.460%**	**PO****
P2	**95%**	**1.280**	**1.676**	**1.357%**	**0.541**	**-2.894%**	**1.469%**	**1.162%**	**1.777%**	**PO****
P7	**89%**	**1.025**	**1.234**	**0.397%**	**0.206**	**-3.848%**	**0.463%**	**0.356%**	**0.571%**	**PO****
P12	76%	1.290	1.298	1.094%	0.225	-2.898%	0.384%	-0.416%	1.184%	NP
P4	73%	1.067	1.120	0.098%	0.027	-3.950%	0.171%	-0.023%	0.365%	NP
P3	70%	1.011	1.147	0.067%	0.020	-3.920%	0.095%	-0.185%	0.375%	NP
P6	**68%**	**0.960**	**1.089**	**-0.162%**	**-0.018**	**-3.568%**	**-0.759%**	**-1.422%**	**-0.096%**	**PU****
P9	54%	0.970	1.083	-0.241%	-0.070	-4.304%	-0.172%	-0.519%	0.175%	NP
P16	30%	0.995	0.957	-0.172%	-0.060	-4.484%	-0.141%	-0.282%	0.001%	NP
P8	**24%**	**0.844**	**0.870**	**-3.802%**	**-0.314**	**-6.764%**	**-4.401%**	**-5.538%**	**-3.264%**	**PU****
P15	**11%**	**0.797**	**0.814**	**-0.763%**	**-0.321**	**-4.975%**	**-0.800%**	**-0.979%**	**-0.621%**	**PU****
P10	**5%**	**0.909**	**0.814**	**-4.754%**	**-0.407**	**-7.556%**	**-4.774%**	**-5.267%**	**-4.281%**	**PU****

Source: Calculated by the author with R and Excel

The mean rolling period omega ratios in excess of one and the positive information ratios and excess returns for P1, P5, P14, P11, P13, P2, and P7 in Table 27 coincide with the full analysis period omega ratio, which is greater than one for all of these persistent outperformers. A similar consistency between the performance observations of the full period omega ratios (less than one) and the mean rolling period performance measures (Mean rolling Ω < 1, and negative mean rolling α_{ex} and IRs) for the persistently underperforming P8, P15, and P10 can also be observed. This implies that the performance histories for 10 of the 11 funds deemed persistent out- or underperformers contain less noisy information.

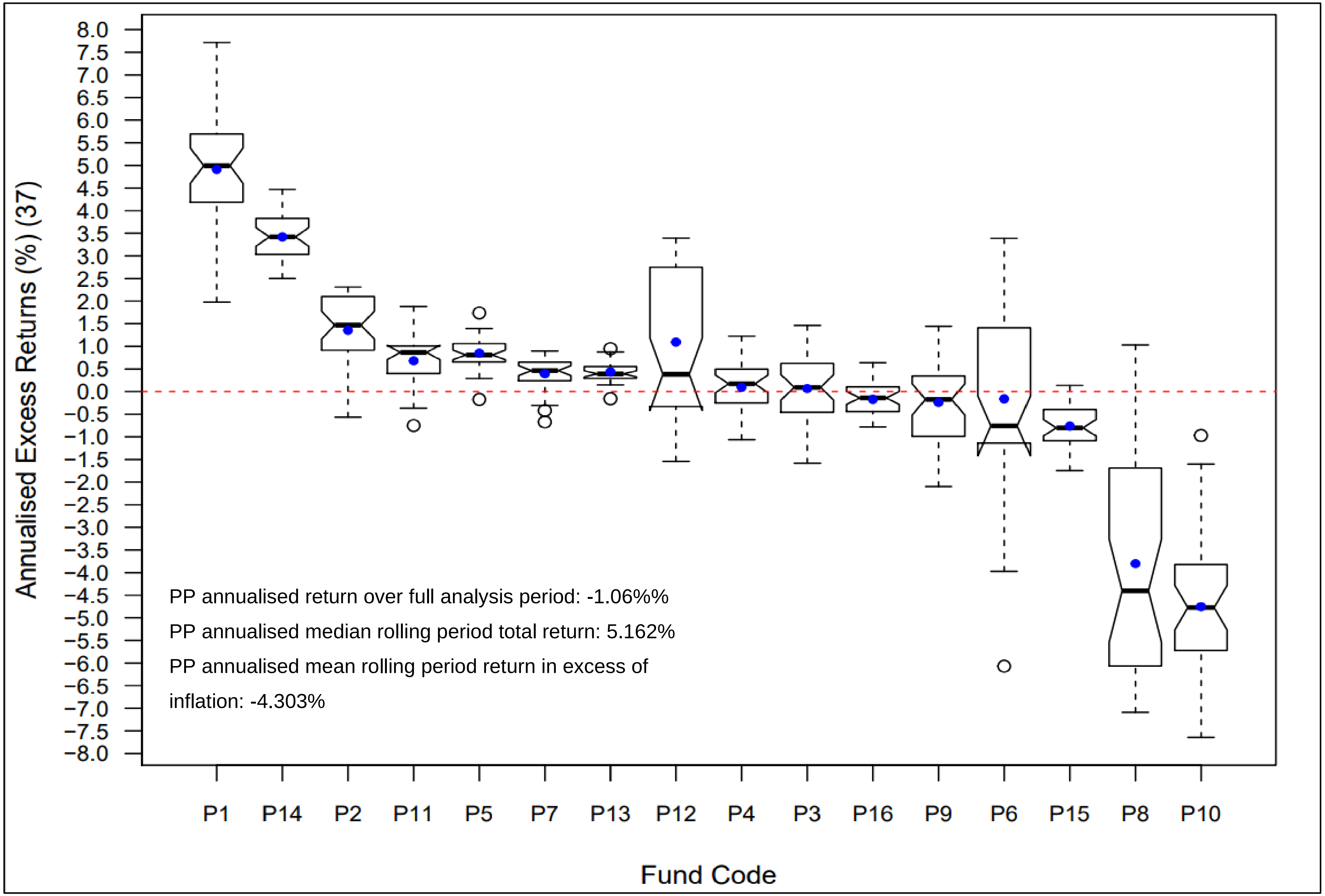


Figure 15: Active general real estate funds – Notched boxplots of annualised rolling holding period excess returns (1 Jan 2013 to 31 Dec 2020)
Source: Constructed by the author with R

However, the results for P6 stand out in contrast to other persistent active funds. Table 27 shows that the mean rolling period omega ratio for P6 is 1.089 and that it outperformed the passive alternative (PP) in most of its rolling holding periods (68%). This conflicts with the performance observations of P6's mean rolling excess return, information ratio (both negative), and its full analysis period omega ratio of 0.96. The conflicting evidence in the mean rolling period performance measures may be attributed to the omega ratio considering the third and fourth moments of P6's excess return distribution. The notched boxplot in Figure 15 shows that P6's excess return distribution is negatively skewed and characterised by periods of sharp underperformance, as shown by the lower whisker of -3.9% and the outlier of -6.1%. This provides a rationale for P6's underperformance over the full analysis period. P6's investment objective is to enhance dividend and rental income, whilst the passive alternative's performance reflects the risk-return attributes of the general real estate category as proxied by the FTSE/JSE Listed Property Index. Hence, P6's investment performance may reflect the effect of its specific investment objective relative to the performance of PP.

4.4.4.1 *Analysis: real estate funds*

The evidence shows that a greater proportion (43.75%) of active general real estate funds persistently outperformed the passive alternative than those that persistently underperformed (25%).

The determinants of market efficiency may offer insight for this observation (Clearly et al., 2019). Real estate investments are classified as alternative investments, which are characterised by a greater degree of heterogeneity in return driving characteristics (Duhon et al., 2019), and a decreased availability of information (Boshoff, 2012). This may reduce the degree of efficiency of the real estate market. Additionally, the potentially decreased level of efficiency of the real estate market in conjunction with the fact that South Africa is an EME may have offered active funds the opportunity to outperform persistently.

The AMH may offer an alternative motivation for the empirical evidence. The full analysis period for the real estate funds coincides with a period (1 January 2017 to 31 December 2020) in which the South African property (real estate) sector was subject to significant losses in value (Heystek, 2021). Therefore, similar to active interest-bearing funds, active real estate funds' performance relative to passive alternatives may have benefitted from the periods of stress on their market sector (Aktan et al., 2018; Peng et al., 2011). Furthermore, it has been argued that the FTSE/JSE Listed Property Index is highly concentrated (Rickens, 2020). Hence, actively managed real estate funds would have been presented with the opportunity to minimise their funds' losses by limiting their exposure to poorly performing assets within the index, as suggested by Lambridis (2017).

Most real estate funds seek to provide investment solutions to investors with a long-term investment horizon (five years or more) who have a primary investment objective of earning real returns, high income yields, as well as the possibility of capital growth. In addition, real estate investments offer diversification potential for a portfolio that consists of traditional asset classes such as equities and fixed-income (interest-bearing) investments (Yau et al., 2007). Therefore, the evidence suggests that some actively managed real estate unit trusts may enhance investors' wealth, provided that superior actively managed funds can be identified prior to investment.

4.4.5 Analysis: all funds

Collectively, 29.771% (39 of 131) of all actively managed funds in the sample persistently outperformed and 54.198% (71 of 131) persistently underperformed their respective passive alternatives. This is consistent with prior evidence which shows that persistently outperforming active funds consists of a small subset of the active funds studied (Cremers et al., 2019). Therefore, actively managed funds that are optimal investments compared to passive alternatives do exist. However, on a comparative basis, passive alternatives dominate the performance of active funds as a greater proportion of active funds persistently underperform.

The descriptive statistics presented in section 4.3 showed that a greater proportion of the active funds (86 of 131 or 65.649%) have lower return standard deviations than their respective passive alternatives. Hence, active funds may benefit investors by acting as risk-diversifiers. Therefore, despite the increased evidence of persistent underperformance, active funds may provide alternative forms of value to their investors. This attribute may be beneficial to investors – particularly since South Africa is an EME that is prone to frequent shocks. The percentage of active funds per category with return standard deviations less (greater) than their respective passive alternative is summarised in Figure 16.

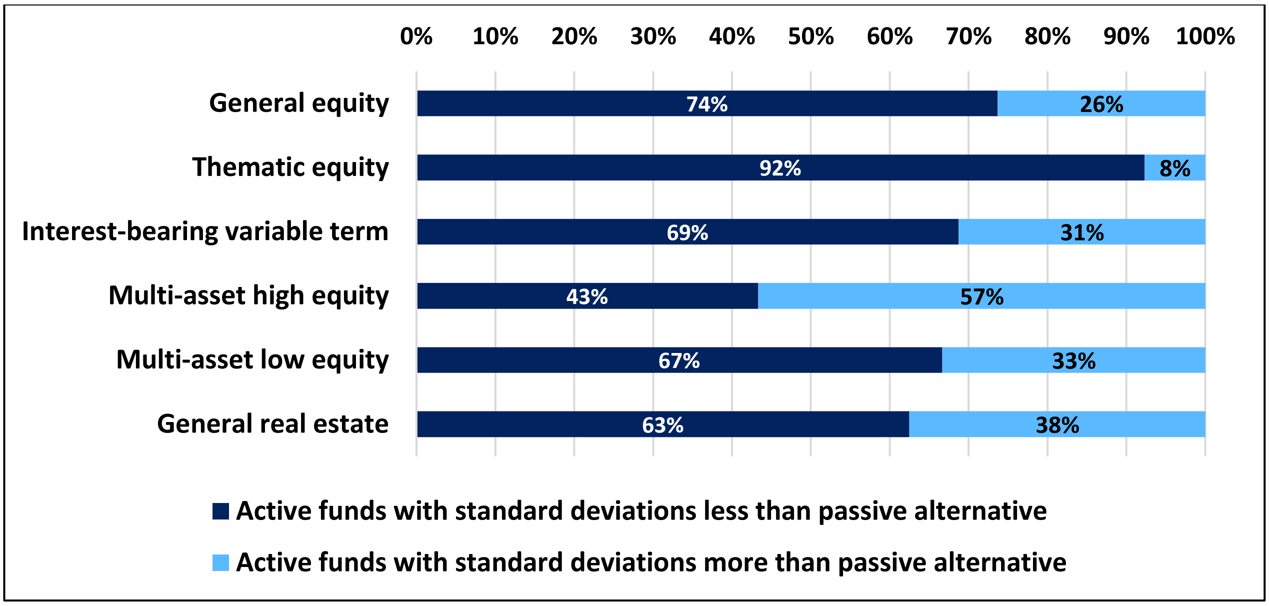


Figure 16: Summary of active fund return standard deviations relative to respective passive alternatives as reported in section 4.3

Source: Constructed by the author with Excel

The equity, interest-bearing, multi-asset, and real estate categories were analysed over different periods based on the availability of data. The variation in the proportions of persistent out- and underperformers indicate the evidence of performance persistency depends on the time period considered, which agrees with the findings of Collinet and Firer (2003) and the concept of time-varying efficiency as proposed by the AMH. Moreover, it indicates that the evidence of performance persistency is dependent on the performance of asset classes in which funds invest. Table 28 presents the average annualised omega ratios and excess returns of all persistent active funds over their respective categories' analysis periods.

Apart from funds in the interest-bearing variable term and the thematic equity categories, inferior active funds' (persistent underperformers) underperformance in terms of excess returns exceed the extent of outperformance among funds classified as superior active funds (persistent outperformers). This suggests that, on average, investors are better off by investing in passive alternatives as they stand to lose more by investing in an inferior active fund than what they stand to gain by investing in a superior active fund. However, the evidence in Table 28 indicates that investors may potentially benefit from attempting to identify superior active funds in the interest-bearing variable term and thematic equity categories.

Table 28: Performance of all persistent active funds

	Average annualised excess returns over category's full analysis period		Average annualised omega ratio over category's full analysis period	
	Persistent outperformers	Persistent underperformers	Persistent outperformers	Persistent underperformers
General equity	0.28%	-3.145%	1.103	0.726
Thematic equity	1.811% (Financial: 1.428%) (Large cap: 0.123%) (Resources: 3.881%)	-1.518% (Financial: -0.293%) (Industrial: -1.756%) (Resources: -2.506%)	1.309 (Financial: 1.286) (Large cap: 1.102) (Resources: 1.54)	0.952 (Financial: 1.028) (Industrial: 0.843) (Resources: 0.986)
Interest-bearing variable term	0.638%	-0.607%	1.663	0.836
Multi-asset high equity	0.125%	-1.517%	1.045	0.759
Multi-asset low equity	-0.129%	-1.202%	0.98	0.765
General real estate	1.64%	-2.699%	1.456	0.877

Source: Calculated by the author with R and Excel

The average outperformance in terms of the omega ratio is greater than the average underperformance for persistent active funds in the general real estate category (1.456 versus 0.877). Since the omega ratio accounts for the third and fourth moments of the excess return distribution, it shows that the average persistently outperforming active real estate fund's ability to reduce risk may be more beneficial than its ability to enhance returns. Hence, investors that value risk-reduction more than wealth enhancement may benefit from attempting to identify persistently outperforming real estate funds. In addition, the average omega ratio indicates that the extent of superior active funds' outperformance is greater than the extent of inferior funds' underperformance in the interest-bearing variable term and thematic equity categories. Hence, identifying and investing in the average persistently outperforming active fund in the interest-bearing variable term and thematic equity categories appears particularly beneficial as benefits in terms of risk-reduction and return enhancement are offered to the investor.

For an investor to access the performance of a superior active fund, they must be able to identify it prior to making the investment. Goetzmann and Ibbotson (1994) and Matallín-Sáez et al. (2016) argued that evidence of performance persistence could be used to inform investors' future decisions to enhance their wealth and Hendricks et al. (1993) stated that evidence of persistent outperformance could be used to select future outperformers, whilst Firer et al. (2001) noted that evidence of persistent underperformance might inform investors about which funds to avoid. Finally, Demiralp and Fernando (2016) found that failing to consider performance persistence may result in suboptimal investment decisions as not all funds perform persistently.

By considering the performance persistency of actively managed funds in terms of the distribution and frequency of active funds' performance relative to a passive alternative offers insight into the noisiness of active funds' performance histories. The noisiness of active funds' performance histories in the general equity, multi-asset high equity and multi-asset low equity varied. This suggests that only some of the persistently performing funds' performance histories would have aided future investment decisions. Conversely, the performance histories of active thematic equity, interest-bearing variable term, and general real estate funds were less noisy (apart from R5, B2, and P6). This suggests that the consideration of the performance histories of active funds in these categories (relative to their respective passive alternatives) may potentially benefit future investment decisions. Nevertheless, evidence of performance persistence in isolation does not appear to be beneficial in all instances that it can be observed. This suggests that the evaluation of the performance histories of active funds should not be considered in isolation and should be supplemented with an evaluation of other determinants of fund performance and the persistency thereof.

In addition to performance persistency, investors may benefit from considering active funds' investment charges as a common trend in the persistently out- and underperforming active funds' total investment charge (TIC) is observable. Figure 17 shows the average annual TIC of all persistently out- and underperforming active funds over their respective categories' full analysis periods. Across all of the ASISA categories studied, persistently outperforming active funds systematically charged investors less compared to persistent underperformers. Hence, active funds' ability to persistently outperform passive alternatives appear to be partially determined by their ability to minimise TIC.

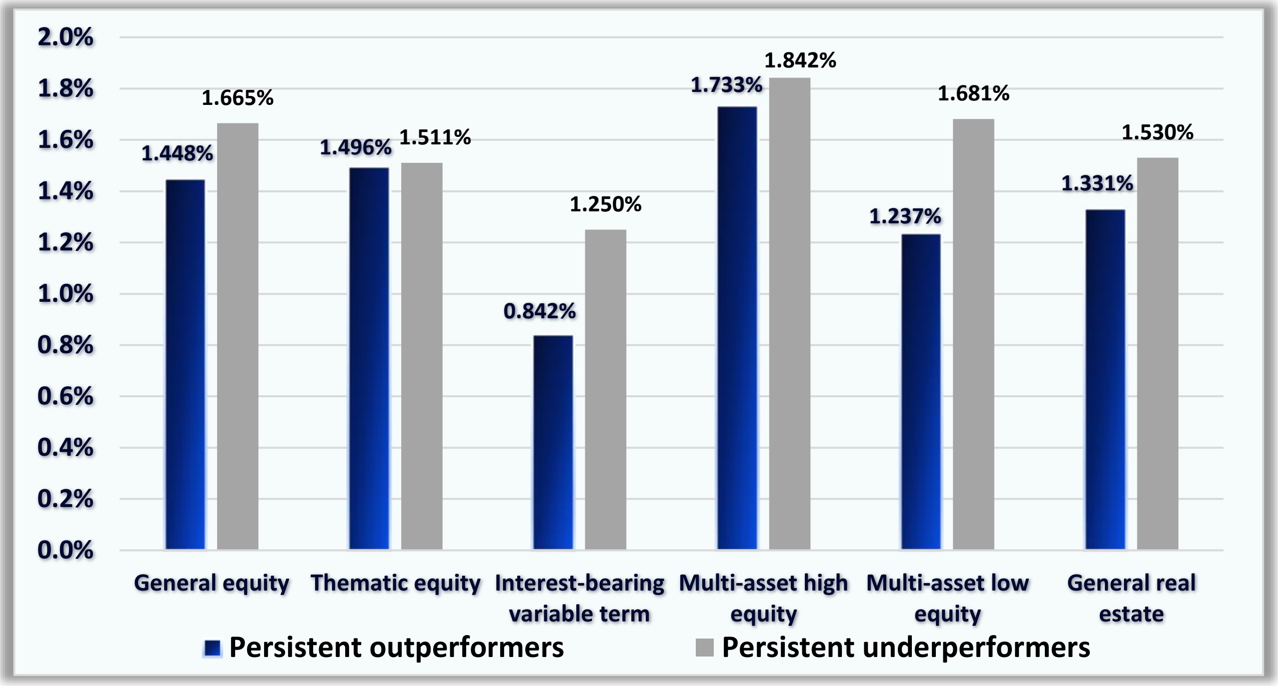


Figure 17: Average annual TIC of all persistent out- and underperformers over their respective full analysis periods

Source: Constructed by the author with Excel

However, an investor must note an important caveat in their active versus passive investment decision. For the investor to access superior active funds, they must be able to identify these funds prior to their investment period. Hence, the investor would require a degree of skill in identifying such active funds. If investors cannot identify superior active funds before investment, investing in passive alternatives would be optimal as it would not subject them to the risk of relative losses of wealth resulting from investments in persistently underperforming active funds.

4.5 SUMMARY

The evidence presented in this chapter shows that for a given set of passive alternatives available to South African retail investors, active funds that persistently out- and underperform these passive options exist within all the categories considered. The proportions of persistently out- and underperforming active funds across different ASISA categories varied. The evidence suggests that the performance histories of active funds vary with respect to their informational value. Investors may benefit from investing in some persistently outperforming active funds, provided that these funds can be identified prior to investment.

CHAPTER 5: CONCLUSION

The previous chapter presented the test results and the analysis thereof. This chapter concludes the study. A summary of the findings is given first, followed by the conclusions to this study's research objectives. Finally, a description of the practical implications of this research and recommendations for future avenues of research concludes this chapter.

5.1 SUMMARY OF FINDINGS

This study examined the research objective of whether actively managed South African unit trusts exhibit performance persistency relative to comparable passive alternatives. Funds from all second-tier Association of Savings and Investment South Africa (ASISA) categories were considered to address the lack of prior research on the performance persistency amongst funds from asset classes other than equity. In addition, this research serves to inform investors regarding the optimality of the two broad investment alternatives. The research objective was addressed by assessing the performance persistence of active funds by evaluating their rolling period excess returns, information ratios, and omega ratios. Furthermore, notched boxplots were utilised to assess the statistical significance of active funds' performance persistency relative to their passive alternatives.

The findings emphasise the importance of evaluating the performance and performance persistency of actively managed unit trusts to investable passive alternatives - particularly in an emerging market economy (EME) such as South Africa. The results have shown that a small subset of actively managed funds are optimal investments once their performance is contrasted with passive funds subjected to a similar set of regulatory constraints. Despite the differences in methodology, this is largely consistent with prior evidence (Brown, 2008; Cremers et al., 2019; Malefo et al., 2016; Otten & Bams, 2002). If superior active funds can be identified before the investment period, the investor will be better off investing in them than a passive alternative. However, passive alternatives are optimal investments compared to most active funds. Therefore, if investors cannot identify superior active funds before making their investment, they stand a greater chance of increasing their wealth by investing in a comparable passive fund. The findings of this study are summarised in Table 29.

Table 29: Summary of findings

Hypothesis tested			
H_0: *Active fund i does not provide median excess returns that are different from zero over time;* and H_a: *Active fund i does provide median excess returns that are different from zero over time.*			
Second-tier ASISA Class	**Number of active funds considered**	**Number (percentage) of active funds for which the null hypothesis is rejected**	**Number (percentage) of active funds for which the null hypothesis fails to be rejected**
Equity	38 general equity funds	33 funds (86.842%): • 10 (26.316%) persistently outperformed • 23 (60.526%) persistently underperformed	5 (13.158%) funds
	13 thematic equity funds	12 funds (92.308%): • 7 (53.846%) persistently outperformed • 5 (38.462%) persistently underperformed	1 (7.692%) fund
Interest-bearing	16 interest-bearing variable term funds	13 funds (81.25%): • 9 (56.25%) persistently outperformed • 4 (25%) persistently underperformed	3 (18.75%) funds
Multi-asset	30 multi-asset high equity funds	27 funds (90%): • 5 (16.667%) persistently outperformed • 22 (73.333%) persistently underperformed	3 (10%) funds
	18 multi-asset low equity funds	14 funds (77.778%): • 1 (5.556%) persistently outperformed • 13 (72.222%) persistently underperformed	4 (22.222%) funds
Real Estate	16 general real estate funds	11 funds (68.75%): • 7 (43.75%) persistently outperformed • 4 (25%) persistently underperformed	5 (31.25%) funds
All categories	**131 funds**	**110 funds (83.969%):** • **39 (29.771%) persistently outperformed** • **71 (54.198%) persistently underperformed**	**21 (16.031%) funds**

To ensure that the active and passive funds were limited by the same set of constraints, the performance of active funds were contrasted to that of passive alternatives that track their respective ASISA category indices. However, active funds may have benefitted from isolating profitable investment styles over different time-frames within the analysis periods considered. As a result, the passive alternatives' performance may have been a generalised representation of fund performance in such instances.

The literature review identified that factors such as the degree of competition and sector-level diseconomies of scale might influence the observed evidence of performance persistency. In addition, Hoberg et al. (2018) suggested that the level of competition and sector-level diseconomies of scale may work in tandem. Hence, these factors could potentially offer some insight into the varying levels of persistent out- and underperformance across different ASISA categories. Table 30 shows the total assets under management (AUM) and the number of funds registered under each ASISA category investigated in this study as at 31 December 2020.

Table 30: Number of funds and total AUM for ASISA categories studied as at 31 Dec 2020

	Number of funds	Assets under management in millions
General equity	239	R347 362
Thematic equity	44	R40 325
Interest-bearing variable term	63	R115 373
Multi-asset high equity	247	R512 141
Multi-asset low equity	187	R212 873
General real estate	58	R37 759

Source: Adapted from ASISA (2021)

Notably, the figures in Tables 29 and 30 indicate that ASISA sectors with fewer funds and fewer assets under management at 31 December 2020 showed more evidence of persistently outperforming funds. The opposite is true for ASISA sectors with more funds and assets under management. This is similar to the findings of Hoberg et al. (2018) that showed that more funds persistently outperformed in smaller sized clusters (or style-industries) of funds that face less competition. Hence, this observation suggests that the influence of the degree of competition, and sector-level diseconomies of scale, may potentially influence the optimality of active and passive management strategies across different ASISA categories. Furthermore, the literature suggested that variation in fund size (fund-level diseconomies of scale) may impact active funds' performance persistency. Figure 18 shows the average AUM of all persistent out- and underperformers over their respective ASISA category's full analysis period.

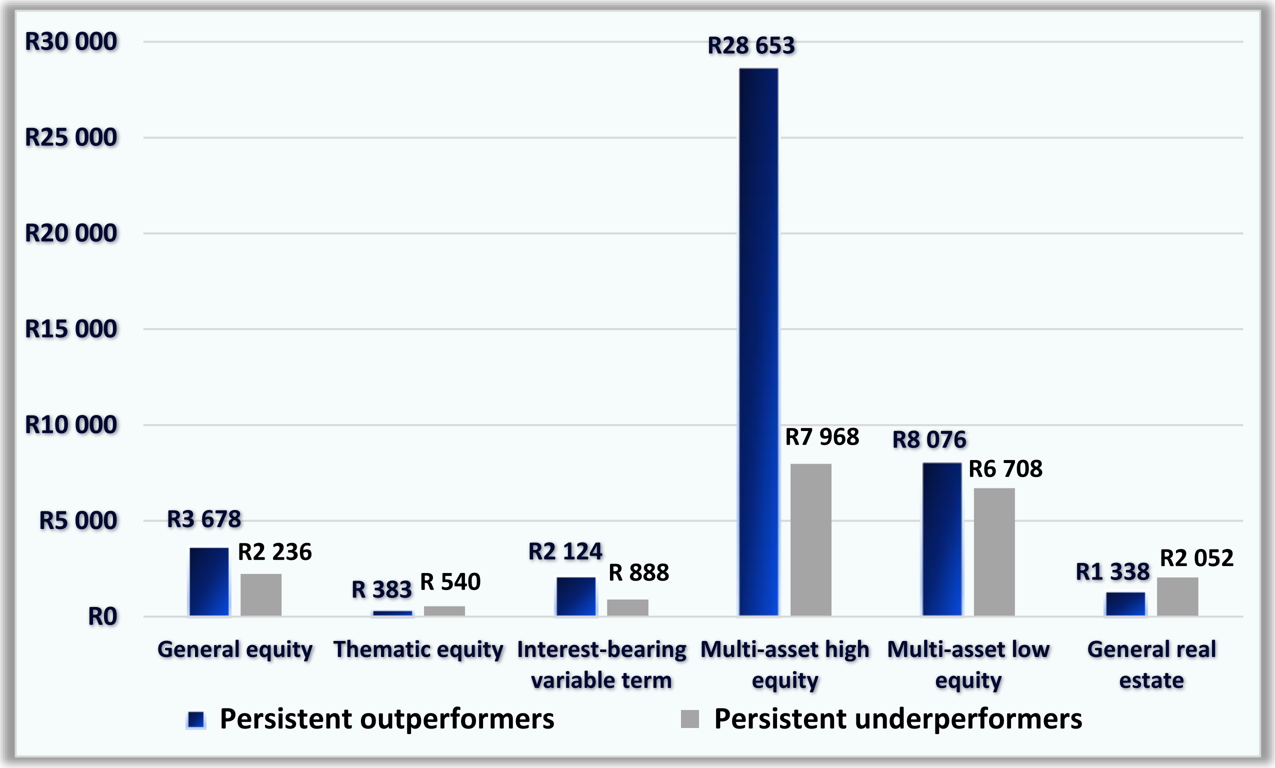


Figure 18: Average AUM of all persistent out- and underperformers over their respective full analysis periods in millions

Source: Adapted from ASISA (2021)

Except for the thematic equity and general real estate categories, Figure 18 shows that persistent outperformers were generally larger funds compared to those that persistently underperformed. This is similar to the findings of Ferreira et al. (2013), who showed that funds outside of the United States of America (US) are more likely to experience increasing returns to scale. Deb (2019) contends that larger funds are more likely to attract and employ more skilled fund managers. Those fund managers are encouraged to put more effort into managing larger funds well as their remuneration is based on a percentage of the AUM. Similarly, the analysis in section 4.4.5 showed that persistent outperformers are more likely to have lower total investment charges (TIC) compared to persistent underperformers.

Hence, larger funds may benefit from internal economies of scale in reducing their TIC as they can distribute fund charges across a greater asset base.

Finally, the evidence of persistent out- or underperformance may be reflective of the nature of the assets that the funds invest in. Amongst the active financial and resource equity funds, 50% and 80% persistently outperformed their respective passive alternatives. However, all three active industrial equity funds persistently underperformed. Financial companies have complex capital structures, whilst resource companies' value is associated with commodity prices, which may diminish the general accuracy of their valuations. In contrast, industrial companies tend to have relatively predictable production schedules, which may increase the general accuracy of their valuations. Hence, the accuracy of the market price relative to the respective assets' intrinsic value may vary across these categories, which speaks to opportunities afforded to active managers within these separate categories.

5.2 CONCLUSIONS

Collectively, when the performance of active funds is contrasted to investable passive alternatives that face similar constraints, more evidence of performance persistence is observed. In the equity and multi-asset ASISA categories, the evidence of performance persistency is mostly concentrated amongst persistent underperformers. Conversely, the evidence of performance persistency is mostly concentrated amongst persistent outperformers in the interest-bearing and real estate categories. The method employed provides insight into the excess return distributions of active funds, which allow for the following conclusions:

- For a given set of passive funds that are available to the South African retail investor, active funds that persistently out- and underperform these passive options exist.
- More active funds persistently underperform the passive alternative compared to active funds that persistently outperform the passive alternative.
- Performance persistency of active funds does not necessarily have informational value that may enhance future investment decisions in all instances that it is observed.
- Evidence of performance persistency is dependent on the time period considered.

- Evidence of performance persistency is dependent on the asset classes in which funds invest.
- Investors are likely to benefit more from investing in passive general equity, multi-asset high equity, and multi-asset low equity funds.
- Provided that superior active funds can be identified before investment, investors could benefit from investing in actively managed thematic equity, interest-bearing variable term, and general real estate funds. On average, investors could expect to earn 1.811%, 0.638%, and 1.64% more annually by investing in superior active funds than passive alternatives in the thematic equity, interest-bearing variable term, and general real estate categories, respectively.
- Persistently outperforming active funds are more likely to have lower TICs compared to persistently underperforming active funds.
- More evidence of persistently outperforming funds was observed in ASISA sectors with fewer funds and AUM. In contrast, more evidence of persistently underperforming funds was observed in ASISA sectors with more funds and AUM.
- Except for funds in the thematic equity and general real estate categories, persistent outperformers were larger funds, on average, compared to those that persistently underperformed.

5.3 PRACTICAL IMPLICATIONS

Goetzmann and Ibbotson (1994) state that funds are primarily selected based on their performance histories and that asset managers use historical performance as a "major selling point". The findings in this study suggest that financial advisors, investors, and fund managers of funds of funds should practice caution in interpreting a fund's performance history - particularly when considering the optimality of a certain active or passive alternative. This is because active funds' performance histories relative to passive alternatives vary with respect to their informational value. Considering other determinants of fund performance and the persistency thereof such as market dynamics, sector-, and fund-level characteristics must supplement the analysis of a fund's performance history. Additionally, investors who are doubtful of their ability to identify superior active funds prior to investment should opt to invest in passive alternatives as this would not subject them to the risk of potentially investing in persistently underperforming active funds.

5.4 RECOMMENDATIONS FOR FUTURE RESEARCH

The first area recommended for further research would be to evaluate the optimality of portfolios that provide simultaneous exposure to both active and passive investment strategies such as smart beta funds or funds that employ core-satellite strategies. As proposed by the Adaptive Markets Hypothesis (AMH), time-varying efficiency suggests that the optimality of active and passive strategies may vary over time and across different markets based on the shocks and structural changes inherent to a particular time-frame or market. Furthermore, active and passive funds complement each other. Passive funds benefit from the price discovery resulting from the research undertaken by active funds whilst active funds take advantage of pricing inefficiencies that passive funds overlook. An evaluation of investment solutions that seek to exploit the benefit of both investment approaches would add value.

In addition, this study identified the need to consider other determinants of fund performance to supplement investment decisions. Therefore, further research on the determinants of fund performance and persistency would expand on this study. The literature review identified competition as well as fund- and sector-level diseconomies of scale as potential determinants of fund performance over time. Further investigation into the extent of these factors' applicability to South African funds can enhance informed fund investment decisions. Fund-level effects can be investigated by evaluating how different funds' performance varies over time based on fund size and TIC changes. The influence of sector-level effects can be evaluated by contrasting the performance of different groups of funds that are stratified in terms of various measures of competition and sector-level diseconomies of scale (Deb, 2019; Ferreira et al., 2019; Keswani & Stolin, 2006; Pástor et al., 2015).

Finally, the concept of performance persistency has been argued to be associated with managerial skill (Goetzmann & Ibbotson, 1994). Further research investigating managerial skill and its association to fund performance over time may provide insight into the determinants of performance persistency.

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APPENDIX A: ACTIVE FUND NAMES AND CODES

Table A1: Names and codes of active funds studied

South African Equity General			
Code	**Fund Name**	**Code**	**Fund Name**
G1	ABSA Prime Equity A	**G20**	Nedgroup Inv Growth A1
G2	ABSA Select Equity A	**G21**	Nedgroup Inv Private Wealth Equity A
G3	Allan Gray Equity A	**G22**	Nedgroup Inv Rainmaker A1
G4	Aylett Equity Prescient A1	**G23**	Nedgroup Inv Value A
G5	Cadiz BCI Equity A	**G24**	Ninety One Equity A
G6	Community Growth Equity	**G25**	Ninety One Value A
G7	Coronation Equity R	**G26**	Oasis Crescent Equity A
G8	Coronation Top 20 A	**G27**	Oasis General Equity A
G9	Denker SCI Equity	**G28**	Old Mutual Albaraka Equity A
G10	Element Earth Equity SCI A	**G29**	Old Mutual Investors R
G11	Element Islamic Equity SCI A	**G30**	Prescient Equity A1
G12	First Avenue SCI Focused Quality Eq A	**G31**	Prudential Dividend Maximiser A
G13	FNB Momentum Growth	**G32**	Prudential Equity A
G14	Foord Equity A	**G33**	PSG Equity B
G15	Harvard House BCI Equity A	**G34**	Sasfin BCI Equity A
G16	Huysamer Equity Prescient A1	**G35**	SIM General Equity A
G17	IFM Technical	**G36**	SIM Top Choice Equity A1
G18	Maestro Equity Prescient A	**G37**	STANLIB Equity R
G19	Marriott Dividend Growth R	**G38**	STANLIB SA Equity A
South African Equity Financial			
Code	**Fund Name**	**Code**	**Fund Name**
F1	Coronation Financial A	**F3**	Nedgroup Inv Financials A
F2	Momentum Financials A	**F4**	SIM Financial A
South African Equity Industrial			
Code	**Fund Name**	**Code**	**Fund Name**
I1	Coronation Industrial P	**I3**	SIM Industrial A
I2	Momentum Industrial A		

Table A1: Names and codes of active funds studied (*continued)*

South African Equity Large Cap			
Code	**Fund Name**	**Code**	**Fund Name**
L1	Prescient Core Top 40 Equity A1		
South African Equity Resources			
Code	**Fund Name**	**Code**	**Fund Name**
R1	Coronation Resources P	**R4**	Ninety One Commodity B
R2	Momentum Resources A	**R5**	Old Mutual Gold R
R3	Nedgroup Inv Mining & Res A		
South African Interest-Bearing Variable Term			
Code	**Fund Name**	**Code**	**Fund Name**
B1	ABSA Bond A	**B9**	Nedgroup Inv Core Bond A
B2	ABSA Multi-Managed Bond A	**B10**	Ninety One Gilt A
B3	Allan Gray Bond A	**B11**	Oasis Bond D
B4	Community Growth Gilt	**B12**	Old Mutual Bond R
B5	Coronation Bond R	**B13**	Prescient Flexible Bond C
B6	FNB Multi Manager Bond B1	**B14**	Prudential High Yield Bond A
B7	Melville Douglas STANLIB Bond A	**B15**	SIM Bond Plus R
B8	Momentum Bond B7	**B16**	STANLIB Bond R
South African Multi-Asset High Equity			
Code	**Fund Name**	**Code**	**Fund Name**
M1	ABSA Managed A	**M13**	Melville Douglas STANLIB Balanced B1
M2	AF Investments Performer Managed A	**M14**	Ninety One Managed A
M3	Allan Gray Balanced A	**M15**	Ninety One Opportunity B
M4	Autus Prime Balanced A	**M16**	Oasis Balanced A
M5	Cadiz BCI Balanced A	**M17**	Old Mutual Balanced A
M6	Coronation Balanced Plus A	**M18**	Personal Trust Managed
M7	Discovery Balanced	**M19**	Plexus Wealth BCI Balanced A
M8	Element Balanced SCI A	**M20**	Prescient Absolute Balanced C
M9	Element Islamic Balanced SCI A	**M21**	Prudential Balanced A
M10	Flagship IP Balanced Fund A	**M22**	PSG Balanced A
M11	FNB Multi Manager Balanced B1	**M23**	Rezco Managed Plus A
M12	Foord Balanced A	**M24**	Rezco Value Trend A

Table A1: Names and codes of active funds studied (*continued)*

South African Multi-Asset High Equity			
Code	**Fund Name**	**Code**	**Fund Name**
M25	Seed Balanced Prescient A1	**M28**	SIM Balanced A
M26	Select BCI Balanced A	**M29**	STANLIB Balanced B1
M27	Sharenet BCI Balanced A	**M30**	STANLIB MM Balanced B1
South African Multi-Asset Low Equity			
Code	**Fund Name**	**Code**	**Fund Name**
N1	ABSA Absolute A	**N10**	Nedgroup Inv Stable A1
N2	ABSA Inflation Beater A	**N11**	Ninety One Cautious Managed B
N3	Allan Gray Optimal A	**N12**	Old Mutual Real Income A
N4	Allan Gray Stable A	**N13**	Old Mutual Stable Growth A
N5	Autus Prime Stable A	**N14**	Personal Trust Conservative Mgd
N6	BCI Income Provider Fund	**N15**	Plexus Wealth BCI Conservative A
N7	Coronation Balanced Defensive A	**N16**	Prudential Inflation Plus A
N8	Element Real Income SCI A	**N17**	SIM Inflation Plus
N9	MI-PLAN IP Inflation Plus 3 B5	**N18**	STANLIB Balanced Cautious B1
South African Property General			
Code	**Fund Name**	**Code**	**Fund Name**
P1	ABSA Property Equity A	**P9**	Ninety One Property Equity A
P2	Catalyst SCI SA Property Equity D	**P10**	Oasis Property Equity A
P3	Coronation Property Equity A	**P11**	Old Mutual SA Quoted Property
P4	Discovery Flexible Property	**P12**	Plexus Wealth BCI Property A
P5	FNB Multi Manager Property B1	**P13**	Prescient Property Equity A1
P6	Marriott Property Income A	**P14**	Sesfikile BCI Property A
P7	Momentum Real Growth Property A	**P15**	SIM Property A
P8	Nedgroup Inv Property A	**P16**	STANLIB Property Income B1

APPENDIX B: DESCRIPTIVE STATISTICS FOR ACTIVE FUNDS

Table A2: Descriptive statistics of total monthly and annualised returns for active general equity funds from 1 Jan 2007 to 31 Dec 2020

Fund Code	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
G1	0.941% (11.895%)	0.972% (12.308%)	4.376% (15.159%)	4.239%	0.96
G2	0.769% (9.628%)	1.104% (14.083%)	3.897% (13.5%)	6.072%	0.912
G3	0.771% (9.655%)	0.827% (10.388%)	3.892% (13.482%)	6.977%	0.883
G4	0.897% (11.311%)	1.122% (14.327%)	3.514% (12.173%)	8.299%	0.829
G5	0.534% (6.6%)	0.622% (7.725%)	4.26% (14.757%)	8.401%	0.839
G6	0.686% (8.55%)	1.083% (13.799%)	4.202% (14.556%)	4.504%	0.953
G7	0.965% (12.215%)	1.323% (17.084%)	4.176% (14.466%)	5.533%	0.929
G8	0.966% (12.228%)	0.965% (12.215%)	4.454% (15.429%)	6.743%	0.901
G9	0.672% (8.369%)	0.617% (7.66%)	3.976% (13.773%)	7.569%	0.862
G10	0.323% (3.946%)	0.518% (6.396%)	3.758% (13.018%)	9.219%	0.788
G11	0.484% (5.965%)	0.504% (6.218%)	3.484% (12.069%)	8.84%	0.803
G12	0.502% (6.193%)	0.653% (8.124%)	4.172% (14.452%)	5.943%	0.918
G13	0.542% (6.701%)	0.583% (7.225%)	4.064% (14.078%)	5.83%	0.92
G14	0.733% (9.159%)	1.058% (13.461%)	3.996% (13.843%)	6.324%	0.905
G15	0.657% (8.175%)	0.996% (12.629%)	3.946% (13.669%)	5.886%	0.918
G16	0.499% (6.155%)	0.845% (10.625%)	4.088% (14.161%)	4.704%	0.948
G17	0.602% (7.468%)	0.574% (7.11%)	3.803% (13.174%)	9.096%	0.795
G18	0.561% (6.944%)	0.576% (7.135%)	3.942% (13.655%)	6.657%	0.894
G19	0.728% (9.094%)	0.675% (8.408%)	3.227% (11.179%)	11.391%	0.648
G20	0.401% (4.92%)	0.79% (9.903%)	4.053% (14.04%)	8.698%	0.82
G21	0.794% (9.955%)	0.767% (9.602%)	4.377% (15.162%)	5.295%	0.938
G22	0.591% (7.327%)	1.007% (12.776%)	3.975% (13.77%)	5.95%	0.916
G23	0.625% (7.763%)	0.831% (10.441%)	3.817% (13.222%)	7.554%	0.861
G24	0.812% (10.191%)	1.012% (12.843%)	4.123% (14.282%)	5.21%	0.937
G25	0.721% (9.003%)	0.802% (10.06%)	6.002% (20.792%)	17.684%	0.55
G26	0.544% (6.727%)	0.597% (7.404%)	3.36% (11.639%)	7.885%	0.849

Table A2: Descriptive statistics of total monthly and annualised returns for active general equity funds from 1 Jan 2007 to 31 Dec 2020 *(continued)*

Fund Code	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
G27	0.574% (7.11%)	0.738% (9.224%)	3.69% (12.783%)	6.796%	0.889
G28	0.559% (6.918%)	0.784% (9.824%)	3.858% (13.365%)	7.276%	0.872
G29	0.666% (8.291%)	0.978% (12.388%)	4.37% (15.138%)	5.537%	0.932
G30	0.693% (8.64%)	0.686% (8.55%)	4.393% (15.218%)	5.572%	0.932
G31	0.834% (10.48%)	1.05% (13.354%)	3.841% (13.306%)	5.618%	0.926
G32	0.884% (11.139%)	1.223% (15.705%)	3.926% (13.6%)	5.604%	0.926
G33	0.695% (8.666%)	0.841% (10.572%)	4.731% (16.389%)	9.593%	0.816
G34	0.725% (9.055%)	1.075% (13.691%)	4.133% (14.317%)	8.854%	0.816
G35	0.841% (10.572%)	1.106% (14.11%)	4.345% (15.052%)	5.493%	0.932
G36	0.968% (12.255%)	0.905% (11.417%)	4.538% (15.72%)	6.935%	0.899
G37	0.718% (8.965%)	1.021% (12.964%)	3.963% (13.728%)	5.649%	0.925
G38	0.435% (5.347%)	0.997% (12.642%)	4.468% (15.478%)	5.567%	0.933

Source: Calculated by author in Excel

Table A3: Descriptive statistics of total monthly and annualised returns for active thematic equity funds from 1 Jan 2007 to 31 Dec 2020

Fund Code	Thematic equity category	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
F1	Financial	0.738% (9.231%)	0.984% (12.472%)	5.301% (18.365%)	4.424%	0.975
F2	Financial	0.745% (9.315%)	0.768% (9.619%)	5.484% (18.998%)	4.435%	0.974
F3	Financial	0.874% (11.002%)	0.854% (10.741%)	5.047% (17.483%)	6.232%	0.95
F4	Financial	0.667% (8.301%)	0.891% (11.226%)	5.145% (17.824%)	5.379%	0.964
I1	Industrial	1.029% (13.077%)	1.2% (15.387%)	3.934% (13.626%)	5.82%	0.92
I2	Industrial	0.791% (9.914%)	0.892% (11.241%)	3.806% (13.183%)	6.178%	0.91
I3	Industrial	1.087% (13.853%)	1.288% (16.598%)	4.09% (14.169%)	7.049%	0.883
L1	Large Cap	0.851% (10.702%)	0.736% (9.197%)	4.64% (16.072%)	1.717%	0.994
R1	Resource	1.078% (13.732%)	1.083% (13.793%)	7.132% (24.707%)	9.735%	0.925
R2	Resource	0.746% (9.334%)	0.422% (5.186%)	6.506% (22.537%)	8.512%	0.944
R3	Resource	1.027% (13.044%)	0.561% (6.938%)	7.039% (24.385%)	8.495%	0.943

Table A3: Descriptive statistics of total monthly and annualised returns for active thematic equity funds from 1 Jan 2007 to 31 Dec 2020 *(continued)*

Fund Code	Thematic equity category	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
R4	Resource	1.107% (14.129%)	0.102% (1.233%)	7.006% (24.269%)	8.269%	0.946
R5	Resource	0.806% (10.108%)	0.103% (1.238%)	10.08% (34.918%)	30.385%	0.531

Source: Calculated by author in Excel

Table A4: Descriptive statistics of total monthly and annualised returns for active interest-bearing variable term funds from 1 Jan 2015 to 31 Dec 2020

Fund Code	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
B1	0.771% (9.656%)	0.943% (11.916%)	2.45% (8.486%)	1.711%	0.981
B2	0.616% (7.651%)	0.647% (8.051%)	1.275% (4.418%)	5.273%	0.877
B3	0.712% (8.888%)	0.702% (8.756%)	2.102% (7.283%)	1.970%	0.985
B4	0.607% (7.533%)	0.605% (7.509%)	2.499% (8.657%)	1.062%	0.993
B5	0.657% (8.169%)	0.621% (7.711%)	2.439% (8.451%)	1.337%	0.988
B6	0.621% (7.712%)	0.648% (8.062%)	2.288% (7.926%)	1.330%	0.992
B7	0.61% (7.565%)	0.639% (7.948%)	2.499% (8.656%)	0.880%	0.995
B8	0.626% (7.772%)	0.622% (7.725%)	2.538% (8.792%)	0.832%	0.996
B9	0.678% (8.442%)	0.703% (8.772%)	2.258% (7.822%)	1.314%	0.993
B10	0.656% (8.162%)	0.696% (8.674%)	2.546% (8.82%)	0.422%	0.999
B11	0.653% (8.122%)	0.675% (8.401%)	1.917% (6.64%)	2.342%	0.989
B12	0.604% (7.489%)	0.633% (7.861%)	2.54% (8.798%)	1.057%	0.993
B13	0.454% (5.582%)	0.48% (5.915%)	2.208% (7.649%)	2.671%	0.955
B14	0.578% (7.157%)	0.62% (7.697%)	2.577% (8.929%)	1.153%	0.992
B15	0.625% (7.767%)	0.68% (8.467%)	2.718% (9.414%)	1.301%	0.993
B16	0.699% (8.716%)	0.812% (10.19%)	2.504% (8.673%)	0.935%	0.994

Source: Calculated by author in Excel

Table A5: Descriptive statistics of total monthly and annualised returns for active multi-asset high equity funds from 1 Jan 2011 to 31 Dec 2020

Fund Code	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
M1	0.594% (7.365%)	0.668% (8.316%)	2.616% (9.063%)	3.142%	0.939
M2	0.718% (8.963%)	0.928% (11.717%)	2.544% (8.811%)	2.453%	0.962
M3	0.775% (9.704%)	0.821% (10.304%)	2.603% (9.017%)	3.983%	0.901
M4	0.759% (9.501%)	0.834% (10.477%)	2.604% (9.02%)	5.01%	0.843
M5	0.505% (6.235%)	0.634% (7.874%)	2.699% (9.349%)	4.459%	0.881
M6	0.808% (10.144%)	0.83% (10.432%)	2.742% (9.499%)	3.333%	0.936
M7	0.785% (9.843%)	0.948% (11.985%)	2.706% (9.372%)	3.103%	0.944
M8	0.551% (6.82%)	0.655% (8.148%)	2.656% (9.2%)	7.24%	0.679
M9	0.491% (6.048%)	0.376% (4.606%)	2.149% (7.445%)	6.772%	0.668
M10	0.533% (6.593%)	0.755% (9.447%)	2.905% (10.063%)	5.121%	0.861
M11	0.774% (9.69%)	1.006% (12.767%)	2.316% (8.024%)	2.881%	0.947
M12	0.762% (9.533%)	0.846% (10.633%)	2.487% (8.615%)	3.92%	0.900
M13	0.8% (10.031%)	0.841% (10.566%)	2.479% (8.587%)	3.28%	0.930
M14	0.84% (10.564%)	0.794% (9.962%)	2.023% (7.008%)	5.811%	0.756
M15	0.754% (9.434%)	0.827% (10.382%)	2.004% (6.942%)	5.58%	0.777
M16	0.543% (6.716%)	0.793% (9.946%)	2.101% (7.28%)	4.111%	0.889
M17	0.67% (8.342%)	0.917% (11.58%)	2.569% (8.899%)	2.284%	0.967
M18	0.803% (10.07%)	0.944% (11.929%)	2.302% (7.976%)	3.353%	0.926
M19	0.548% (6.78%)	0.649% (8.075%)	2.673% (9.26%)	4.256%	0.891
M20	0.517% (6.386%)	0.669% (8.336%)	2.616% (9.062%)	3.431%	0.927
M21	0.775% (9.704%)	1.033% (13.127%)	2.707% (9.376%)	2.62%	0.960
M22	0.686% (8.553%)	0.7% (8.725%)	3.196% (11.07%)	6.359%	0.819
M23	0.853% (10.728%)	0.766% (9.59%)	2.263% (7.838%)	7.305%	0.624
M24	0.912% (11.505%)	0.908% (11.451%)	2.257% (7.817%)	7.241%	0.630
M25	0.72% (8.985%)	0.829% (10.417%)	2.772% (9.602%)	3.652%	0.925
M26	0.638% (7.934%)	0.992% (12.57%)	2.561% (8.871%)	3.572%	0.919
M27	0.533% (6.589%)	0.402% (4.931%)	2.478% (8.585%)	4.06%	0.892
M28	0.652% (8.117%)	0.683% (8.51%)	2.688% (9.312%)	2.502%	0.963

Table A5: Descriptive statistics of total monthly and annualised returns for active multi-asset high equity funds from 1 Jan 2011 to 31 Dec 2020 ***(continued)***

Fund Code	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
M29	0.74% (9.257%)	0.872% (10.986%)	2.255% (7.812%)	3.152%	0.936
M30	0.734% (9.168%)	0.84% (10.553%)	2.604% (9.021%)	2.06%	0.974

Source: Calculated by author in Excel

Table A6: Descriptive statistics of total monthly and annualised returns for active multi-asset low equity funds from 1 Jan 2011 to 31 Dec 2020

Fund Code	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
N1	0.553% (6.842%)	0.619% (7.692%)	1.103% (3.822%)	2.792%	0.863
N2	0.61% (7.567%)	0.706% (8.815%)	0.748% (2.593%)	4.428%	0.557
N3	0.425% (5.215%)	0.4% (4.91%)	1.332% (4.616%)	6.721%	0.089
N4	0.679% (8.466%)	0.598% (7.423%)	1.772% (6.138%)	4.46%	0.706
N5	0.691% (8.61%)	0.776% (9.726%)	1.645% (5.698%)	3.523%	0.798
N6	0.718% (8.965%)	0.792% (9.923%)	1.598% (5.534%)	1.883%	0.941
N7	0.592% (7.344%)	0.74% (9.249%)	1.653% (5.728%)	3.611%	0.789
N8	0.643% (7.99%)	0.69% (8.607%)	1.355% (4.694%)	2.251%	0.906
N9	0.727% (9.08%)	0.844% (10.606%)	1.599% (5.54%)	3.244%	0.822
N10	0.612% (7.601%)	0.642% (7.981%)	1.558% (5.399%)	3.041%	0.839
N11	0.697% (8.694%)	0.691% (8.62%)	1.344% (4.656%)	3.728%	0.728
N12	0.6% (7.441%)	0.596% (7.394%)	0.903% (3.127%)	3.486%	0.778
N13	0.619% (7.689%)	0.669% (8.334%)	1.419% (4.915%)	1.762%	0.944
N14	0.724% (9.048%)	0.838% (10.534%)	1.695% (5.873%)	2.716%	0.887
N15	0.528% (6.519%)	0.58% (7.18%)	2.053% (7.111%)	3.577%	0.873
N16	0.654% (8.138%)	0.924% (11.668%)	2.054% (7.115%)	2.739%	0.944
N17	0.704% (8.778%)	0.68% (8.475%)	1.323% (4.583%)	2.483%	0.884
N18	0.682% (8.5%)	0.748% (9.355%)	1.379% (4.779%)	2.127%	0.916

Source: Calculated by author in Excel

Table A7: Descriptive statistics of total monthly and annualised returns for active general real estate funds from 1 Jan 2013 to 31 Dec 2020

Fund Code	Monthly (Annualised) Mean Total Return	Monthly (Annualised) Median Total Return	Monthly (Annualised) Standard Deviation	Annual Tracking Error Versus Passive Alternative	Correlation with Passive Alternative
P1	0.558% (6.901%)	1.502% (19.584%)	6.571% (22.764%)	7.573%	0.943
P2	0.223% (2.715%)	0.668% (8.311%)	6.487% (22.471%)	3.287%	0.989
P3	0.126% (1.522%)	0.541% (6.686%)	6.171% (21.378%)	3.46%	0.988
P4	0.152% (1.835%)	0.668% (8.323%)	6.22% (21.547%)	3.991%	0.983
P5	0.19% (2.301%)	0.889% (11.201%)	5.688% (19.705%)	3.261%	0.994
P6	0.027% (0.321%)	0.481% (5.921%)	5.266% (18.242%)	8.471%	0.928
P7	0.128% (1.544%)	0.555% (6.863%)	6.182% (21.414%)	2.421%	0.994
P8	-0.183% (-2.169%)	0.573% (7.102%)	5.154% (17.855%)	12.321%	0.828
P9	0.128% (1.541%)	0.637% (7.914%)	6.455% (22.361%)	4.055%	0.983
P10	-0.145% (-1.726%)	0.201% (2.439%)	4.1% (14.202%)	12.871%	0.831
P11	0.244% (2.971%)	0.701% (8.748%)	5.937% (20.565%)	4.743%	0.977
P12	0.28% (3.41%)	0.799% (10.018%)	6.262% (21.692%)	5.492%	0.968
P13	0.162% (1.96%)	0.696% (8.684%)	6.354% (22.013%)	1.56%	0.997
P14	0.413% (5.074%)	0.826% (10.38%)	5.836% (20.218%)	3.837%	0.987
P15	0.076% (0.914%)	0.383% (4.688%)	6.523% (22.595%)	2.864%	0.992
P16	0.133% (1.613%)	1.055% (13.42%)	6.371% (22.069%)	3.184%	0.990

Source: Calculated by author in Excel

APPENDIX C: SCATTERPLOTS OF FUNDS

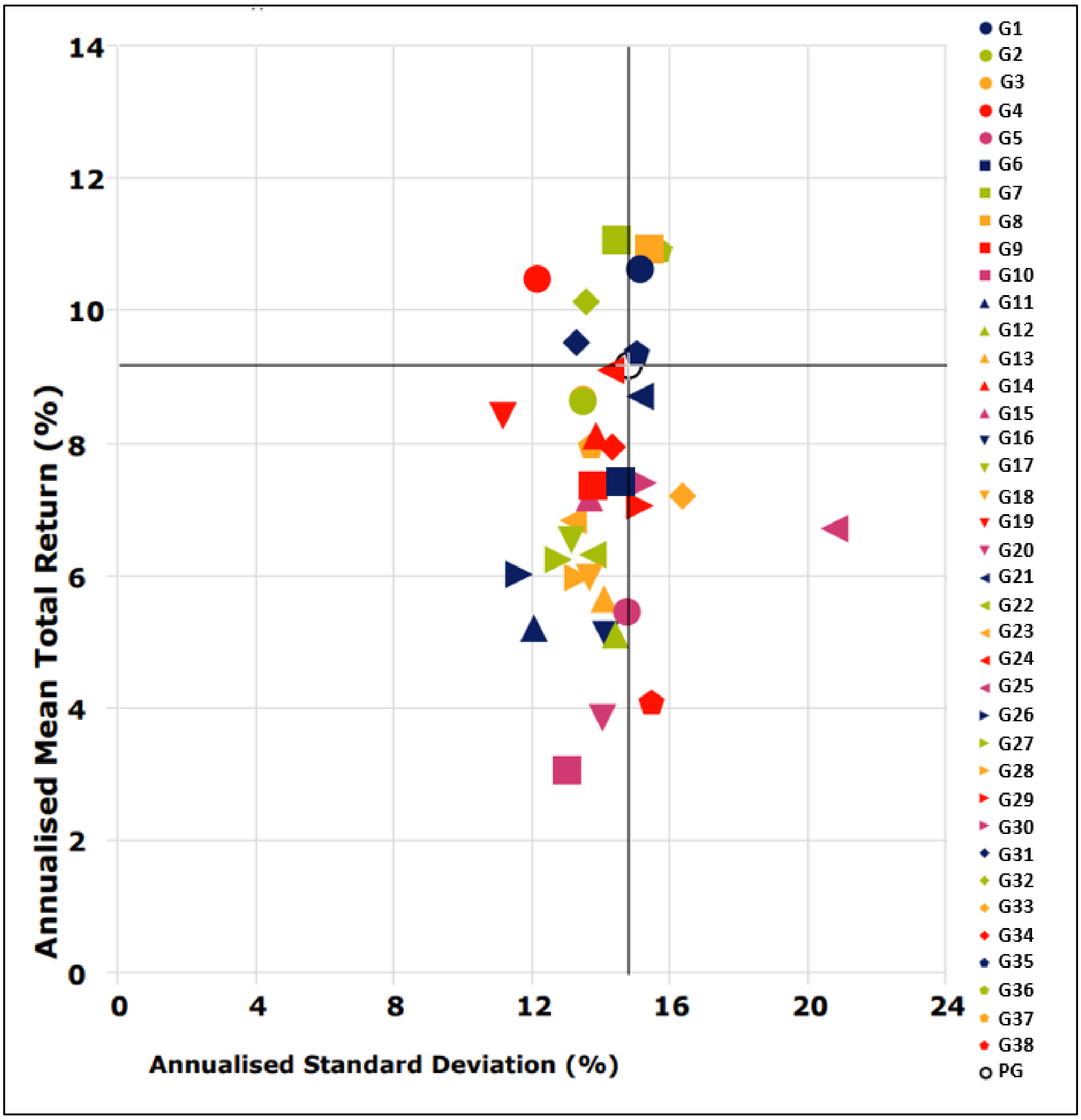

Figure A1: Scatterplot of annualised monthly total returns (%) and standard deviation (%) of general equity funds from 1 Jan 2007 to 31 Dec 2020

Source: Constructed by author in Morningstar Direct

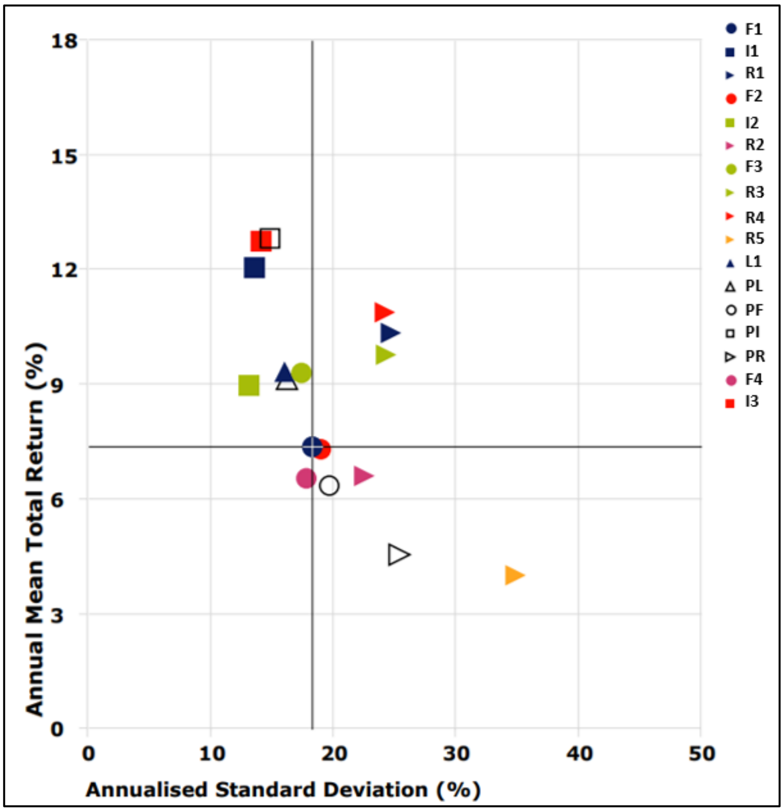

Figure A2: Scatterplot of annualised monthly total returns (%) and standard deviation (%) of thematic equity funds from 1 Jan 2007 to 31 Dec 2020

Source: Constructed by author in Morningstar Direct

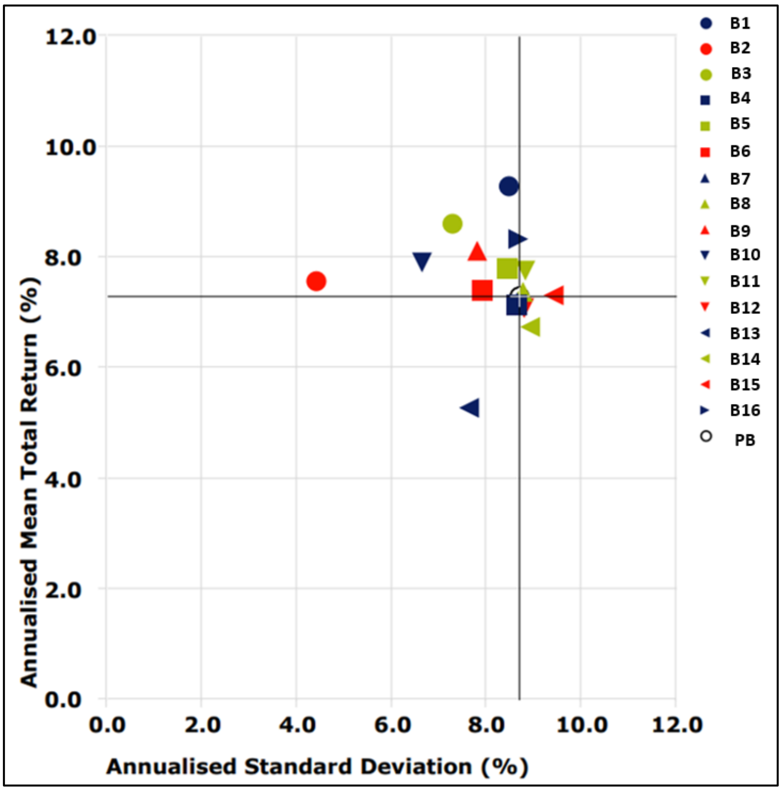

Figure A3: Scatterplot of annualised monthly total returns (%) and standard deviation (%) of interest-bearing variable term funds from 1 Jan 2015 to 31 Dec 2020

Source: Constructed by author in Morningstar Direct

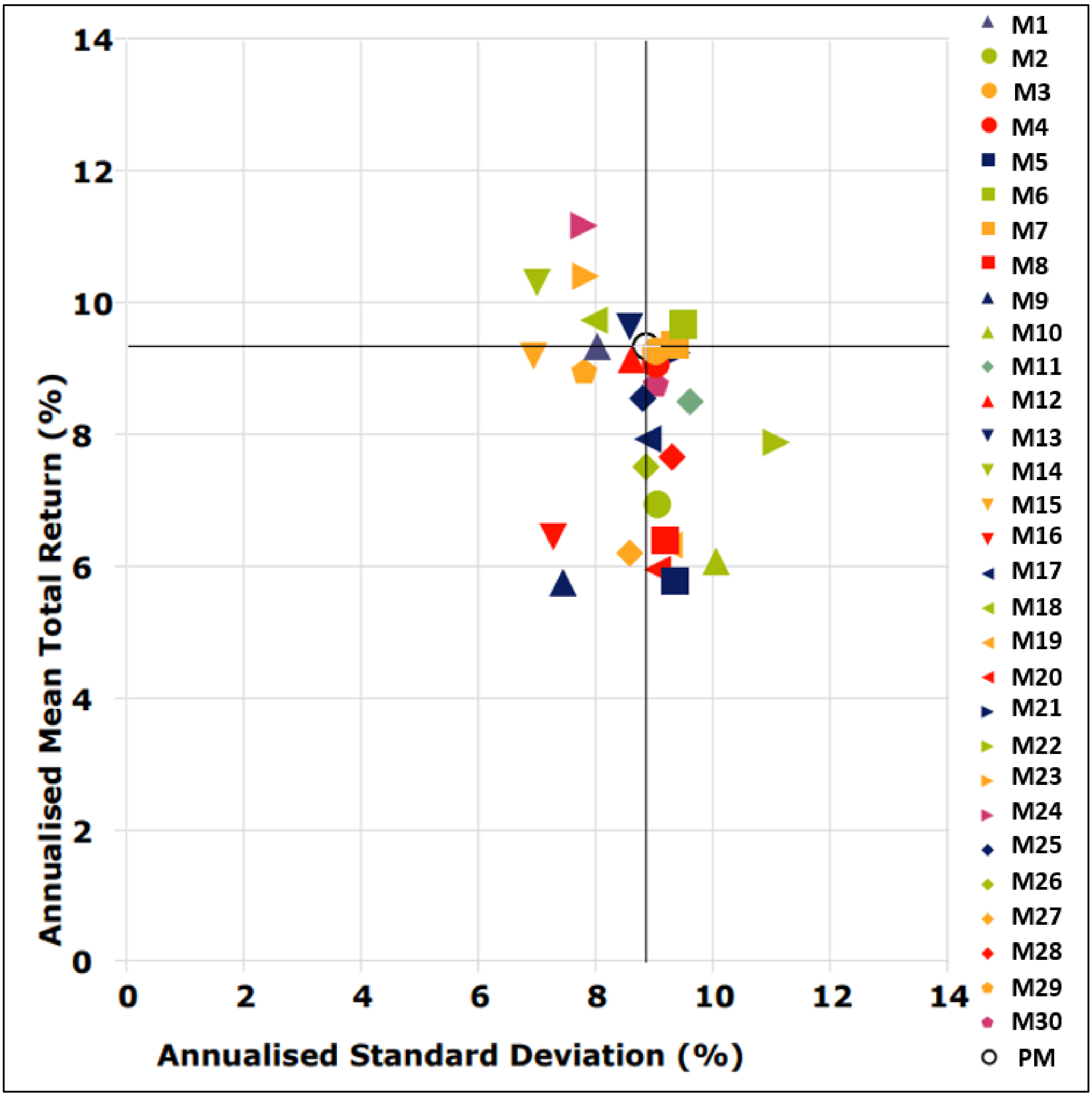

Figure A4: Scatterplot of annualised monthly total returns (%) and standard deviation (%) of multi-asset high equity funds from 1 Jan 2011 to 31 Dec 2020

Source: Constructed by author in Morningstar Direct

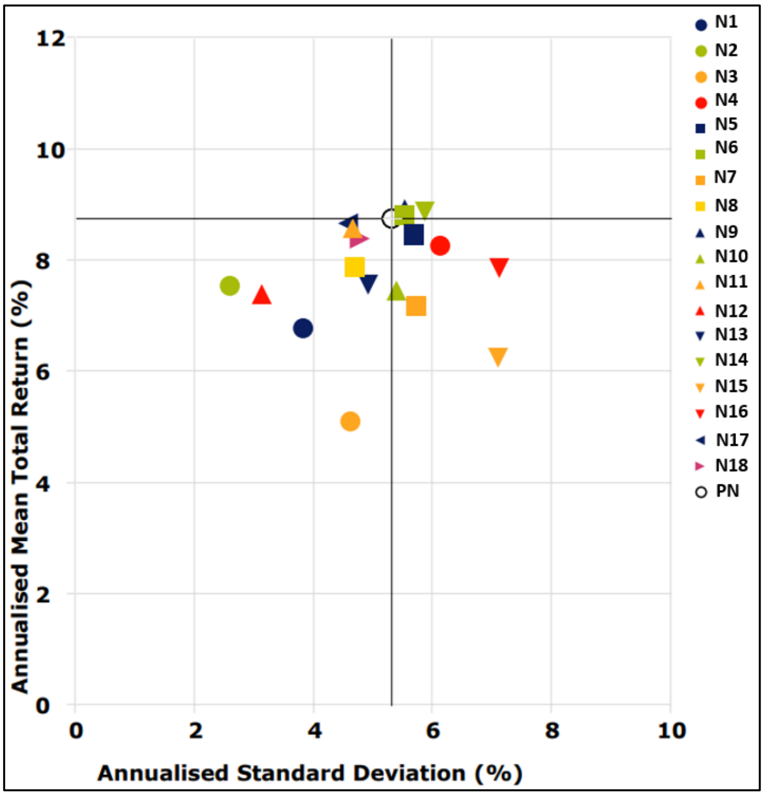

Figure A5: Scatterplot of annualised monthly total returns (%) and standard deviation (%) of multi-asset low equity funds from 1 Jan 2011 to 31 Dec 2020

Source: Constructed by author in Morningstar Direct

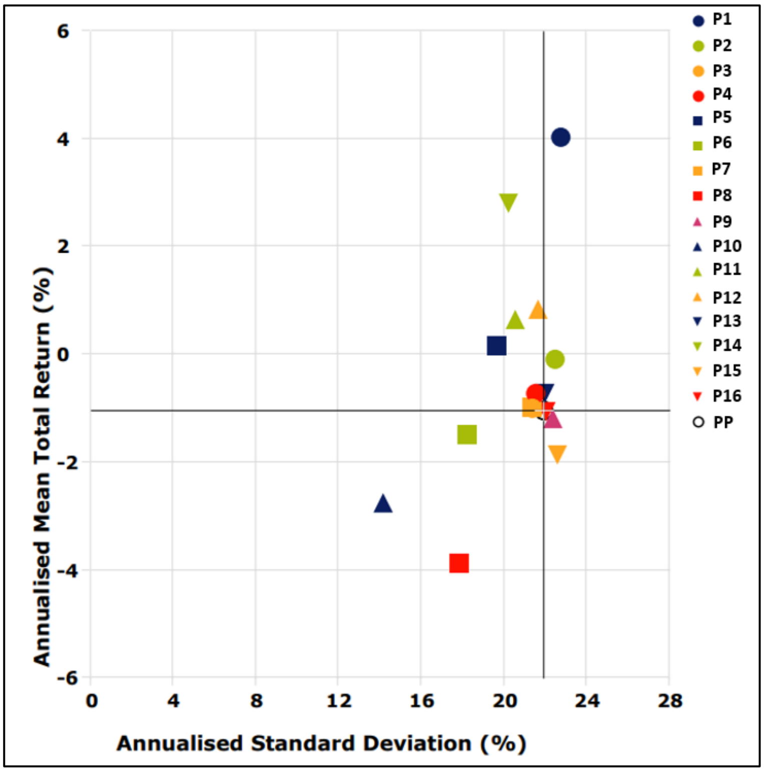

Figure A6: Scatterplot of annualised monthly total returns (%) and standard deviation (%) of general real estate funds from 1 Jan 2013 to 31 Dec 2020

Source: Constructed by author in Morningstar Direct