The Tracking Error of JSE-Listed ETFs and their Determinants

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ABSTRACT

This study examines the tracking errors of exchange-traded funds (ETFs) listed on the Johannesburg Stock Exchange (JSE) and the factors that influence them. Despite the increase in the popularity of ETFs as an investment instrument judging by the more than $1.75 Trillion and 12.6 Billion in asset under management in the United States and South Africa respectively (Hill, Dave, & Matt, 2015; South African Reserve Bank, 2006), there is a dearth of academic research on the subject in South Africa. The few existing academic papers concentrate on equity tracking ETFs while other asset classes such as commodities, bonds and property ETFs have largely been ignored. This study, therefore, looked into the tracking errors and their determinants for JSE-listed ETFs across several asset classes. The tracking error for each ETF in the sample population was calculated using four different methods and the effect of frequency of observation on tracking error was also examined by comparing the tracking error calculated from daily return data with monthly return data. The relationship between tracking error and identified fund characteristics such as fund age, fund size and total expense ratio (TER) were tested using ordinary least square (OLS) regression models to examine the effects of these hypothesised determinants on tracking errors.

The research results indicate that JSE-listed ETFs exhibit tracking errors and was found to be higher than those exhibited by ETFs in more developed markets like the US, but similar in magnitude compared to the tracking error exhibited by other emerging market ETFs. The frequency of the returns data used (daily, weekly or monthly) was also found to have a moderating effect. With respect to the determinants of tracking errors, the research found that the age of the fund and its total expense ratio (TER) influenced tracking errors. Contrary to expectation and to the findings in other comparative studies, there was no clear relationship between fund size and tracking error. The study attributed this to the structure of the South African ETF industry. Many of these funds fall under the umbrella of well-established South African financial institutions and as such, are under one strategic group, thereby possessing similar economies of scale and bargaining power (Porter, 1980), which appears to renders the effects of a fund’s size redundant.

DECLARATION

I, Akintunde Akinsete, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Akintunde Akinsete

Signed at ………………………………………………………

On the ……………………………. day of ………………………… 2017

DEDICATION

To Abisola, Fedile and Toluwani.

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CHAPTER 1. INTRODUCTION

1.1 Purpose of the study

The purpose of this research is to examine the tracking errors of exchange-traded funds (ETFs) listed on the Johannesburg Stock Exchange (JSE) in relation to the performance of various underlying asset classes. The persistence of tracking error in an ETF instrument can be used by investors as a proxy for portfolio performance. Furthermore, the research investigates the factors influencing the tracking errors where there are any errors. Understanding the determinants associated with the tracking error may provide investors with information to consider when selecting an ETF product.

1.2 Context of the study

An ETF is essentially a basket of shares with constituent securities selected to replicate the performance of a benchmark index as closely as possible. They provide investors with a simple, low-cost and tax-efficient exposure to the stock market and it can be bought and sold on an intraday basis (Kosev & Williams, 2011). For example, Satrix, a leading South African passive investment products provider, offers ETF products to an investor for as little as R300/month or R1000 once-off lump sum investment (Satrix, 2014b). With such a small outlay, an investor can have exposure to the entire index on the Johannesburg stock exchange (JSE).

Exchange-Traded Funds (ETFs) were first launched in Canada in 1990 (Hill et al., 2015) and were first traded on the American Stock Exchange in 1993 and have since become one of the rapidly growing investment instruments in the world (Poterba & Shoven, 2002). ETFs have been described as an outstanding financial innovation since the advent of financial futures (Deville, 2008) and a disruptive invention (Hill et al., 2015).

The origin of ETFs can be traced to the seminal work of Michael Jensen in 1968, where he posited that individual actively managed unit trusts are unable to consistently beat the market and his work is seen as the inception of passive management (Hassine & Roncalli, 2013). This led to a surge in the interest of passively managed index fund investment instruments which retained the unit trust structure and were a precursor to ETFs. Although index funds are similar to ETFs in that they track an underlying index, a major difference is that ETFs can be traded throughout the day, while index funds can only be traded at the end of a trading day. This difference gives ETFs an added advantage of being used as an instrument to implement short positions (Aroskar & Ogden, 2012).

Since its launch, the popularity of ETFs has grown (Deville, 2008; Hill et al., 2015; Kosev & Williams, 2011; Poterba & Shoven, 2002; Sharifzadeh & Hojat, 2012) with over 1500 ETFs listed in the United States which is equivalent to more than $1.74 trillion in market capitalisation as at Q1 2014 (Hill et al., 2015). The growth of this financial instrument is not restricted to developed financial markets but is available in developing and emerging markets as well. In South Africa, the first ETF product, Satrix Top 40 was launched on the Johannesburg Stock Exchange (JSE) in November 2000 (Charteris, 2013; Satrix, 2014a). At the end of December 2000, the ETF market capitalisation in South Africa was R3 billion and it grew to R12.6 billion at the end of July 2006 (South African Reserve Bank, 2006). Currently, the South African ETF market comprises 46 funds, with a combined capitalisation of over R71 billion as of March 2015 (ETFSA, 2015) as illustrated in

Figure 1.

As the popularity of ETFs grew so did its comparison with other financial products, such as unit trusts and index funds. Although all three instruments have substantial followings, the debate between active and passive management rages on. ETFs still lag behind traditional mutual[1] funds in proportion to overall mutual fund assets under management (AUM), but its growth over the years has been phenomenal. For instance, in the US, ETFs have grown from 2% of the total mutual fund assets under management to 11% between 2003 to 2013 and they

[1] US Mutual funds are analogous to South African unit trusts

make up between 25% and 40% of the total volume of trades on US stock exchanges (Hill et al., 2015).

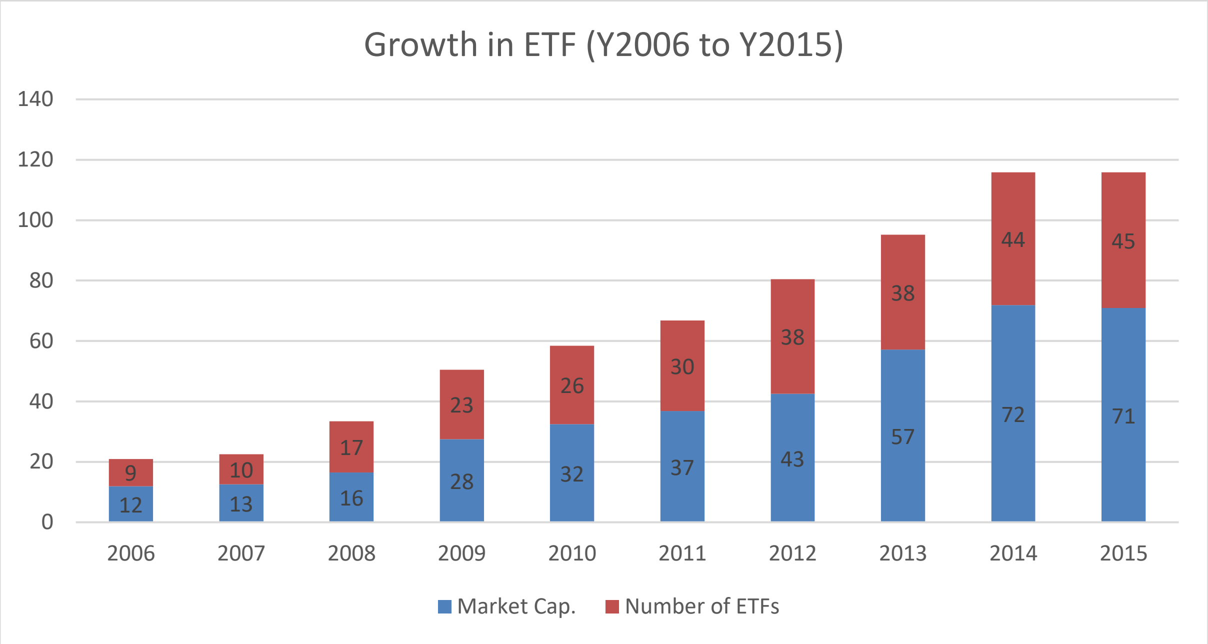

Figure 1: Growth in JSE-listed exchange traded funds from 2006 to 2015

Not only do ETFs provide investors with access to the equity stock market, they also provide exposure to other asset classes as well. On the JSE, ETFs are categorised into Top 40 equity (includes ETFs that provide exposure to the top 40 shares on the JSE), other equity (includes ETFs that provide exposure to a variety of indices such as the Mid-Cap index, sub-indices such as the financial, industrial and resources indices), international equity (includes ETFs that provide exposure to international stock markets such as the MSCI world, USA and Japan indices), bonds (includes ETFs that provide exposure to government bonds), commodity (includes ETFs that provide exposure to commodities such as gold, platinum and palladium), money market (includes an ETF that provides exposure to the three-month Barclays Capital / ABSA Capital ZAR Tradable Cash Index), property equity (includes ETFs that provide exposure to property equity stocks on the JSE) and multi-asset class (includes ETFs that provide exposure to more than one asset for example, the Newfunds MAPPS Growth ETF that provides investors with exposure to 75% South African equities; 10% nominal bonds; 10%

inflation-linked bonds and 5% cash or money-market) (JSE, 2016). Refer to APPENDIX A for a list of JSE-listed ETFs. This shows that ETFs are convenient and relatively inexpensive for an investor to access a myriad of asset classes.

Tracking error is a measure of how closely a portfolio is able to mimic a set benchmark and as a result, used as a proxy or measure of a portfolio's performance (Hill et al., 2015). With regards to index funds as well as ETFs, one of the prime mandates of a fund manager is to replicate the return and risk of the underlying benchmark index and the inability to do so consistently suggests a failure in meeting investment objectives (Chu, 2011). Persistence in the tracking error between an ETF and its underlying index is also used to judge a fund manager's effectiveness. Taken at face value, the administration of an index fund or ETF should be straight forward in as much as a fund manager is simply expected to ensure that the constituent assets (e.g. shares) that make up the ETF are in the same proportion as the underlying index. However, indices are not subject to fees or operating costs and as such, on that basis alone, the performance of an ETF would differ from the performance of its underlying index (Hill et al., 2015). According to Frino and Gallagher (2001), an index is not subject to the same market friction faced by index funds. As a result, there would always be a delta between an ETF and its underlying index. Tracking errors are therefore inevitable, but it is the magnitude of the delta that matters (Frino & Gallagher, 2001). As such, a fund manager must continually monitor tracking errors as well as ensure that any disparity is kept to a minimum so that the fund's objectives are achieved.

Other causes of ETF tracking errors include changes to underlying index securities, volatility in the EFT's asset class or specific underlying securities, regulatory or tax requirements, exchange rates, treatment of dividends and corporate activity (Frino & Gallagher, 2001; Hill et al., 2015; Shin & Soydemir, 2010). Tracking errors are therefore not only a concern for the fund manager but also important from the perspective of an investor in selecting an ETF product. Management fees are one of the most common yardsticks used by investors to select an ETF, but this is only part of the story, investors should take cognisance of other possible sources of tracking errors when selecting an ETF (Frino & Gallagher, 2001).

Despite the popularity of ETFs and the fact that they have been in existence in South Africa for 16 years, there is a dearth of scholarly work on the subject compared to the generous attention accorded to unit trusts. Scholarly work on ETFs in the South African context is limited to performance comparison with unit trusts and price efficiency. Charteris (2013) examined the price efficiency of seven South African listed EFTs and found that five of these ETFs trade at a premium to their respective net asset value (NAV), while the other two traded at a discount. Strydom, Charteris, and McCullough (2015) compared the tracking errors of South African listed ETFs and Index funds and found that the magnitude of tracking errors in ETFs was lower than that found in the index funds examined. However, this study was restricted to tracking errors within the equity asset class. As explained above, tracking error is an important measure in selecting ETFs, not only for equity tracking ETFs, but also for other asset classes, such as property, bonds, commodities, and currency, and is required, especially for investors who use these instruments.

Although there are numerous international studies on ETF tracking errors and the attendant determinants, to the author's knowledge, no other study exists in South Africa that looks at tracking errors in different asset class categories. South African investors utilising ETFs as an investment instrument do so to gain exposure to more than one asset class category. Therefore, it is important that tracking errors are examined for all available asset class categories. Furthermore, Blitz and Huij (2012) reported that tracking error of ETFs providing exposure to emerging markets is substantially higher than those exposed to the developed market. As ETFs is one of the avenues used by international investors to gain exposure to the South African stock market, the magnitude of major South African ETFs would be of interest to this group of investors.

1.3 Problem statement

1.3.1 *Main problem*

The purpose of this research is to evaluate possible tracking errors of selected exchange-traded funds (ETF) listed on the Johannesburg Stock Exchange (JSE) for different asset class categories and in addition, determine factors responsible for the tracking errors.

1.3.2 *Sub-problems*

The first sub-problem is to determine how closely exchanged-trade funds listed on the JSE match their underlining index. Stated differently, the first subproblem is to determine how closely exchange-traded funds track their underlining index.

The second sub-problem is to determine possible factors responsible for the tracking error between the returns of an exchange traded fund and its underlining index.

1.4 Significance of the study

Compared to traditional unit trusts and index fund unit trusts, ETFs are relatively new investment instruments. Despite being new, they are a popular investment instrument judging by the growth experienced in ETF's AUM since inception. Besides its popularity and maybe because of its relative newness, there has been a dearth of academic research into the subject. Only a few South African academic publications, such as Charteris (2013), Strydom et al. (2015) have delved into ETFs, only one to the knowledge of the author has researched the tracking ability of funds and this was limited only to equity tracking ETFs. The aim of this study is to assess the tracking ability of ETFs for each asset class category on the JSE as well as to identify the sources of the tracking errors.

Based on the efficient market hypothesis school of thought, it is impossible to beat the market (Malkiel, 2003) and several pieces of evidence have proved that many traditional unit trusts are unable to consistently beat the market once management fees have been taken into account (Carhart, 1997; Wermers, 2000). Therefore, the efficient market hypothesis espouses a passive investment strategy and suggests that it is wise for an investor to invest in an ETF rather than in a unit trust investment. The reasoning is that investment returns will be eroded in the long-run by fees charged by the fund manager to actively manage the portfolio. ETFs investing also incur fees but they are largely lower than those charged by unit trust fund managers due to their virtue of being passively managed. However, large tracking errors between an ETF and its underlying index could undermine the investment mandate of an ETF fund manager and would call into question the investment principle espoused by the efficient market hypothesis, i.e., passive investment strategies are a better alternative to active ones.

This study contributes to the very sparse South African literature on ETFs and provides an insight into trackability of ETFs that track not only the equity asset class, but also other asset classes such as property, bonds and commodities, where no known South African literature exists.

1.5 The structure of the report

The study is structured as follows: chapter two provides a literature review of the research topic. Chapter three presents the research methodology employed. Chapters four and five present the results and a discussion of results respectively. Chapter six concludes the study, presents some recommendations and suggests areas of further research.

1.6 Delimitations of the study

Most ETFs tend to replicate the index of a single asset class i.e. stocks, bonds, properties, commodities, etc. Multi-asset ETFs are unlike traditional ETFs in that they provide investors access to numerous asset classes and do not track a single index. This study excludes multi-asset ETFs.

The aim of this study is to examine the tracking errors of ETFs within different asset classes, therefore an ETF was selected from each asset class category based on the depth of available historical data. ETFs with insufficient data were not considered in the analysis.

Exchange-trade products (ETP) include both ETFs and exchange traded notes (ETNs). ETNs were introduced to the JSE in 2010 and like ETFs have increased in popularity and currently compete with ETFs (JSE, 2014a). This study did not include ETNs and only focused on ETFs.

1.7 Definition of terms

Active Management	An investment strategy which attempts to out-perform the market or a set benchmark (Hassine & Roncalli, 2013).
Collective Investment Schemes	An investment portfolio that pools the resources of many investors
Exchange Traded Products	A term used to describe the combination of exchange traded funds and exchange traded notes
Frequency of Observation	The time interval over which data is observed or reported. This refers to the time interval of returns data used in calculating tracking error. The frequency of observation could be daily, weekly or monthly (Johnson, Bioy, Kellett, & Davidson, 2013).
Passive Management	An investment strategy which attempts to replicate the return of the market or a set benchmark (Hassine & Roncalli, 2013).

1.8 Abbreviations

AUM	Asset Under Management
CIS	Collective Investment Schemes
EFN	Exchange Traded Notes
EFT	Exchange Traded Funds
ETP	Exchange Traded Products
FSB	Financial Services Board
JSE	Johannesburg Stock Exchange
NAV	Net Asset Value
SER	Error of Regression
TER	Total Expense Ratio

1.9 Assumptions

- The data used in this study are time series data and as by their nature tend to be serially correlated. It is assumed that the effects of serial correlation on the results of this study are minimal and should be taken into account when interpreting the result of the study.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The purpose of this research study is to examine the tracking errors of a range of JSE-listed ETFs as well as to identify possible factors that are responsible for the tracking errors.

Academic research into ETFs and their tracking errors from a South African perspective is sparse and existing research studies mostly focus on equity tracking ETFs, predominantly the Top 40 index. The quantity of research work in this area is not commensurate with the popularity and the growth experienced in the South African ETF industry since its inception 16 years ago. The study, therefore, aims to swell the volume of ETF literature from a South African perspective and especially with regard to tracking error and its determinants.

The literature review is presented in four parts. The first part provides an overview and a contextual discussion on ETFs, benefits and risks, types of ETFs, and the creation and redemption process of ETFs as well as the arbitrage opportunity that exists due to its two parallel market structures. The second section focuses on tracking error while the third focuses on sources of ETF tracking error. The chapter concludes with a formulation of hypotheses related to the research problem.

2.2 Overview of ETFs

The debate between actively and passively-managed portfolio has had a long history both internationally as well as in South Africa as investors strive to increase their investment horizon. The first mutual fund was created in the late 19th century while the concept of passive investment started with Harry Markowitz in 1952 and was further enriched by both William Sharpe and Michael Jensen in 1964 and 1968 respectively (Hassine & Roncalli, 2013; Hill et al., 2015). While the proponents of mutual funds espouse the stock-picking capabilities of a fund manager and their ability to beat the market (Wermers, 2000), research has shown that it is impossible to consistently beat the market (Carhart, 1997; Malkiel, 2003). The passive investment school of thought originated as an antithesis to the actively-managed portfolio philosophy and this was captured in the seminal work of Michael Jensen (1968, p. 415), who, after measuring the performance of 115 mutual funds, came to the conclusion that:

> "The evidence on mutual fund performance discussed above indicates not only that these 115 mutual funds were on average not able to predict security prices well enough to outperform a buy-the-market-and-hold policy, but also that there is very little evidence that any individual fund was able to do significantly better than that which we expected from mere random chance. It is also important to note that these conclusions hold even when we measure the fund returns gross of management expenses (that is assuming their book-keeping, research and other expenses except brokerage commissions were obtained free)"

This work laid the foundation for passive investment and since then, there has been an increase in index fund investments. An ETF is simply an extension of an index fund (Hill et al., 2015), however, unlike index funds, ETFs have relatively lower costs, are more tax efficient, can be traded throughout the day and can be used as an instrument to implement short positions (Aroskar & Ogden, 2012).

2.2.1 *Description of ETF*

An ETF is a basket of shares, bonds or commodities or a combination of different assets, with the constituent securities selected to replicate the performance of a benchmark index as closely as possible (JSE, 2014b; Kosev & Williams, 2011). ETFs can be bought and sold like an ordinary share through a broker at a stock exchange. It also provides investors with an inexpensive means of access to a wide variety of stocks as well as exposure to various investment asset classes. Hill et al. (2015, p. 9) describe ETFs as a disruptive invention that provides investors with an investment instrument that has "lower fees, greater transparency, expanded access, and greater tax efficiency" compared to traditional unit trust funds. It is also the fastest growing sector in the investment management business universe.

2.2.2 *Types of Exchange Trade Funds*

ETFs can be categorised broadly, based on the asset class that make up the underlying index and replication technique used in replicating the underlying index. Hill et al. (2015) categorise ETFs into Equity ETFs, Fixed-income ETFs, Commodity ETFs, Currency ETFs, Alternative ETFs and Leveraged and Inverse ETFs.

2.2.2.1. Equity ETFs

The majority of ETFs are equity based, for example, equity ETFs make up more than 65% of the ETFs listed on the JSE (JSE, 2016). They range from an overall market index to a narrowly focused index such as the Satrix FINI, INDI and RESI, which tracks the JSE’s financial, industry and resources indices respectively. Also, most equity ETFs listed on the JSE either track locally based indices e.g. Satrix Top 40 or an internationally based one e.g. Db x-trackers FTSE 100.

2.2.2.2. Fixed Income ETFs

Fixed income ETFs provide investors with low-cost access to institutional-level bond portfolios. Bonds were traditionally sold over the counter and, as a result involved costly bid-ask spreads which were prohibitive for an ordinary investor. Bond ETFs enable individual investors to pool resources and invest in a portfolio of bonds. However, unlike single bonds, a bond portfolio does not have a maturity date and these funds have no provision for principal protection. Although some ETF managers provide principal protection, however, investors still have to contend with reinvestment risks (Hill et al., 2015). An example of bond ETFs listed on the JSE includes the Ashburton inflation ETF that tracks the government inflation-linked bonds index.

2.2.2.3. Commodity ETFs

Prior to the advent of ETFs, investors interested in investing in commodities had to contend with stringent entry barriers such as opening a futures account, obtaining approval from a broker and maintaining a margin to cover any movements in commodity contracts being held. A commodity ETF, therefore, provides investors with easy and cost-efficient access to a range of commodities, free of the aforementioned requirements. Types of commodity ETFs range from physically-backed, single-commodity funds to futures-based, multi-commodity funds (Hill et al., 2015). An example of a commodity ETF listed on the JSE is the AfricaGold ETF which is backed by physically held gold bullion and the ETF provides investors with returns equivalent to gold prices (Standard Bank, 2015).

2.2.2.4. Currency ETFs

Like commodity ETFs, currency ETFs have helped lower the entry barrier for investors involved in this asset class. Investors interested in trading currencies needed to have a separate account and it involved high capital outlay. Currency ETFs provides a low and cost effective way for investors to trade currencies. Currency ETFs are backed by foreign cash deposits or futures contracts. Currency ETF is also used by investors who wants to hedge their exposure to foreign currencies (Hill et al., 2015). There are, currently, no listed currency ETFs on the JSE.

2.2.2.5. Alternative ETFs

Alternative ETFs are multi-asset ETFs that provide exposure to a number of asset classes that provide investors with diversification, reduced portfolio risk, a hedge against declines in equities or bonds and reduced volatility. Alternative investment strategies have previously been the preserve of institutional investors and high-net-worth individuals because of the large investment outlay, limited regulation and illiquidity. The attractiveness of alternative ETFs is that there is a possibility for the fund to appreciate irrespective of market direction. Management fees charged for this category of ETFs are higher than those for conventional ETFs, however, the fees are much lower than that required to access a traditional alternative fund, but it does share some unwanted idiosyncrasy with traditional alternatives such as illiquidity (Hill et al., 2015).

2.2.2.6. Leveraged and Inverse ETFs

Inverse ETFs are designed to profit when the underlying index being tracked declines while leveraged ETFs provide investors with a multiple of the return of the underlying index being tracked. Usually, inverse ETFs are also leveraged to provide investors with amplified returns. Both ETFs are constructed using derivative instruments and debt. Like alternative ETFs, leveraged and inverse ETFs are substantially more expensive than conventional ETFs (Hill et al., 2015).

2.2.3 *Replication Techniques*

ETFs can also be categorised based on the replication technique used by the fund manager to mimic the underlying index. Replication techniques employed by fund managers include full physically-backed replication, synthetic replication and statistical or representative replication.

As mentioned above, an ETF is a basket of assets constituted by a fund manager to replicate an index. When a fund manager decides to physically hold all the assets contained in the underlying index and reflecting the weighting of each constituent of the index, this is known as full physically-backed replication. For example, a gold ETF is either backed by physically-held gold bullion, individually located and stored in a secured vault. If the gold ETF is backed by derivative instruments such as “futures, forwards, options and swaps” to simulate the return of a physically-held asset, this is synthetic replication (Hill et al., 2015; Kosev & Williams, 2011). With statistical or representative replication, the fund manager does not replicate the index fully but rather selects portions of the underlying index as a representative to track the performance of the index. Representative replication employs either physical assets or derivatives instruments in replicating the portfolio. This replication technique is used when some constituent or the entire index is illiquid, which could potentially increase the risk of physically or synthetically holding such assets. This replication technique tends to have lower trading cost but is susceptible to high tracking errors (Blitz & Huij, 2012).

An ETF fund manager can also decide to use a combination of these techniques in replicating an index (Kosev & Williams, 2011). The technique employed is at the discretion of the fund manager or dictated by local legislation (Hill et al., 2015). For example, as a result of regulatory requirements in the US, there are some restrictions on the use of derivatives in the constitution of an ETF which has contributed to the dominance of physically-backed replication, compared to Europe where regulatory controls are more favourable towards synthetic ETFs. In South Africa, the regulatory authority, the Financial Services Board, does not permit the use of synthetic instruments as well as the use of derivatives to leverage a portfolio (Financial Services Board, 2013) and JSE regulations require all listed ETFs “to exactly replicate the index being tracked and must hold 100% physical backing for the securities in issue” (Brown & Visser, 2015, p. 2) .

Physically backed ETFs are less complex and risky compared to synthetic ETFs. They are more transparency and provide more surety for the investors as there are physically held assets which can be sold in the event the fund is liquidated. On the other hand, physically backed ETFs are more susceptible to tracking errors because when the underlying index changes or there is a change in the weightings of the constituent assets, the ETF manager would have to physically buy or sell assets to match the new index constitution (Kosev & Williams, 2011). In the process, additional transaction costs are incurred by the fund managers (Frino & Gallagher, 2001).

Synthetic ETFs are more complex and less transparent compared to physically backed ETFs. However, they have lower costs and because of the use of derivatives, a fund manager can provide local investors with exposure to a foreign market without physically holding assets in the foreign country. It also offers greater tracking accuracy compared to physically-backed ETFs because the rebalancing of the underlying index is the responsibility of the swap counterparty. The presence of the swap counterparty also introduces inherent risk into the arrangement, especially when the counterparty is unable to fulfil its obligation. Furthermore, synthetic ETFs can be used to replicate an index in cases where physical replication is not possible. For example, with foreign ownership restriction in China, synthetic ETFs are used to provide investors with exposure to the Chinese stock market indices (Kosev & Williams, 2011).

2.2.4 *Benefits and risks of ETFs*

2.2.4.1 Benefits

The popularity, growth and appeal of an ETF are as a result of the numerous benefits it offers investors. It provides investors with a simple and straightforward means of investing in a basket of shares or assets and provides access to areas that were formerly the preserve of institutional investors. Another appeal of ETFs is their low-cost structure. According to ETFSA (2016), the total expense ratio for JSE-listed ETFs ranges from 0.12% to 0.85% compared to unit trust products e.g. the Absa SA Core Equity, that charges more than 5% (Fundsdata, 2016). Also, because ETFs are typically passively managed, it is devoid of attendant costs that come with actively managed portfolios such as an annual fund management fee (Hill et al., 2015; Kosev & Williams, 2011). Compared to unit trusts, ETF investors in South Africa save between 1% to 2% in annual management fees (ETFSA, 2016). The primary and secondary market structure (discussed in section 2.2.3 below) mean that the market makers or authorised participants that transfer ETF share between the primary and secondary market are willing to buy or, in some cases, are obliged to buy ETF shares sold into the market. This structure ensures that EFT shares are liquid and investors are able to easily enter and exit their position (JSE, 2010).

ETFs are listed on the stock exchange and can be bought and sold on the bourses at any time during market hours. Comparative investment products, such as traditional unit trusts and index funds, can only be bought at certain times during a trading day. This allows ETF investors to employ traditional share trading and risk management techniques such as stop-loss orders, limit orders, short sales etc. in optimising their returns from trading ETFs (Deville, 2008; Kosev & Williams, 2011; Kostovetsky, 2003; Sharifzadeh & Hojat, 2012). Since ETFs are publicly traded and designed to mimic a known index, the constituent of assets that make up the fund is clear and transparent to an investor unlike traditional unit trusts, that are only mandated to declare their holdings periodically (Hill et al., 2015).

ETFs offer investors a low-cost portfolio and geographical diversification. There are ETFs for various asset class such as equities, bonds, properties, commodities etc., therefore an investor can build a well-diversified portfolio composed of different ETFs (Kosev & Williams, 2011). Also, ETFs provide easy access to assets in other global markets and even markets where foreign ownership of shares is restricted. For example, Deutsche Bank offers five ETF products that provides South African investors with exposure to three international equity markets (FTSE100, MSCI Japan and MSCI USA) and two regional indices (DJ Euro Stoxx 50 and MSCI World) (Deutsche Bank, 2016), allowing investment in local currency while providing returns with foreign currency exposure.

As a result of the passive management style of ETFs, it provides investors with better tax efficiency compared to traditional unit trusts. Firstly, because actively managed unit trusts are given the mandate to beat the market, they tend to have greater asset volume turnover as they frequently buy and sell assets. As a result, the fund accrues greater capital gains which in turn, increases the investor's tax burden. ETFs, on the other hand, only buy and sell assets when the underlying index changes and therefore have lower capital gains. Secondly, when an individual investor leaves a unit trust, the fund manager has to sell off some of the assets to pay the investor thereby increasing the fund's capital gains and the tax burden of other investors within the fund. In contrast, by virtue of being traded daily on the bourses, an ETF investor can enter and leave the fund without the knowledge of the fund manager and with no tax implications for investors that remain within the fund (Hill et al., 2015). ETFs transactions on the stock exchange, unlike normal shares, are exempted from securities transfer tax. However, individual ETF investors are liable for taxes on capital gains that accrue when exiting a fund (JSE, 2010).

ETFs are regulated investment instruments, thus providing the investor with an added level of confidence. In South Africa, a large portion of the JSE-listed ETFs are Collective Investment Schemes (CIS) and, as such, are regulated by both the financial services board (FSB) and the JSE. ETFs that are not CIS based are not regulated by the FSB but are regulated by the JSE (JSE, 2010).

2.2.2.7. 2.2.4.2 Risks and demerits

Like any investment instrument, ETFs do have market risks associated with them. According to Hill et al. (2015), risks associated with ETFs include expectation-related risk, structural risk, holdings-based risk and fund closure risks. Expectation-related risk pertains to unrealistic expectation or view held by an investor because of a misunderstanding or lack of education on how ETFs work. For example, unlike unit trusts, ETFs are sold intra-day and it is possible that at any given time it is valued at a premium or discount to its NAV. An investor needs to be cognisant of this risk. A proper understanding of the ETF concept is, therefore, necessary for a novice investor.

Holding risks are mostly found in ETFs that use derivatives such as swaps to mimic an index. These types of ETFs require a swap counterparty and this introduces additional risks. In the event the counterparty defaults, investors could be at risk because it could lead to the dissolution of the fund. However, regulatory controls are put in place, such as ensuring swap accounts are settled as frequently as possible e.g. daily, based on the movement of the underlying index. This helps to minimise the fund’s exposure to a potential default or bankruptcy of the counterparty (Hill et al., 2015). Another risk of investing in ETFs is the premature closure or winding up of a fund. The possibility of an outright loss for investors in this scenario is quite remote, especially for physically-back ETFs. This is because the ETF fund’s securities are protected within a trust structure (JSE, 2010), this means that the assets of investors are protected. However, an investor could be adversely affected by the impromptu sale of share and/or other assets being held by the fund manager which would result in capital gains accruing and a consequent increase in an investor’s tax burden (Hill et al., 2015).

Also, unlike owning a company’s share, ETF investors only own part of a fund and as such do not have voting rights at the annual general meetings (AGMs) of companies whose shares or securities are held by the ETF fund manager (JSE, 2010). Finally, ETFs like traditional unit funds or index funds are susceptible to tracking risks (Hill et al., 2015), which is the focus of this study.

2.2.5 *Creation and Redemption Process*

The transaction and operation of ETFs occur in the primary and secondary markets. The primary market is where ETF shares are created and redeemed, while the secondary market is where ETF share are traded. A typical ETF investor can only buy ETF shares from the secondary market i.e. the stock market via a stockbroker, and in some cases, directly from the ETF fund. ETF shares available in the secondary market are supplied by authorised participants who in turn, get the ETF shares from the primary market.

The creation and redemption of ETF shares occur in the primary market between the fund manager and authorised participants. Authorised participants are usually market makers or institutional investors registered with the ETF manager. During the creation process, the ETF manager creates large blocks of ETF shares, usually between 25,000 to 200,000 units. The authorised participant then exchanges a basket of securities equivalent to the value of ETF units created and that comprises the shares/assets that make up the underlying index being tracked. The authorised participant then breaks up the ETF units and sells into the secondary market (Hill et al., 2015; Kosev & Williams, 2011).

The redemption process is the opposite of the creation process. The authorised participant buys ETF units from the secondary market, aggregates it and exchanges it for a basket of securities equivalent to the value of ETF units being redeemed and comprises the shares of the underlying index being tracked. The creation and redemption process is not static or a once-off process, but one that is continuous. The value of assets being exchanged between the fund manager and the authorised participant is based on the NAV of the fund. As a result of the frequency of the creation and redemption process, it is the duty of the ETF manager to update and publish the NAV and the securities asset holding of the fund regularly (Hill et al., 2015; Kosev & Williams, 2011).

The process described above is for a physically-backed ETF, as mentioned above, synthetic ETFs are not backed by assets but by derivatives such as swaps. In this case, cash is used in the creation and redemption of ETF units. Physically-backed ETFs also use cash or a combination of cash and securities in the creation and redemption process (Hill et al., 2015; Kosev & Williams, 2011). For example, Satrix, a South African ETF fund manager accepts cash from institutional investors interested in partaking in the ETF creation and redemption process (Satrix, 2014c).

The separation of the ETF structure into primary and secondary markets provides an opportunity for arbitrage. As mentioned above, the creation and redemption of ETFs are carried out in the primary market while the purchase and sales occur in the secondary market. As a result of market sentiments, the price of an ETF could deviate from the NAV of the underlying index. As such, the authorised participants would act as arbitragers profiting from the difference. In the event the ETF share is trading at a discount to its NAV, the authorised participants buy ETF shares from the market and exchanges it for a basket of assets from the fund manager and sell it for profit. When the ETF is trading at a premium to its NAV, the authorised participants will buy assets on the open market and exchange them for ETF shares, which are then sold on the secondary market for a profit. This action by the authorised participant is vital within the structure of an ETF fund and it is responsible for keeping the ETF share price close to the NAV of the underlying index being tracked (Hill et al., 2015).

2.3 Tracking errors

Tracking error is the difference between the return of an investment portfolio and its benchmark (Roll, 1992). The return of an actively managed fund is usually judged using a pre-specified benchmark that “typically contains a broadly diversified index of assets”. It is therefore implied that tracking error is a measure of how successfully a portfolio is able to achieve its mandate. For an actively managed portfolio, its benchmark is either a single index or group of indices selected by the portfolio sponsor to measure performance (Daniel, Grinblatt, Titman, & Wermers, 1997; Hill et al., 2015). For a passively managed fund, its benchmark is the underlying index being tracked (Hill et al., 2015).

Therefore, the tracking error of an ETF can be defined as the difference between the return or performance of an ETF and the underlying index being tracked (Shin & Soydemir, 2010). Tracking error is a means of identifying and measuring the tracking quality of a fund (Johnson et al., 2013).

make a distinction between tracking error and tracking difference. They define tracking difference as “the annualised difference between a fund’s actual return and its benchmark return over a specific period of time”. They suggested that tracking error does not elicit the extent of an ETF’s performance because tracking differences are either positive or negative and this shows outperformance and underperformance respectively. Tracking error, on the other hand, is typically shown as an absolute value. However, because the mandate of a passively managed fund is to track the index as closely as possible, consistency in the match-ability and trackability is very important. Therefore, tracking error is vital as an indicator of consistency in the periodic deviations between the return of an ETF and the underlying index being tracked. This means the higher the tracking error the more likely the fund will deviate from its benchmark and a low tracking error implies the fund is fulfilling its mandate (Chu, 2011; Johnson et al., 2013).

Some industry commentators seem to regard tracking error as an artefact of academic literature and suggest that tracking difference is a more meaningful metric because it provides a direct indication of out-performance and under-performance (Hougan, 2014). While tracking difference is useful from the perspective of an individual investor in selecting funds in which to invest, it does not tell the full story. According to Johnson et al. (2013), tracking error communicates the risk that the performance of a fund would deviate from that of the index being tracked. Furthermore, while out-performance is desirable for any given investment, tracking error can reveal fundamental problems with the way the fund is being managed and it is a metric that prompts interested parties to investigate further as it is important to understand the exact cause when the divergence in fund and index return occurs.

2.3.1 *Tracking error of emerging economy ETFs*

Probably due to the slow growth being experienced in the developed markets and the recent increased growth rate in emerging markets, countries such as Brazil, China, India, Russia, South Korea and South Africa, these markets have become important destinations for investment flows from developed markets. ETF are one of the means through which investors from development markets get exposure to these emerging economies (Blitz & Huij, 2012). A handful of academic literature delve into the comparison of the magnitude of tracking errors found in ETFs tracking developed and emerging markets indices.

The magnitude of tracking errors seems to vary between these two markets. As cited by Chu (2011), Frino and Gallagher (2001) studied a sample of S&P 500 index funds over a period of March 1, 1994, to February 28, 1999, and found that the average tracking error of individual funds ranged between 0.039% and 0.110% per month. Their study was extended to a sample of Australian index funds and they were found to have a higher average tracking error that ranges between 0.079% and 0.224% per month. Chu (2011), using similar methods employed in this study, calculated average daily tracking error for 18 Hong Kong based ETFs within the range of 0.279% and 3.523%. If results from Chu (2011) are used as a proxy for emerging markets, it can be inferred that the magnitude of emerging market ETF tracking errors is substantially greater than those experienced in a developed market. This was also corroborated by Blitz and Huij (2012). Their study showed that compared to developed markets, the tracking error of emerging market was quite considerable.

2.3.2 *Tracking error of JSE-listed ETFs*

Strydom et al. (2015) compared the tracking ability of three JSE-listed ETFs tracking the JSE Top 40 shares with five index funds tracking the same underlying index. The average tracking error for the ETFs ranged from 0.245% to 0.416% per month and 0.362% to 01.205% for the index funds. They concluded that South African ETFs have better track-ability than their index fund counterpart and the magnitude of ETF tracking error observed was in line with that experienced in Europe, Australia and in other emerging markets. The ETF tracking error results from by Strydom et al. (2015) is also consistent with tracking error displayed by the Hong Kong ETFs studied by Chu (2011). However, the study from Strydom et al. (2015) only addressed ETFs tracking the JSE Top 40 index, but the result can be extrapolated and we can postulate that the tracking error of other JSE-listed ETFs tracking other asset classes would show a similar trend.

2.3.3 *Hypothesis 1*

H1: The tracking errors between the JSE listed ETFs and the underlying assets are insignificant. $H_o: R_{i.t} - R_{j,t} = 0$

$$H_1: R_{i.t} - R_{j,t} \neq 0$$

2.4 Sources of tracking errors

According to Frino and Gallagher (2001), for the mere fact that an index is not subject to the same market friction as an index tracking fund, a delta between the return of the index and the fund would exist. Perold (1988), as cited by Cresson, Mike Cudd, and Lipscomb (2002), likened the activities of an index to a fictitious paper transaction which incurs no cost and is frictionless. Therefore, there is bound to be a disparity between an ETF and the index it tracks, the question is by how much and what are the predominant factors responsible?

The sources of ETF tracking error are wide and numerous and they stem mainly from the structure and policies of the ETF as well as market friction (Drenovak, Urošević, & Jelic, 2014). Frino and Gallagher (2001) observed that the magnitude of a fund's tracking error is dependent on fund expenses, the manner with which dividend payments are handled and the size of an index rebalancing as well as its timing. Deville (2008) also mentioned compositional changes in the make-up of an index as well as the dividend policy and management fees. Kostovetsky (2003) identified three sources of tracking error, ETF dividend policy, costs and timing mismatches when assets within an index are replaced and the weighting of constituent assets changes. Cresson et al. (2002) cited transactions costs, client cash inflows and outflows, volatility of the underlying index, changes in index composition, corporate activity, and dividends policy as the culprit of tracking error between an index tracking fund and its underlying index. Johnson et al. (2013) suggest transaction and rebalancing costs, cash drag, differing dividend reinvestment assumptions, dividend taxation, securities lending, sampling, variable swap spreads, total expense ratio and operational risks.

Rowley Jr and Kwon (2015) studied a cross-sectional sample of ETFs. They posited that the following variables affected the tracking error of an ETF: expense ratio, portfolio turnover, fund replication technique, AUM, fund tenure, weighting methodology, fund structure and cash balance. They, however, found that higher expense ratios were related to higher levels of tracking error.

Similar to the magnitude of tracking errors, emerging and developed markets tend to have different prevailing determinants of tracking error. In the study carried out by Chu (2011) on ETFs in Hong Kong, the determinants of the tracking error were fund size and expense ratio. Blitz and Huij (2012) found that replication technique was the prevalent determinant of tracking errors because many of the funds studied employed representative replication techniques. Other factors included withholding tax on dividend and expense ratios. Shin and Soydemir (2010) found that ETFs tracking a foreign market index are susceptible to exchange rate fluctuations compared to those tracking a U.S. based index and they concluded that exchange rate changes significantly influence the tracking errors of these ETFs. Strydom et al. (2015) measured the tracking errors of three JSE-listed ETFs tracking the JSE Top 40 index but did not provide reasons for the tracking errors. With no basis for comparison, JSE-listed ETFs are expected to have tracking error determinants similar to other emerging markets.

2.4.1 *Tracking error determinants of JSE-listed ETFs*

Based on the determinants highlighted in the above section, TER, fund size and ETF replication technique are the predominant factors that influence emerging market ETFs. These factors are likely to be possible determinants that prevail on the tracking error of JSE-listed ETFs as well, except for the replication technique since JSE-listed ETFs are physically-backed as a result of JSE regulations.

The total expense ratio is the annual expense charged by the fund manager to cover the cost of administering an ETF fund (Johnson et al., 2013). According to Strydom et al. (2015), JSE-listed ETFs incur less TER than their index fund counterparts and they found TER influenced tracking error but to a lesser degree for ETFs due to its lower TER compared to index funds. In the studies carried out by Chu (2011) and Frino and Gallagher (2001), they found a positive relationship between tracking error and TER. This implies that lower TER results in lower tracking errors. The study by Cresson et al. (2002) showed little significance in the relationship between tracking error and TER and this was attributed to the small sample population used in the study.

Frino and Gallagher (2001) found a significant relationship between fund size and tracking error, however, in this case, the relationship is negative. This implies that large funds tend to have lower tracking error. Chu (2011) attributed this to economies of scale as large funds are more likely to incur lower trading costs compared to smaller ones. This view was also supported by the study carried out Cresson et al. (2002).

Compared to developed markets like the US, JSE-listed ETFs are relatively young funds. The oldest ETF, Satrix 40, commenced operation in 2000 and the youngest ETF, is about a year old. At present, there are 47 funds, with varying fund ages. As observed by Cresson et al. (2002), tracking error has a positive relationship with fund age and they suggested that an experienced manager will be more adept at tracking than a less experienced manager. Although fund age is not a common determinant of tracking error amongst emerging market ETFs, the age distribution of JSE-listed ETFs makes it an interesting proposition to test this relationship.

It is therefore proposed that fund age, fund size and TER JSE-listed ETFs would influence their tracking error.

2.4.2 *Hypothesis 2*

H2: Fund age, fund size, and total expense ratio significantly influence the JSE-listed ETFs tracking errors

$$H_0: \beta_1 > 0 , \beta_2 > 0 , \beta_3 < 0$$

$$H_1: \beta_1 < 0 , \beta_2 < 0 , \beta_3 > 0$$

2.5 Conclusion of Literature Review

Based on the literature reviewed, it is clear that ETF tracking error is inevitable by the mere presence of market friction. However, the magnitude of the tracking error provides an indication that the ETF, as well as its manager, are complying with the fund's mandate. The magnitude of the tracking error is somewhat linked to the maturity of the market where the index being tracked is domiciled. The magnitude of tracking errors for ETFs tracking an emerging market index tend to be greater that those exhibited by ETFs tracking an index in more developed markets as corroborated by the studies carried out by several authors (Blitz & Huij, 2012; Shin & Soydemir, 2010; Strydom et al., 2015). Based on the outcome of the study by Strydom et al. (2015), the magnitude of the tracking error measure by ETFs tracking the JSE Top 40 shares was in line with the tracking error found in similar emerging markets. Although not reported by Strydom et al. (2015), the tracking errors of ETFs tracking asset classes other than the JSE Top 40 equity index are expected to show a similar trend.

The determinants of an ETF tracking error can be as a result of myriad reasons. South Africa, being an emerging economy, the sources of tracking error exhibited for its ETFs will more or less behave like the tracking errors observed for other emerging markets as well as have other determinants in line with the idiosyncratic nature of the South African investment and regulatory environment. For example, South African ETFs are required by the JSE to employ full physically-backed replication technique in mimicking their underlying indices. Therefore, it is expected that this would influence the magnitude of observed tracking error. As noted in the literature review, unlike ETFs employing full physically-backed replication technique, synthetic ETFs are better at tracking their underlying index and they display lower tracking errors.

Total expense ratio (TER) appears to be a common determinant of tracking errors regardless of whether the ETF is based in a developed or emerging market, however, it tends to vary across asset classes. For example, multi-asset ETFs have higher TER compared to regular single-asset ETFs. Other determinants such as fund size and currency fluctuations were common tracking error determinants among emerging market ETFs. From a South African perspective, the age of the fund could also have an effect on the tracking error exhibited by a fund.

With the flow of foreign investments into emerging ETFs, as investors seek better returns, South African ETFs could improve the tracking quality of their product and enhance the attractiveness of their offering. Furthermore, the determinants of tracking error in South African ETFs could assist investors in selecting ETF products.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Research methodology

The research paradigm employed in this research study is the quantitative approach. According to Leedy and Ormrod (2014), the quantitative approach lends itself well to a situation whereby a research study seeks to explain and predict, confirm or validate the association or connection between sets of variables so that it can be generalised and contribute to existing theories. The approach requires numerical data which are analysed using statistical analysis and deductive reasoning.

As stated in the previous chapters, the aim of this study is to determine the tracking error of JSE-listed ETFs and then examine possible factors responsible for the tracking error. Tracking error is defined as the difference between the return or performance of an ETF and the underlying index being tracked (Shin & Soydemir, 2010). The return for each ETF and its underlying index is calculated from published stock market numerical data, which is then analysed using statistical means. Therefore, the quantitative approach is most suited to this research work.

The chapter is organised as follows: Section 3.2 presents the research design. Section 3.3 discusses the data and the sources of data used in the study while Section 3.4 presents the limitations of the study. The chapter concludes with the discussion on the validity and reliability of the research results.

3.2 Research Design

The methodological approach proposed for this study is statistical analysis. There are several ways the tracking error of a portfolio can be calculated. The statistical methodologies used are adapted from previous studies carried out by Chu (2011), Cresson et al. (2002) and Pope and Yadav (1994). The tracking errors were measured using four different methods. Three of these methods are adapted from Pope and Yadav (1994) and Chu (2011), while the fourth is adapted from Cresson et al. (2002). The tracking error is measured using the absolute difference, the standard deviation of the difference, standard error of regression (SER) and R^2 from the regression of the single index model.

3.2.1 *Absolute Difference Method*

This method is based on the tracking error definition that equates tracking error to the difference between the return or performance of an ETF and the underlying index being tracked (Shin & Soydemir, 2010). This method takes the absolute difference between the ETF and the underlying index over a period of time. The model is specified as follows:

$$E_{AD} = \frac{\sum_{t=1}^{n}|e_{i,t}|}{n}, \text{ where } e_{i,t} = R_{i,t} - R_{j,t} \quad (1)$$

Where	E_{AD}	=	Tracking error, based on absolute difference
	$R_{i,t}$	=	Return of ETF, i
	$R_{j,t}$	=	Return of underlying index, j

3.2.2 *Standard deviation of the difference method*

This second method is based on the most widely used definition of tracking error, which is a "measure of the standard deviation of a fund's excess returns", where excess returns are the absolute difference between the return of the ETF and its benchmark (Johnson et al., 2013, p. 5). The model in this method is specified as follows:

$$E_{SD} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left(e_{i,t} - \overline{e_i}\right)^2} \quad (2)$$

where	E_{SD}	=	Tracking error, based on standard deviation of return differences

$\overline{e_i}$ = mean of the difference between the return of the ETF, i and underlying index, b

This method has two drawbacks. Firstly, in the event the fund being analysed constantly out-performs or under-performs the index by the same degree, the tracking error would result in zero. Secondly, when using this method, it is assumed that the return differences, $e_{i,t}$, are serially uncorrelated and may not be suitable for daily frequency data (Chu, 2011; Pope & Yadav, 1994).

3.2.3 *Standard Error of Regression (SER) method*

This method and the R^2 method described below are based on the single-index market model. The single-index market model is an asset pricing model used to measure the returns and the risk of a given security as represented by the linear regression model in equation (3) below. The intercept of the regression model alpha, α, represents excess return, while the coefficient of regression beta, β, represents a systemic risk of a security or portfolio (Francis & Fabozzi, 1979).

The SER of a regression provides an indication of the predictive accuracy of a regression line (Fraser, 2012) and similar to the standard deviation of the difference of the ETF return and its underlying index, when the returns of the ETF and its underlying index are regressed as per equation (3), the SER of the regression provides an indication of the tracking error between the ETF and its underlying index (Chu, 2011).

$$R_{i,t} = \alpha + \beta \,.\, R_{b,t} + e_t \tag{3}$$

This main drawback of this measure relates to the value of beta, β. If the value of beta is not exactly 1, the tracking error calculated using this method will be different from the value obtained from the standard deviation of the difference method, E_{AD}. The beta, β coefficient is discussed further in the following section.

3.2.4 *R^2 method*

In a regression analysis, R^2 is a measure of the degree of variation in a dependent variable accounted for by an independent variable (Fraser, 2012). In this case, it is used to represent how well the return of the ETF (dependent variable) tracks its underlying index (independent variable). It is basically an indication of how well the return of an ETF can be explained by the return of the underlying index (Strydom et al., 2015).

The value of R^2 ranges between 0 and 1. A value of 0 means there is no correlation between the dependent and independent variable. Consequently, an ETF with low tracking error is expected to have an R^2 value closer to 1.

It is also noteworthy to mention an important component of the SER and R^2 methods. The alpha, α and beta, β coefficient in equation (3), reflect the excess return and the systemic risk of the ETF respectively. An ETF that matches its underlying index perfectly is expected to have an alpha value that is not statistically meaningfully different from zero. The beta coefficient connotes the aggressiveness of the fund manager's management approach. An ETF that matches its underlying index perfectly should have a beta value equal to 1 (Drenovak et al., 2014; Strydom et al., 2015), as ETF managers are not mandated to be aggressive but to simply replicate the market. As mentioned in section 3.2.3 above, if the value of beta, β is not exactly equal to 1, the tracking error calculated using this method will be different from E_{SD}. Therefore, an ETF that perfectly mimicking its underlying index should have alpha, beta and R^2 values that correspond to 0, 1 and 1 respectively. (Drenovak et al., 2014; Strydom et al., 2015).

3.2.5 *Determinants of tracking error*

Tracking errors are influenced by operating characteristics of ETF funds such as ETF replication technique, TER, fund size, dividends, currency fluctuations, etc. Some operating characteristics influence tracking errors more than others and some have no effect at all. Operating characteristics such as total expense ratio (TER), fund size and ETF replication technique were moderating factors that influence emerging market ETFs (Blitz & Huij, 2012; Chu, 2011). The effect of replication technique cannot be tested because, as mandated by the FSB and the JSE, ETFs listed on the JSE are required to adopt full physically-backed replication and synthetic replication techniques are not allowed. The selection of fund operating characteristic is discussed in Chapter 2, section 2.4.1 of this study.

In determining the operating characteristics that influence the tracking error of JSE-listed ETFs, the tracking errors calculated in the methods described in section 3.2 above are regressed on selected fund operating characteristics as shown in equation (4) below. The selected fund operating characteristics were based on the literature reviewe in Chapter 2. The magnitude of the β coefficients thus reflects how strongly or otherwise each of the selected operating characteristic influence the tracking error of JSE-listed ETFs.

$$\left|E_{i,t}\right| = \beta_0 + \beta_1 * FA_{i,t} + \beta_2 * FS_{i.t} + \beta_3 * TER_{i,t} + \varepsilon_{i,t} \quad (4)$$

Where $\left|E_{i,t}\right|$ = Absolute value of the tracking error in period, t, for ETF, i.

$FA_{i,t}$ = Fund age for ETF, i.

$FS_{i,t}$ = Fund size for ETF, i.

$TER_{i,t}$ = Total expense ratio for ETF, i.

Four regression models were created with the dependent variable for each model being the tracking error determined from the four methods, while the four models have the same independent variables; fund age, fund size and total expense ratio. The intention of the four models is the same, to determine the factors that influence the tracking error of JSE-listed ETFs. Prior to the regression analysis, the dependent and independent variables were analysed to ensure that the basic assumptions of a linear regression model were not violated and to perform necessary adjustments in the event there are violations. The key assumptions upon which a linear regression model is based includes:

1. The linearity of the relationship between the dependent variable and independent variables.

2. Normality of the regression variables
3. Normality of the residual or errors of regression.
4. The absence of or minimal collinearity between the regression variables
5. Autocorrelation and
6. Homoscedasticity i.e. the variance in the residual or error term is equal across all observations.

The variables used in the four regressions models were analysed and the results of the analyses are presented in APPENDIX B. The assumptions for linear multiple regression models were fulfilled. The relationship between the dependent variable and the independent variables appeared to be linear for each of the models, the risk of heteroscedasticity and multicollinearity were remote and the residuals of each regression model were normally distributed. Although some of the regression variables were skewed and not normally distributed, the log transformation of the skewed variables improved the normal distribution of the data and the log transformed variables were used. The Durbin-Watson (D-W) test showed the presence of autocorrelation but the D-W statistics for the four regression models were greater than 1 and somewhat close to 2, thus it was assumed that the effect of autocorrelation is minimal.

3.3 Data and data sources

The research sample of this study includes all ETFs listed on the JSE. As at June 30, 2016, there were 47 ETF funds listed on the JSE (see Appendix 1). The sample period was from November 1, 2000, to June 30, 2016. Only the ETFs that have full data points were included in the analysis. To avoid survivorship bias, the tracking error to test hypothesis 1 was calculated from inception to June 30, 2016. The data needed for this research include the daily and monthly closing price of each ETF and their respective indices, the asset under management (AUM), total expense ratio and fund commencement date for each ETF. All the data was obtained from Bloomberg and validated against other fund databases, such as iNet Bridge and ShareMagic.

The asset under management (AUM) is used as a proxy for the size of each fund while the commencement date is used to calculate the age of each fund.

In the analysis of factors that influence tracking errors, the tracking errors used were based on a common period in order to remove periodic effects that could bias the analysis. In order to accommodate all the ETFs in the sample population, a period spanning June 1, 2015, to June 30, 2016, was used. Also, only daily returns were considered in testing hypothesis 2 due to the paucity of monthly data within the chosen period.

The collected data was assessed for completeness to ensure that all data points for each dataset are available for the period under review. The closing prices were plotted on a Cartesian plane to aid visual inspection of the data. This assisted in identifying potential errors, e.g. typing errors as well as identify outliers. According to Johnson et al. (2013, p. 8), errors in the dataset in itself is a potential source of ETF tracking error. They also mentioned possible sources of data error which include "missing or misaligned data, outliers, and rounding". Therefore, it is pertinent that the data is free of errors as much as possible.

To ensure the reliability and consistency of the data collected and avoid the errors highlighted by Johnson et al. (2013), the data collected from Bloomberg was sampled randomly and compared to data from other sources such as *Profile Data, Morning Star* and *I-Net Bridge*.

The inclusion of an ETF in the sample population required the ETF to be listed on the JSE, have available fund information and a homogenous underlying index that it tracks. Based on these criteria, only 39 funds out of the 46 that were listed on the JSE, as at the time of the research, were included in the research sample. The ETFs in the sample population, including their respective underlying indices, are summarised in Appendix 1 along with summarised fund data for each of the ETFs.

3.4 Limitations of the study

- The study was limited to physically-backed ETFs because South African regulation does not permit synthetic ETFs. The replication technique used by a fund manager has an impact on tracking error. According to literature surveyed, synthetic ETFs are able to replicate an index better than physically-backed ones. The presence of synthetic funds would have made the study richer.
- According to Field (2009), for each independent variable in a regression model, it is prudent to have 10 to 15 data points and this depends on the size of the effect this is being detected. Another common rule of thumb recommends a minimum of 50 data points. With 37 funds in the sample population and 3 independent variables, this invariably represents a paucity of data points and the results, especially for the multiple linear regression of tracking error against fund operating characteristics, should be treated with caution.

3.5 Validity and reliability

According to Leedy and Ormrod (2014, p. 39), “validity of a measuring instrument is the extent to which the instrument measure what it is intended to measure”(p. 91) while “reliability is the consistency with which a measuring instrument yields a certain, consistent when the entity being measured hasn’t changed”.

3.5.1 *External validity*

This research study deals with the tracking error and tracking error determinants of JSE-listed ETFs and the sample of funds included in the research is deliberate to ensure the inclusion of diverse asset classes. Idiosyncratic characteristics of each asset class, if significant, would be reflected in the measured tracking error. As such, this would make it possible for results to be generalised for cohorts within each asset category. With respect to the determinants of the tracking error, the measure tracking error will be regressed on identified fund operating factors.

Therefore, the results from this study can be generalised to other JSE-listed ETFs.

Previous international studies have found that the tracking errors for emerging market ETFs exhibit tracking errors that are higher than those experienced in the more developed markets. Although South Africa is an emerging market, there are some idiosyncratic elements such as unique economic circumstances and market regulations, that sets it apart from other emerging markets. As such, result from this research should not be blindly generalised and applied to other emerging markets.

3.5.2 *Internal validity*

The models, statistical tools and methods used in this study are based on published scholarly studies such as (Chu, 2011; Pope & Yadav, 1994; Strydom et al., 2015). These studies were published in reputable academic journals, have been peer-reviewed and cited by other reputable journals.

3.5.3 *Reliability*

In ensuring the research meets the reliability criteria, collected data that was used in the research was cross-checked with data from another source. As mentioned in previous sections, errors in the dataset is a possible source of ETF tracking error (Johnson et al., 2013), as such, it is crucial that the dataset is free of errors.

As mentioned in section 3.2.2, the standard deviation method for measuring tracking error is susceptible to estimation bias because when the fund being analysed constantly out-performs or under-performs the index by the same degree, the tracking error output from this method would result in zero even though there is a difference between the return of the ETF and its underlying index. However, the use of three other methods would assist in contextualising and identifying inconsistencies that could potentially result from the E_{SD} method.

As noted by Pope and Yadav (1994), because the price data for the ETFs and their underlying indices are time series, using daily or weekly data could result in estimation bias as daily and weekly data are more susceptible to serial correlation issues. However, the study by Cresson et al. (2002) used daily return data and they compared their results to previous studies that used monthly return data. The comparison of the two sets of results showed similar beta values but tracking errors for the two sets of studies were not similar. However, the study was conducted with both daily and monthly data.

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CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

This chapter presents the findings of the research. The chapter is organised as follows: Section 4.2 provides a description of data collected for this research. The data includes closing prices for all ETFs under consideration, closing prices of all underlying index under consideration, and fund data for each ETF such as net asset value, fund age and total expense ratio while Section 4.3 presents the results of the hypotheses test proposed in Chapter 2. The results are further discussed in Chapter 5.

4.2 Results pertaining to Hypothesis 1

Hypothesis 1 refers to the tracking error exhibited by JSE-listed ETFs. The mandate of an ETF is to track or mimic its underlying index as close as possible. Hypothesis 1 tests the statistical significance of the difference between the ETF and its underlying index. The tracking error for the ETFs in the sample population was calculated using the four methods on a daily and monthly basis. The results from the four measures of tracking error as well as the result of the statistical significance of the tracking errors are presented below.

4.2.1 *Tracking errors in ETFs from the absolute returns method*

Table 1: Tracking error using the absolute difference, E_{AD}

S/N	Fund	N	Mean, E_{AD}	SD	Min	Max	p-Value
Panel 1 Tracking errors using daily price returns							
1	ASHT40	1925	0.1285%	0.3476%	0.0000%	5.3207%	0.016%
2	STAN40	1424	0.5291%	1.3188%	0.0002%	25.3859%	0.069%
3	STX40	3895	0.3672%	0.4370%	0.0002%	6.4890%	0.014%
4	NFSH40	1806	1.1408%	2.4508%	0.0003%	45.3122%	0.113%
5	STXRAF	1924	0.5090%	0.6121%	0.0008%	6.7491%	0.027%
6	NFSWIX	1105	0.3981%	1.1194%	0.0003%	20.3664%	0.066%
7	STANSX	1424	0.5137%	1.0988%	0.0003%	12.2848%	0.057%

S/N	Fund	N	Mean, E_{AD}	SD	Min	Max	p-Value
8	STXSWX	2554	0.6645%	0.9607%	0.0002%	15.0259%	0.037%
9	CSEW40	1499	0.4639%	0.9153%	0.0000%	13.2404%	0.046%
10	CGREEN	742	0.5611%	0.9505%	0.0004%	8.0186%	0.069%
11	CTOP50	284	0.3316%	0.3032%	0.0015%	1.8483%	0.035%
12	DIVTRX	551	0.3882%	0.4912%	0.0024%	4.8757%	0.041%
13	LVLTRX	550	0.3178%	0.3599%	0.0008%	2.8061%	0.030%
14	PREFTX	1062	0.4381%	0.5610%	0.0010%	8.4468%	0.034%
15	GIVISA	1816	0.7321%	1.4215%	0.0000%	30.5362%	0.065%
16	GIVFIN	1755	0.7423%	1.5236%	0.0003%	35.6423%	0.071%
17	GIVIND	1757	0.6578%	0.8116%	0.0003%	9.1627%	0.038%
18	GIVRES	1757	1.1371%	2.4091%	0.0009%	45.2651%	0.113%
19	ASHMID	967	0.2457%	0.7282%	0.0003%	15.4297%	0.046%
20	STXDIV	2207	0.6760%	0.7946%	0.0000%	12.6519%	0.033%
21	STXFIN	3591	0.6901%	0.8097%	0.0003%	10.0165%	0.026%
22	STXIND	3591	0.4650%	0.5652%	0.0002%	11.6196%	0.018%
23	STXRES	2547	0.6508%	0.8817%	0.0002%	9.4772%	0.034%
24	DBXEU	2679	1.1083%	1.5673%	0.0002%	41.3370%	0.059%
25	DBXJP	1991	1.4034%	1.3869%	0.0000%	10.8811%	0.061%
26	DBXUK	2643	1.0063%	0.9861%	0.0000%	10.8620%	0.038%
27	DBXUS	2018	1.3403%	1.4938%	0.0000%	20.9942%	0.065%
28	DBXWD	2061	1.1974%	1.7898%	0.0000%	26.4219%	0.077%
29	ASHINF	1779	0.2620%	0.4759%	0.0002%	10.5234%	0.022%
30	NFILBI	1105	0.2382%	0.4834%	0.0000%	6.3178%	0.136%
31	NFGOVI	1104	0.4868%	2.2947%	0.0006%	39.2812%	0.029%
32	ETFGLD	554	0.8173%	3.8493%	0.0003%	58.6350%	0.322%
33	ETFPLD	566	1.1046%	1.7467%	0.0032%	16.4952%	0.144%
34	ETFPLT	555	0.7991%	1.4033%	0.0011%	14.2620%	0.117%
35	GLD	2914	0.7899%	0.7350%	0.0000%	8.1260%	0.025%
36	NGPLD	563	0.8689%	0.7829%	0.0021%	6.1932%	0.065%
37	NGPLT	793	0.6451%	0.5177%	0.0002%	2.6198%	0.036%
38	PTXSPY	2190	0.5741%	0.6889%	0.0001%	8.1219%	0.029%
39	STPROP	842	0.4656%	1.7648%	0.0015%	23.5150%	0.119%

Panel 2 Tracking errors using monthly price returns

S/N	Fund	N	Mean, E_{AD}	SD	Min	Max	p-Value
1	ASHT40	92	0.2947%	0.3009%	0.0008%	1.5497%	0.063%
2	STAN40	68	1.1526%	1.8328%	0.0030%	8.9750%	0.447%
3	STX40	187	0.4988%	0.4449%	0.0073%	1.9941%	0.064%
4	NFSH40	86	1.7104%	2.0501%	0.0189%	9.7072%	0.442%
5	STXRAF	92	0.6581%	0.5433%	0.0071%	2.4497%	0.113%
6	NFSWIX	51	0.6383%	0.6019%	0.0097%	2.6935%	0.171%

S/N	Fund	N	Mean, E_{AD}	SD	Min	Max	p-Value
7	STANSX	68	1.6035%	2.5880%	0.0018%	11.0504%	0.631%
8	STXSWX	122	0.6437%	0.5724%	0.0042%	3.2988%	0.103%
9	CSEW40	71	0.8084%	0.7538%	0.0259%	3.2181%	0.180%
10	CGREEN	37	1.1518%	1.5216%	0.0007%	6.9936%	0.514%
11	CTOP50	13	0.4435%	0.4123%	0.1329%	1.7028%	0.259%
12	DIVTRX	26	0.4502%	0.3317%	0.0454%	1.0125%	0.137%
13	LVLTRX	26	0.5026%	0.3725%	0.0315%	1.3781%	0.153%
14	PREFTX	51	0.9003%	0.6112%	0.0054%	2.7584%	0.174%
15	GIVISA	87	1.2212%	0.9896%	0.0052%	3.9559%	0.212%
16	GIVFIN	84	1.5603%	1.7075%	0.0226%	9.0300%	0.373%
17	GIVIND	84	1.7591%	1.4591%	0.0198%	8.0064%	0.319%
18	GIVRES	84	3.0561%	2.8403%	0.0004%	13.4969%	0.620%
19	ASHMID	46	0.3355%	0.2535%	0.0304%	0.9294%	0.076%
20	STXDIV	106	0.7035%	0.6208%	0.0027%	3.0202%	0.120%
21	STXFIN	172	1.0462%	1.3230%	0.0057%	7.6128%	0.200%
22	STXIND	172	0.6079%	0.6954%	0.0012%	5.5112%	0.105%
23	STXRES	122	0.7172%	0.9193%	0.0109%	5.2245%	0.165%
24	DBXEU	128	3.2427%	2.7963%	0.0291%	12.0715%	0.491%
25	DBXJP	98	3.8387%	3.6499%	0.0376%	23.6488%	0.736%
26	DBXUK	128	3.4121%	2.9744%	0.0202%	18.8136%	0.522%
27	DBXUS	98	4.0051%	3.5942%	0.0476%	19.4785%	0.724%
28	DBXWD	98	4.1031%	3.5166%	0.0171%	17.4980%	0.709%
29	ASHINF	83	0.5323%	0.4758%	0.0021%	2.4652%	0.105%
30	NFILBI	49	0.4683%	0.4196%	0.0088%	1.5741%	0.122%
31	NFGOVI	52	2.2971%	7.4904%	0.0167%	39.6384%	2.106%
32	ETFGLD	26	0.6625%	0.5900%	0.0209%	2.4594%	0.243%
33	ETFPLD	27	0.8981%	0.6137%	0.0022%	2.1591%	0.247%
34	ETFPLT	26	0.9351%	1.0352%	0.0260%	4.1241%	0.426%
35	GLD	139	0.9317%	0.8154%	0.0059%	4.4820%	0.137%
36	NGPLD	27	1.0865%	0.8628%	0.0473%	3.7870%	0.348%
37	NGPLT	38	0.7164%	0.4746%	0.0130%	1.8714%	0.158%
38	PTXSPY	105	0.9579%	0.9359%	0.0120%	5.2865%	0.182%
39	STPROP	40	0.7047%	1.0515%	0.0283%	6.5244%	0.341%

Table 1 above shows the tracking errors estimated using the absolute difference method. Panel 1 in Table 1 above shows the tracking error estimated from daily returns while the tracking error estimated from monthly returns are shown in Panel 2.

The tracking errors estimated from daily returns range from 0.1285% to 1.4034% while the tracking error estimated from monthly returns range from 0.2947% to

4.1031%. The results show that returns of JSE-listed ETFs deviate from their underlying indices. The mean tracking errors were tested to determine whether they were statistically significant from zero. The p-values shown in Table 1 above indicates that all the calculated mean tracking errors are statistically significant at the 5% level. Therefore, the null hypothesis can be rejected.

4.2.2 *Tracking errors in ETFs from the absolute returns method*

Table 2: Tracking error using the standard deviation of the difference, E_{SD} method

S/N	Fund	N	SD, E_{SD}	Mean	p-Value
Panel 1 Tracking errors using daily price returns					
1	ASHT40	1925	0.3706%	-0.0002%	0.017%
2	STAN40	1424	1.4210%	-0.0003%	0.074%
3	STX40	3895	0.5708%	-0.0002%	0.018%
4	NFSH40	1806	2.7033%	-0.0033%	0.125%
5	STXRAF	1924	0.7960%	0.0080%	0.036%
6	NFSWIX	1105	1.1881%	0.0124%	0.070%
7	STANSX	1424	1.2129%	-0.0001%	0.063%
8	STXSWX	2554	1.1681%	-0.0001%	0.045%
9	CSEW40	1499	1.0261%	-0.0013%	0.052%
10	CGREEN	742	1.1037%	-0.0014%	0.080%
11	CTOP50	284	0.4493%	-0.0012%	0.053%
12	DIVTRX	551	0.6261%	-0.0016%	0.052%
13	LVLTRX	550	0.4801%	-0.0025%	0.040%
14	PREFTX	1062	0.7118%	-0.0013%	0.043%
15	GIVISA	1816	1.5989%	-0.0166%	0.074%
16	GIVFIN	1755	1.6948%	0.0034%	0.079%
17	GIVIND	1757	1.0446%	-0.0166%	0.049%
18	GIVRES	1757	2.6640%	0.0015%	0.125%
19	ASHMID	967	0.7685%	0.0010%	0.049%
20	STXDIV	2207	1.0433%	-0.0006%	0.044%
21	STXFIN	3591	1.0639%	0.0000%	0.035%
22	STXIND	3591	0.7319%	-0.0001%	0.024%
23	STXRES	2547	1.0959%	0.0009%	0.043%
24	DBXEU	2679	1.9194%	0.0267%	0.073%
25	DBXJP	1991	1.9729%	0.0258%	0.087%
26	DBXUK	2643	1.4088%	0.0198%	0.054%
27	DBXUS	2018	2.0068%	0.0286%	0.088%

S/N	Fund	N	SD, E_{SD}	Mean	p-Value
28	DBXWD	2061	2.1532%	0.0298%	0.093%
29	ASHINF	1779	0.5430%	-0.0138%	0.025%
30	NFILBI	1105	0.5389%	-0.0012%	0.139%
31	NFGOVI	1104	2.3457%	0.0005%	0.032%
32	ETFGLD	554	3.9351%	-0.0027%	0.329%
33	ETFPLD	566	2.0667%	-0.0047%	0.171%
34	ETFPLT	555	1.6149%	-0.0042%	0.135%
35	GLD	2914	1.0789%	-0.0029%	0.037%
36	NGPLD	563	1.1696%	-0.0074%	0.097%
37	NGPLT	793	0.8271%	-0.0056%	0.058%
38	PTXSPY	2190	0.8967%	0.0011%	0.038%
39	STPROP	842	1.8252%	-0.0044%	0.124%

Panel 2 Tracking errors using monthly price returns

S/N	Fund	N	SD, E_{SD}	Mean	p-Value
1	ASHT40	92	0.4210%	0.0116%	0.088%
2	STAN40	68	2.1651%	0.0047%	0.528%
3	STX40	187	0.6684%	-0.0027%	0.097%
4	NFSH40	86	2.6694%	-0.0510%	0.576%
5	STXRAF	92	0.8335%	0.1832%	0.174%
6	NFSWIX	51	0.8564%	0.1904%	0.243%
7	STANSX	68	3.0445%	-0.0011%	0.742%
8	STXSWX	122	0.8614%	-0.0028%	0.155%
9	CSEW40	71	1.1053%	-0.0008%	0.263%
10	CGREEN	37	1.9073%	0.0620%	0.645%
11	CTOP50	13	0.5989%	-0.0892%	0.377%
12	DIVTRX	26	0.5580%	-0.0374%	0.230%
13	LVLTRX	26	0.6228%	-0.0590%	0.257%
14	PREFTX	51	1.0879%	-0.0234%	0.309%
15	GIVISA	87	1.5514%	-0.2525%	0.333%
16	GIVFIN	84	2.3117%	0.0803%	0.505%
17	GIVIND	84	2.2604%	-0.3375%	0.493%
18	GIVRES	84	4.1722%	-0.0020%	0.911%
19	ASHMID	46	0.4203%	0.0140%	0.126%
20	STXDIV	106	0.9382%	0.0027%	0.182%
21	STXFIN	172	1.6867%	-0.0005%	0.255%
22	STXIND	172	0.9237%	-0.0021%	0.139%
23	STXRES	122	1.1658%	0.0196%	0.210%
24	DBXEU	128	4.2472%	0.5439%	0.746%
25	DBXJP	98	5.2572%	0.6475%	1.059%
26	DBXUK	128	4.5108%	0.3767%	0.792%

S/N	Fund	N	SD, E_{SD}	Mean	p-Value
27	DBXUS	98	5.3462%	0.6141%	1.077%
28	DBXWD	98	5.3609%	0.6797%	1.080%
29	ASHINF	83	0.6467%	-0.3026%	0.142%
30	NFILBI	49	0.6288%	-0.0046%	0.182%
31	NFGOVI	52	7.8347%	-0.0238%	2.202%
32	ETFGLD	26	0.8863%	-0.0387%	0.365%
33	ETFPLD	27	1.0823%	-0.1093%	0.436%
34	ETFPLT	26	1.3934%	-0.0672%	0.574%
35	GLD	139	1.2375%	-0.0386%	0.208%
36	NGPLD	27	1.3824%	-0.1176%	0.557%
37	NGPLT	38	0.8583%	-0.0422%	0.286%
38	PTXSPY	105	1.3390%	0.0220%	0.260%
39	STPROP	40	1.2605%	-0.1160%	0.408%

Table 2 above shows the tracking errors estimated using the standard deviation of the difference, E_{SD} method. Panel 1 in Table 2 above shows the tracking error estimated from daily returns while the tracking error estimated from monthly returns are shown in Panel 2.

The tracking errors estimated from daily returns range from 0.3706% to 3.9351% while the tracking error estimated from monthly returns range from 0.4203% to 7.8347%. The results show that by using the standard deviation of the difference methods, returns of JSE-listed ETFs deviate from their underlying indices. The mean tracking errors based on this method were tested to determine whether they were statistically significant from zero. The p-value shown in Table 2 above indicates that all the calculated mean tracking errors are statistically significant at the 5% level. Therefore, the null hypothesis can be rejected.

4.2.3 *Tracking errors in ETFs from the SER and R^2 methods*

Table 3 presents the tracking errors for the sampled JSE-listed ETFs using the standard error of regression and regression R^2 methods.

Table 3: Tracking error using the standard error of regression and R^2 methods

S/N	Fund	N	SER, E_{SER}	Alpha	Beta	R^2, E	p-Value
Panel 1 Tracking errors using daily price returns							
1	ASHT40	1925	0.3687%	0.0000	0.9699	0.9221	0.0E+00
2	STAN40	1424	1.3698%	0.0001	0.6423	0.2005	3.8E-71
3	STX40	3895	0.5655%	0.0000	0.9417	0.8342	0.0E+00
4	NFSH40	1806	2.6706%	0.0000	0.6918	0.1149	8.4E-50
5	STXRAF	1924	0.7575%	0.0002	0.8064	0.6469	0.0E+00
6	NFSWIX	1105	1.1809%	0.0002	0.8665	0.3707	4.7E-113
7	STANSX	1424	1.1719%	0.0001	0.7072	0.2977	2.9E-111
8	STXSWX	2554	1.1394%	0.0001	0.8081	0.4786	0.0E+00
9	CSEW40	1499	1.0124%	0.0001	0.8343	0.4214	4.4E-180
10	CGREEN	742	1.0362%	0.0002	0.5366	0.1559	4.4E-29
11	CTOP50	284	0.4320%	0.0000	0.8989	0.8758	9.1E-130
12	DIVTRX	551	0.6109%	0.0000	0.8719	0.7150	9.2E-152
13	LVLTRX	550	0.4637%	0.0000	0.8513	0.7131	1.1E-150
14	PREFTX	1062	0.6640%	-0.0001	0.4024	0.0642	5.2E-17
15	GIVISA	1816	1.5738%	0.0000	0.7064	0.1613	2.4E-71
16	GIVFIN	1755	1.6185%	0.0003	0.5643	0.1409	8.2E-60
17	GIVIND	1757	0.9502%	0.0002	0.5484	0.2364	6.4E-105
18	GIVRES	1757	2.6040%	0.0002	0.6069	0.1023	4.6E-43
19	ASHMID	967	0.7683%	0.0000	0.9509	0.4995	3.3E-147
20	STXDIV	2207	1.0292%	0.0000	0.8553	0.4994	0.0E+00
21	STXFIN	3591	1.0495%	0.0001	0.8694	0.5554	0.0E+00
22	STXIND	3591	0.7113%	0.0001	0.8510	0.6591	0.0E+00
23	STXRES	2547	1.0723%	0.0000	0.8857	0.7315	0.0E+00
24	DBXEU	2679	1.7691%	0.0002	0.5073	0.1587	1.4E-102
25	DBXJP	1991	1.9108%	0.0003	0.6916	0.2523	9.0E-128
26	DBXUK	2643	1.1834%	0.0002	0.3916	0.1477	9.5E-94
27	DBXUS	2018	1.5557%	0.0005	0.0831	0.0054	9.1E-04
28	DBXWD	2061	1.9814%	0.0003	0.2860	0.0284	1.4E-14
29	ASHINF	1779	0.4426%	0.0001	0.2231	0.0401	1.4E-17
30	NFILBI	1105	0.5329%	0.0001	0.7377	0.1624	2.1E-44
31	NFGOVI	1104	2.3463%	0.0000	0.8375	0.0330	1.2E-09
32	ETFGLD	554	3.9395%	0.0000	0.8812	0.0704	2.2E-10
33	ETFPLD	566	2.0200%	0.0000	0.7269	0.2632	2.6E-39
34	ETFPLT	555	1.6029%	0.0000	0.8224	0.2855	2.7E-42
35	GLD	2914	0.9503%	0.0002	0.7485	0.5305	0.0E+00
36	NGPLD	563	1.1116%	0.0000	0.7763	0.5722	1.7E-105
37	NGPLT	793	0.7693%	0.0000	0.7563	0.6048	1.3E-161

S/N	Fund	N	SER, E_{SER}	Alpha	Beta	R^2, E	p-Value
38	PTXSPY	2190	0.8540%	0.0001	0.6970	0.3542	5.2E-210
39	STPROP	842	1.8273%	0.0000	0.9848	0.2439	5.7E-53

Panel 2 Tracking errors using monthly price returns

S/N	Fund	N	SER, E_{SER}	Alpha	Beta	R^2, E	p-Value
1	ASHT40	92	0.4097%	-0.0001	1.0272	0.9913	1.9E-94
2	STAN40	68	2.1550%	0.0010	0.8783	0.6756	8.7E-18
3	STX40	187	0.6673%	-0.0002	1.0152	0.9844	3.9E-169
4	NFSH40	86	2.5498%	0.0002	0.8308	0.7466	9.2E-27
5	STXRAF	92	0.8358%	0.0021	0.9751	0.9621	9.3E-66
6	NFSWIX	51	0.8700%	0.0017	1.0248	0.9358	7.0E-31
7	STANSX	68	2.8443%	0.0033	0.6333	0.3499	1.1E-07
8	STXSWX	122	0.8685%	0.0000	0.9972	0.9624	2.4E-87
9	CSEW40	71	1.1114%	0.0003	0.9565	0.8948	1.9E-35
10	CGREEN	37	1.9581%	0.0009	0.9650	0.6985	1.2E-10
11	CTOP50	13	0.6177%	-0.0009	1.0547	0.9763	2.7E-10
12	DIVTRX	26	0.5703%	-0.0006	1.0279	0.9805	5.1E-22
13	LVLTRX	26	0.6378%	-0.0008	1.0397	0.9575	5.7E-18
14	PREFTX	51	1.0400%	-0.0008	0.8269	0.7601	8.3E-17
15	GIVISA	87	1.5679%	-0.0028	1.0212	0.8271	3.9E-34
16	GIVFIN	84	2.3108%	0.0017	0.9098	0.7192	2.5E-24
17	GIVIND	84	2.0117%	0.0019	0.7026	0.6209	5.9E-19
18	GIVRES	84	4.1135%	0.0013	0.8527	0.6433	4.8E-20
19	ASHMID	46	0.4271%	0.0000	1.0140	0.9849	1.1E-41
20	STXDIV	106	0.9461%	0.0001	0.9898	0.9580	2.1E-73
21	STXFIN	172	1.6966%	0.0000	1.0009	0.8988	1.8E-86
22	STXIND	172	0.9261%	-0.0002	1.0162	0.9626	3.1E-123
23	STXRES	122	1.1754%	0.0002	0.9993	0.9759	6.6E-99
24	DBXEU	128	4.1356%	0.0052	0.7901	0.5029	7.5E-21
25	DBXJP	98	4.0257%	0.0056	0.4269	0.2914	9.7E-09
26	DBXUK	128	4.1342%	0.0045	0.5310	0.2116	4.7E-08
27	DBXUS	98	4.5080%	0.0088	0.3794	0.1401	1.5E-04
28	DBXWD	98	4.2853%	0.0071	0.3806	0.1841	1.0E-05
29	ASHINF	83	0.6373%	-0.0037	1.0911	0.8877	3.3E-40
30	NFILBI	49	0.6381%	0.0002	0.9632	0.8946	1.3E-24
31	NFGOVI	52	7.9767%	-0.0014	1.2067	0.1011	2.2E-02
32	ETFGLD	26	0.9224%	-0.0004	1.0033	0.9625	1.3E-18
33	ETFPLD	27	1.1203%	-0.0011	1.0140	0.9769	5.6E-22
34	ETFPLT	26	1.4491%	-0.0007	1.0103	0.9409	3.0E-16
35	GLD	139	1.2421%	-0.0001	0.9821	0.9547	6.6E-94
36	NGPLD	27	1.4363%	-0.0012	1.0043	0.9619	3.0E-19

S/N	Fund	N	SER, E_{SER}	Alpha	Beta	R^2, E	p-Value
37	NGPLT	38	0.8818%	-0.0004	1.0001	0.9788	9.7E-32
38	PTXSPY	105	1.3517%	0.0003	0.9940	0.9187	6.2E-58
39	STPROP	40	1.2897%	-0.0010	0.9784	0.9171	3.8E-22

Table 3 reports the result of the regression of the CAPM model for each of the ETFs in the sample population. The result of the regression produces two measure of tracking error; the standard error and R^2 of the regression. As explained in Chapter 3, both measures indicate how closely an ETF mimics its underlying index. Table 3 reports the SER and R^2 for each of the ETFs as well as the alpha and beta values for the respective CAPM model. Panel 1 in Table 3 above shows the regression results based on daily returns while Panel 2 shows results based on monthly return data.

As per literature, the tracking errors estimated from the SER method is similar to that estimated from the E_{SD} method. The tracking error from the SER measure based on daily returns ranges from 0.3687% to 3.9395% while the tracking error estimated from monthly returns range from 0.4097% to 7.9767%.

The tracking error from the R^2 measure based on daily returns range from 0.0054 to 0.9221 while the tracking error estimated from monthly returns range from 0.1011 to 0.9913. The results show that returns of JSE-listed ETFs deviate from their underlying indices.

The results from both methods show that JSE-listed ETFs exhibit tracking errors. The F Statistic of the respective CAPM regression was used as an indication of the statistical significance of the calculated tracking errors. The p-value of the F Statistic is shown in Table 3 for each of the CAPM regression based on daily and monthly return data. The Table shows that all the regression models are statistically significant at the 1% level. Hence the null hypothesis can be ignored.

4.3 Tracking errors by assets classes

While analysing the results, it was found that the magnitude of tracking error tends to differ for the different asset class. In general, it was observed that ETFs in the similar asset class exhibit similar magnitude of tracking errors while certain asset classes, as a group, exhibited a lower magnitude of tracking error compared to other asset classes. Table 4 below presents the tracking errors for the different asset classes.

Table 4: Tracking error range for different asset classes

Panel 1: Tracking errors using daily price returns

Asset Class	EAD		ESD		SER		R^2	
	Min	Max	Min	Max	Min	Max	Min	Max
Equity	0.1285%	1.1408%	0.3706%	2.7033%	0.3687%	2.6706%	0.9221	0.0642
International Equity	1.0063%	1.4034%	1.4088%	2.1532%	1.1834%	1.9814%	0.2523	0.0054
Bond	0.2382%	0.4868%	0.5389%	2.3457%	0.4426%	2.3463%	0.1624	0.0330
Commodity	0.6451%	1.1046%	0.8271%	3.9351%	0.7693%	3.9395%	0.6048	0.0704
Property Equity	0.4656%	0.5741%	0.8967%	1.8252%	0.8540%	1.8273%	0.3542	0.2439

Panel 2: Tracking errors using monthly price returns

Asset Class	EAD		ESD		SER		R^2	
	Min	Max	Min	Max	Min	Max	Min	Max
Equity	0.2947%	3.0561%	0.4203%	4.1722%	0.4097%	4.1135%	0.9913	0.0025
International Equity	3.2427%	4.1031%	4.2472%	5.3609%	4.0257%	4.5080%	0.5029	0.1401
Bond	0.4683%	2.2971%	0.6288%	7.8347%	0.6373%	7.9767%	0.8946	0.1011
Commodity	0.6625%	1.0865%	0.8583%	1.3934%	0.8818%	1.4491%	0.9788	0.9409
Property Equity	0.7047%	0.9579%	1.2605%	1.3390%	1.2897%	1.3517%	0.9187	0.9171

4.3 Results pertaining to Hypothesis 2

Hypothesis 2 refers to the determinants of the tracking error of JSE-listed ETFs. The results of the multivariate linear regression models that regressed the tracking errors of the sampled JSE-listed ETFs against fund operating characteristics such as fund age, fund size and TER are summarised in the tables below. Hypothesis 2 was tested using four models with each model using tracking errors from the four different methods employed in quantifying the magnitude of the tracking error. All four models use the same fund operating characteristics (fund age, fund size and TER) summarised in Appendix 1.

Table 5 summarises the results for the four regression models. Panel 1 in Table 5 shows that results of the tracking error estimated from the E_{AD} method regressed on fund characteristics: fund age, fund size and TER. The estimated coefficient for TER is statistically significant at 1% while the estimated coefficient for fund age and fund size are statistically significant at the 5% level. The coefficient for fund age is less than zero while and the coefficient for TER is greater than zero, this is in line with expectation and therefore the null hypothesis can be rejected. However, contrary to expectation, the coefficient for fund size was greater than zero indicating a positive relationship.

The F Statistic for Model 1 exhibits statistical significance at the 1% level.

Panel 2 in Table 5 shows that results of the tracking error estimated from the ESD method regressed on fund characteristics: fund age, fund size and TER. The estimated coefficient for fund age is statistically significant at the 1% level, while both fund size and TER are significant at 10%. The model also predicts an inverse relationship between tracking error and fund age while fund size and TER both have a positive relationship. Therefore, the null hypothesis can be rejected.

The F statistic for Model 2 exhibits statistical significance at the 1% level.

The results, as expected, are similar to the results for the E_{AD} regression model.

Table 5: Results of EAD regression model

Panel 1: Result for regression Model 1			
Variables	*coefficient*	*t-stats*	*p - value*
Intercept	-8.259	-8.223	< 0.0001
Fund Age	-0.071	-2.644	0.012
LOG - Fund Size	0.132	2.402	0.022
TER	148.3	3.112	0.004
F Statistic	7.733		0.0004

Panel 2: Result for regression Model 2			
Variables	*coefficient*	*t-stats*	*p - value*
Intercept	-7.191	-6.405	< 0.0001
Fund Age	-0.088	-2.953	0.006
LOG - Fund Size	0.122	1.981	0.055
TER	90.1	1.691	0.100
F Statistic	4.554		0.0085

Panel 3: Result for regression Model 3			
Variables	*coefficient*	*t-stats*	*p - value*
Intercept	-7.174	-6.515	< 0.0001
Fund Age	-0.089	-3.037	0.004
LOG - Fund Size	0.124	2.055	0.047
TER	66.5	1.273	0.211
F Statistic	4.263		0.0115

Panel 4: Result for regression Model 4			
Variables	*coefficient*	*t-stats*	*p - value*
Intercept	1.414	2.856	0.007
Fund Age	0.036	2.744	0.009
LOG - Fund Size	-0.037	-1.362	0.182
TER	-69.4	-2.955	0.006
F Statistic	5.772		0.0026

Panel 3 in Table 5 shows that results of the tracking error estimated from the SER method regressed on fund characteristics: fund age, fund size and TER. The estimated coefficients for fund age is statistically significant at 1% while fund size is statistically significant the 5% level. The model also indicates that tracking error has an inverse and positive relationship with fund age and fund size respectively. Therefore, the null hypothesis can be rejected.

The F Statistic of Model 3 exhibits statistical significance at the 5% level.

Panel 4 in Table 5 shows that results of the tracking error estimated from the R^2 method regressed on fund characteristics: fund age, fund size and TER. The estimated coefficients for both fund age and TER are both statistically significant at the 1% level, while fund size is statistically significant at the 5% level. The model also predicts that tracking error has an inverse and positive relationship with TER and fund age respectively. Therefore, the null hypothesis can be rejected.

The F Statistic for Model 4 exhibits statistical significance at the 1% level.

It should be noted that the R^2 measure of tracking error is fundamentally different from the other three measures. The trackability improves as tracking error as measured by E_{AD}, E_{SD} and SER tends toward zero and deteriorates the further it gets from zero. On the contrary, the R^2 measure of trackability improves as tracking error tends towards 1 and deteriorates as trackability tends to zero. This is the reason why the fund size and TER coefficients are negative for the R^2 model and positive for the E_{AD}, E_{SD} and SER models.

4.4 Summary of the results

The calculated tracking errors resulting from the four different methods have been described. The results from each method show a persistence in tracking errors in the sampled JSE-listed ETFs. The results indicate that the mean of the tracking error for each of the sample ETFs, calculated using the E_{AD} and E_{SD} methods are statistically significant at the 5% level. The null hypothesis that tracking error = 0 can, therefore, be rejected. The results from the regression of the CAPM model methods i.e. the SER and R^2 methods followed a similar outcome. The tracking error from both methods indicates the presence of tracking error and the F-Statistics for the regression models shows statistical significance that indicates that the tracking errors are significantly different from zero.

The results from the four regression models suggest that all three estimators influence the tracking error of JSE-listed EFTs, and as expected, fund age has an inverse relationship with tracking error while the tracking error relationship with TER and fund size is positive.

The inverse relationship between tracking error and fund age means the older the fund (a proxy for the fund manager's experience), the better the trackability of the fund i.e. the smaller the tracking error. This means that funds that have been in existence longer post lower tracking errors and younger funds tend to have higher tracking errors. The four regression model tests confirmed the relationship between tracking error and fund age. The t-test was statistically significant across the four-regression model. The findings for fund age are supported by literature and are in line with expectations.

In the case of TER, the positive relationship predicted by the regression models means that funds with lower TER are expected to have a smaller tracking error compared to funds with higher TER. The findings from the regression models are in line with expectations and support the findings from other studies. The t-test for the predicted regression coefficient for TER was only found to be significant in only three models. However, it can be concluded that the result of the models supports the hypothesis that tracking error of JSE-listed ETFs is influenced by TER.

However, the expectation was that fund size would have an inverse relationship with tracking error because larger funds are expected to possess economies of scale and as such, should exhibit lower tracking errors. The findings from the four regression models are contrary to expectations and not in line with other studies, although three of the four regression models produced statistically significant t-test result for fund size coefficient of regression and the results consistently showed a positive relationship between tracking errors and fund size (i.e. the smaller the size of the fund, the smaller the tracking error) across the four regression models. This suggests that, contrary to evidence found in studies on other developed and emerging market ETFs, JSE-listed ETFs seem to exhibit a positive relationship between fund size and tracking error.

CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 Introduction

This chapter discusses the results in relation to the literature and the chapter is organised as follows: Section 5.2 and 5.3 discusses the results pertaining to hypotheses 1 and 2 respectively. The discussion of results is concluded in Section 5.4.

5.2 Discussion pertaining to Hypothesis 1

The results show that the returns of the ETFs diverge from the returns of their respective underling indices and that the divergence in the returns is statistically significant. The results also indicate that the measured tracking errors vary with asset classes, the frequency of observation upon which the tracking error calculation was based i.e. daily returns versus monthly returns and the method used in the tracking error calculation.

The result indicates that the tracking error of JSE-listed ETFs is line with other emerging markets. According to a comparative study by Chu (2011), using daily data and the same measures of tracking errors, he reported tracking errors using similar measures used in this study and the range of tracking error for each measure is as follows: E_{AD}: 0.2786% to 2.1736%, E_{SD}: 0.3942% to 3.5231%, SER: 0.3902% to 3.0923% and R^2: 0.0000 to 0.9417.

Other studies, such as Frino and Gallagher (2001) and Frino and Gallagher (2002), reported tracking error on a monthly basis, ranging from 0.039% to 0.110% for the US and 0.074% to 0.224% for Australia. Cresson et al. (2002), using the R^2 measure found tracking error to be within 0.9052 to 0.9609 for the S&P index funds while Frino and Gallagher (2001) reported 0.997 to 1.000 in US and 0.993 to 1.000 in Australia.

Strydom et al. (2015), in a South African study, reported tracking error on a monthly basis for three ETF funds tracking the JSE Top 40 Index and found tracking error for these funds to 0.2252% to 0.3835%, 0.2450% to 0.4163%, 0.2454% to 0.4215 and 0.9935 to 0.9980 for the EAD, ESD, SER, and R^2 respectively. The values are comparable to the results for this asset class as shown in the results.

The tracking error found in this study is invariably higher and even has a larger range tail compared to the tracking error reported by Chu (2011). This is probably due to the presence of other asset classes included in this study, as the other studies included only equity tracking ETFs.

As mentioned in Chapter 4, while analysing the results, it was noticed that there was a variability in tracking error with the different asset classes. This study posits that the consistency in tracking errors along asset classes is because of the different idiosyncratic characteristics of each asset class. The local equity and property equity asset classes seem to provide the best trackability of all the ETF asset classes, while the international equity and bond asset classes produced the worst trackability. These observations are consistent, regardless of the method used in calculating the tracking error and regardless of whether daily or monthly returns were used in calculating the error.

The study also found that the method used in calculating the tracking error produces a different magnitude of tracking errors. As mentioned in Chapter 3, the tracking error estimated from the E_{SD} and SER methods should be similar, particularly for the funds where the calculated beta values for the CAPM model is equal to or close to 1. The results from these two methods produced a tracking error greater in magnitude when compared with results from the EAD method. The higher magnitude in tracking error was also consistent regardless of whether daily or monthly returns were used in calculating the error.

The frequency of observation upon which the tracking error calculation was based i.e. daily returns versus monthly returns had some attributional effect on the results. The results consistently showed that the tracking errors calculated using monthly returns were greater in magnitude compared to ones calculated using daily data. This was similarly observed by Johnson et al. (2013). They found that on average, the tracking errors calculated on a monthly basis were higher than those calculated on a daily or weekly basis over the same period of time.

As explained in Chapter 3, the R^2 method is fundamentally different from the other three methods of evaluating tracking errors. A R^2 measure closer to 1 shows good trackability, while a measure closer to 0 shows a fund whose returns diverge greatly from the returns of its underlying index. The results are in consonance with the other three methods: local equity and property equity asset classes exhibit the best trackability of all the ETF asset classes and the attribution effect of the frequency of observation upon which the tracking error calculation was based.

The results indicate that it is pertinent for a fund manager to disclose the data frequency upon which the tracking error calculation was based, as well as the method used in the calculation when reporting tracking errors. These criteria affect the magnitude of a tracking error measure and it is essential when an investor is comparing EFT products that tracking error calculated using the basis is used.

The results also highlight the idiosyncratic nature of the JSE-listed ETFs, with locally based equity asset class, as well as property-equity EFTs, exhibiting better trackability compared to international and bond ETFs.

5.3 Discussion pertaining to Hypothesis 2

The results from the four regression models indicate that the three hypothesised estimators indeed influence the tracking error of JSE-listed ETFs. As expected, fund age and TER exhibited an inverse and positive relationship with tracking error respectively. The relationship between tracking error and fund size was expected to be inverse, but the result indicated a positive relationship.

Fund age is somewhat a proxy for the fund manager’s experience. This means that the more mature the fund, the better the trackability of the fund i.e. the smaller the tracking error. Funds that have been in existence for longer are expected to post lower tracking errors while younger funds are expected to have higher tracking errors. The four regression model tests confirmed the relationship between tracking error and fund age as hypothesised and as per other studies.

Funds with low TER are expected to have smaller tracking error compared with funds with higher TER. The results support this expectation as also found in previous studies.

However, the expectation was that fund size would have an inverse relationship with tracking error. According to Chu (2011), large funds possess economies of scale which help to negotiate better transaction cost thereby reducing the fund's overhead cost which invariably translates to a lower tracking error and as such, should exhibit lower tracking errors. The results from this study contradict this assertion and it rather supports a positive relationship between fund size and tracking error.

To put this outcome in context, a scatterplot of tracking error and fund size are shown in the diagrams below. Each diagram shows the relationship between each measure of tracking error and fund size.

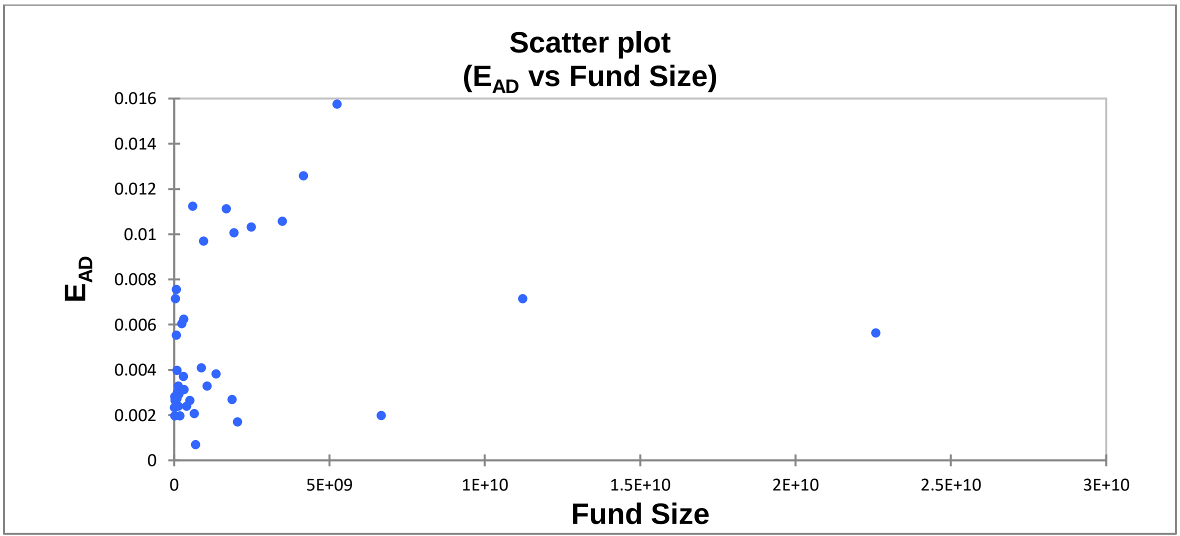

Figure 2: Showing the linearity of tracking error (from E_{AD} method) against fund size

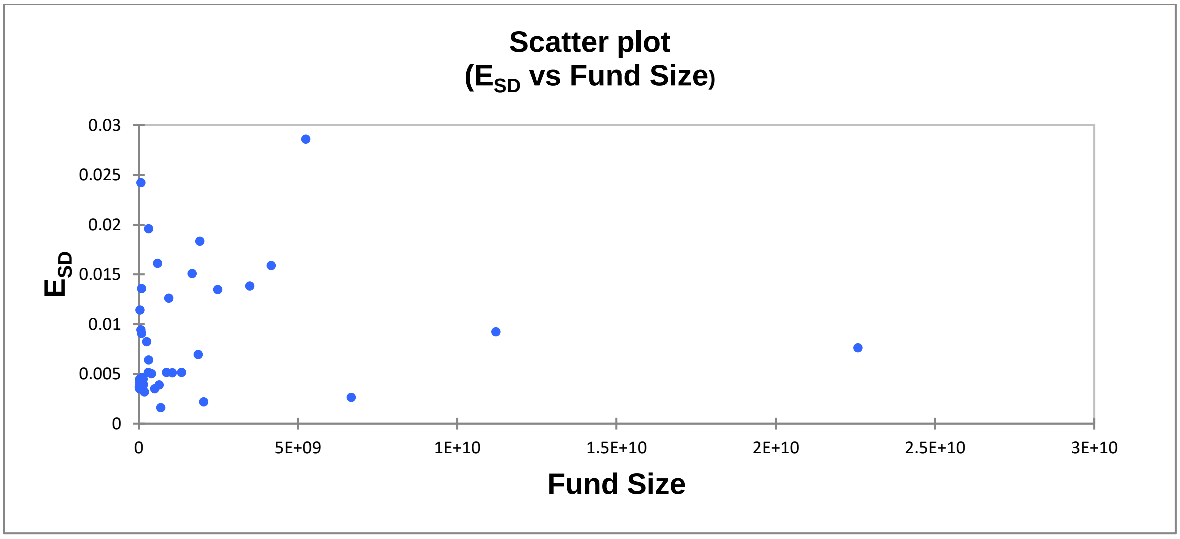

Figure 3: Showing the linearity of tracking error (from E_{SD} method) against fund size

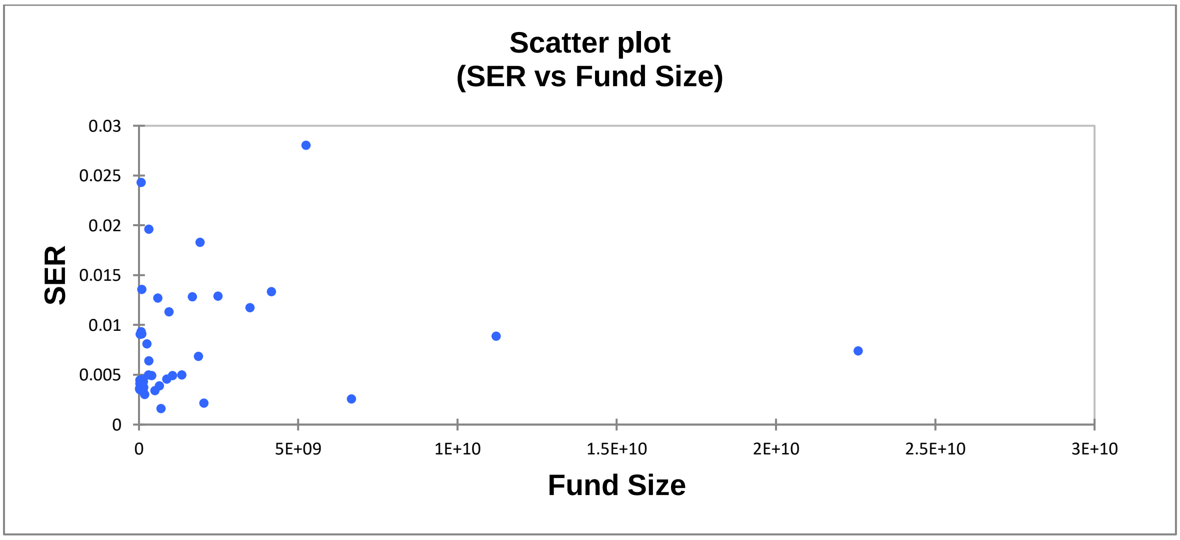

Figure 4: Showing the linearity of tracking error (from SER method) against fund size

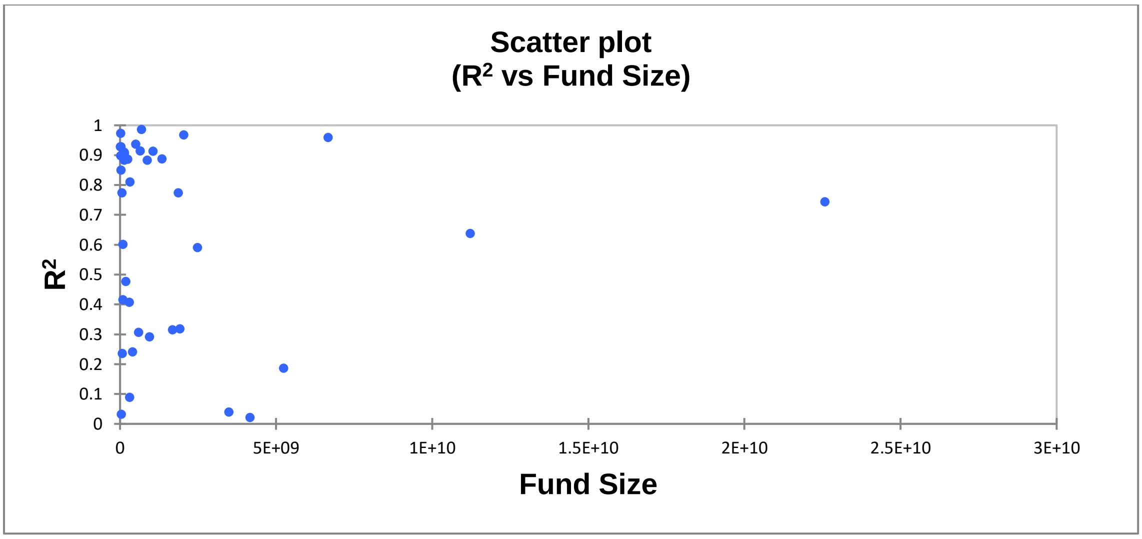

Figure 5: Showing the linearity of tracking error (from R^2 method) against fund size

The four diagrams show that there is no linear relationship between tracking error and fund size and as such the regression results cannot be conclusive for this particular fund operating characteristic. The scatterplots for fund age and TER are shown in Appendix B and these two fund characteristics exhibit linearity with tracking error.

The absence of linearity between tracking error and fund size is a departure from expectation and this could be attributed to the idiosyncratic structure of the ETF management in South Africa. Although each fund has a dedicated fund manager, many of the funds are under the umbrella of the investment arm of some of the South African financial institutions such as ABSA, FNB, Satrix, etc. Through visual inspection of fund data information for all the funds, it does not appear that there are funds that belong to managers who are outside the sphere of influence of these large financial institutions. This could be a probable explanation on why fund size does not influence tracking error.

5.4 Conclusion

JSE-listed ETFs exhibit tracking errors and the magnitude of the tracking errors is larger than those found in more developed financial markets, such as the US and

Australia. However, the magnitude of the tracking error is in line with those exhibited by ETFs in emerging markets. The magnitude of the tracking errors reported in this study is comparable to those reported by Chu (2011) for ETFs listed on the Hong Kong stock exchange.

The tracking error of JSE-listed ETFs is influenced by fund age and TER. The study found that funds that have been existence longer tend to have lower tracking error while younger funds are susceptible to higher tracking error. It can be inferred that as the fund manager becomes more adept in managing the fund, the competency level of minimising tracking error increases. As expected, fund managers are required to charge fees and these fees invariably reduce an investor’s return, albeit minimal in most cases. The study supports the fact the TER influences tracking errors in ETFs.

The study also tested the effects of the size of an ETF, as measured by its net asset value, and it was expected that larger funds should post lower tracking error as it is expected that size gives a fund manager scale as well as bargaining power to negotiate lower transaction cost that should translate to lower tracking error. Contrary to this, the results indicate a positive relationship between tracking error and fund size, meaning large funds have higher tracking error. It was however noticed that there was no linearity between tracking error and fund size. The author believes that the results indicate an idiosyncratic characteristic of the South African ETF structures, where a group of funds belong to the well-established financial institutions and all fund managers enjoy similar economies of scale and bargaining power, as such, has no moderating effect on the fund’s tracking error. It was therefore concluded that contrary to what was found in other markets, JSE-listed ETFs are not influenced by fund size. The results, however, support that JSE-listed ETFs are influenced by fund age and TER.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

This chapter summarises the findings of the research, compares the findings to other published research and provides the recommendations of the study. The chapter also provides suggestions for further research based on the findings of this work.

6.2 Conclusions of the study

The study concludes that JSE-listed ETFs exhibit tracking errors and the magnitude of the tracking errors are similar to those found in other emerging market ETFs. The study also found that the age of a fund and TER are some of the factors that influence tracking error of JSE-listed ETFs. Contrary to expectation, the size of the fund was found not to be a moderating factor.

The study found that the different measures of tracking error and the frequency of the returns data used in the estimation tend to affect the magnitude of the calculated tracking errors. The differences in the result from the four methods of calculating tracking error are consistent with the observation by other studies by Chu (2011), Johnson et al. (2013) and Strydom et al. (2015). The magnitude of the tracking error was found to increase with an increase in the frequency of observation i.e. tracking errors estimated from monthly return data produce higher tracking error compared to the one estimated from daily return data. The result is consistent with the findings by Johnson et al. (2013). This implies that ETF investors need to take cognisance of the basis used in estimating the tracking error, especially if is used in making investment decisions.

The study further found that the magnitude of the tracking errors also differs across asset classes. It was found that local equity and property equity tracking ETFs showed better trackability when compared to other asset classes such as bonds, commodities and local ETFs tracking foreign indices. This is probably due to the fact that local equity ETFs have been in existence longer compared to other ETFs tracking other asset classes, as the study by Strydom et al. (2015) found that funds in existence longer have the propensity to track their underlying indices better, compared to newer funds.

With regards to the determinants of tracking errors, the study concludes that fund age and TER are two of the factors that influence tracking error. The study also found that there is limited linearity between tracking error and fund size which was contrary to expectations and the findings of other comparative studies.

As expected, the study found that funds that have been in existence longer tend to have better tracking errors compared to younger funds. This implies that the experience of a fund manager at tracking an index improves over time. A similar observation was made in the study by Strydom et al. (2015) where they found that their sampled ETF population closely tracked their underlying indices over time.

Although the expense ratio of an ETF product is supposed to be lower compared to other active and passive investment products such as unit trusts and index funds, the presence of fees and other costs invariably reduces investment capital and as such, affects returns. The study supports this assertion and it was found that the higher the TER, the more the returns of the ETF diverge from the returns of the underlying index. This outcome is similar to the observations made by Frino and Gallagher (2001) and Chu (2011). As such, investors should be aware of the TER when selecting ETFs for investment because by their nature ETFs are supposed to have a beta that is close to 1 and as such, are not expected to earn returns greater that the market, therefore, TER should be an important criterion in selecting ETFs.

Finally, the size of the fund was found not to be a moderating determinant of tracking error. This finding was contrary to expectations and to the findings of comparative studies e.g. Chu (2011). It was therefore concluded that impact of fund size was less moderating because of the idiosyncratic structure of the South African ETF industry. Basically, the size of a fund provides a fund manager with better economies of scale and bargaining power to lessen the cost burden of the fund and as such, should translate to lower tracking error. In South Africa, the majority of the funds belong to well-established financial institutions such as FNB, ABSA, Standard Bank, Satrix, etc., as such, the author postulates that these institutions belong to the same strategic group and have similar attributes and structure. A strategic group is "a group of firms in an industry following the same or a similar strategy along the strategic dimension (Porter, 1980, p. 129)". This implies that since these funds are under the umbrella of these institutions, they are all likely to possess similar economies of scale and bargaining clout regardless of their respective size and as such the net effect of fund size is nullified.

6.3 Recommendations

The tracking error of an exchange traded fund is an important metric for both the fund manager and the investor. It indicates whether the fund manager is keeping up with the fund's mandate and it is also a proxy for fund performance. Only a few fund managers publish their fund's tracking error and fund manager that do publish them, do not indicate the calculation basis. Therefore, as a bare minimum, fund managers should be mandated to publish their tracking error along with the basis of the tracking error measure, as well as the frequency of the returns data from which it was derived. This is not only of value to existing investors but to prospective ones.

The absence of linearity between fund size and tracking error could mean that fund managers are not leveraging their size advantage to bring about better economies of scale and improved bargaining power for the fund. This is a signal of potential lack of competition within the industry. Regulatory authorities such as the South African Financial Services Board (FSB) and the JSE should promote policies that will spur better competitiveness among fund managers that benefit the market and attract more investors.

6.4 Suggestions for further research

Further research could include the following:

- Examine the reason why the size of JSE-listed ETFs has no moderating effect on their tracking errors.

- Investigation into the tracking error of JSE-listed exchange traded notes (ETN).
- Investigation into the determinants of JSE-listed exchange traded notes (ETN) tracking error.
- Investigation into the competitiveness of the South African exchange trade products industry.

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APPENDIX A

List of Sampled JSE-Listed ETFs and Fund Data

List of Sampled JSE-Listed ETFs and Fund Data

S/N	Fund	Full Name	Underlying Index	Fund Inception date	Fund Age (years)	AUM	TER
1	ASHT40	Ashburton Top 40 ETF	FTSE / JSE Top 40 index	16 October 2008	7.7	R 694 000 000	0.19%
2	STAN40	STANLIB Top 40 Fund	FTSE / JSE Top 40 index	18 October 2010	5.7	R 647 680 000	0.25%
3	STX40	Satrix 40 Portfolio	FTSE / JSE Top 40 index	27 November 2000	15.6	R 6 672 000 000	0.39%
4	NFSH40	NewFunds Shari'ah Top 40 ETF	FTSE / JSE Shari'ah 40 index	06 April 2009	7.2	R 68 989 340	0.28%
5	STXRAF	Satrix RAFI 40 Portfolio	FTSE / JSE RAFI 40 index	16 October 2008	7.7	R 876 000 000	0.52%
6	NFSWIX	NewFunds SWIX 40	FTSE / JSE SWIX 40 index	26 January 2012	4.4	R 15 981 570	0.33%
7	STANSX	STANLIB SWIX 40 Fund	FTSE / JSE SWIX 40 index	18 October 2010	5.7	R 1 868 870 000	0.32%
8	STXSWX	Satrix SWIX Top 40 Portfolio	FTSE / JSE SWIX 40 index	10 April 2006	10.2	R 502 000 000	0.43%
9	CSEW40	CoreShares Equally Weighted Top 40	FTSE / JSE Equally Weighted Top 40 index	25 March 2010	6.3	R 317 324 755	0.31%
10	CGREEN	CoreShares Green	Nedbank Green Index	01 December 2011	4.5	R 43 202 243	0.48%
11	CTOP50	CoreShares Top 50	S&P South Africa 50 Index	13 May 2015	1.1	R 139 409 062	0.32%
12	DIVTRX	CoreShares DivTrax	S&P South Africa Dividend Aristocrats Index	14 April 2014	2.2	R 101 058 822	0.39%

S/N	Fund	Full Name	Underlying Index	Fund Inception date	Fund Age (years)	AUM	TER
13	LVLTRX	CoreShares LowVolTrax	S&P South Africa Low Volatility Index	14 April 2014	2.2	R 29 938 768	0.41%
14	PREFTX	CoreShares PrefTrax	FTSE/JSE Preference Share Index	28 March 2012	4.3	R 303 873 668	0.57%
15	GIVISA	NewFunds S&P GIVI SA Top 50 ETF	S&P GIVI SA Top 50 Index	23 June 2008	8.0	R 93 731 533	0.13%
16	GIVFIN	NewFunds S&P GIVI SA Financial 15 ETF	S&P GIVI SA Financials Index	15 June 2009	7.0	R 31 832 883	0.14%
17	GIVIND	NewFunds S&P GIVI SA Industrial 25 ETF	S&P GIVI SA Industrials 25 Index	15 June 2009	7.0	R 26 600 425	0.14%
18	GIVRES	NewFunds S&P GIVI SA Resource 15 ETF	S&P GIVI SA Resources Index	15 June 2009	7.0	R 19 246 044	0.15%
19	ASHMID	Ashburton MidCap ETF	FTSE/JSE MidCap Index	15 August 2012	3.8	R 135 000 000	0.80%
20	STXDIV	Satrix DIVI Plus Portfolio	FTSE/JSE DIVI Plus Index	29 August 2007	8.8	R 1 348 000 000	0.39%
21	STXFIN	Satrix FINI Portfolio	FTSE / JSE Financial 15 Index	08 February 2002	14.3	R 1 058 000 000	0.39%
22	STXIND	Satrix INDI Portfolio	FTSE / JSE Industrial 25 Index	08 February 2002	14.3	R 2 039 000 000	0.40%
23	STXRES	Satrix RESI Portfolio	FTSE / JSE Capped Resources 10 Index	10 April 2006	10.2	R 248 000 000	0.36%
24	DBXEU	Db x-trackers DJ eu ST 50	EURO STOXX 50 Index	10 October 2005	10.7	R 1 682 640 000	0.86%

S/N	Fund	Full Name	Underlying Index	Fund Inception date	Fund Age (years)	AUM	TER
25	DBXJP	Db x-trackers MSCI Japan	MSCI Japan Index	01 April 2008	8.2	R 594 540 000	0.86%
26	DBXUK	Db x-trackers FTSE 100	FTSE 100 Index	10 October 2005	10.7	R 950 454 000	0.86%
27	DBXUS	Db x-trackers Col in USA	MSCI USA Index	01 April 2008	8.2	R 4 166 190 000	0.86%
28	DBXWD	Db x-trackers Col in Wld	MSCI World Index	01 April 2008	8.2	R 3 488 400 000	0.68%
29	ASHINF	Ashburton Inflation ETF	South African Government Inflation-Linked Bond Index	19 May 2009	7.1	R 400 700 000	0.45%
30	NFILBI	NewFunds Inflation Linked Bond Index ETF	South African Government Inflation-Linked Bond Index	26 January 2012	4.4	R 184 675 603	0.38%
31	NFGOVI	NewFunds GOVI ETF	South African Government Bond Total Return Index	26 January 2012	4.4	R 310 059 163	0.28%
32	ETFGLD	AfricaGold ETF	Gold Spot	07 April 2014	2.2	R 72 180 000	0.25%
33	ETFPLD	AfricaPalladium ETF	Palladium Spot	24 March 2014	2.3	R 5 243 392 000	0.35%
34	ETFPLT	AfricaPlatinum ETF	Platinum Spot	07 April 2014	2.2	R 1 924 944 000	0.30%
35	GLD	New Gold ETF	Gold Spot	01 November 2004	11.6	R 22 584 198 976	0.40%
36	NGPLD	New Palladium ETF	Palladium Spot	27 March 2014	2.3	R 2 484 557 284	0.40%
37	NGPLT	New Platinum ETF	Platinum Spot	26 April 2013	3.2	R 11 219 057 411	0.40%

S/N	Fund	Full Name	Underlying Index	Fund Inception date	Fund Age (years)	AUM	TER
38	PTXSPY	CoreShares PropTrax SAPY	FTSE/JSE SA Listed Property Index	25 September 2007	8.8	R 151 214 099	0.57%
39	STPROP	STANLIB SA Property ETF	FTSE/JSE SA Listed Property Index	13 February 2013	3.3	R 90 310 000	0.39%

APPENDIX B

Multiple Regression Model Results

Result of E_{AD} Regression Model

Regression equation:

$$|E_{AD}| = \beta_0 + \beta_1 * FA_{i,t} + \beta_2 * FS_{i.t} + \beta_3 * TER_{i,t} + \varepsilon_{i,t}$$

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
LOG - EAD	39	-7.280	-4.151	-5.499	0.694
Fund Age	39	1.100	15.600	6.744	3.653
LOG - Fund Size	39	16.587	23.841	19.846	1.856
TER	39	0.001	0.009	0.004	0.002

R^2	0.399
Adjusted R^2	0.347

Analysis of variance (LOG - EAD):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	3	7.296	2.432	7.733	**0.0004**
Error	35	11.006	0.314		
Corrected Total	38	18.302			

Model parameters (LOG - EAD):

Source	Value	Standard error	t	Pr > |t|
Intercept	-8.259	1.004	-8.223	**< 0.0001**
Fund Age	-0.071	0.027	-2.644	**0.012**
LOG - Fund Size	0.132	0.055	2.402	**0.022**
TER	148.272	47.643	3.112	**0.004**

Result of E_{SD} Regression Model

Regression equation:

$$|E_{SD}| = \beta_0 + \beta_1 * FA_{i,t} + \beta_2 * FS_{i.t} + \beta_3 * TER_{i,t} + \varepsilon_{i,t}$$

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
LOG - ESD	39	-6.448	-3.556	-4.997	0.709
Fund Age	39	1.100	15.600	6.744	3.653
LOG - Fund Size	39	16.587	23.841	19.846	1.856
TER	39	0.001	0.009	0.004	0.002

R^2	0.281
Adjusted R^2	0.219

Analysis of variance (LOG - ESD):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	3	5.368	1.789	4.554	**0.009**
Error	35	13.750	0.393		
Corrected Total	38	19.118			

Model parameters (LOG - ESD):

Source	Value	Standard error	t	Pr > |t|
Intercept	-7.191	1.123	-6.405	**< 0.0001**
Fund Age	-0.088	0.030	-2.953	**0.006**
LOG - Fund Size	0.122	0.061	1.981	0.055
TER	90.063	53.251	1.691	0.100

Result of SER Regression Model

Regression equation:

$$|E_{SER}| = \beta_0 + \beta_1 * FA_{i,t} + \beta_2 * FS_{i.t} + \beta_3 * TER_{i,t} + \varepsilon_{i,t}$$

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
LOG - SER	39	-6.445	-3.575	-5.042	0.689
FA	39	1.100	15.600	6.744	3.653
LOG - Fund Size	39	16.587	23.841	19.846	1.856
TER	39	0.001	0.009	0.004	0.002

R^2	0.268
Adjusted R^2	0.205

Analysis of variance (LOG - SER):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	3	4.834	1.611	4.263	**0.011**
Error	35	13.228	0.378		
Corrected Total	38	18.061			

Model parameters (LOG - SER):

Source	Value	Standard error	t	Pr > |t|
Intercept	-7.174	1.101	-6.515	**< 0.0001**
FA	-0.089	0.029	-3.037	**0.004**
LOG - Fund Size	0.124	0.060	2.055	**0.047**
TER	66.485	52.230	1.273	0.211

Result of R^2 Regression Model

Regression equation:

$$|E_{R2}| = \beta_0 + \beta_1 * FA_{i,t} + \beta_2 * FS_{i.t} + \beta_3 * TER_{i,t} + \varepsilon_{i,t}$$

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
R^2	39	0.021	0.985	0.636	0.324
FA	39	1.100	15.600	6.744	3.653
LOG - Fund Size	39	16.587	23.841	19.846	1.856
TER	39	0.001	0.009	0.004	0.002

R^2	0.331
Adjusted R^2	0.274

Analysis of variance (R^2):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	3	1.323	0.441	5.772	**0.003**
Error	35	2.674	0.076		
Corrected Total	38	3.997			

Model parameters (R^2):

Source	Value	Standard error	t	Pr > |t|
Intercept	1.414	0.495	2.856	**0.007**
FA	0.036	0.013	2.744	**0.009**
LOG - Fund Size	-0.037	0.027	-1.362	0.182
TER	-69.404	23.484	-2.955	**0.006**

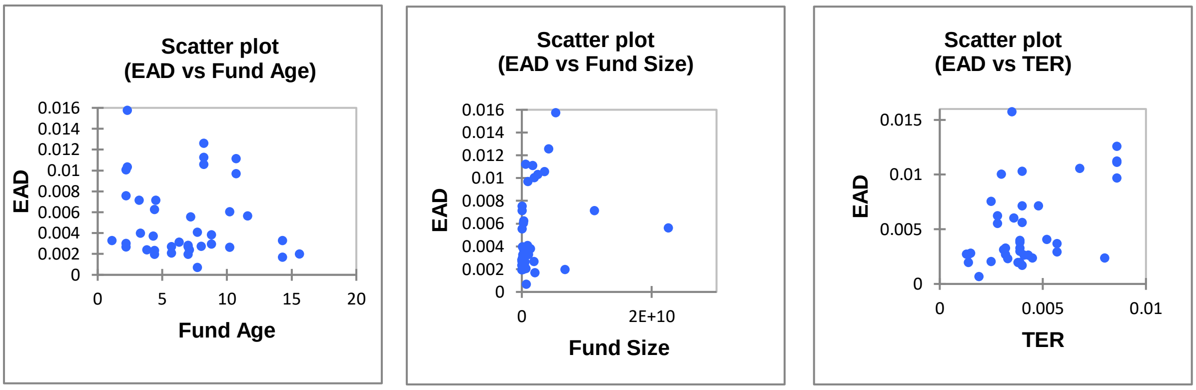
APPENDIX C

Analysis of Regression Variables

The key assumptions upon which linear regression models are based include:

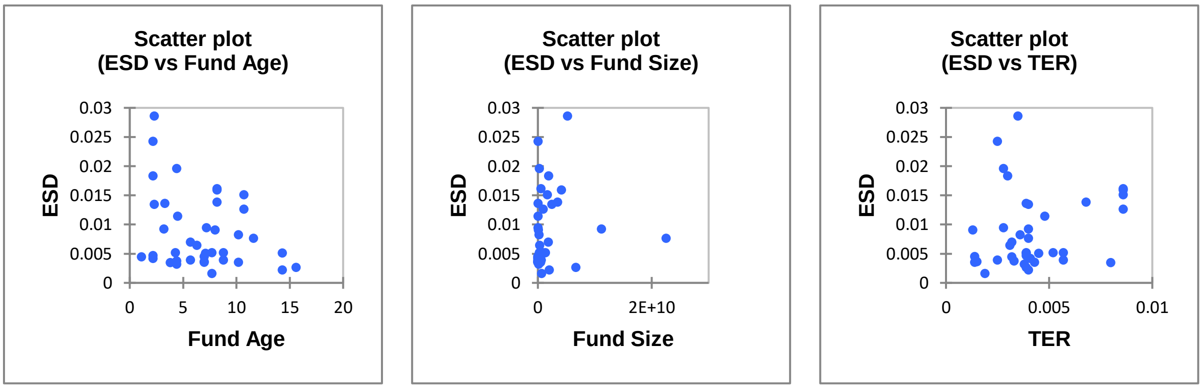
1. The linearity of the relationship between the dependent variable and independent variables.
2. Normality of the regression variables
3. Normality of the residual or errors of regression.
4. The absence of or minimal collinearity between the regression variables.
5. Autocorrelation and
6. Homoscedasticity i.e. the variance in the residual or error term is equal across all observations.

Firstly, the linearity of the regression data was analysed using scatterplots. The scatterplots below, show the relationship between each of the measure of tracking error against the independent variables: fund age, fund size and total expense ratio. By visual inspection, the four measures of tracking errors have a strong linear relationship with both fund age and TER. The fund size plots, however, show no clear relationship between any of the four measures of tracking error and it seems to have outliers which could affect the regression result for this variable.



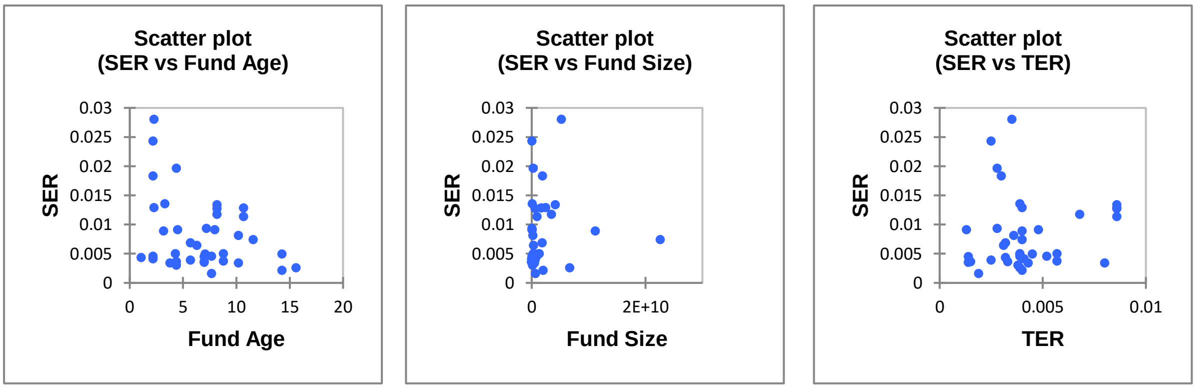
(A) (B) (C)

Showing the linearity of tracking error EAD against independent variable (A) fund age (B) fund size and (C) total expense ratio



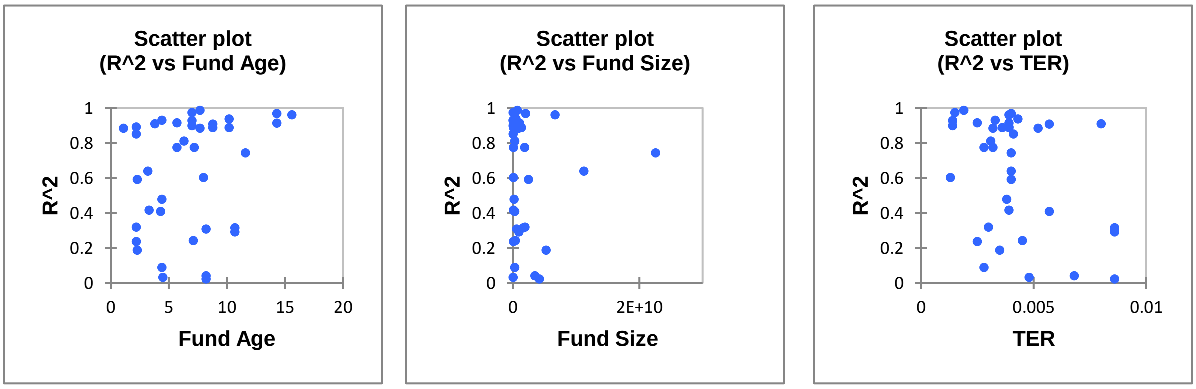
(A) (B) (C)

Showing the linearity of tracking error ESD against independent variables (A) fund age (B) fund size and (C) total expense ratio



(A) (B) (C)

Showing the linearity of tracking error SER against independent variables (A) fund age (B) fund size and (C) total expense ratio



(A) (B) (C)

Showing the linearity of tracking error R^2 against independent variable (A) fund age (B) fund size and (C) total expense ratio

Secondly, the distribution of the dependent and independent variables was tested for normality using the Kolmogorov-Smirnov test as well as a fitted normal curve. The null hypothesis of the Kolmogorov-Smirnov is that the sample is normally distributed. In the event the test returns a statistically significant result; the null hypothesis would be rejected and the alternate hypothesis, that the sample is not normally distributed, is accepted. The Kolmogorov-Smirnov test results for the dependent variables for each of the four models are presented in table below, while the common independent variables are shown in figure below. The fitted normal curves for the variables are also shown below.

Normality test for regression model dependent variables

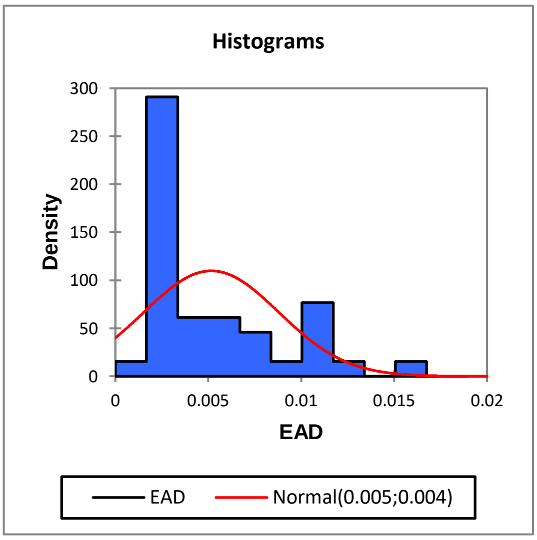
	Skewness	Kurtosis	Kolmogorov-Smirnov (Sig.)
EAD	1.078	0.108	0.025**
ESD	1.24	0.894	0.035**
SER	1.453	1.688	0.045**
R^2	-0.59	-1.238	0.044**

*** denote test statistical significance at the 5% level.*

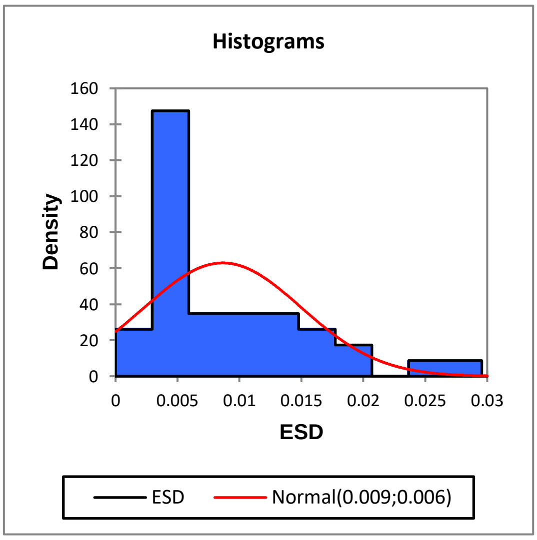
Normality test for the common regression model independent variables

	Skewness	Kurtosis	Kolmogorov-Smirnov (Sig.)
Fund Age	0.527	-0.395	0.611
Fund Size	3.72	15.062	0.0004**
TER	0.904	0.069	0.051

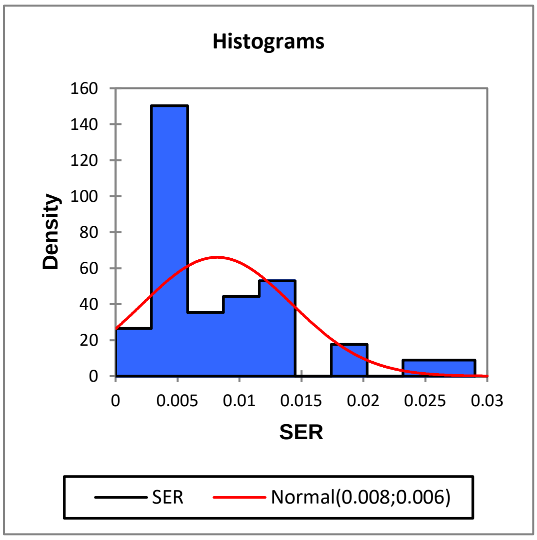
*** denote test statistical significance at the 5% level.*

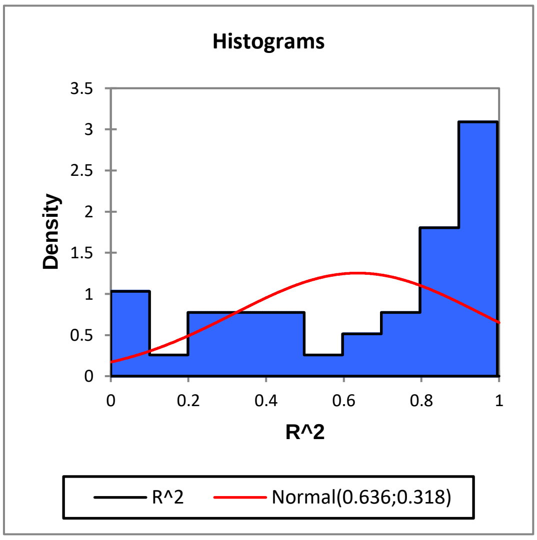


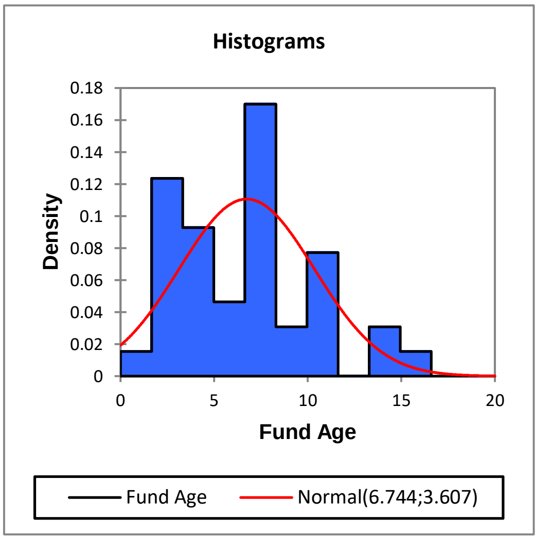
(A)

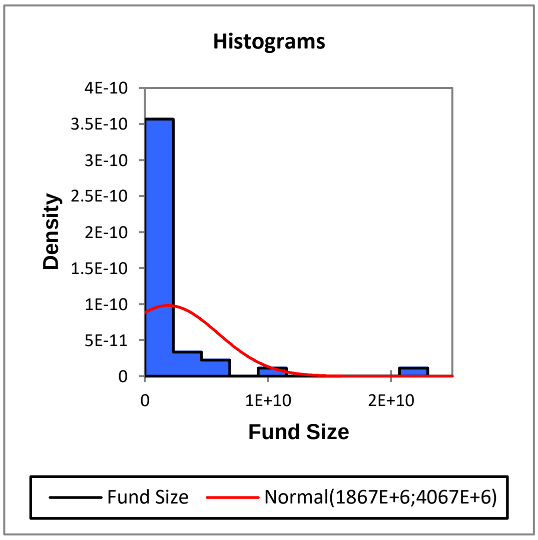


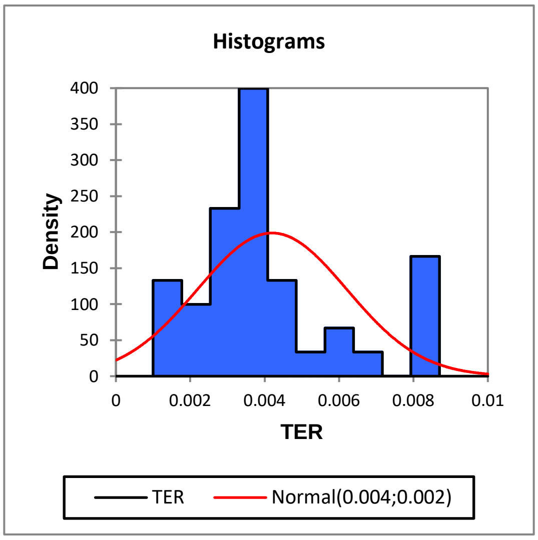
(B)


Histograms
Density
SER
SER
Normal(0.008;0.006)
(C)


Histograms
Density
R^2
R^2
Normal(0.636;0.318)
(D)


Histograms
Density
Fund Age
Fund Age
Normal(6.744;3.607)
(E)


Histograms
Density
Fund Size
Fund Size
Normal(1867E+6;4067E+6)
(F)



(G)

Frequency distribution of regression variables (A) Tracking error EAD (B) Tracking error ESD (C) Tracking error SER (D) tracking error R^2 (E) fund age (F) fund size (G) TER

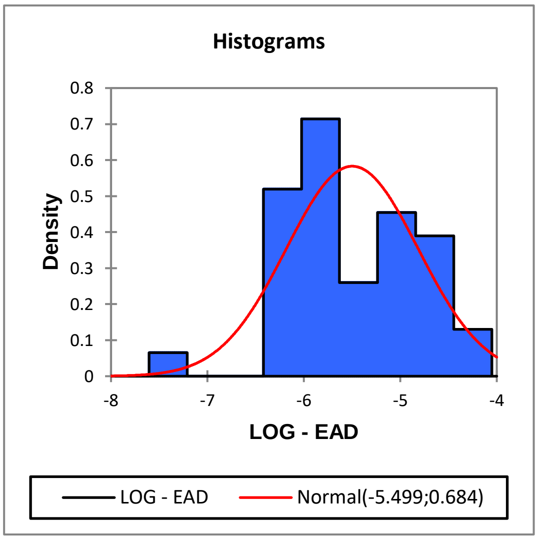
The Kolmogorov-Smirnov tests and the fitted curves show that all the dependent variables, EAD, ESD, SER and R^2, and independent variable, fund size, are all skewed and not normally distributed. On the other hand, independent variables, fund age and TER are to some extent normally distributed.

Log transformation of skewed data helps to improve the skewness of the data (Benoit, 2011). Therefore, the data for the four dependent variables along with fund size were log transformed to obtain a more normal distribution. To test the normality of the transformed data, Kolmogorov-Smirnov tests and fitted normal curves were generated for the transformed data. The Kolmogorov-Smirnov tests for the log transformed variables and the fitted normal curves for the transformed variables are shown below.

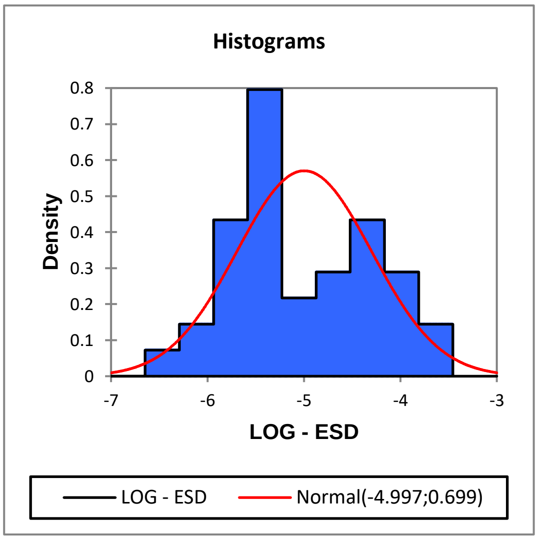
Normality test for transformed regression model variables

	Skewness	Kurtosis	Kolmogorov-Smirnov (Sig.)
Log EAD	0.059	-0.532	0.4
Log ESD	0.189	-0.959	0.215
Log SER	0.237	-0.799	0.225
Log R^2	-1.744	2.254	0.020**
Log Fund Size	0.102	-0.902	0.987

*** denote test statistical significance at the 5% level.*



(A)



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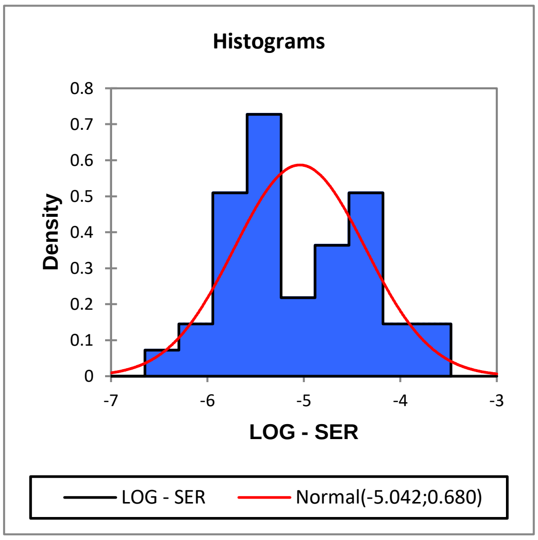

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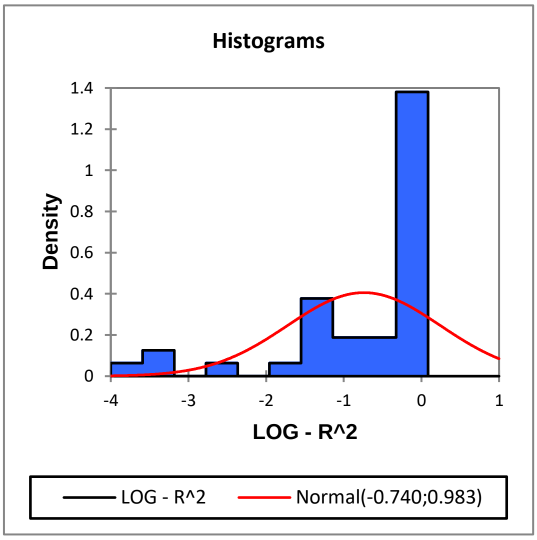
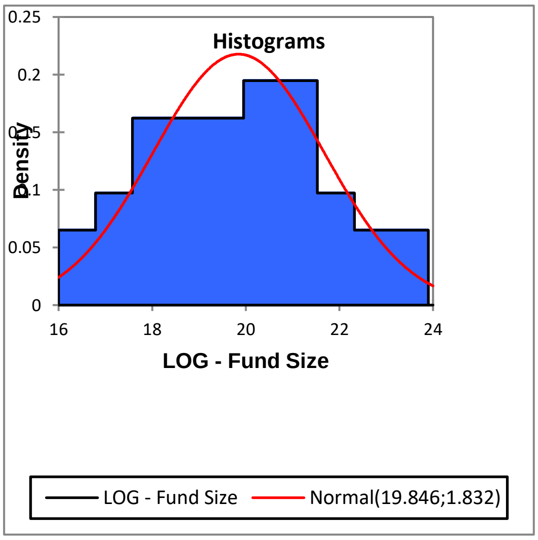


(D)



(E)

Frequency distribution of transformed regression variables (A) log of tracking error EAD (B) log of tracking error ESD (C) log of tracking error SER (D) log of tracking error R^2 (E) log of fund size

The results show that the log transformation of the variables has improved the skewness of the data and they appear to be more normally distributed. However, the skewness of the log transformed R^2 has further deteriorated. Therefore, the untransformed R^2 was used in the regression.

Thirdly, the linear regression model assumes that there is little or no relationship between independent variables (Gujarati, 2012). This means that the independent variables; fund age, fund size and total expense ratio should be independent of each other. The consequence of the variables exhibiting a high degree of collinearity would result in large variance and covariance that would substantially affect the estimation of the regression coefficients. This could also render some of the predicted regression coefficients to be statistically insignificant. A correlation matrix for each of the model and the variance inflation factor (VIF) for each of the variables were calculated to determine the extent of multicollinearity of each model. VIF refers to the “measure of the degree to which the variance of the regression estimator is inflated because of collinearity”. The average VIF for each model was also calculated.

Correlation matrix for regression model 1 - EAD

	Fund Age	LOG - Fund Size	TER	LOG - EAD
Fund Age	**1**	0.356	0.201	-0.159
LOG - Fund	0.356	**1**	0.341	0.368
TER	0.201	0.341	**1**	0.481
LOG - EAD	-0.159	0.368	0.481	**1**

Correlation matrix for regression model 2 - ESD

	Fund Age	LOG - Fund Size	TER	LOG - ESD
Fund Age	1	0.356	0.201	-0.289
LOG - Fund Size	0.356	1	0.341	0.244
TER	0.201	0.341	1	0.276
LOG – ESD	-0.289	0.244	0.276	1

Correlation matrix for regression model 3 - SER

	FA	LOG - Fund Size	TER	LOG - SER
FA	**1**	0.356	0.201	-0.314
LOG - Fund Size	0.356	**1**	0.341	0.232
TER	0.201	0.341	**1**	0.215
LOG – SER	-0.314	0.232	0.215	**1**

Correlation matrix for regression model 2 – R^2

	FA	LOG - Fund Size	TER	R^2
FA	**1**	0.356	0.201	0.245
LOG - Fund Size	0.356	**1**	0.341	-0.214
TER	0.201	0.341	**1**	-0.426
R^2	0.245	-0.214	-0.426	**1**

The correlation matrix for each of the regression models show correlation coefficients that are less than 1, hence it can be concluded that there is little collinearity between the variables. Furthermore, the correlation matrices shown above in indicate that the dependent variable has an inverse relationship with fund age and a positive relationship with both fund size and TER. Also, as expected, the correlation matrix indicate that the relationship between R^2 and the independent variable is opposite to the relationship between EAD, ESD and SER and their respective independent variable. This is in line with expectation and literature as R^2 measure of tracking error is the inverse of the other measures of tracking error.

Tolerance and variance inflation factor for the common regression independent variables

	Tolerance	VIF
Fund Age	0.866	1.155
LOG - Fund Size	0.798	1.254
TER	0.877	1.141
Average		**1.183**

According to Montgomery (2001), when the VIF values exceed 5 or 10, it implies that there is collinearity among the regression variables. It is also a rule of thumb that the average VIF should be close to unity. The table above shows an average VIF of 1.183. Based on the results above, it can be concluded that the models are not susceptible to inaccuracies due to multicollinearity.

Fourthly, the data were checked to see whether the data are autocorrelated. Time series data is susceptible to autocorrelation and in this case, it refers existence of a correlation between the residuals of observations in a regression model. The presence of autocorrelation was tested for each of the models using the Durbin-Watson (D-W) test. The null hypothesis for the (D-W) is that autocorrelation is present, while the alternative hypothesis is the absence thereof. The table below shows the results of the D-W tests for each of the models.

	Durbin-Watson Statistic	p-Value
EAD	1.294	0.006
ESD	1.318	0.007
SER	1.311	0.007
R^2	1.289	0.005

The test shows the presence of autocorrelation for each of the models but according to Field (2009), a D-W statistic closer to 2 can be conservatively acceptable although may still be problematic. However, values less than 1 or greater than 3 should be avoided. In this case, the values are greater than 1 and it is assumed that the effects of autocorrelation are minimal.

Lastly, the data was tested for homoscedasticity. The linear regression model assumes that the residuals of a regression model are homoscedastic i.e., the variance in the error term is equal across all observations. In the absence of homoscedasticity (the presence of heteroscedasticity), the regression models would produce unreliable results such that the statistical significance of the estimates regression coefficient produced that model would be inaccurate and cannot be trusted.

The Breusch-Pagan and White's tests were used to test the presence of heteroscedasticity in each of the regression models. The null hypothesis for both tests is that the error variance of the regression is homoscedastic while the alternate hypothesis is that the errors are heteroscedastic. The results of the Breusch-Pagan and White's tests are shown below.

Homoscedasticity test results for the four regression models

Model	Breusch-Pagan Test (Sig.)	White's test (Sig.)
EAD	0.896	0.06
ESD	0.375	0.031**
SER	0.368	0.044**
R^2	0.043**	0.133

*** denote test statistical significance at the 5% level.*

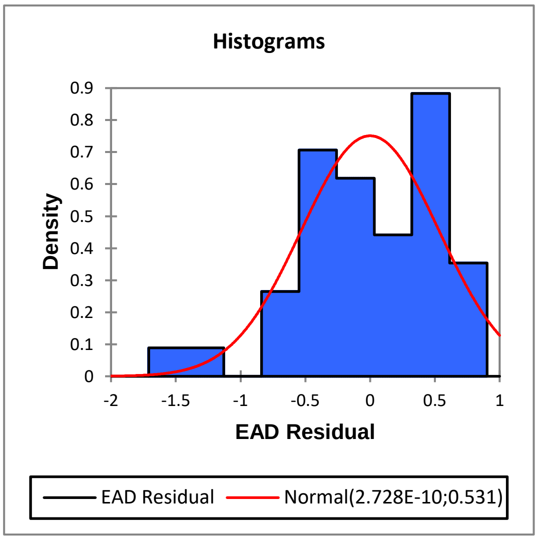
The results for EAD is consistent across both tests while only one of the tests confirmed the absence of heteroscedasticity in ESD, SER and R^2. Despite the inconsistence between the p-values reported for the tests on the ESD, SER and R^2, it can be concluded that the residuals of the four-models are homoscedastic.

It is also important to check the normality of the residuals. This is a critical assumption of regression analysis. The residuals are the differences between the expected and predicted values. They are sort of the unexplained variation in the data that is unexplained by the fitted regression model. As such, it is expected that distribution of the residuals is normal and independently distributed with a mean of 0 and with a constant variance. Non-conformance with these conditions means that there are elements within the residuals that are not accounted for in the regression model.

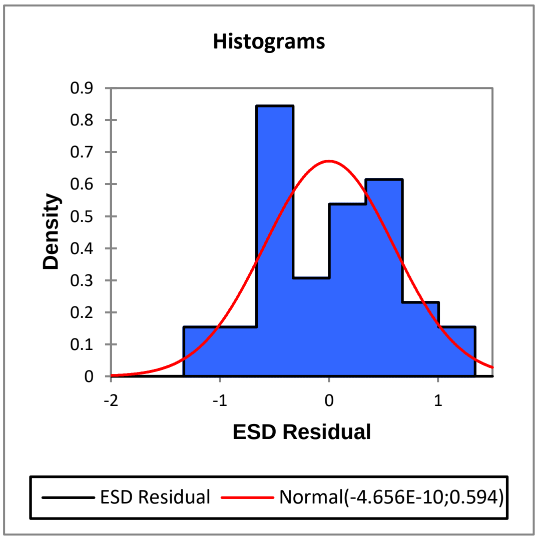
Therefore, to ensure that the residuals for each model are normally distributed, The Kolmogorov-Smirnov test was carried out on the regression residuals along with a fitted normality curve.

Normality tests for the residuals of the four regression models

Residual of regression model	Skewness	Kurtosis	Kolmogorov-Smirnov (Sig.)
EAD	-0.493	-0.26	0.719
ESD	0.015	-0.887	0.814
SER	0.07	-0.842	0.79
R^2	-0.3	-0.406	0.88



(A)



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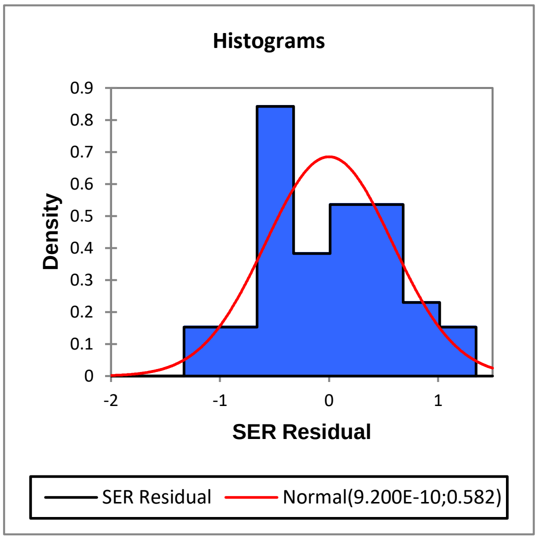

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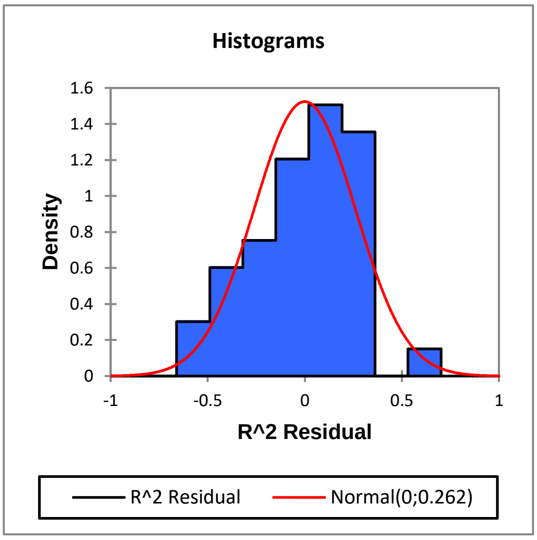

(D)

Test for normality of regression residual (A) frequency distribution of EAD regression residuals (B) frequency distribution of ESD regression residuals (C) frequency distribution of SER regression residuals (D) frequency distribution of R^2 regression residuals

The results of the Kolmogorov-Smirnov tests are not significant at the 5% level, therefore, the null hypothesis that the residuals are normally distributed cannot be rejected. This conclusion is also supported by the fitted normal distribution curves for the residuals shown above.

Based on the above analyses, the assumptions for linear multiple regression models have been fulfilled. The relationship between the dependent variable and the independent variables appears to be linear for each of the models, the risk of heteroscedasticity and multicollinearity are remote. Although some of the variables were skewed and not normally distributed, the log transformation of the skewed variables has improved the normal distribution of the data.

APPENDIX D

Consistency matrix

Consistency matrix

Research problem stated here: The purpose of the research is to examine the tracking errors of exchange-traded funds (ETFs) listed on the Johannesburg Stock Exchange (JSE) for different asset classes as well as the factors influencing the tracking errors. **Research design:** Quantitative analysis					
Sub-problem	**Literature Review**	**Hypotheses**	**Source of data**	**Type of data**	**Analysis**
The study seeks to determine how closely exchanged-trade funds listed on the JSE match their underlining index.	Cresson et al. (2002); Chu (2011); Kosev and Williams (2011); Strydom et al. (2015); Hill et al. (2015)	JSE-listed ETFs exhibit tracking errors and the magnitude of the tracking errors are similar to those exhibited by other emerging markets.	Stock market data from Bloomberg database terminal.	Numerical data	Descriptive statistical and regression analysis.
The study seeks to identify possible factors responsible for the tracking error between the returns of an exchange traded fund and its underlining index.	Chu (2011), Cresson et al. (2002), Drenovak et al. (2014), Pope and Yadav (1994), Blitz and Huij (2012)	Fund size, total expense ratio and fund age fluctuations are the determinants of JSE-listed ETFs tracking errors.	Stock market data from Bloomberg database terminal.	Numerical data	Descriptive statistical and regression analysis.