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The impact of Exchange Traded Funds on the microstructure of their constituent shares: A South African case

By

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DECLARATION

I, Faeezah Peerbhai declare that

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DEDICATION

For my two girls, Alaynah and Aria. The unseen costs of this project were borne mostly by you, but my hope is that as you grow older, it serves as a source of inspiration, and a lesson in ambition, persistence, and resilience.

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"So which of the favours of your Lord will you deny?"

Quran, Surah Ar-Rahman, 55:13

My greatest gratitude goes to my Creator, Whose vision for my life has always been much greater than my imagination can comprehend, Who has surrounded me with a loving and motivating support system, and Who has gifted me with my two greatest inspirations in life: my daughters.

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ABSTRACT

The creation of the Exchange Traded Fund (ETF) has revolutionised the global asset management industry since its inception three decades ago, with the result that this investment product has propelled passively managed products to the forefront of the financial market. Whilst the superficial benefits and costs to this product are often debated, the potential impact of these investment assets on the microstructure elements of the financial market, and thus its overall impact on market stability, is less well known. The necessity for a greater understanding of the potential positive or detrimental impacts of this asset class on market operation has been the driving force in recent international developments in this field. This study therefore aims to fill this gap in the literature, by evaluating the impact of ETF-related market activities, on the microstructure elements of information efficiency, and liquidity of the South African equity market.

The analysis of liquidity aims to evaluate the influence of ETF introduction on the relative liquidity of its underlying assets. The sample therefore consists of 147 JSE-listed firms which are the constituents to the 23 JSE-listed, domestic equity ETFs that were listed between 2006 and 2019. In contrast, the informational efficiency analysis attempted to examine the impact of ETF ownership and trade, on the efficiency of its underlying constituents, and this analysis therefore makes use of 94 underlying JSE-listed firms, which are included in a sample of both domestic and international ETF between the periods of 2009 to 2019. The research methods made use of the event study approach, fixed effect panel data estimations, and the Generalised Method of Moments (GMM) estimation method.

The results produced largely find support for Merton's (1987) hypothesis, that the inclusion of a company into the ETF, increases investor awareness, which thus facilitates further informed trading in the underlying asset. This is evidenced by findings of improved liquidity and information efficiency in the underlying constituents to the ETFs surveyed, with the smaller, less well-known companies in the analysis enjoying the benefits of ETF membership more. The study therefore concludes that the evidence of improved market function and stability due to ETFs, is beneficial for investors who usually face adverse portfolio effects due to the high concentration of large firms on the JSE. Therefore regulators should actively encourage growth in this market by relaxing current pension fund regulations, and revising the taxation environment for ETFs to allow this asset class to become more competitive relative to the actively managed fund industry in South Africa.

Keywords: Exchange Traded Funds, South Africa, liquidity, information efficiency, synchronicity, JSE.

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LIST OF ACRONYMS

2SLS:	2 Stage Lease Squares
3SLS:	3 Stage Lease Squares
ALSI:	All Share Index
AMEX:	American Stock Exchange
AP:	Authorized Participant
AR:	AutoRegressive
BATS:	Better Alternative Trading System
CAPM:	Capital Asset Pricing Model
CIS:	Collective Investment Schemes
CISCA:	Collective Investment Schemes Act
DIAMONDS:	Dow Jones Industrial Average 30
DJIA:	Dow Jones Industrial Index
EIV:	Error- in-variables
EMH:	Efficient Market Hypothesis
EPS:	Earnings Per Share
ERC:	Earnings Response Coefficient
ERSB:	European Systemic Risk Board
ETF:	Exchange Traded Fund
FAIS:	Financial Advisory and Intermediary Services Act
FE:	Fixed Effects
FERC:	Future Earnings Response Coefficient
FGLS:	Feasible Generalised Least Squares
FICA:	Financial Intelligence Centre Act
FSB:	Financial Services Board
FSCA:	Financial Sector Conduct Authority
GMM:	Generalised Method of Moments
HHI:	Herfandihl Hirschman Index
ICI:	Investment Company Institute
IIV:	Intraday Indicative Value
IMF:	International Monetary Fund
iNAV:	Intraday Net Asset Value
IPO:	Initial Public Offer
IS:	Implementation Shortfall
IV:	Instrumental Variable
JSE:	Johannesburg Stock Exchange

LIBOR:	London InterBank Overnight Rate
LP:	Liquidity Providers
MSCI:	Morgan Stanley Capital International
MTB:	Market to Book Ratio
NASDAQ:	National Association of Securities Dealers Automated Quotations
NAV:	Net Asset Value
NYSE:	New York Stock Exchange
OEF:	Open-Ended Funds
OFR:	Office of Financial Research
OLS:	Ordinary Least Squares
PT	Permanent-Transitory
QQQ:	Nasdaq 100 ETF
RE:	Random Effects
REE:	Rational Expectations Equilibrium
SA:	South Africa
SASI:	South African Savings Institute
SARS:	South African Revenue Service
SEC:	US Securities and Exchange Commission
SENS:	Stock Exchange News Service
SIFI:	Systemically Important Financial Institutions
SIFMA:	Securities Industry and Financial Markets Association
SPDR:	Standard & Poor's 500 Depository Receipt
STD:	Standard Deviation
SUR:	Seemingly Unrelated Regression
SWIX:	Shareholder-Weighted Index
TER:	Total Expense Ratio
TFSA:	Tax-Free Savings Account
TIPs:	Toronto Index Participation Units
TNA:	Total Net Assets
UIT:	Unit Investment Trust
US:	United States
VECM:	Vector Error Correction Model

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CHAPTER ONE: INTRODUCTION

1.1. BACKGROUND AND PROBLEM DEFINITION

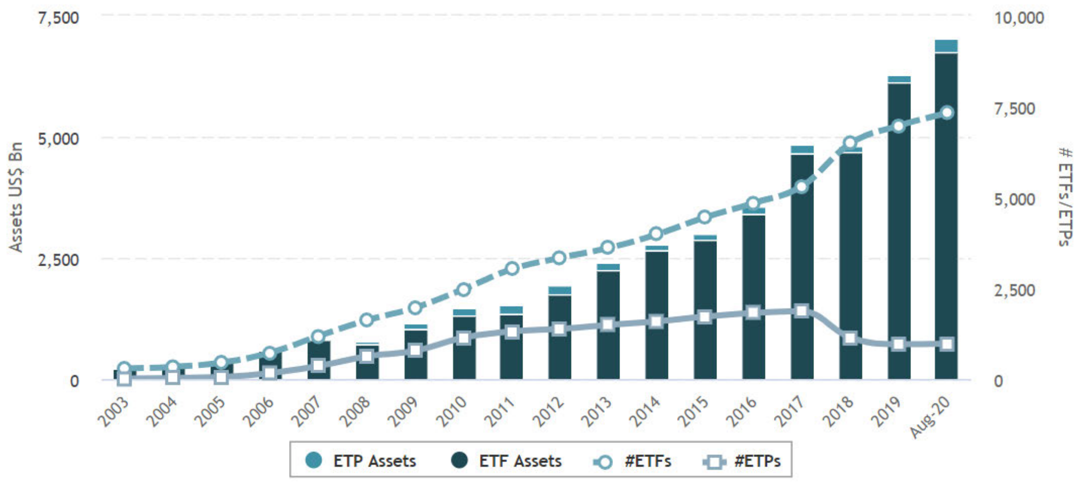
The current financial environment is constantly evolving, and the continual creation of new investment instruments has created a plethora of different opportunities for investors. The creation of the Exchange Traded Fund (ETF) is one such investment vehicle that has experienced phenomenal growth in recent years. When new asset classes are introduced into the financial market, whilst these have the potential to bring widespread benefits to market microstructure elements such as market efficiency, market liquidity, volatility and risk sharing, they also have the potential to negatively impact these elements (Harris, 2003). This chapter therefore begins with a background to ETFs, after which the importance of microstructure is discussed further. This discussion thereafter culminates in a discourse about the research problem, and the significance of this study to the South African environment. Thereafter the central research objectives of this thesis are discussed, and chapter concludes with a brief overview of the format for the remainder of this thesis.

1.1.1. Background to Exchange traded Funds

The introduction of Exchange Traded Funds (ETFs) has represented an important financial innovation in recent history, which has revolutionised the market for asset management products. An ETF is a financial asset, which allows investment into a basket of securities that is designed to track a pre-specified index or benchmark (Madhavan, 2016). ETFs form part of a broader classification of index funds, with the additional important feature of it being listed and traded on a stock exchange. Whilst Index funds have been around since 1976 (Culloton, 2011), the first ETF dates back to Canada, where the Toronto Index Participation units (TIPs) was launched in 1990 (Huang & Guedj, 2009). This ETF contains a portfolio of shares tracking the Toronto Stock Exchange Top 60 index. The United States then introduced its first ETF in 1993 when the American Stock Exchange (AMEX) listed an ETF named Standard and Poor's Depository Receipt (SPDR) that tracks the S&P500 (Huang & Guedj, 2009). Introduction in the European market was slow, with the first ETF (iShares DJ Stoxx 50) listed in April 2000. However at the end of the first ten years of trade, the European market totalled 1071 ETF assets, which represents a phenomenal growth (Blackrock, 2010).

In the early years of its trade, US-based ETFs were found to occupy only a small portion of the total index assets under management, however in the period of 1995 to 2001 alone, the popularity of this product surged, with average growth rates amounting to 132 percent (Gastineau, 2001). Deville (2008) finds that since the introduction of the Nasdaq 100 ETF (QQQ, also known as Cubes) in 1999, ETFs have become the most actively traded asset in the US market, a result that was reinforced by Ben-David, Franzoni, and Moussawi (2018), who find that in 2018, ETF trading accounted for 35 percent of the total trading volume in the US market. Since its introduction, the global ETF market has grown exponentially, not only in market value, but also in the variety and number of products being offered. The ETF growth trajectory shown in figure 1-1, indicates that the total market capitalization of ETFs globally has grown from $416 billion in 2005, to $6.75 trillion in August 2020. In addition, the number of ETF products offered on a global scale has expanded from approximately 500 ETF products in 2005, to 7315 products as at August 2020.

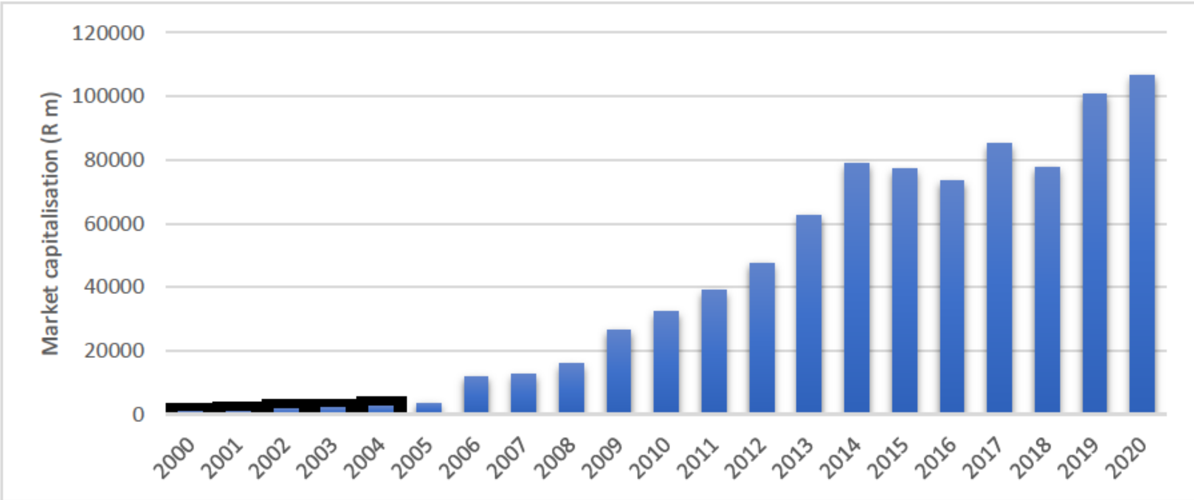
Figure 1-1: Growth of ETFs globally from 2003 to 2020



Source: (ETFGI, 2020)

South Africa welcomed this financial innovation in November 2000, where the first ETF – the Satrix 40 (designed to replicate the Top 40 index) was listed on the Johannesburg Stock Exchange (JSE) (Charteris, 2013). Since its inception however, there have been major strides in the South African ETF market, with the current offerings across the board of commodity and equity offerings, which have both domestic and global alternatives. The current South African ETF market is shown in Figure 1-2, and illustrates that whilst the South African ETF market constitutes a small proportion of the overall global market, it has also grown steadily from just one product offered in 2000, to 78 products in July 2020, with a total market capitalization of R106,6 billion.

Figure 1-2: Market capitalisation of ETFs (in Rm) from 2000 to July 2020 in South Africa



Source: (ETFSA, 2020a)

The goal of an ETF is to provide investors with a well-diversified, index portfolio at a low cost – which is achieved by using economies of scale to buy large quantities of shares, at lower prices (Kostovetsky, 2003). The aim of an ETF is therefore exactly the same as its predecessor, index funds, however, it differs in some key characteristics. Index funds, which fall under the general category of unit trusts, sell an unlimited amount of shares at the Net Asset Value (NAV) of the fund. The proceeds of this are then used to purchase shares proportional to their holding in the index, and a portion is kept aside to pay back investors who want to redeem their shares (Gastineau, 2010). In contrast, the core advantage of ETFs originates from the in-kind creation and redemption process that is used to create these investment vehicles.

ETFs are created by sponsors or trustees who choose the investment objectives of the fund, its underlying index or benchmark, and thus the constituents and holdings necessary to replicate this benchmark (Madhavan, 2016). The fund therefore creates and issues shares to an Authorised Participant (AP) in the primary market. APs are usually large financial institutions and market makers who are authorised by the fund manager to buy or sell shares with the fund (Deville, 2008). To purchase a creation unit, an AP will create a basket of all the stocks in the fund in proportion to their weightings. This is called the creation basket. The AP will then deliver this basket to the ETF manager in exchange for ETF shares of equal value. The AP can then go out and sell these shares to investors in the secondary market, such as the JSE (Hill, Nadig, & Hougan, 2015).

Whilst holders of index funds therefore have to bear both operating and transaction costs, holders of ETFs only incur brokerage costs, thus making them cheaper products. In addition, whilst index funds only trade at the close of the trading day, ETFs allow trading flexibility, since they can be traded throughout the day, and can even be sold short, much like individual shares (Kostovetsky, 2003). The main advantage of ETFs is therefore that it provides the return and diversification benefits of traditional index funds, whilst allowing for the flexible trading characteristics of individual shares. In 2015, the Wall Street Journal reported that ETFs had become so popular that more than 80 percent of the advisors surveyed, were using ETF products for their customers (up from 40 percent in 2006) (Chaille, 2015). Khomyn, Putniņš, and Zoican (2020) documents that ETFs are traded at least 20 times a second, making it the most actively traded asset class in the world. During the current market uncertainty around Covid-19, ETFs still proved to be the product of choice for many investors, with ETF trading on US exchanges amounting to more than a third of total equities traded[1] (Lim & Frankl-David, 2020). A report by Blackrock (2020) demonstrated that this observed increase in trade could be attributed to investors using these products to rebalance their portfolio positions, and hedge away unsystematic risk. In addition, these ETFs were found to provide transparency and liquidity to the various asset markets which they replicate, and have thus been shown to provide market stability during periods of market volatility, thus further reinforcing their importance as an asset class (Blackrock, 2020).

In South Africa, ETFs have proven to be a valuable asset, both for individual investors, as well as institutional investors. The introduction of a Tax-Free Savings Account (TFSA)[2] in 2015 is an ongoing initiative by the South African government, to encourage non-retirement savings (South African Savings Institute (SASI), n.d). These accounts can be used to invest in fixed income securities, and selected equities, such as unit trusts and ETFs (South African Revenue

[1] This statistic has been produced despite the ETF market making up only 10% of the US equity market (measured by market capitalisation) (Khomyn et al., 2020), which provides proof of its popularity as an asset class.
[2]South Africans' are allowed a capped contribution each year into the TFSA, and any income received on this investment (such as capital gains, dividends and interest income), is free from taxation (South African Savings Institute (SASI), n.d)

Service (SARS), n.d). The inclusion of ETFs in the list of possible investments for a TFSA, as well as its simplicity has led to increased awareness of this product by individual investors. This investment vehicle has also proven to be efficient in assisting institutional and professional money managers in their liquidity management objectives, as well as allowing for hedging for market risk (Liedtke, 2020). This has resulted in the daily ETF trading on the JSE averaging R600 million daily in the first half of 2020 (IOL, 2020).

Since an ETF trades on two markets, it has two prices. The first price, the NAV, is the net value of the fund's holdings divided by the number of shares, computed at the end of each trading day. The second price, the market price per share, depends on the supply and demand on the stock exchange (Madhavan, 2012). If buying or selling pressure is high, these two prices may deviate from each other (Deville 2008). Theoretically, due to the creation and redemption in-kind process, the deviation between NAV and market price of an ETF should be eliminated by the process of arbitrage, which means that ETFs should be efficiently priced. If the ETF share price in the secondary market rises too far above its NAV, the AP will make a creation basket, deposit it in the trust, and receive new ETF shares (Lettau & Madhavan, 2018). If the ETF share price falls below the NAV of the underlying assets, institutions will purchase ETF shares from the market and redeem them for the underlying securities (Poterba & Shoven, 2002). If this process holds, investors therefore do not need to incur an additional cost in the form of a mispriced ETF.

In practice however, the effectiveness and implementation of this process is due to factors such as the bid-ask spread, transaction costs and the individual requirements of the creation and redemption process. Empirical evidence on this topic has been varied. Studies by Ackert and Tian (2000), Elton, Gruber, Comer, and Li (2002) and Lin, Chan, and Hsu (2006) find the pricing of US ETFs to be efficient, whilst Curcio, Lipka, and Thornton (2004) find significant pricing deviations for the QQQ ETF. A study of developed and emerging market ETFs by Hilliard (2014), discovers that emerging market ETFs are more likely to display significant, and persistent premiums, relative to their developed market counterparts. A study by Charteris (2013), which evaluates four domestic, and four foreign-listed ETFs in the South African market, proves that all ETFs tested were price inefficient, however the deviation from NAV did not last more than 2 days in the sample period. Badenhorst (2017) also finds evidence of significant discounts and premiums in his sample of South African ETFs, with some ETFs in the sample presenting a 6 percent difference between NAV and market price.

In addition to the afore-mentioned research on ETF's pricing inefficiencies, there is also a growing amount of literature dedicated to evaluating the effect of ETF formation on the microstructure of the market, and in particular, on the impacts observed in the assets that underlie these ETFs.

1.1.2. Impact of ETF formation on market microstructure

There are two major functions of any financial market: the provision of liquidity in order to facilitate trade for various purposes (hedging, investment, diversification), and to enable an efficient price discovery process (O'Hara, 2003). These two functions contain strong linkages, and the attainment of one is nearly impossible without the other. Market microstructure is a broad field of study that aims to provide insights into these two functions, and can be defined as the investigation of "how securities are traded, and the influence that trading systems have on their market behaviour and success"(Glen, 1994, p. 2). This field has the overarching aim of market stability, and has been divided into four main categories of study by Madhavan (2000, p. 207) as follows:

- **Price formation and price discovery**, which examines how information gets incorporated into prices over time;
- **Market structure and design issues**, which investigates the way in which different trading rules and protocols affect market quality components such as liquidity;
- **Information and disclosure**, which aims to evaluate the levels of market transparency present, and how the level of information that can be observed affects trader behavior; and,
- **Informational issues arising from the interface of market microstructure**, which involves the process of how market microstructure affects other areas of finance such as asset pricing, or corporate finance.

Wurgler (2010) purports that the introduction of index-based products like ETFs have generated new phenomena on the stock market that were previously not observed. He therefore rationales that ETFs are not only reducing their ability to deliver on their advertised benefits, but also negatively impact on all four aforementioned categories of market microstructure, which thus negatively impacts overall market function. Bhattacharya and O'Hara (2018) also express the concern that markets could become more fragile if the information reflected in ETF markets does not perfectly mirror the information reflected in the underlying assets. This sentiment has been echoed by regulators, especially in the aftermath of the flash crashes of 2010 and 2015, which led to a commission of inquiry by the US Securities and Exchange Commission (SEC) into the possible detrimental effects of ETFs on market function (Hu & Morley, 2019). This was followed by many more reports by international market regulators on the topic, a full review of which is available in Chapter 2 (section 2.4.2).

The growing concern that ETF introduction and trading has potentially negative impacts on their underlying assets has led to an increase in interest on the subject over recent years. These concerns about ETFs impacting market microstructure mostly stem from their effect on information flows between informed and uninformed traders, amidst market frictions such as transaction costs. The pivotal theoretical works of Merton (1987), Fremault (1991), Subrahmanyam (1991) and Gorton and Pennacchi (1993) were amongst the first to evaluate the possible positive or negative impacts of basket securities on market function, with more recent additions to the theoretical literature by Cong and Xu (2016), Malamud (2016) and Bhattacharya and O'Hara (2018)[3].

Since ETFs have been introduced, their low cost and trading flexibility has meant that these assets are popular amongst uninformed traders, who have minimal expertise in trading (Subrahmanyam, 1991). As a result, these traders migrate away from the market for the underlying asset, to the ETF market, leaving less investors available to conduct fundamental analysis in the market for the underlying asset. The resultant impact of less trading activity in these assets is therefore lower levels of liquidity, an increase in adverse selection costs, and thus low levels of information efficiency (Subrahmanyam, 1991). Whilst individual assets may therefore co-move more with alongside broad market movements, these assets will reflect less asset-specific information (Cong & Xu, 2016). In addition, Malamud (2016) asserts that the

[3] This theoretical framework is detailed further in Chapter 3 (sections 3.4.5 - 3.4.7).

unique creation and redemption mechanism used to keep ETF prices in line with their NAV, may also propagate shocks from the ETF market, to the market for the underlying asset. In this instance, any demand shock in the ETF market which causes the market price to deviate from its NAV, will incite the AP to eliminate the mispricing in the primary market. This creation or redemption activity has the potential to transfer the shock to the market for the underlying securities, even if the shock was independent of the underlying asset (Malamud, 2016). If ETF formation significantly affects factors like volatility, price formation, firm value and liquidity of the underlying securities, this implies that the market price of shares, and their result returns are distorted, which then leads to discrepancies in many other areas, since the investment decisions of both investors and professionals are guided by the share price (Yu, 2005).

The current empirical evidence on the potential microstructure impacts of ETFs is predominantly based on international data, and has shown varied results. Whilst studies such as Yu (2005), Chelley-Steeley and Park (2010) and De Winne, Gresse, and Platten (2014) all find evidence of improved liquidity and information efficiency after the introduction of ETFs, others such as Ben-David et al. (2018), Broman and Shum (2018) and Israeli, Lee, and Sridharan (2017) find evidence of decreased liquidity, increased volatility, a negatively impacted price discovery process, and higher co-movement with market returns (reflected as higher stock synchronicity). These studies look at the effects of ETF formation and trading on the underlying assets that make up the replicated index in order to evaluate possible systemic dangers posed by ETFs, and represent just a few results from an otherwise burgeoning literature[4].

Studies of this type are imperative as their results provide important implications for individual investor's portfolio construction, as well as for corporations. Whilst current empirical evidence on ETFs in the South African environment provides some intuition about their potential impact, they do not explicitly evaluate microstructure elements such as liquidity, adverse selection, informational efficiency, or stock synchronicity. This then raises the question of the other potentially damaging impacts arising from ETFs in the unique JSE environment, and leads this research to fill a significant gap in the current South African literature.

[4] More coverage of the related literature will be conducted in Chapter 2 (section 2.4.2.7), Chapter 4 (section 4.2) and Chapter 5 (section 5.2).

1.1.3. Research Problem

Since the introduction of first official Stock Market in the 1600s, the quantity, nature and diversity of the products offered on the stock exchange have increased vastly beyond just stocks and bonds. The current financial environment grants exposure to a number of diverse products that provide key advantages to investors and financial managers. The dangers of these products however are not often known, as they represent themselves as changes to the microstructure of the market, and are only exposed after empirical studies are performed. Elements such as price discovery, market liquidity, market volatility, informational efficiency and stock synchronicity are all important ones, which contribute to systemic risk and thus the overall quality of the market (Harris, 2003).

The asset management industry in particular, has evolved over time to now play a key role in the process of credit intermediation (which previously was borne solely by banks), and these institutions are now systemically important to the financial stability of both local and global economies (Goodspeed, 2015). The size and favour of the ETF market, as noted in section 1.1.1 has thus led to investigations on the potential of ETFs to generate systemic risk as commissioned by the Bank of International Settlements, as well as the European Systemic Risk Board (ERSB) (Bradley & Litan, 2010, 2011; ERSB, 2019; Ramaswamy, 2011). The concern noted by these reports, is that if ETFs are found to cause excess volatility, diminished liquidity, or decreased efficiency in the market, this can result in greater market fragility. This is a cause for regulatory concern, particularly in an emerging market such as South Africa, where the stability of the financial sector is necessary to ensure economic growth and thus lower the unemployment rate and income inequalities inherent in the country (Chipeta, 2020).

This issue of ETFs impact on microstructure is particularly interesting in the South African context, where the JSE encompasses less than 1 percent of the global investable universe, and where a few large companies dominate the equity market (Nogantshi, 2019). Whilst there are 342 listed companies on the JSE as at 31 August 2020 (Ceicdata, 2020), the top 40 companies in terms of market capitalisation (which forms the JSE Top 40 index), represents more than 80 percent of the total JSE market capitalisation at any point in time (Mans-Kemp & Viviers, 2019). In particular, the top 10 companies listed on the JSE constitute between 50 and 60 percent of the JSE All Share Index (Nogantshi, 2019), and one company, Naspers (JSE: NPN), accounts for a 20 percent weighting in the JSE Top 40 index (Murison, 2020). Lambridis (2019) documents that the JSE SWIX[5] Top 40 index has a concentration level, measured by the Herfandihl Hirschman Index (HHI), that is 9 times higher than the concentration level of the S&P 500. The concentration issues on the JSE are noted by Bradfield and Kgomari (2004) and Kruger and Van Rensburg (2008), with Bradfield and Munro (2017) noting that 25 percent of the risk captured on the JSE All Share Index (ALSI) is attributed to the concentration risk faced.

The implications of these findings is that the passive investing approach (in particular, ETF investing) takes on a unique dimension in the South African market, which is not present in international studies. Whilst international investors therefore only require between 20 and 30 stocks in their portfolio for effective diversification of risk, South African investors require 33 stocks for a 90 percent risk diversification and up to 60 stocks for a 95 percent reduction in portfolio risk (Bradfield & Munro, 2017). This important conclusion raises the implication that many of the ETFs on JSE (which contain fewer than 60 and even 33 assets) are not efficiently diversified portfolios, and thus do not provide this well-advertised benefit to passive investors (Lambridis, 2019).

In their study, Kruger and Van Rensburg (2008) note that whilst passive portfolio managers need to be mindful of the index informational inefficiencies created by the level of concentration risk, the formation of diversified portfolios is also extremely dependent on the level of liquidity in the underlying assets, since illiquidity negatively impacts the possibility of uninhibited entry and exit into asset classes. These two elements of liquidity and efficiency have been noted by O'Hara (2003) as being the two major functions of any financial market, and have had direct impacts from the concentrations issues on the JSE (Kruger & Van Rensburg, 2008). This therefore motivates the direction of this study to focus solely on liquidity and information efficiency as the principal microstructure effects in the South African equity market. These elements also have extenuating implications on both the passive and active

[5] The Shareholder-Weighted Index (SWIX) aims to address the concentration issue in the South African context by adjusting the proportions of dual-weighted shares downward, to eliminate the inclusion of their foreign holdings (Kruger & Van Rensburg, 2008). However, Rousseau and Zwonnikoff (2002) postulate that this method is insufficient in eliminating concentration, as it makes no adjustment in weighting to non-dual listed companies which have high weightings.

management environment, whose efficient functioning is reliant on aspects such as risk sharing, volatility, liquidity and information efficiency.

The dominant literature on ETFs in the South African context has focused on pricing efficiency (Badenhorst, 2017; Charteris, 2013; Charteris, Chau, Gavriilidis, & Kallinterakis, 2014), tracking efficiency (Charteris & McCullough, 2020; Steyn, 2019; Strydom, Charteris, & McCullough, 2015), and price discovery (McCullough, 2017). The only study to the author's knowledge, which aims to evaluate the impact of ETF trade on the underlying assets, is Matarutse and Sibanda (2014), who investigate the changes in volatility of the underlying assets of the Satrix Top 40 ETF. Whilst the authors attribute their findings of reduced volatility after ETF introduction to an improvement in trading volume, liquidity and efficiency in the underlying assets, the study does not provide a direct analysis of these aspects, and it is limited to the analysis of a single ETF in the South African market. In addition, Merton (1987) postulates that the potential impact could be different for large and small firms, where one category experiences potential benefits, and the other category faces detriment. None of the afore-mentioned studies have evaluated this possibility.

The study of ETF microstructure has focused mainly on international, developed markets such as the US and Europe. As a result, there is limited evidence provided in an emerging market context, which has been found to be fundamentally different from developed markets in terms of their relative market sizes, risk, correlations and market structures (Bekaert & Harvey, 2017; Marozva, 2020). Thus, the dearth of literature evaluating the impact of ETF introduction on the liquidity and information efficiency of its underlying assets provides a challenge to South African regulators, and investors of this asset class, who may not properly understand its implications on financial market stability.

1.1.4. Research Aim, Objectives and Questions

The aim of this thesis, which serves as an encompassing goal intended to analyse the impact of the introduction and trading of Exchange Traded Funds on the microstructure components of the underlying assets listed on the South African Equity Market. To achieve this aim, the following research objectives are developed:

I. To examine the effect of the introduction of Equity ETFs on the JSE on changes in liquidity for the stocks that constitute the ETF;
II. To examine the effects of the weight of a company in the Equity ETFs listed on the JSE on the liquidity change experienced by the underlying firms;
III. To determine the impact of ETF ownership and trading activity on the informational efficiency of the JSE-listed companies which are constituents of both international and domestic equity ETFs; and,
IV. To assess the impact of ETF ownership and trading activity on stock synchronicity of the JSE-listed firms which underlie both domestic and international equity ETFs.

In achieving these objectives, this study answers the following research questions:

I. How does the introduction of Equity ETFs on the JSE, impact the liquidity of the stocks that constitute the ETF?
II. How does the weighting of a company in the Equity ETFs listed on the JSE, affect the liquidity change experienced by the underlying firms?
III. What is the effect of ETF ownership on the informational efficiency of the JSE-listed companies, which are constituents of both international and domestic equity ETFs?
IV. How does the informational efficiency of the JSE-listed companies respond to changes in ETF trading activity?
V. How does the ETF ownership affect stock synchronicity of the JSE-listed firms which underlie both domestic and international equity ETFs?
VI. How does the stock synchronicity of the JSE-listed companies respond to changes in ETF trading activity?

Whilst research questions I and II focus on ETF introduction, research questions III and V have a focus on ETF ownership, and the remaining questions, IV and VI, focus on ETF trading. The focus of this study therefore, whilst centred on market microstructure, is also focused on the different measures which capture ETF market activities.

1.2. THE SCOPE AND RESEARCH METHODS OF THIS STUDY

The two major microstructure elements that are addressed by this thesis are: liquidity and information efficiency. The organisation of this thesis therefore addresses the details of each of these microstructure elements in two separate chapters, each of which will be focused entirely on the literature, sample and data, research methods and results from the analysis. Since the focus of each chapter is on different elements of microstructure, each has its own unique method of analysis, with different samples used for each chapter. The summary of these chapters is contained below.

1.2.1. Chapter Four: Liquidity

The research objective of this chapter aims to evaluate the impact of ETF introduction on the liquidity of its underlying assets. In particular, answers to the following research questions will be sought:

I. How does the introduction of Equity ETFs on the JSE, impact the liquidity of the stocks that constitute the ETF?
II. How does the weighting of a company in the Equity ETFs listed on the JSE, affect the liquidity change experienced by the underlying firms?

The research sample focusses on the South African ETF market, which currently hosts 76 different exchange traded products (ETFSA, 2020a).The analysis of liquidity required the use of the underlying constituents to these ETFs, which had to meet the data requirements of the study. The resultant sample therefore consisted of 23 domestic equity JSE-listed ETFs and their 147 different underlying constituents. These assets were utilised in an event study analysis as adopted by the studies of Hegde and McDermott (2004), Van Ness, Van Ness, and Warr (2005) and Richie and Madura (2007). The listing date of the relevant ETF was used as the event of interest, and associated examinations of the data were conducted on a 30 and 50 day period around this event.

The chosen liquidity proxies in this chapter are the liquidity measures of quoted spread (in rands), percentage spread, the Amihud illiquidity measure, and quoted depth. These variables are calculated, alongside commonly used control variables for both a 30 day and 50 day pre- and post- event window (using daily data), after which univariate and multivariate methods of analysis are employed, to provide statistical interpretations which will assist in achieving the research objectives posed. The multivariate method of analysis used in this study is therefore a fixed effects panel estimation technique, which is a useful approach that allows for the modelling of individual heterogeneity, and is an estimation approach that is supported by its extensive use in the literature (Evans, Moussawi, Pagano, & Sedunov, 2019; Israeli et al., 2017; White, 2018)

1.2.2. Chapter Five: Information efficiency

The second microstructure element that is investigated in this study is the informational efficiency of the underlying constituents to ETFs. Whilst Chapter Four evaluates the introduction of ETFs as the event under consideration, this chapter makes use of different ETF market activity variables, as measured by ETF ownership, and ETF trading activity. The aim of this chapter is therefore to evaluate whether ETF ownership, and ETF trading activity has any impact on the price discovery process in their underlying securities. Since the focus of this chapter diverges from the previous one, a different sample and research variables is used. In particular, the research questions which this chapter seeks to answer are as follows:

III. What is the effect of ETF ownership on the informational efficiency of the JSE-listed companies, which are constituents of both international and domestic equity ETFs?
IV. How does the informational efficiency of the JSE-listed companies respond to changes in ETF trading activity?
V. How does the ETF ownership affect stock synchronicity of the JSE-listed firms which underlie both domestic and international equity ETFs?
VI. How does the stock synchronicity of the JSE-listed companies respond to changes in ETF trading activity?

The main variable of analysis for this chapter is the ETF ownership of JSE-listed firms, which aims to capture the number of issued shares in a firm that are owned by ETFs. The sample therefore makes use of only South African listed firms, but includes both domestic equity ETFs, as well as foreign equity ETFs which invest in JSE-listed companies according to their respective mandate. In addition, since the dependent and control variables included in the chapter are based on inputs from each firm's financial statements, the data frequency selected is on a quarterly basis, and the sample period starts in quarter 1 of 2009, and ends in quarter 3 of 2019. The primary variable of information efficiency, is measured by two proxies. The first proxy makes use of the relationship between return and earnings to estimate the Earnings Response Coefficients (ERC), whilst the second proxy uses the measure of return synchronicity to capture systematic efficiency. The estimation techniques for this chapter includes the use of both the Fixed Effects panel data method, and the Generalised Method of Moments (GMM) method, the latter of which is meant to account for the possibility of endogeneity in the data.

1.2.3. Delimitations of the study

The delimitations of the study are as follows:

- The central focus areas of this study are on the microstructure elements of liquidity and information efficiency. Whilst there are many other microstructure elements that require investigation in the South African market, such as volatility, correlation and firm value, each of these elements is extensive in its investigation and would increase the complexity, length and focus of the current study vastly.
- Only ETFs which are physically replicated, and therefore directly invested in their underlying assets, were selected for inclusion in this study. Synthetic replication does not directly invest in its chosen asset class, and instead uses derivatives to achieve the same outcomes. The effect of these ETFs on their underlying assets may be very different by virtue of its derivation method. In addition, the formation of ETFs in South Africa is legally obliged to be via physical replication, according to the Collective Investment Schemes Act (CISCA), which thus precludes the presence of any synthetic ETFs in our financial market.
- The study attempts to evaluate the microstructure effects of ETFs, on the equity asset class only. At present, approximately 78 percent of the global market for ETFs consists of physically replicated, equity ETFs. The use of this asset class therefore ensures a larger dataset for analysis, and thus greater efficiency in the results produced.
- The liquidity chapter makes use of only domestic equity ETFs listed on the JSE, as the inclusion of international ETFs with varied different underlying assets, listed on multiple exchanges, is considered complex and subject to many more external factors which go beyond the scope of this study.
- The study of information efficiency has a central focus on the level of ETF ownership in individual firms listed on the JSE, therefore this analysis makes use of holdings information from both domestic and international ETFs, to ensure that the ETF ownership data used is correct, and fully representative of the amount of a firm's shares which are "locked up" in ETF warehouses.

1.3. STRUCTURE OF STUDY

The thesis consists of six chapters, the details of which are contained below:

- **Chapter Two - Background and Conceptualization of ETFs**

  This chapter provides an overview of ETFs and discusses in detail its original inception, the ETF environment in South Africa, and the relative advantages and disadvantages of this investment product. The chapter concludes with a discussion of the regulatory environment in which ETFs operate in South Africa, and aims to provide a context to the remainder of the thesis.

- **Chapter Three- Financial Market Microstructure Theories**

  Chapter three outlines in detail the theoretical microstructure theory which form the foundation of the hypotheses surrounding the ETF market. The chapter begins with an introduction to market microstructure, with a discussion of the relevant elements which are discussed in the theoretical microstructure models. The chapter thereafter proceeds to a dialogue on the seminal theories developed in market microstructure theory (by Grossman and Stiglitz (1980) and Kyle (1985)), which form the basis for the later developed theories on liquidity and information efficiency. The chapter thereafter details liquidity- and information efficiency-related theoretical models, in anticipation of the remaining chapters in the thesis.

- **Chapter Four: Investigating ETF liquidity**

  Chapter Four aims to discuss the impact of ETF introduction on liquidity of the underlying assets in detail, and attempts to address research questions I and II. The theoretical foundation of the issue is found in chapter 3, therefore this chapter begins with a critical analysis and literature review, after which the methodological approach and data are discussed. Finally, the chapter concludes with a discussion of the data analysis results, and aims to provide conclusions relative to the stated objectives.

- **Chapter Five: Informational efficiency**

  Chapter Five investigates the impact of ETF ownership and trading activity on the information efficiency of the underlying assets, and attempts to address research questions III – VI. Since the theoretical foundation of this chapter is contained in

Chapter 3, the chapter begins with an extensive discussion of the empirical literature on the topic, followed by a discussion of the sample, data, and research methods applied. The chapter thereafter concludes with a discussion of the results, relative to the research objectives posed.

- **Chapter Six – Conclusion**
  This chapter contains a summary of the motivation for the study, the research objectives and the results produced, with the aim of drawing relevant inferences from the data, and providing answers to the research objectives provided. The final portion of this chapter discusses the relevant weaknesses of chapters three and four, together with recommendations for further research.

CHAPTER TWO: CONCEPTUALIZATION OF ETFS AS A PASSIVE INVESTMENT STRATEGY

2.1. INTRODUCTION

The asset management industry has evolved in recent decades to pose an extremely important role in the global economy. Whilst earlier years saw an emphasis on the banking industry for services such as financial intermediation and the provision of savings vehicles, the strict regulations on this industry has contributed to a shift towards the asset management industry to provide these functions (IMF, 2015). Not only does it provide an alternative to allow easy diversification for investors, but it also acts as a supplier of funds when banks are subject to regulations that are too stringent, or are distressed and unable to supply funds (IMF, 2015). The asset management industry is further subdivided into active and passive management, each of which are based on different assumptions, and the debate between which one is superior has been an ongoing one amongst academics and practitioners for many years. Whilst active portfolio management has its emphasis on outperformance, and thus has always been a popular approach for investors (Fuller, Han, & Tung, 2010), the introduction of the passive approach to investing in the 1970s (which coincided with an increase in technological innovation that made handling large portfolios of assets easier) has led many to advocate this style as being better (Lettau & Madhavan, 2018). The passive approach to investing aims to replicate a specific benchmark, thus providing equivalent levels of diversification, risk, and return, for decreased levels of cost (Fuller et al., 2010).

Whilst passive management products encompassed just 20 percent of the US market in 2017, this proportion grew to 45 percent at the end of 2017 (Whyte, 2018). In addition, statistics produced in 2019 have indicated that for the first time in history, the Total Net Assets (TNA) of passively managed products outweighs that of actively managed products (Gittelsohn, 2019). The increased popularity of passively managed products has been driven partly by the increasing popularity of ETFs[6] (Sushko & Turner, 2018), which provide an opportunity to invest in an index fund, with a number of associated benefits. This chapter therefore begins with a discussion of the passive management approach to investing, and aims to identify the

[6] Whilst ETFs comprised 30 percent of the passive management market in 2007, this grew to a 40 percent proportion in 2017 (Sushko & Turner, 2018)

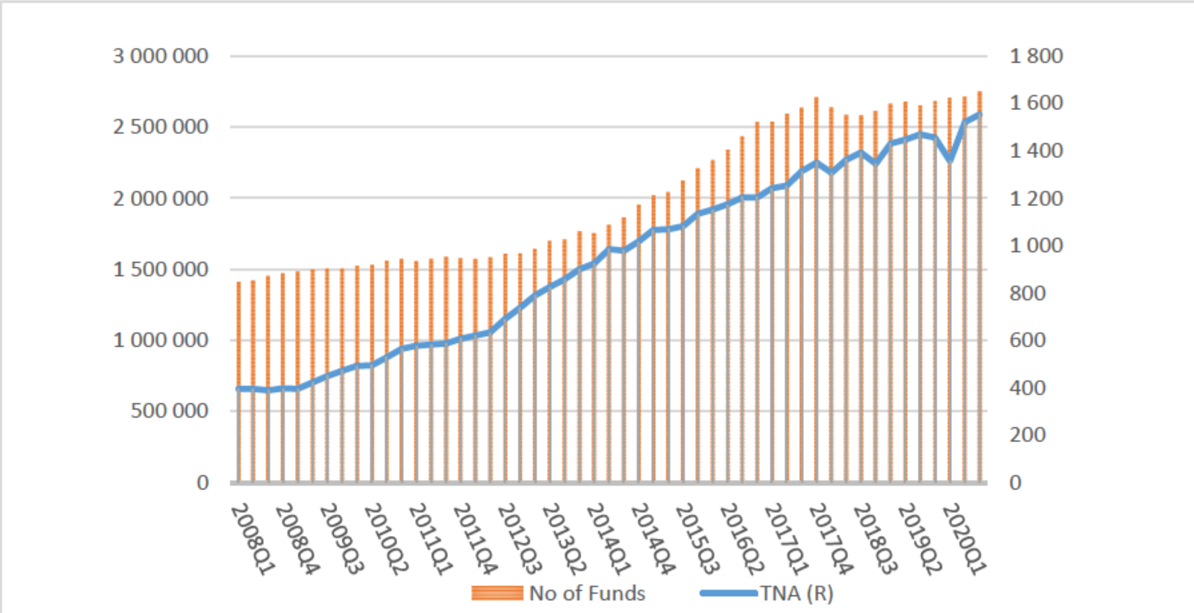
manner in which ETFs have transformed the industry since their inception. The chapter thereafter reviews the unique underlying structure of ETFs, the different types of ETFs that are currently available in the global market, and the relative advantages and risks posed by this product. The chapter thereafter concludes with a discussion of the regulatory environment in which this asset class operates.

2.2. THE PASSIVE APPROACH TO MANAGING INVESTMENTS

An investment philosophy can be defined as the core beliefs that guide the decision making process of an investors, and the two dominant philosophies in financial markets today, is that of active and passive management (Bodie, Kane, & Marcus, 2013). The active management philosophy is characterised by an overarching aim to exceed equity market returns, by utilising active manager's skill and knowledge to identify mispriced stocks (Vanguard, 2017). This style of management results from the core belief that markets are not efficient, thus profits can be earned from utilising resources to actively search for mispriced assets (Fuller et al., 2010).

Passive management on the other hand, results from an underlying belief that markets are efficient, and therefore there is no need to actively seek mispricing in the market, since assets already reflect all available information (Sushko & Turner, 2018). Proponents of this strategy are therefore content in replicating the returns on a market portfolio or pre-specified benchmark (this is also known as indexing), which is achieved at a lower cost, since the purchasing and selling of securities is limited (Card, 2019; Vanguard, 2017). Investors who follow passive management should therefore invest passively within their chosen asset class, and should rather utilise their resources to make quality asset allocation decisions (Flood & Ramachandran, 2000). The graph presented in Figure 2-1 details the asset management industry in South Africa, which encompasses both active and passively management products, excluding Fund of Funds. The total number of unit trusts, ETFs and institutional funds has almost doubled from 844 in 2008, to 1650 in Quarter 3 of 2020. Similarly, the TNA has increased from R658 million to R2.6 billion over the 12 year period.

Figure 2-1: Total Net Assets (in R million) of the Asset management industry in South Africa from 2008Q1 to 2020Q3



Source: Author's own construction (ASISA, 2020)

Proponents of the active management approach advocate that the returns provided, more than compensate for the higher cost of the additional analysis required for this approach (Flood & Ramachandran, 2000). Based on the methods employed, with the use of professional money managers, active purchasing and selling, and an overall intent to outperform the rest of the market, it is a reasonable expectation that the active strategy outperforms the passive approach (Card, 2019). However, recent empirical evidence has shown that passive management (in particular ETFs), has consistently outperformed active management techniques, both in the US and in South Africa.

A study by Morningstar of the US market found that only 23 percent of the active funds surveyed managed to beat the performance of the passive funds in the sample (Riquier, 2019). A study by Mike Brown (2019) indicates that only 28 out of 130 active fund managers in South Africa were able to outperform the JSE ALSI over a three year period, and only 14 out of 104 outperformed over a 5 year period. Similarly, looking at investments over one to ten year periods have consistently found that passive ETFs are the top performing funds in South Africa, in contrast to actively managed unit trusts, as shown in figure 2-2:

Figure 2-2: Top performing funds in South Africa

Top-performing individual collective investment schemes*			
		% Per Annum	ETF Ranking
1 Year			
CoreShares PrefTrax	ETF	19,24%	1
Alexander Forbes Investments US Dollar Feeder	Unit Trust	18,38%	
2 Years			
Coronation Resources	Unit Trust	16,66%	
Satrix RESI	ETF	16,19%	2
3 Years			
Coronation Resources	Unit Trust	30,72%	
Old Mutual Mining & Resources	Unit Trust	21,87%	
Satrix RESI 10	ETF	20,57%	3
5 Years			
Sanlam INDA Opportunities Feeder	Unit Trust	14,87%	
Sygnia Itrix USA Index	ETF	14,32%	2
7 Years			
Sygnia Itrix MSCI USA	ETF	20,97%	1
Old Mutual Global Equity	Unit Trust	20,81%	
10 Years			
Nedbank Investments Financials	Unit Trust	18,12%	
Centaur BCI Flexible	Unit Trust	16,84%	
Sygnia Itrix USA Index	ETF	16,83%	3
** Measuring all funds in the CIS Survey.*			

Source: Brown (2019)

These results confirm findings from many years ago, such as the work of Bhattacharya and Galpin (2005) which found that from 1995 to 2004, active investment was at declining levels worldwide, with developed markets declining at a higher rate than emerging. A later study on the South African market by Muller and Ward (2011) of the South African market, found that the level of active investing on the JSE declined from 50 percent in 1988 to 15 percent in 2001, a level which it maintained through to December 2010. This shift towards the preference of indexed products over actively managed investment products[7] is partly the reason for the exponential growth in ETFs witnessed globally. In August 2019, it was found that for the first time in history, the assets under management in the unit trust and ETF market in the US

[7] Stalwarts of the financial world such as Eugene Fama and Warren Buffett also advocate the use of passive, index-linked products over active investments (Arnott & Darnell, 2003; Fama, 2007).

surpassed that of actively managed funds ($4.27 trillion vs $4.25 trillion) (Gittelsohn, 2019). The relative outperformance of passive funds over active funds was also noted during the COVID-19 period, with only 42 percent of global active funds outperforming their passive peers during this extremely volatile period (Wilkinson, 2020).

Anadu, Kruttli, McCabe, and Osambela (2020) attribute the growth in the passive management industry to the following factors: the development of the Efficient Market Hypothesis (EMH) which questioned the ability for fund managers to "beat the market", the lower cost of passive investing, the relative inability of active managers to beat their benchmarks, and the ease of investing that products like ETFs offer[8]. A study by Sushko and Turner (2018) also attributes the growth in passive investing to the increased usage of Artificial intelligence initiatives such as robo-advisers (which offer investment advice at lower cost), as well as the increased regulatory focus on transparency in fund management fees. These structural changes in the asset management industry may therefore further propel the popularity of passively managed products in the coming years.

2.2.1. Index investing as the preferred approach to passive management

The initial passive management process, made use of a buy-and-hold method (Bogle, 2016), which entailed buying a portfolio of blue chip stocks, and holding them in the long term, regardless of short term fluctuations in portfolio value (Annaert et al., 2011). This process was the dominant one used, until the introduction of the first index unit trust, created by John Bogle of Vanguard fame, in 1975 (Hill et al., 2015). This index unit trust, or index fund, attempts to replicate the market returns, or the returns of a specific benchmark, by purchasing and holding all the constituents of the chosen index, in their relative proportions (Vanguard, 2017). Since its initial introduction, the rapid proliferation of technology enabled the growth of the index fund, by making the processing of large portfolios of assets much easier (Lettau & Madhavan, 2018). The creation of the index fund served to revolutionise the passive management industry, with the term "index investing" now considered synonymous with passive management. The creation of ETFs in 1993 thereafter further expanded the availability of index-tracking

[8] These characteristics will be discussed further in section 2.4.

products, since a large proportion of these funds are designed to track a specific benchmark (Gastineau, 2010).

Index funds today, are typically structured as either open-or closed-ended funds, or ETFs. Whilst all these products allow investors the opportunity to pool their investments to obtain pre-defined investment products, they differ in terms of their overall structure. Unit trusts are structured as open-ended funds, which allow a theoretically endless stream of investment into the fund, and can continually issue shares, or redeem them at the investor's will (Madhavan, 2016). Closed-ended funds however are issued through an Initial Public Offer (IPO) at inception, and then the limited number of shares in issue are traded on the stock market (Hill et al., 2015). This results in a situation where the NAV of the fund might differ from its sale price, since the sale price is dependent on supply and demand factors; unlike open-ended funds, which only have one price (the NAV). ETFs are hybrid products, which combine the creation and redemption mechanism of open-ended funds, with the trading flexibility of being listed on the secondary market, which is a benefit offered by closed ended funds (Deville, 2008).

Regardless of the manner in which the indexed products are formed, they provide important functions for the average investor, by providing easy diversification, at lower risk, lower costs, and as recent research has proved, sometimes even superior returns (Fuller et al., 2010). In addition, the ease of trade, and transparency of these investment products, has meant that even institutional investors are utilising these products as the preferred method of entry into a particular market (Blitz, 2014). The ETF, with its unique structure and advantages has contributed greatly to this development. The remainder of this chapter therefore focuses on the creation, and structure of the ETF investment product, which thereafter leads to a discussion on the relative advantages and disadvantages of this product.

2.3. ETF STRUCTURE AND DESCRIPTION

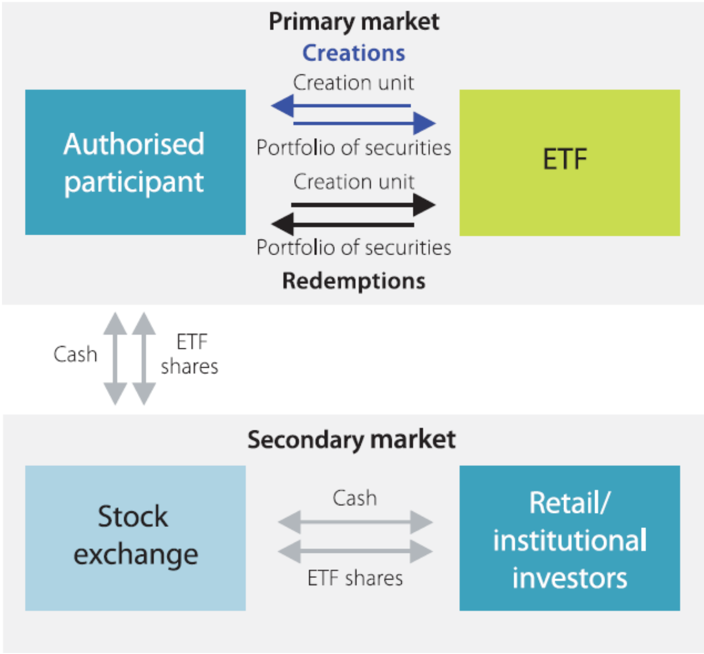
The first ETF was introduced on the Toronto Stock Exchange in 1990, called the TIPs, which tracked the Toronto 35 (Abner, 2010). Thereafter, in 1993, the American Stock Exchange (AMEX) began trading the Standard & Poor's 500 Depository Receipt (SPDR). In the US market, adoption of the ETFs was slow, and it wasn't until the NASDAQ listed their Nasdaq 100 ETF (also known as QQQ or Cubes), in 1999, that interest in these instruments peaked (Deville, 2008). This subsequently led to the introduction of ETFs in the Hong Kong, South African and European markets in 1999, 2000 and 2001 respectively (Charteris, 2013; Haslem, 2003). ETFs mimic the structure of closed-ended funds, and the first ETFs were all created via physical replication, which entails the ETF sponsor physically holding the underlying assets of the chosen benchmark, in their relative proportions (Deville, 2008). The ETF is essentially a hybrid product, which combines the creation and redemption mechanism process from open-ended funds, with the trading process of closed-ended funds. It is this unique structure that creates many advantages of this product over its predecessor index funds.

2.3.1. ETF creation and redemption process

ETFs are created using a complex process of creation and redemption. Once a specific ETF provider (also known as a sponsor or trustee) decides to create an ETF tracking a specific index, they must generate processes for determining the target index, and then submit this along with a detailed plan to the Financial Sector Conduct Authority (FCSA) for approval (Visser, 2014). Once approval is obtained, the sponsor must approach an Authorized participant (AP), which are usually large institutional investors who have large purchasing power and are thus market makers, to assist them in creating and redeeming the ETF shares (sometimes the sponsor has the ability to act as the AP as well). These APs are the only ones who are authorised to create new ETF shares, which occur in blocks of 25 000 to 250 000 shares, known as creation units (Liebi, 2020). They create these units by purchasing large amounts of the shares, which form the index, in proportions that mirror the index. These stocks are then transferred to the sponsor fund, in exchange for creation units, which are then broken up into individual ETF shares, and sold on the secondary market to retail and individual investors (Deville, 2008). Because this transfer happens "in-kind", and there is no cash changing hands, there are no tax consequences of the creation and redemption process (Deville, 2008; Hill et al., 2015; Rongala, 2009). This stands in contrast to conventional open-ended unit trusts, when shares need to be sold, and capital gains taxes paid, whenever there is a redemption.

The redemption process is the opposite of the creation process, but redemption can only occur in creation unit sizes, and not in individual shares. If an AP has a block of shares (creation unit) that they want to redeem, they will return this to the sponsor, and receive the individual shares in return. The process of creation and redemption is shown in figure 2-3 below:

Figure 2-3: Creation and redemption process of ETFs



Source: Kosev and Williams (2011, p. 57)

This creation and redemption process is ongoing, can occur at any time during the ETF's life, and is priced at the NAV of the ETF at that time (Lettau & Madhavan, 2018). Because the subsequent ETFs created are listed and traded on the stock exchange, they have two values: the intraday NAV (iNAV), which is the actual pro-rata value of the holdings (calculated at 15 second intervals), and the market value based on supply and demand (which changes intra-daily) (Madhavan, 2016). The iNAV also known as the Intraday Indicative Value (IIV), and differs from unit trusts, where the NAV can only be calculated at the end of the trading day (Madhavan, 2016). If there is price pressure from purchasers or sellers at any particular time, this may result in the market price of the ETF deviating from its NAV. The creation and redemption process therefore plays a crucial role in being able to eliminate any mispricing when ETF shares are trading at a premium or discount to their NAV, and absorbing any liquidity shocks faced by the ETF market (Deville, 2008). Since ETF portfolios are transparent and generally quite liquid, this arbitrage activity to eliminate mispricing can be implemented by APs (in the primary market), or any arbitrageur who sees an opportunity (in the secondary market)[9] (Aggarwal & Schofield, 2014). Theoretically, ETFs therefore have unlimited supply as creation units are always able to be created by APs in response to increased demand (Bradley & Litan, 2010). These APs therefore play a pivotal role in the efficient functioning of the ETF market, as they are the only entity that is allowed to deal directly with the ETF. Many APs also act as market makers which are tasked with providing liquidity to the ETF market, by being able to act as both buyer and seller (Abner, 2010), thus creating a market for the ETF shares.

2.3.2. Types of ETFs

The first ETFs introduced to investors were all physically-replicated, equity based ETFs, and this form still occupies 78 percent of the overall ETF market. These ETFs hold almost all the stocks of the benchmark index, and investors therefore receive returns based on the basket of securities (net of transaction costs) (Madhavan, 2016). Physically replicated ETFs might not perfectly replicate the index, but is required to resemble 90% of the benchmark index (CISCA, 2002), and are often referred to as "plain vanilla" index ETFs. Whilst broad-based ETFs attempt to mirror a broad-based index as the S&P 500 (US), FTSE 100 (UK), or JSE ALSI (SA), a sector-based ETF attempts to mirror a specific sector of the market, such as the Financials index, or the Resource index (Hill et al., 2015). As the ETF market grew, the offerings expanded to other asset classes, such as commodities and fixed income securities, and the methods used to create the ETF also evolved to include the use of derivatives (synthetic replication, inverse ETFs, leveraged ETFs).

The global ETF market therefore currently constitutes a rich tapestry of different ETFs, such as:

- **Fixed income ETFs**, which hold money market securities such as bonds.
- **Commodity ETFs**, which hold physical commodities, such as gold or platinum.
- **Currency ETFs,** which aim to track the return of a particular currency, or a basket of different currencies.

[9] A study by Ben-David et al. (2018) found that half of the daily trading volume for the SPDR ETF was attributed to arbitrage activity.

- **Thematic ETFs,** which focus on niche markets, such as cybersecurity, solar power, artificial intelligence or cannabis (Ponczek, 2019). These ETFs allow for easy access into the thematic investing market, which aims on identifying disruptive macro-level developments and investing in the underlying assets which stand to benefit from the realization of these trends (Rosenbluth, 2020).
- **Synthetically-replicated ETFs,** which make use of derivatives such as options and swaps to replicate the chosen broad-based or sector index, rather than the process of physical replication. This process was introduced in 2001 in the European market (Mateus & Rahmani, 2017), but was only allowed in the US market from 2008 (ICI, 2020). Current South African legislation disallows synthetic replication, and dictates that all JSE-listed ETFs should be formed via physical replication (CISCA, 2002). Aggarwal and Schofield (2014), note that at the time of their study, most of the ETFs in the US market are still physically replicated, but half of the European ETFs produced are synthetically replicated. This method can result in lower costs incurred, and are particularly useful when the benchmark index is illiquid (Goodspeed, 2011).
- **Leveraged ETFs,** which utilize derivatives and leverage in order to amplify the returns on an underlying index.
- **Inverse ETFs,** which aim to return the exact opposite return of a benchmark. These are created using derivatives, and allow you to go "short" on a market.
- **Smart-beta ETFs,** which cross the bridge between active and passive management products, by altering the weightings of securities in the ETF with an aim to outperform the index.
- **ETF-wraps,** which are like funds-of-funds, and include many ETFs in one portfolio.

(Hill et al., 2015; Lettau & Madhavan, 2018)

The total value of the global ETF market (as at 31 December 2019) amounted to $6.2 trillion, with US ETFs constituting 70 percent of the global market. European and Asian-Pacific ETFs constituted 16 percent and 11 percent respectively of the global ETF market, with the ETFs from the rest of the world constituting a miniscule 3 percent (ICI, 2020). Whilst the nature and types of ETFs are constantly being introduced and growing, a large proportion of the ETF market globally is still made up of the plain vanilla ETFs. In addition to the South African market being legally obligated to only offer physically replicated ETFs, our current ETF market has no exposure to leveraged, inverse or thematic ETFs either. The recent addition of several smart beta ETFs however, indicates that the South African ETF market is evolving as well, albeit at a slower pace than developed markets.

2.4. CRITICAL APPRAISAL OF THE ETF ASSET CLASS

The ETF has many widely known benefits, which has led to its popularity as an asset class. The drawbacks however, are not commonly known or advertised, and sometimes manifest themselves as threats to financial stability or market quality. The ensuing section therefore aims to discuss both the advantages and disadvantages of ETFs, with specific attention on the reasons why this asset has been the focus of many regulator's attention in recent years.

2.4.1. Advantages of ETFs

The hybrid structure of ETFs, which combines the use of the in-kind creation and redemption process used by open-ended funds, alongside the trading flexibility of a closed-end fund, leads to its many advantages, which favour its use over other index funds. These advantages are widely documented, and has resulted in interest from both retail and institutional investors, which has in turn propelled the global growth of this asset class.

2.4.1.1. Providing a ready-diversified product

The creation of an ETF, which combines the underlying assets of a pre-specified benchmark, ensures that it offers an already diversified investment product to the public, which could otherwise only be achieved at a much greater cost. This product also allows for investors to invest in a specific sector, style or country without specialised knowledge necessary (Deville, 2008).

2.4.1.2. Tax efficiency

The in-kind creation and redemption process implies that investors will only incur capital gains tax upon the sale of the ETF, whilst conventional index fund investors will incur multiple capital gains taxes throughout the life of the investment (due to the fund meeting redemptions, rebalancing or changing their asset allocation)[10] (Abner, 2010).

2.4.1.3. Elimination of cash drag

The creation-and-redemption process also eliminates the necessity of keeping cash aside to meet possible investor redemptions, thus removing the possibility of the fund experiencing a "cash drag". In contrast, unit trusts are legally obligated to keep a certain portion of cash aside in order to fund any investor redemptions (Haslem, 2003).

2.4.1.4. Trading flexibility

Similarly, since these ETFs are listed on the stock exchange, this offers the trading flexibility of being able to trade at any time during the trading day, and of being able to sell short, purchase on leverage, or even write an option on the ETF. This stands in contrast to conventional unit trusts which are only able to be traded at the end of the closing day, and which cannot be purchased on leverage, or sold short (Madhavan, 2016).

2.4.1.5. Low transaction costs

ETFs also tend to have lower fees than their unit trust counterparts, as portfolio securities are only sold to rebalance portfolios, which results in lower transaction costs (Abner, 2010). The resultant lower TER of ETFs when compared to unit trusts has been noted in the studies of Blitz, Huij, and Swinkels (2012), Strydom et al. (2015) and Rompotis (2015).

2.4.1.6. Facilitating easy access into different asset classes

In addition, ETFs which replicate commodities allow investors to access these returns without physically purchasing the commodity (whose actual cost might be prohibitive, and includes costs for storage and insurance) (Kosev & Williams, 2011). Thus, the emergence of thematic ETFs such as ETFs based on cannabis and cryptocurrency allow investors access to these markets without having to physically farm cannabis, and without requiring a cryptocurrency

[10] This advantage is relevant to International ETF markets, which do not recognise in-kind transactions as taxable events (Deville, 2008). In South Africa, both ETFs and Index funds receive the same taxation treatment, which eliminates this benefit for South African investors (Lambridis, 2019).

wallet (Ponczek, 2019). ETFs therefore offer trading versatility, with lower costs, for individual investors, who generally use these instruments as part of a full portfolio to meet specific needs (eg. Income needs are met by fixed income ETFs) (Gastineau, 2010). In South Africa, given the constraint on international investment[11], investing in a global ETF allows investors to attain global exposure without impacting on their yearly international allowance.

2.4.1.7. Transparency

ETFs also offer the advantage of transparency as their portfolio composition is always known, and their creation and redemption activity is also declared in their Stock Exchange News Service (SENS) (Gastineau, 2010). This is useful especially in the case of active-ETFs such as smart-beta products, which compete against actively managed products that display less transparency.

2.4.1.8. Use by Institutional Investors

The uses of ETFs for institutional investors extend beyond the core benefit of investment purposes, with many utilising ETFs to assist in managing cash (by using bond ETFs), to assist in matching duration, to assist in shorting a particular market or industry sector, or to cheaply hedge against currency exposures (Madhavan, 2016). The most important role however lies in its role in transition management, which has been one of the reasons behind its exponential growth. This process occurs when institutional investors[12] such as pension funds need to eliminate one investment, or terminate the services of one investment manager, and start a new fund, or employ a new manager (Deville, 2008). The transition manager thus ensures a smooth shift, and handles the purchase and sale of securities needed to end, and begin, a new portfolio. Whilst derivatives such as futures are often used for this purpose, ETFs and their relatively liquid markets have also offered a simple, cost-effective way to manage this process (Grayswan, n.d; van Obelitz & Suskind, 2012).

[11] Investors are only allowed to transfer up to a maximum of R11 million a year abroad (Mercury, 2020), and funds are not allowed to invest more than 30% of their assets under management offshore (Paine, 2020).

[12] This process can also happen on a smaller scale for individual investors who want to change their money managers, but maintain exposure to a specific sector or asset class in the interim.

2.4.1.9. Positive impact of ETFs on the underlying assets

Some advantages of ETFs result from their positive impacts on overall market quality, which are observations that can only be achieved through empirical studies on the topic. Hasbrouck (2003) is one such study that found positive effects of ETF formation, as he found that the ETF improved the price discovery process for the underlying stocks. Boehmer and Boehmer (2003) found that the introduction of ETFs increased the liquidity and market quality of the constituent assets, whilst Glosten, Nallareddy, and Zou (2016) discovered that ETFs increased the informational efficiency of the underlying assets. Madura and Ngo (2008) find that ETF trading increases the trading activity and valuation accuracy of the smaller components in the benchmarked index. In the South African market, Matarutse and Sibanda (2014) evaluated the Satrix Top 40, and found that its constituents displayed a decrease in volatility after inception of the ETF. A driven by higher liquidity and a reduction of asymmetric information. In her evaluation of price discovery, McCullough (2017) found that the presence of ETFs in the market facilitated faster price discovery between the spot and futures market.

2.4.2. Limitations of ETFs

The number of advantages documented in section 2.4.1 are many, and it is primarily these advantages that have propelled ETFs to become such a popular investment choice for both institutional and individual investors. These products however, are not free from risk, and their disadvantages stem from their structure, as well as the potential impacts that they have on the efficient functioning of the equity market, both for ETFs as well as for their underlying assets. These will be discussed in detail in this section, to provide a firm basis for the premise of this study.

2.4.2.1. Tracking error

ETFs, like index funds, can also suffer from tracking error, which arises when market imperfections such as transactional costs, dividends and index composition impact on the ability of the fund manager to perfectly replicate the index (Peyper, 2014). Studies such as Rompotis (2009), Shin and Soydemir (2010), Blitz and Huij (2012) and Strydom et al. (2015) all find evidence of tracking errors in their respective ETF markets. The potentially damaging effect of ETF tracking errors is noted by Blitz and Huij (2012), who hypothesise that if ETFs contain very large tracking errors, this impedes on their ability to act as passive products.

2.4.2.2. Not all ETFs are diversified products

An additional drawback of ETFs lies in the lack of diversification inherent in some products. Whilst ETFs based on broad-based indices can be considered diversified products, ETFs that are based on sectoral or thematic traits may contain over-exposure to one segment of the market, and thus can face greater losses in the face of market volatility (Baiden, 2011). In addition, an issue that is unique to the South African market, noted by Lambridis (2019), is the concentration of the equity market. Whilst a product like a Top40 ETF[13] would usually be considered diversified as it contains exposure to 9 different industry sectors on the JSE, in reality, this index has a is 9 times more concentrated than the S&P500 index (based on the Herfindahl-Hirshman Index (HHI)), with Naspers occupying close to 20% of the index (Lambridis, 2019). This therefore poses a risk to investors, who may be under the perception that they are procuring a diversified product.

2.4.2.3. Illiquidity

Whilst ETFs based on popular segments of the market may be fairly liquid, other ETFs based on commodities or sectors that are relatively illiquid may suffer from the same illiquidity as their underlying securities. This in turn, will increase the bid-ask spread for these products, which may result in the cost of the ETF becoming prohibitively more expensive than its index fund counterparts (Wierzycka, 2014). Results from the Flash crash studies (which is discussed further in section 2.4.2.4.1) also showed that usually liquid ETFs may suffer from illiquidity in conditions of market volatility (Foucher & Gray, 2014).

2.4.2.4. Systemic risks

Some of the disadvantages of ETFs also manifest themselves as systemic risks to global market stability. Systemic risk refers to the "risk of breakdown or major dysfunction in financial markets" (Hansen, 2013, p. 4). There are three possible definitions of systemic risk offered by Kaufman and Scott (2003), each of which indicate different sources. The first definition focuses on a macroeconomic shock, such as an event that affects the entire banking system, which then spreads to the broader economy. This shock then causes a disruption in the flow of information in the general economy, and leads to difficulty obtaining funds. The second definition relates

[13] This ETF is meant to replicate the performance of the JSE Top40, an index which is composed of the largest 40 companies in South Africa, based on market capitalisation.

more specifically to the way in which financial distress is transmitted throughout the economy, with a failure of one party to meet its contractual financial obligations then causing other participants in the economy to default, thus causing a chain reaction. The final definition refers to indirect causation, whereby if one large financial firm defaults on a payment, or experiences some kind of financial difficulty, the perception created for market participants is that all related firms will suffer the same fate and have the same risk levels, thus leading investors to flee from the market entirely and search for safer havens. Since ETFs, and largely all asset managers, function differently from the banking economy and are largely fiduciary agents for their investors, the systemic risks experienced here are attributed largely to the third definition, which is the indirect impact on the economy (Roncalli & Zheng, 2014).

Concerns about the asset management industry (in particular ETFs) and its systemic role in the global economy began after the financial crisis, and led to the call by the G20 leaders to evaluate whether these institutions qualify as Systemically Important Financial Institutions (SIFI)[14], which require more regulation (Goodspeed, 2015). This call led to a subsequent reports by the OFR (2013) and IMF (2015) which focused on the asset management industry as a whole. Reports by Ramaswamy (2011) for the Bank of International Settlements, Bradley and Litan (2010), Bradley and Litan (2011) and ERSB (2019), all placed an emphasis on ETFs in particular and their role in generating systemic risk.

Recent years has seen the role of credit intermediation shifting from being primarily bank-based, to the asset management industry (especially after all the regulations placed on banks after the financial crisis). The increased importance of the asset management industry has many benefits to the economy; such as the ability to provide finance to the economy even when banks may be unable to, and their overall structure ensuring greater financial stability[15].However, the concern lies in the size of the industry being as large as the banking industry, and as concentrated as the banking industry as well (IMF, 2015). The study by Fichtner, Heemskerk, and Garcia-Bernardo (2017) found that, at the time of their study, the US market was

[14] A Systemically Important Financial Institution (SIFI) is an institution whose distress would cause a disruption to the financial system as a whole due to its size, complexity and interrelation with other institutions in the economy (Roncalli & Zheng, 2014).

[15] Banks tend to be financed with short-term debt which exposes them to solvency and liquidity risks, whilst investment funds do not have this problem as their leverage levels are low.

concentrated on 3 main ETF providers – BlackRock, Vanguard and State Street who collectively owned 71 percent of the ETF market in the US. A similar analysis of the South African environment yields the same result, with 75 percent of the current ETF market occupied by the 3 largest providers, viz. Absa Capital, Sygnia/Itrix and Satrix[16] (Brown, 2020).

A crisis in the ETF market therefore could be transferred to the rest of the economy either because of the exposure of the other market participants to these instruments, or due to the possible disruption created by fire sales[17] (OFR, 2013). Systemic risks therefore pose a threat to the financial stability of the entire market, and since barriers between countries have increasingly declined due to globalisation, this may lead to financial instability in other economies as well. These systemic risks are off particular concern for this study, as they affect the microstructure of the market and thus could impact the behaviour of the assets that underlie these portfolios. The major concerns expressed by authors of the various reports are therefore discussed further in subsections 2.4.2.4.1 to 2.4.2.4.7.

2.4.2.4.1. Flash crash

The main reason for the enquiry into ETFs and their contribution to systemic risk is due to the Flash crash in the US market in 2010. A flash crash is termed as such, as it refers to a rapid fall of security prices in a very short space of time. On May 6th 2010, the Dow Jones Industrial Average (DJIA) index fell 1000 points, but recovered 600 points of that loss in just 20 minutes. Whilst many individual securities also traded at unreasonable prices, the market price of many ETFs diverged significantly from their iNAVs (Madhavan, 2012). Whilst many exchanges ended up having to cancel trades where the price of assets fell below 60 percent of their pre-crash value, those with market stop loss orders still had these orders executed. Exchange traded products made up 65 percent of the cancelled trades on this day (Ramaswamy, 2011). Bradley and Litan (2011) attribute this observation to the use of ETFs by hedge funds and institutional investors to profit from the practice of "naked short selling"[18], and thus contribute to systemic

[16] It should be noted however, that the magnitude of the South African ETF market pales in comparison to the US market, in which case the concentration here might not be as big a risk factor as it poses in the US.

[17] A fire sale occurs when an ETF provider is experiencing financial distress, and has to sell the assets in his portfolio for discounted prices (OFR, 2013)

[18] Short selling allows traders to profit from falling prices, by selling shares that the trader borrows from the broker, with the requirement that these shares are returned at a later date. Naked short selling occurs when the trader initiates the sale before possession of the borrowed share is ascertained, and is often initiated by individuals who have no intention of delivering the actual shares (Christian, Shapiro, & Whalen, 2006).

risk in times of market stress. Market makers also suffered losses during this flash crash, with many being forced to sell at the low prices. In addition, those who were aiming to hedge by short selling substitute securities, were disadvantaged when the long orders were cancelled by exchanges, with the result that their short orders rebounded in price very quickly (Madhavan, 2012). The resultant observation of ETF illiquidity and price disruptions is what prompted the investigation by the SEC into the microstructure of ETFs (Borkovec, Domowitz, Serbin, & Yegerman, 2010).

The investigation by the SEC attributed the cause of the flash crash to be due to a lone trader's incorrect usage of a broker algorithm. A study by Madhavan (2012) however, found that the cause of the flash crash was fragmentation in the market, and not the basic ETF structure. Madhavan (2012) attributed the movements in ETF values to one of the circuit breakers that was introduced after the initial flash crash, which is a limit up and limit down. This circuit breaker stops trade or five minutes if the price of a security moves beyond the limit up or limit down values. Therefore, when ETF prices fell drastically due to extensive usage of market and stop-loss orders, trading was stopped for a period of time, after which, when the ETF price tried to recover, it hit the limit up price and was halted again. As noted by Madhavan (2016, p. 234), "ironically, exchange rules imposing halts for stock prices experiencing volatility slowed the recovery to equilibrium". A report on the Flash crash published by Blackrock (2015) found that this volatility impeded the flow of order and price information, and impaired the ETF arbitrage mechanism which usually eliminates any deviations from NAV. These findings resulted in the SEC instituting a rule that trading on high volatility securities and ETFs will be halted under certain market conditions (Liebi, 2020)

Despite rules and market-wide circuit breakers being put into place by exchanges following the 2010 flash crash, this phenomenon was repeated in August 2015, when the S&P500 and DJIA fell 5 percent and 6.6 percent respectively, shortly after markets opened due to selling pressure because of global stresses (Aldridge, 2016). This led to 1278 trading halts across mainly ETF securities, with the result that large ETFs completely disconnected from their underlying iNAV. Large ETFs such as the Guggenheim S&P500 Equal Volatility Weight ETF and the Powershares S&P500 Low Volatility ETF traded at large discounts or premiums from their NAV in a matter of minutes, even though these ETFs historically traded very close to NAV (Reklaitis, 2015).

The results of the two flash crashes indicate that the origination of the shock cannot be traced back to ETFs. However, the propagation of the shock has been proven by Ben-David, Franzoni, and Moussawi (2011) to have been exacerbated by ETFs, which transmitted the volatility from the futures market into the equity market. Furthermore, the behaviour of ETFs on the days of the flash crash raised questions about ETF reaction to volatility, which has important policy and regulatory implications (Aggarwal & Schofield, 2014). Since ETFs now account for about a quarter of the daily turnover in the US (Evans & Wilson, 2018), the possibility of ETFs contributing to contagion is an important issue for consideration. As argued by Elliott (2014) whether ETFs are found to create shocks, transmit shocks, or amplify existing shocks, the differentiation does not matter as all present a systemic risk and need to be addressed by regulators.

2.4.2.4.2. Contribution of ETFs towards contagion risk

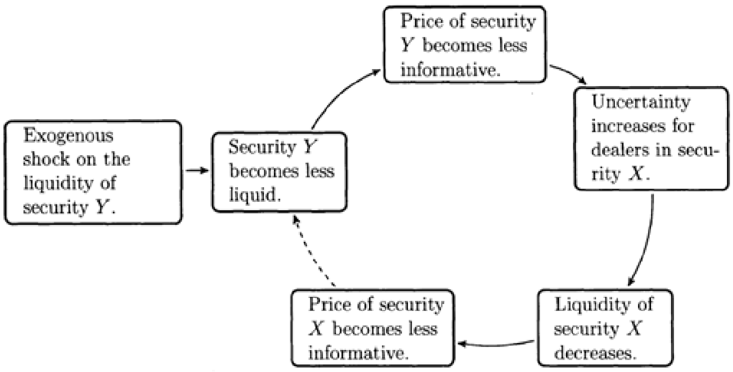
Contagion occurs when a crisis in one market/economy spreads to other markets even though they may be unrelated. There are three main channels through which this could occur, which are:

- **The correlated information channel** – this occurs when uninformed investors assume that the price variations of another market reveal investors superior information and therefore act accordingly (Pritsker, 2001);
- **The correlated liquidity shock channel** – when liquidity traders are forced to liquidate their positions due to to their desire for liquidity, and therefore sell financial assets in several markets (Cespa & Foucault, 2014); and
- **The cross-market rebalancing channel** – this occurs when risk-averse traders react to a shock in one market by adjusting their portfolios in other markets (Greenwood, 2005; Kodres & Pritsker, 2002).

The seminal paper by Ben-David et al. (2011) evaluated whether ETF arbitrage activity in one market can lead to contagion. They conjecture that if an institution has a need for liquidity(and therefore initiates a large sell order) this would lead to a decrease in price of the ETF, thus prompting arbitrageurs to purchase it at the cheaper price, whilst hedging their position by selling the underlying assets. This activity would thus cause the ETFs NAV to decrease[19], but for no fundamental reason, and simply because of the liquidity shock. Therefore, the arbitrage activity in the ETF can lead to contagion in the market for the underlying asset, and could spread to related markets as well, which will ultimately cause an increase in volatility that is not due to fundamental reasons. Their results confirmed this hypothesis, which implies that the presence of ETFs in the market increases the risk for contagion spreading liquidity shocks to other asset markets, and this observation is exacerbated for smaller, less liquid securities (Ben-David et al., 2011).

A similar result was found by Cespa and Foucault (2014), who hypothesise that market makers of ETFs use activity in the underlying assets to gain information. Therefore, if there is a drop of liquidity in the market for the underlying asset, this leads to its price containing less information for ETF market makers to gauge, which thus causes a decrease of liquidity in the ETF market as well. They therefore find evidence for contagion being due to the "illiquidity spill-over mechanism", which is depicted in Figure 2-4.

Figure 2-4: Liquidity spill-over via cross-asset learning



Source: Cespa and Foucault (2014, p. 1314)

[19] This occurs when there are limits to arbitrage faced by arbitrageurs in the ETF market, such as limited capital or risk aversion due to previous losses (Ben-David et al., 2011)

The figure depicts a feedback loop, where a small shock to the liquidity of one asset, is not only propagated to the next asset via the cross-asset learning mechanism, but it is also amplified. This correlation in liquidity exists even in the absence of cross-market arbitrageurs, and is found to be stronger in assets, which display easier access to information. This amplification of liquidity shocks can therefore lead to contagion, and market instability. Both Ben-David et al. (2011) and Cespa and Foucault (2014) therefore find support for contagion being present in the ETF market via the cross-market channel.

In their paper, Bhattacharya and O'Hara (2018) also document a mechanism for information feedback between ETF prices, and the prices of their underlying assets, although not via the liquidity channel. The creation and redemption process for ETFs is an important function that assists in linking the price of the ETF to the price of the basket of underlying securities. Bhattacharya and O'Hara (2018) focus their study on ETFs, which are made up of hard-to-trade assets, and where immediate arbitrage may be difficult. These hard-to-trade assets in the equity market may consist of ETFs that trade illiquid companies, or ETFs that hold international assets with nonsynchronous trading times; suggesting that the trading in the ETF market might carry on after the market for the underlying is closed, and vice versa.

In these hard-to-trade markets, it is often found that market makers might use ETF prices to infer information about the underlying assets, and vice versa. The challenge for the market makers however, is that it is nearly impossible to differentiate between price changes caused by fundamental information, and price changes caused by noise which is irrelevant to them (Bhattacharya & O'Hara, 2018). The result is that unsystematic risks in one stock could cause changes in another unrelated asset through this channel, which can therefore lead to contagion and market instability. This may be especially true for stocks which have a high weighting in the ETF, and which exhibit high betas. Bhattacharya and O'Hara (2018) conclude that even though ETFs can be considered derivative securities (their value is derived from the value of another asset), instead of the market for the underlying asset informing the price of the ETF, the opposite effect is now found, which could have a destabilising effect on the overall economy. This phenomenon could also deter private firms from listing on the stock exchange, in fear of subsequent ETF membership disrupting their share prices (Liebi, 2020).

2.4.2.4.3. Dependence of Authorised Participants

The APs in the ETF system plays a pivotal role as liquidity provider. Furthermore, it is often found that a few APs serve as liquidity provider to all the ETFs in the market (Lettau & Madhavan, 2018). However, APs generally do not receive any compensation from the ETF sponsor, neither are they legally obligated to create or redeem shares of the ETF. Instead they enter into creation and redemption transactions in the pursuit of arbitrage profits. There have been a few cases in history where APs have reneged on their duties, for example, in the US, Citigroup Inc stopped being a redemption agent for the ETFs that were serviced, due to their internal limits (Madhavan, 2012). Similarly, in 2012, Knight Trading Group had to restrict their creation and redemption activity due to internal operational losses (and this company served as AP to hundreds of ETFs in the market at that time) (Lettau & Madhavan, 2018).

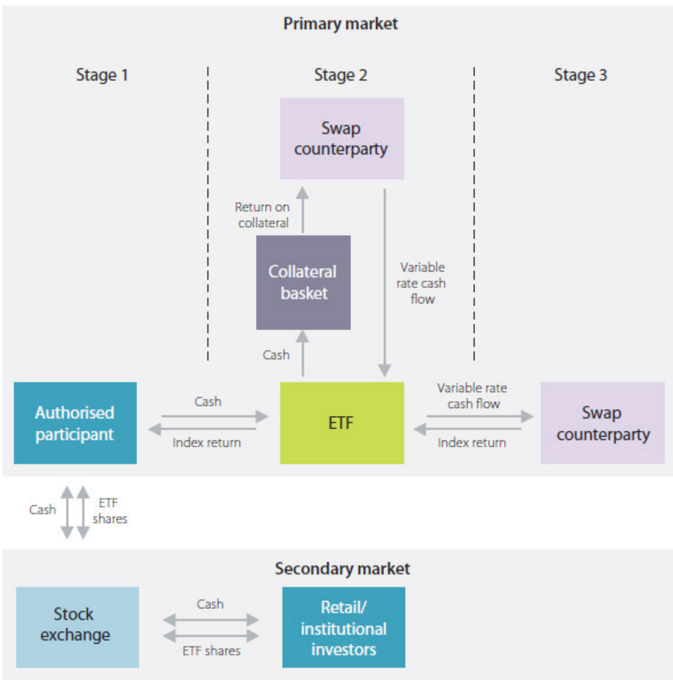
Bradley and Litan (2010) drew parallels in the growth of the ETF market and its construction as a derivative, with the mortgage securities that led to the Global subprime crisis. They state that as more ETFs are created, which are interlinked, the higher the risk of a meltdown being caused by a small risk factor. If there is a "run" on ETFs and many investors want to liquidate their positions, the market makers might not be able to honour their obligations, which could lead to the government needing to bailout these SIFIs, similar to the way AIG was bailed out (Bradley & Litan, 2011). The OFR (2013) report also notes that during times of market distress, market makers may choose to stop providing liquidity due to their lack of reliable information on the underlying security markets, thus exacerbating any negative price movements in response to the market turbulence.

This danger would not be applicable in the US however, with many other APs being available to fulfil the obligations of a defaulting AP should the need arise (Madhavan, 2016). This was demonstrated in the case of both Citigroup and Knight Trading Group, where other APs stepped in to fulfil their duties. The analysis by Antoniewicz and Heinrichs (2014) confirms this, with data at the time of their study indicating on average 34 APs present, per ETF provider. Furthermore, as noted in the ICI (2020) review, most of the activity around ETFs occurs in the secondary market, with only 10 percent of equity market activity in the US from 2015 – 2018 occurring in the primary market. Madhavan (2016) does accept though, that in the event of a chain reaction, with many or all APs withdrawing from the primary market, this would lead to large deviations in NAV in the secondary market and this could create a systemic risk to the overall market, even though this has not occurred as yet. In the aftermath of the August 2015 flash crash, the report conducted by Blackrock (2015, p. 14) shows that the liquidity problems faced in the market on that day, was due to the disappearance of liquidity providers who "have no obligations to make markets", and they appealed to regulators to help identify activity which will ensure market resiliency.

2.4.2.4.4. Increase in complexity of ETF structure

Physically-replicated ETFs are often referred to as plain vanilla ETFs as these were the first type to be derived, and involve the physical purchase of at least 90 percent of the constituents underlying the benchmark index (Aldridge, 2016). However, as noted in section 2.3.2, many ETFs in the US, European and Asian markets are currently being replicated using synthetic means, such as the purchase of derivatives like futures, forwards, options and total return swaps, instead of the underlying asset. The need for synthetic ETFs arose due the increased demand for ETFs, but limited availability of liquid underlying assets (Ramaswamy, 2011). The structure of a synthetic ETF is shown in Figure 2-5.

Figure 2-5: Structure of a Synthetic ETF



Source: Kosev and Williams (2011, p. 58)

A total return swap is an agreement between two parties, to exchange one type of return for another. In order to implement the exchange, a swap counterparty will need to be involved in order to return the performance (capital gains and dividends) of the specified benchmark, in return for a cash payment. Figure 2-5 shows this process being achieved in 3 stages. Stage 1 involves the AP purchasing a creation unit using cash (in contrast to physical replication which makes use of a portfolio of shares). The ETF then uses the cash to invest in a basket of shares different from the index being tracked, in order to form the ETFs collateral. This basket of shares is usually made up of very liquid, high quality shares. The return that is earned on this collateral basket of shares is thereafter swapped in Stage 2, for a stream of cash flows based on some flexible rate such as the London InterBank Overnight Rate (LIBOR). This stream of cash flows is then swapped in Stage 3 for the return on the chosen benchmark index, in a second swap. The ETFs sponsor usually serves as the counterparty to both swaps (Kosev & Williams, 2011). The derivation of these synthetic ETFs therefore mean they are more complex, and have less transparency than physically-replicated ETFs, and thus limited ability for investors to assess risk levels (Ramaswamy, 2011). This use of swap agreements also exposes the fund to counterparty exposure, something which is absent in the conventional form of ETFs. This complexity and its relevant issues extends beyond synthetically replicated ETFs to leveraged and inverse ETFs as well.

Since the counterparty to ETF swaps are generally banks (either a single bank or a consortium of banks), if there are any problems experienced by these parties, this could spread to the ETF market, and thus present a source of contagion to other parts of the market. Some ETF sponsors also have a dual role of being the swap counterparty, as well as the ETF provider which then results in a conflict of interest (Madhavan, 2016). The redemption activity of synthetically replicated ETFs may also prove challenging, especially if the collateral basket is made up of illiquid securities, or low rated corporate bonds[20] (FSB, 2011), which may result in a suspension of redemption activities, or a liquidity shortfall. The use of synthetic ETFs are therefore similar to hedge funds in their ability to use complex derivatives, but they do not enjoy the same restriction that hedge funds employ on investor withdrawals when market liquidity is low (Ramaswamy, 2011). This therefore allows synthetic ETFs no mechanism with which it can manage redemption and liquidity risks (Ramaswamy, 2011).

[20] There is currently no legislation which impacts on the construction of the collateral basket for ETF swaps.

2.4.2.4.5. Securities lending, and counterparty risks

Securities lending refers to the temporary transfer of ownership of a security from the owner (individual or institutional fund), to a borrower for the purpose of short selling. The owner usually charges a fee (collateral ranging from 102 percent to 112 percent) for the process, and since physically replicated ETFs have a large number of different shares in their possession, this allows a method of earning a return on shares which would otherwise be lying dormant (Abner, 2010). A study by Blocher and Whaley (2015) of the US ETF market found that, many ETFs use the securities lending process as an extra source of income. This might be driven by the current low margins being earned by plain vanilla ETFs, and it's been reported by the IMF (2015) that some ETFs generate more funds from securities lending than from their mainstream activities. The regulations in the US currently imposes a 50 percent limit on ETFs, which means that not more than 50 percent of the ETF securities can be lent out at any point in time, however according to Madhavan (2016), no more than 10 percent of ETF securities are on loan in the current market.

Securities lending was introduced in the South African market in the late 1990s, and the Financial Services Board (FSB) (now known as FSCA), commissioned a report on this practice in 1999 to determine if there was a link between securities lending and reported turbulence in the market, which was found to be non-existent. Since then, the FSB has been encouraging of its use as a market stabiliser, with the result that as at 2015, approximately R20 billion worth of South African equities was estimated to be lent out at any point in time[21](Analytics, 2015). The Collective Investment Schemes Act (CISCA) (which is discussed in section 2.5.2) also imposes a 50 percent limit of securities lending on ETF securities, which also asserts that collateral is required from the borrowers, who need to meet certain qualifying criteria (Finance, 2010).

Whilst the process of securities lending and short selling has positive effects on the market, such as reducing mispricing and increasing liquidity, the risk of the borrower defaulting (known as counterparty risk) does exist, which would then impair the creation and redemption

[21] In South Africa, all assets lent out by a CIS must be held by the custodian (trustee), instead of the asset manager (Finance, 2010) This therefore serves as protection for the investors of the CIS, as the trustee must meet strict guidelines as part of his fiduciary responsibility.

process for APs (Madhavan, 2016). The process of securities lending (even in the event of no default) could also impair the APs ability to meet demands for liquidity by investors, especially in times of market stress when there are many outflows from the ETF (IMF, 2015). Whilst Lettau and Madhavan (2018) note that there are current safeguards in place is that the owner has the ability to recall loans, and liquidate the collateral posted in the event of default, if ETF providers are forced to recall all securities that are currently on loan, this can create a short squeeze[22] in the underlying assets, and thus be detrimental to overall market liquidity (FSB, 2011).

2.4.2.4.6. Redemption risks

One of the concerns raised by many of the reports reviewing ETFs is that of redemption risk. ETFs are sometimes comprised of assets that are relatively illiquid, such as those that hold fixed income assets, small cap securities, or even cryptocurrencies. In the event that the market becomes distressed for any reason, there may be an incentive for investors to sell their positions early, thus creating a "first mover advantage", similar to bank runs (IMF, 2015). The necessity of fire sales to satisfy investors needs to withdraw their funds, may require the use of unprofitable trades and costly measures taken to meet investor demands.

If there were a run on a particular ETF, this would spread to the underlying asset, which would then spread to other similar funds and underlying assets, and would propagate the shock to other asset markets. It should be noted that this is related to the previous subsection, since a simultaneous halt in primary ETF market activity by APs could also lead to investor runs on the indexed fund and underlying asset market (FSB, 2011; Madhavan, 2016; OFR, 2013). This issue is more pronounced for bond ETFs, as previous studies have found that investors in the bond market react more negatively to any market distress than equity market investors (Goldstein, Jiang, & Ng, 2017). However, fire sales in the equity market can be amplified if a particular ETF holds a large proportion of a single asset, sector, or index, or if its shares are tied up in an important specialised market that is not fully transparent, and does not have the required levels of liquidity (FSB, 2011). Similarly, a fire sale for one ETF would result in

[22] A short squeeze occurs when there is a sharp increase in price of an asset that causes short sellers to close their positions hurriedly in order to limit losses (Jarrow, 1992).

similar occurrences in all other ETFs provided by that sponsor, because of the negative impact on the firm's reputation (OFR, 2013).

If market liquidity decreases in the event of market stress, redeemers will have to be willing to accept a market price for their ETF shares that will probably be lower than the NAV of the ETF, since APs are not forced to redeem at NAV, unlike open-ended funds. Similarly, any fire sales will impact negatively on the investors who want to trade, but not the ETF, and not any long-term investors who have a buy and hold strategy, which is a disincentive to investors, to limit the impact of redemption risk (IMF, 2015).

2.4.2.4.7. Negative Impact of ETFs on the underlying assets

An issue that was raised in the introduction chapter of this thesis, is the possibility that ETFs have undesirable effects on their underlying assets, a phenomenon that is currently being evaluated in academic literature. The seminal works of Subrahmanyam (1991) and Gorton and Pennacchi (1993) hypothesise that the introduction of basket securities such as ETFs, results in a migration of investors away from the market for the underlying securities, into the market for the ETF. This therefore results in a decrease in liquidity for the underlying assets, which, according to Israeli et al. (2017) could also result in a decrease in the informational efficiency of the underlying assets. These two phenomena are the focus of this study, which are elaborated upon in Chapters 4 and 5 respectively.

Studies by Malamud (2016) and Bhattacharya and O'Hara (2018) showed that the presence of ETFs can also increase the volatility of the stocks that make up these assets. This result was confirmed by Curcio, Anderson, Guirguis, and Boney (2012), Lin and Chiang (2005) and Ben-David et al. (2018), all of whom found a significant increase in the volatility of underlying asset returns after ETF introduction. Krause, Ehsani, and Lien (2014) find in their study that volatility shocks in the ETF market also spill over into the market for their largest constituents. In contrast, studies of liquidity impacts such as Van Ness et al. (2005), De Winne et al. (2014), Hamm (2014) and Sağlam, Tuzun, and Wermers (2019) found that the introduction of ETFs decreases the liquidity of its constituent assets. Whilst Bae, Wang, and Kang (2012) found an increase in liquidity for stocks included in ETFs, they also found that ETF membership negatively impacts individual firm value. In his South African study, Badenhorst (2017) found evidence that when ETFs sell at a premium, this is usually because the liquidity (captured by bid-ask spreads) of their underlying assets is lower, which provides evidence of investors migrating to the ETF market, especially when it is made up of illiquid assets.

ETFs are also proposed to have a negative effect on the correlations of their constituent assets, according to Wurgler (2010), who conjectures that simultaneous purchase and sale of unrelated assets for inclusion into index-based securities, lead to these securities being more correlated to one another than previously. This result was confirmed by the studies of Vijh (1994), Barberis, Shleifer, and Wurgler (2005), Glosten et al. (2016); Broman (2016) and Da and Shive (2018), who found that the introduction of ETFs have caused the correlations of their underlying assets to increase, and this increase is due to non-fundamental factors. A recent study by Israeli et al. (2017) also finds that ETF increase synchronicity, which means that the prices of shares are less dependent on their individual information, and more dependent on movements in the ETF.

2.5. BACKGROUND ON REGULATION OF ETFS

An investment product such as an ETF requires avid regulation from authorities, as they hold large amounts of wealth from the general public, who need to be protected from predatory or unfair practices. The regulation of these instruments has also evolved in recent years, to focus on their broader impact on overall market stability, in response to growing empirical evidence on their potential adverse impact (which is discussed in section 2.4.2). This section focuses on the regulatory environment of the US as the market initiator and current market leader of ETFs, after which the South African regulatory environment is discussed and contrasted.

2.5.1. Regulation of ETFs in the US

In the US, ETFs are governed by the Securities Exchange Commission (SEC), subject to the Securities Act of 1933, the Securities Exchange Act of 1934 and most importantly, the Investment Company Act of 1940 (Madhavan, 2012). The Investment Company Act was designed for application to investment companies, to prevent mismanagement and corruption that caused a large amount of shareholder losses during the 1930 Great Depression

(McLaughlin, 2007). The Act enforces regulations on key issues such as corporate governance, fund registration, debt issues, asset valuation, trading of securities, the agency issue and performance presentation. All ETFs are also governed by this act, however since they are not explicitly accounted for in the Act, ETF sponsors have to register their ETFs as either Unit Investment Trusts (UITs) or Open-Ended Funds (OEFs) (Kosev & Williams, 2011). UITs must physically replicate the index, and are not allowed dividend reinvestment, use of derivatives or security lending. OEFs allow for immediate reinvestment of dividends, as well as the use of derivatives and security lending, and generally display more flexibility than UITs (Abner, 2010).

Usually, the structure of UITs and OEFs involves the issue and redemption of "units", which are the securities that the fund manager is able to buy back from the investors, at the security's NAV, at the close of trading. However, ETFs issue and redeem bundles of 50 000 shares or more, and these securities can trade constantly in the secondary market, characteristics that are not specifically accounted for in the Act (Hu & Morley, 2018; McLaughlin, 2007). Until 2019, the SEC has had to evaluate each ETF registration and grant special exemption[23] from these operational characteristics that do not fit ETFs underlying structure (Ahmed, 2019). It is this exemption that prevented the proliferation of ETFs in the early years of its introduction, as each issuer and fund required the granting of exemptions, which involved considerable delays and as additional costs (Gastineau, 2010). It also meant that different ETFs that were similar in construction and purpose, were subject to different rules depending on the timing of their introduction – earlier ETFs were subject to less stringent requirements than newer ETFs (SIFMA, 2018). Similarly, the process was often referred to as cumbersome and opaque as there were no clear guidelines present to be applied consistently to all ETFs (Hu & Morley, 2018). The regulatory environment also suffered from fragmentation (a commodity ETF is subject to different legislature than an equity ETF), which is exacerbated by the procedure of each different exchange in the US (BATS, NYSE, NASDAQ) having different listing and trading requirements.

[23] There are five exemptions required for ETFs (Yoder & Howell, 2012)

In a bid to improve the regulatory environment after many years of criticism, as of 26 September 2019, the SEC published rule 6c-11, which removes the requirement for exemptive relief for OEFs, and allows easier listing for US ETFs (Ahmed, 2019). This also promotes greater transparency as it requires ETFs to post their portfolio holdings on their website daily, and requires disclosure of previous discounts and premiums, bid-ask spreads, as well as creation and redemption information (SIFMA, 2018). This rule also allows ETFs to create their own custom basket that might not represent a pro-rata version of the benchmark, which assists sponsors who are not always able to replicate benchmarks completely (due to illiquid securities or market frictions). This also generates a favourable regulatory environment for the emergence of more active ETFs.

However, whilst this amendment represents a step in the right direction, the regulation still fails to recognise the complexities of the arbitrage mechanism, and leveraged and inverse ETFs still have to follow the exemption process (which has the drawback of providing inconsistent rulings over the years and under different commissioners) (Hu & Morley, 2019). In 40 different commentary articles submitted to the SEC by ETF providers, further changes were recommended that would incorporate market complexity into the regulatory regime (Weinberg, 2018). In their article, Hu and Morley (2019) advocate for a dedicated framework of regulation, that takes into account the trading frictions present in ETFs which trade continuously throughout the day, as well as the innovation that undertones this evolving asset class.

2.5.2. Regulation of ETFs in South Africa

In South Africa, ETFs are currently regulated by the Financial Sector Conduct Authority (FSCA), according to the Collective Investment Schemes Control Act No. 45 of 2002 (CISCA), the Financial Advisory and Intermediary Services Act (FAIS), as well as the Finance Intelligence Centre Act (FICA) (Matarutse & Sibanda, 2014). CISCA specifies collective investments as unit trusts, hedge funds, and ETFs, and provides a framework that specifies how a manager should handle the administration, marketing, sales and operation of the fund (CISCA, 2002). FAIS (2002) stipulates a code of conduct for financial advisors to adhere to, and FICA (2017) allows for the detection of suspicious activity by forcing financial institutions to conduct customer verification tests.

Whilst the US regulatory environment allows for exotic ETF structures, the current SA regulation is simpler. All assets denoted as Collective Investment Schemes (CIS) must be structured in the form of a trust, with an appointed trustee whose main aim is to ensure good governance and regulatory compliance in the fund (CISCA, 2002). It is also legislated that a trustee cannot be the manager of the fund, and must be an independent person, which enhances investor protection (Peyper, 2014). CISCA allows for securities lending and dividend reinvestment, but prohibits the use of derivatives or leverage in South African ETFs[24]. The Act also maintains that all ETFs formed in South Africa need to be via the means of physical replication (Matarutse & Sibanda, 2014).

The current financial environment in South Africa places certain constraints on offshore investment behaviour, such as the limitation of international investments to a maximum of 40% for fund managers, and a maximum of R1 million for individuals (Campbell, 2020). The use of international ETFs therefore allows exposure to different countries, but without impacting on the foreign allowance. The relatively small ETF market in South Africa could be attributed to Regulation 28. According to South African law, all retirement annuities and pension funds held in South Africa must adhere to Regulation 28 in the Pension Funds Act, which prohibits certain types of investments, and stipulates a maximum proportion for different asset classes[25] (Paine, 2020). This therefore prohibits Retirement annuities and pension funds to include some types of ETFs in their portfolios, which led to ETFSA introducing a specific Retirement annuity fund in 2013, which is made up of purely ETFs, but still adheres to the Regulation 28 requirements (ETFSA, 2013).

[24] This legal requirement implies that it is not possible to create a leveraged or synthetic ETF in the South African market. All discussion in this dissertation therefore focuses on the only structure that is allowed according to South African law, which is a physically replicated ETF (also known as “plain vanilla” ETFs).
[25]The current proportions (as at 5 August 2020) is 75% equity exposure, 25% listed property exposure and a maximum of 30% offshore exposure (Paine, 2020).

2.6. CHAPTER SUMMARY AND CONCLUSION

This chapter described in detail, the structure, uses and misuses of ETFs, with specific reference to the South African environment. Whilst ETFs offer many important advantages, both for investors as additions to their portfolios, and to the overall market function, these assets also pose potential systemic risks which cannot be ignored. In particular, there is a growing field of literature on the impact of ETF introduction and trading on the microstructure effects of its underlying securities (such as liquidity, volatility, pricing efficiency). The results of many of these studies document negative impacts, which has important implications for investors and regulators alike.

The quality of the financial market is an extremely important construct, as the primary reason for its creation is the benefit of its market participants. Equity markets in particular, provide the important mechanism of facilitating price discovery, and as such, any disruption in market quality may result in an equity market which does not allocate capital effectively, and which disrupts the trade and efficiency of the market. The afore-mentioned microstructure effects of liquidity, volatility and pricing efficiency are therefore extremely important in maintaining the quality of the equity market, and thus the arrival of new market products, like ETFs, should be evaluated in terms of their respective impacts.

CHAPTER THREE: FINANCIAL MARKET MICROSTRUCTURE THEORIES

3.1. INTRODUCTION

The efficient and smooth operation of the financial market is an integral component to the functioning of any economy, and as such can be considered a very important link to overall market stability. The initial development of financial theories were all based on the assumption of frictionless markets, and therefore made assumptions of homogenous expectations, no transaction costs, and symmetric information (De Jong & Rindi, 2009). The elements relaxed by these assumptions however, are very relevant in the real world, and along with issues such as investor behaviour and institutional structure, have a significant impact on the price discovery and trading process in financial markets (Biais, Glosten, & Spatt, 2005). Since the 1970s however, there has been an increasing focus on the various elements that contribute to price formation, and is broadly termed as "market microstructure". O'hara (1997, p. 1) defines market microstructure as the "study of the process and outcomes of exchanging assets under explicit trading rules", and its design is to focus on the various elements that affect intraday price dynamics.

The development of the microstructure literature has great importance, as it allows for the capture of effects that would otherwise be ignored, in financial markets through which large amounts of wealth pass through on a daily basis. Recent statistics in the US indicates that fund flows from the US have reached $252 billion in 2020 (Gurdus, 2020), whilst SA statistics show that R600m in ETF value is traded on a daily basis (IOL, 2020). The study of the microstructure elements of the ETF market therefore allows for the modelling of price formation, and is expected to provide a better understanding of the returns earned by these financial assets (Laruelle & Lehalle, 2018). It also challenges the market efficiency paradigm by evaluating the strategic behaviour of various market participants on price diversions from their informationally efficient equilibrium (Naes & Skjeltorp, 2006). Furthermore, at a time when new markets, products, and technology are rapidly being introduced, the study of market microstructure allows for an informed analysis of whether these elements contribute to market quality or not. Similarly, the current use of high frequency data allows for empirical analysis to capture details inherent in the market that were impossible to observe previously (Yuan, Mu,

& Zhou, 2020). The applications of the market microstructure theories developed also have far reaching applications, from investment management to corporate and international finance, and provide a basis for understanding the microstructure of ETF markets.

This chapter therefore attempts to discuss the microstructure of the ETF market, particularly the potential impacts on liquidity and informational efficiency. The discussion therefore begins with a discussion of the central tenets to the microstructure theory, which form the basis of the seminal studies of Grossman and Stiglitz (1980) and Kyle (1985). The implications derived from these two models are thereafter discussed with reference to the theoretical literature surrounding microstructure impacts of ETFs.

3.2. BACKGROUND TO DEVELOPMENT OF MARKET MICROSTRUCTURE THEORIES

The central precept of microstructure theories is the way in which prices are formed (Gerety & Mulherin, 1994). The initial method of price formation in markets takes the form of a Walrasian market, where the auctioneer is tasked with setting a potential trading range for a product. Based on this price, buyers place their order bids, sellers specify their requests, and if there is an imbalance a new price is suggested, until a market price is agreed upon by all parties. Only after this market price is determined, can trade occur, so the demand curve of a Walrasian equilibrium[26] effectively reflects all potential investors (O'hara, 2001). This was first questioned by Demsetz (1968), who opined that in a Walrasian auction, over time, the number of buyers and sellers might eventually be matched, but at any particular point in time this is not guaranteed. Therefore if the number of buyers who want to purchase the product immediately does not match the number of sellers who want to sell immediately, there will not be an equilibrium price found at time t. As a result, buyers who wish to purchase immediately will either have to wait for a seller to arrive, or he can offer a higher price to induce more sellers to want to trade now (this higher price represents a cost of immediacy). The same can be done for

[26] In a Walrasian equilibrium, all information is considered exogenous, and traders are unable to use knowledge of the equilibrium price to alter their buy/sell decisions. In addition, all traders are assumed to receive the same information (ie. information is homogenous), and there is no uncertainty about the value of the products being exchanged (Hasbrouck, 2007).

sellers who require immediacy, by simply lowering their price they could induce more buyers to trade at that point in time.

Demsetz (1968) therefore argues that this would result in two different equilibrium prices, and as more traders require liquidity, this would ultimately affect the structure of the market. His article was an extremely influential one in market microstructure literature, as it challenged the notion that there is only one equilibrium price, and implied that the structure of the market (characterised by bid-ask spread, number of traders and volume), also impacts on the market price. The term “Market microstructure” was subsequently coined by Garman (1976), and forms two major branches: Inventory-based models, and Information-based models. Inventory-based models are derived from the price-setting issues outlined in Demsetz (1968). This strand of literature asserts that market makers have the primary role in markets, as providers of liquidity[27], and indicates how the bid-ask spread then compensates them for bearing price risk on their inventory (De Jong & Rindi, 2009). The empirical literature on inventory-based models begins with Demsetz (1968), and continues with the seminal studies of Stoll (1978) and Amihud and Mendelson (1980).

The fundamental principle behind the development of the information-based models in contrast, is that the price of an asset contains information that traders use when making decisions (Biais et al., 2005). Whilst under a Walrasian equilibrium, the decrease in the price of an asset will cause an increase in demand for that asset, according to the information-based models, this price fall might signal a further decrease in the price of an asset due to poor fundamentals, in which case demand for the asset will actually decrease as well (Biais et al., 2005). In particular, these models take into account the role of information asymmetry, which is the possibility that one party in a trade has more information than the other. The presence of asymmetric information leads to traders having to bear adverse selection costs, which is a component of the bid-ask spread[28], and is the premium that dealers demand in order to deal with traders who have superior information (De Jong & Rindi, 2009). Therefore, whilst under

[27] Providers of liquidity have to maintain inventory for both sides of the market, buyers and sellers. They must therefore purchase inventory when their stock is low, and sell when their inventory levels are above their targets. The possibility that prices could move against the inventory planning of the dealer is referred to as inventory risk, and can be very expensive for dealers (Harris, 2003)

[28] The other components of the bid ask spread are the transaction costs borne, as well as the dealers cost of holding inventory in order to satisfy order flows from both buyers and sellers (Schmidt, 2011)

the inventory-holding models, the transaction costs determine the bid-ask spread, and thus the market price of an asset; under this theory, the market price of an asset is not dependent on its transaction cost, but rather the information it contains. This initial idea was introduced by Bagehot (1971), and was followed by the influential studies of Grossman and Stiglitz (1980) and Kyle (1985), which forms the foundation of many empirical studies in this field.

The cost of adverse selection, which is the underlying theme of the information-based models, is also a central component to the discussion about both information efficiency, and liquidity. In particular, shares which have lower levels of adverse selection, are likely to have higher levels of efficiency, and thus higher liquidity as well. The theories based on ETF microstructure which are reviewed in section 3.4, are therefore all part of this sub-theme of microstructure. The discussion therefore begins with coverage of the two seminal studies in this field, which are the Grossman and Stiglitz (1980) and Kyle (1985). These two studies were developed based on equity markets, and form the foundation of the ETF microstructure theories reviewed.

3.3. INFORMATION-BASED MODELS OF MICROSTRUCTURE

This section attempts to discuss the seminal studies of Grossman and Stiglitz (1980) and Kyle (1985), which form the foundation of many information-based models of microstructure, especially the ones related to information efficiency and liquidity, which are discussed in section 3.5. The discussion therefore begins with an analysis of the type of market participants accommodated in the models, after which the theoretical coverage ensues.

3.3.1. Market Participants

There are 3 main market participants categorised by the Grossman and Stiglitz (1980) and Kyle (1985) theories, are informed traders, uninformed traders, and noise traders. The ensuing discussion therefore aims to provide more detail on each of these categories.

3.3.1.1. Informed traders

Profit-motivated traders exist in the market, because they expect to make a profit from their market activity. Informed traders therefore conduct fundamental analysis on the securities in the market, and then trade based on any mispricing that is present, in order to make a profit (Biais et al., 2005). A stock will be purchased if it is below fundamental value, and sold/short sold if it is above fundamental value, so that profit is made when the prices approach their fundamental values (Harris, 2003). These are the only types of traders who cause mispricing in the market to correct, by moving markets towards their fundamental values (Harris, 2003). Whilst informed traders trade for the sole purpose of profits, their actions in the market also leads to the market being more informationally efficient, since their trading activity is based on fundamental information, this allows for the better transmission of information into prices (Hachmeister, 2007). Market makers (such as dealers) are also considered as informed traders as they also profit from providing liquidity in the market. Yu (2005) found evidence of informed trading in ETF assets, as she found that price formation occurs in the ETF market, as opposed to the market for the underlying asset.

3.3.1.2. Utilitarian traders

Utilitarian traders exist in the market to trade for some other benefit besides a profit motive. This includes trading to hedge a position, or to facilitate the tax avoidance process (Harris, 2003). These traders therefore use the financial market as a means to solve problems that originate outside of this market. These investors make their decision to trade independently from the fundamental value of an asset, therefore whilst informed traders use private information to calculate their estimations, these uninformed investors simply use public information, and make their trading decision based on their liquidity needs. Utilitarian traders usually desire liquid markets as this allows them to meet their objectives at lower costs, therefore these traders are sometimes referred to as liquidity traders in the literature (Hachmeister, 2007). Since the ETF market is usually found to be the easiest, cheapest and most liquid market for trade, this is often the preferred market for liquidity traders (Poterba & Shoven, 2002).

3.3.1.3. Noise traders

Futile, or noise traders, trade on what they believe is superior information, and they think that they are profit-motivated traders. They could be irrational, or simply trading based on incorrect information (Harris, 2003). Whilst early studies such as Grossman and Stiglitz (1980) and Hellwig (1980) assert that noise arises from the random changes in supply of an asset, Glosten and Milgrom (1985) attribute noise to liquidity traders who exhibit random cash requirements. Later studies accommodate for the incorporation of behavioural elements, by asserting that noise arises from the irrational expectations of traders[29] (De Long, Shleifer, Summers, & Waldmann, 1990; Shiller, Fischer, & Friedman, 1984; Shleifer & Summers, 1990). A recent study by Chinco and Fos (2019) postulate that in the current modern financial markets in which many assets are indexed, rebalancing of these funds can occur for many reasons, and often happens simultaneously. However, because it is impossible for the average investor to understand the reason for the rebalancing, this serves as an additional source of noise in the market. The misinterpretation of information by noise traders thus leads to incorrect trading decisions, which then results in more opportunities for informed traders to profit off them (Teall, 2018). On average, both utilitarian and noise traders lose to the informed traders, and therefore both categories are usually referred to as uninformed traders (Hachmeister, 2007).

When Fama (1965) developed the EMH, he argued that uninformed, irrational traders are present in the market, but that the actions of informed investors will quickly eliminate any mispricing created. This view that irrational investors would lose their money in the long run was supported by Figlewski (1979), but he asserted that it could take a very long time for mispricing to correct, and for noise traders to lose their money, and thus be pushed out of the market. Black (1986) however, conjectures that these noise traders are integral to an efficient market as without them no one would trade. He asserts that if all investors were informed, a person with fundamental information that signals he/she should buy would hesitate to purchase in the event that the person who is willing to sell, has superior information to him/her. No trade would therefore occur. The presence of noise traders therefore ensures that informed traders will trade, as on average, the noise traders would lose money, and the informed traders would make money from them. Evidence from Poterba and Shoven (2002) indicates that ETFs attract traders who want to trade frequently (namely, short term traders), whilst a more recent study by Ben-David et al. (2018) also finds that stocks which display a higher level of ETF ownership are considered more attractive to noise traders. Ivanov (2016) also concluded in his study that ETFs seem to attract more uninformed, individual investors.

[29] Evidence of irrational behaviour in the ETF market was found by the following studies: Madura and Richie (2004) found evidence of overreaction, Chau, Deesomsak, and Lau (2011) proved the presence of investor sentiment in the ETF market, and Chen, Ho, Lai, and Morales-Camargo (2011) found evidence of herding behaviour.

3.3.2. Grossman and Stiglitz (1980) Model

The Rational Expectations Equilibrium (REE) generated by Grossman and Stiglitz (1980) provides the root for many microstructure theories developed thereafter. This model is developed based on the existence of two types of traders in the market, informed traders (who trade based on fundamental information that has a cost of attainment, *c*), and uninformed traders, who do not have any access to fundamental information, and instead trade based on their observations of market price. All traders in the market are assumed to be price takers, which means that they disregard the impact of their transactions on the market price of an asset, but they do understand that market prices of assets contain information. The quantity of a particular asset demanded by a trader is therefore dependent on the information that is revealed to them in the price of the asset.

The model begins with an assumption that there are two assets in the market: a risk-free asset, which yields a safe return of R, and a risky asset whose return, u, varies randomly over time. The risky asset's return therefore consists of two different parts, viz. a fundamental component (θ) and a random unobservable error component (ε) as shown in equation 3.1:

$$u = \theta + \varepsilon \tag{3.1}$$

All variables in the above equation are assumed to be normally distributed, and θ and ε are assumed to be uncorrelated. The fundamental component of the return (θ) can be obtained by an investor by incurring a cost, c.

Whilst informed traders observe θ, uninformed traders can only observe the price (P) of an asset. Grossman and Stiglitz (1980) assume that all traders are identical, and whether they become informed or stay uninformed, is simply dependent on whether they have chosen to incur the cost to obtain the fundamental information. The proportion of traders who choose to become informed is captured by γ, and their demand can be modelled as a function of the fundamental information, θ, and the price of the asset, P. Uninformed investors however, generate their demand function only based on P, and the proportion of uninformed investors in the market is captured by 1- γ (Grossman & Stiglitz, 1980). The price, P, therefore impacts on uninformed investors demand via two avenues, viz: to directly affect demand by determining the cost of the asset, and indirectly affect demand by revealing information to them about the fundamental information, θ. By using the price to derive the fundamental information, uninformed investors are therefore said to have rational expectations (Schmidt, 2011).

If the exogenous supply of the asset is denoted by x, which uninformed investors cannot observe, an equilibrium price can be obtained where demand is equal to supply. For informed traders therefore, the price can be determined as a function of both supply, as well as the fundamentals of an asset, so $P_\gamma(\theta, x)$. Whilst $P_\gamma(\theta, x)$ will reveal some information to the uninformed investors, they cannot observe all the information as it is impossible to distinguish between changes in price due to fundamental information, and the changes that are due to changes in demand and supply (O'hara, 1997).

The Grossman and Stiglitz (1980) model then goes on to solve for equilibrium, by assuming that the i^{th} trader has an initial wealth of W_{0i}, therefore if the price of the risk free asset is normalised to 1, his budget constraint can be represented by equation 3.2.

$$W_{0i} = M_i + PX_i \tag{3.2}$$

Where: M_i represents the trader's proportion of the risk free asset, X_i represents his proportion of the risky asset, and P is the equilibrium price of the risky asset.

Since the risk-free asset earns a return of R, and the risky asset earns a return of u, his final wealth at the end of the period for his portfolio will be:

$$W_{i1} = RM_i + uX_i \tag{3.3}$$

Each individual is also assumed to have the same utility function $V(W_{1i})$, which is exponential, therefore:

$$V(W_{1i}) = -e^{-aW_{1i}}, \qquad a > 0 \tag{3.4}$$

Where a represents the coefficient of absolute risk aversion. Since the variables in equation 3.1 are all considered to be normally distributed, Grossman and Stieglitz (1980) thereafter use equations 3.2 and 3.3 to model the demand, and supply equations for a risky asset (for both the informed and uninformed traders in the model). Whilst the informed trader makes his decision based on θ, the uninformed agent bases his decision on the market price of the asset, and the equilibrium condition can be expressed as follows:

$$(1-\gamma)\frac{\frac{1}{\sigma_\theta^2}\bar{\theta}+\frac{1}{\sigma_x^2}\left(\frac{a_{2\gamma}}{a_{3y}}\right)^2\left(\frac{P-a_{1\gamma}}{a_{2\gamma}}\right)-RP\left(\frac{1}{\sigma_\theta^2}\bar{\theta}+\frac{1}{\sigma_x^2}\left(\frac{a_{2\gamma}}{a_{3y}}\right)^2\right)}{a+a\sigma_\varepsilon^2\left(\frac{1}{\sigma_\theta^2}\bar{\theta}+\frac{1}{\sigma_x^2}\left(\frac{a_{2\gamma}}{a_{3y}}\right)^2\right)}+\gamma\frac{\theta-RP}{a\sigma_\varepsilon^2}=x$$

(3.5)

Since $a_{2\gamma}$ can be found to be equivalent to $-\frac{\gamma}{a\sigma_\varepsilon^2}a_{3y}$ in the preceding equation, the price of the asset can be obtained using equation 3.6 below:

$$P_\gamma(\theta,x)=a_{1\gamma}+a_{2\gamma}\left(\theta-\frac{a\sigma_\varepsilon^2}{\gamma}x\right)$$

(3.6)

The above equation is the main conclusion from the Grossman and Stiglitz (1980) model, and indicates that the price reflects the highest level of fundamental information (θ) under the following conditions:

- when there is a high value for γ (ie. More informed traders),
- When a is low (ie. There is less risk aversion), and
- When σ_ε^2 is low (ie. There is less noise in the risky asset).

In equilibrium, the expected utility of both informed and uninformed parties should be equal. If the expected utility of the informed traders becomes greater than that of uninformed traders, some individuals will switch from being uninformed to informed, and vice versa. Grossman and Stiglitz (1980) conjecture that, if more individuals become informed, this will lead to a decrease in utility for informed investors and thus equilibrium for two main reasons. Firstly, any changes in the fundamental information of assets, θ, would have an increased influence on demand and price due to there being more informed investors in the market. Uninformed traders would therefore be able to gauge more fundamental information from the price, and the mispricing in the market (over- or under-pricing) would be reduced. Since this is the method through which informed investors derive their utility, the expected utility of informed investors would decrease proportionately until equilibrium is established. Secondly, even if the process described above did not occur, the relative ratio informed to uninformed participants would increase, therefore on a per capita basis, the gains achieved from trading with uninformed participants would be reduced until equilibrium is reached.

The preceding discussion therefore indicates that a lower cost to acquiring information will result in an increase in the amount of informed traders, which is directly proportional to the price informativeness or informational efficiency of the market (Schmidt, 2011). However, there may be no equilibrium found in this REE framework. In a situation where it becomes possible to ascertain all the available information on an asset from its market price, there will no longer be any incentive for market participants to collect fundamental information, let alone incur a cost in the pursuit of this information. However, this results in a paradox, as the decrease in the amount of agents acquiring fundamental information, θ, would cause market prices to lose informational efficiency, which would thus create a new incentive to obtain information (De Jong & Rindi, 2009). Once prices start to incorporate more information however, this will again result in the disincentive to acquiring fundamental information.

In order to provide a solution to this paradox, the authors introduce the presence of a "noise trader" as the third party in the market. Noise traders have been previously defined as non-fundamental traders, who trade based on "noisy" data, or simply merely for the sake of trading (Cuthbertson & Nitzsche, 2005). This therefore implies that the price can never be fully informative, as uninformed investors will not be able to differentiate between fundamental information and the "noise" from the noise traders[30]. The framework and conclusions from the Grossman and Stiglitz (1980) provides the foundation for Merton's (1987) development of the "Investor Recognition Hypothesis", which is discussed in section 3.4.1.

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[30] The seminal study of De Long et al. (1990) found that returns on securities become extremely volatile in the presence of noise traders. They develop a model that indicates that even when informed and uninformed traders share the same views, prices will still not equal fundamental value simply because of the presence of noise traders in the market. These agents therefore constitute an additional risk factor in the market.

3.3.3. Kyle (1985) Model

The REE of Grossman and Stiglitz (1980), whilst very beneficial, cannot be easily extended to a real financial market because their model assumes all investors are price takers and therefore do not consider their impact on the price of an asset. The influential model of Kyle (1985) is rooted in the REE, but extends it to a more game theoretic approach to account for more complex interaction between financial market participants. The model derivation begins with the assumption that this is a one-period, single asset market, and all random variables are assumed to be independent and jointly distributed, with positive standard deviations.

Trade in the market is modelled in its simplest form, as an auction by Kyle (1985) in which there are three participants: an insider, a noise trader, and the market maker (all of whom are assumed to be risk neutral). Any trade therefore occurs in two steps. In the first step, the insider and noise trader simultaneously decide the quantity of the asset that they want to trade, based on their relative information bases. The insider possesses special information about the fundamentals of the share and he can calculate the future value of an asset in advance, therefore, at time t=0:

$$\tilde{V} = \bar{V} + \tilde{\delta} \tag{3.7}$$

Where V denotes the future value of the asset, and $\tilde{\delta}$ refers to the perfect signal of information to the insider, with $\tilde{\delta} \sim N(0, \sigma_V^2)$. The net demand of the insider is therefore equal to $x(\tilde{V})$, which is expected to maximize the expected payoff at time t=1 to the insider. This insider is only aware of previous trades (quantities and prices) that he made, as well as his observation of fundamental value. He is unable to observe any current or future prices or quantities, and is not aware of the quantity traded by noise traders. He is also considered a monopsonist, as he is the only party in the market with possession of this information. The noise trader, as mentioned under the REE model, trades for random reasons and is considered an uninformed investor. His net demand is therefore random and at time t=1, can be denoted by $\tilde{z} \sim N(0, \sigma_z^2)$. The decision of how much of the asset to purchase is also made independently of any previous trades by both the noise trader and the insider, and he is therefore considered as exogenous to the system in the Kyle (1985) model.

The second step in an auction is for the market makers to clear the market by selecting the best price at which trade can occur. Since Kyle (1985) assumes a batch auction, this implies that dealers accumulate trades and execute them simultaneously. Therefore, market makers select the equilibrium price based on the information of both current and previous trades made by both insiders and noise traders (also known as order flow). However, this market maker can only observe aggregate net order flow and is therefore unable to observe what portion of the order flow is attributable to insiders ($x(\tilde{V})$), and what portion is due to liquidity traders ($\tilde{z}$). This order flow is therefore equal to $\widetilde{w} = x(\tilde{V}) + \tilde{z}$. The price function of the market maker can therefore be expressed as $p(\widetilde{w}) = E(\tilde{V}|\widetilde{w})$. A market maker does not make any use of fundamental information, and their sole purpose is to balance the supply and demand pressure from traders by finding an equilibrium. This agent is therefore assumed to be in a perfectly competitive position, and will clear prices so that his expected profit nets to zero at the end of the period. Therefore:

$$E(\tilde{\pi}_{MM}|w) = E\left(\left(p(\widetilde{w}) - \tilde{V}\right)\widetilde{w}\middle|\widetilde{w}\right) = E\left(\left(p(\widetilde{w}) - E(\tilde{V}|\widetilde{w})\right)\widetilde{w}\right) = 0 \tag{3.8}$$

The insider holds an informational advantage in this market where he/she is the only one in possession of this information, and will therefore act to exploit this advantage. Since he/she is also aware of the impact of his trades on market price, he/she will therefore determine his demand and trading intensity based on this information (O'hara, 1997). The insider's profit ($\tilde{\pi}_I$) will therefore be maximised by choosing his/her demand quantity $x(\tilde{V})$, dependent on the market marker's price function ($p(\widetilde{w})$):

$$\tilde{\pi}_I = E[x(\tilde{V} - (p(\widetilde{w}))|\tilde{V}]^{31} \tag{3.9}$$

Kyle therefore obtains the Bayesian equilibrium price[32] by allowing for market makers to maximise their profits based on their Bayesian interpretation of the aggregate order flow, and for the insider to maximise his expected profits based on his rational expectations of the impact

[31] Since Kyle (1985) assumes risk neutrality (a=0), utility maximisation will be achieved by maximising profits.
[32] This is referred to as a Bayesian equilibrium as market makers are assumed to use Bayes rule to update their information.

of his order flow on price. Kyle (1985) therefore derives the market makers pricing rule ($p^*(\widetilde{w})$) as specified by equation 3.10:

$$p(\widetilde{w}) = E(\tilde{V}|\widetilde{w}) = E(\tilde{V}) + \frac{cov(\tilde{V},\widetilde{w})}{Var\ (\widetilde{w})}(\widetilde{w} - E(\widetilde{w})) = \bar{V} + \frac{\beta\sigma_V^2}{\beta^2\sigma_V^2 + \sigma_z^2}\widetilde{w}$$

$$= \bar{V} + \lambda\widetilde{w} \text{ with } \lambda = \frac{\beta\sigma_V^2}{\beta^2\sigma_V^2+\sigma_z^2} \qquad (3.10)$$

The equilibrium solutions for λ^* and β^* can therefore be solved to prove $\lambda^* = \frac{1}{2}\frac{\sigma_V}{\sigma_z}$, and $\beta^* = \frac{\sigma_z}{\sigma_V}$. The equilibrium condition displayed in equation 3.10 is therefore derived based on the actions of the informed trader, who considers the effect of his trade on the market price of the asset, and thereafter behaves strategically to try and extract the most benefit from his informational advantage. This concept is termed price impact and is captured by λ in the equation, whilst β captures the trading frequency of the informed trader.

There are two main findings from equation 3.10 that have been extended and applied to many other studies of market microstructure. The first conclusion based on the equation for β^* suggests that the order flow submitted by the informed trader (and thus his level of trading aggression), is dependent on the variance of the uninformed trader's demand (σ_z). The informed trader cannot directly observe the quantity of the uninformed trader's order flow, however he utilises this variance in order flow to camouflage his activity from the market maker. Therefore, the larger the value for σ_z, the more trading aggression he/she will present, and the higher his/her profits will be.

The most important finding from Kyle (1985) is that of λ which is commonly known as "Kyle's lambda", and is a common measure of market illiquidity as it measures the amount by which the market maker adjusts the price of an asset, to reflect the information content of trades (in other words, price impact). The inverse of Kyle's lambda ($1/\lambda$) is a proxy for market depth (which is the quantity necessary to change prices in either direction by \$1) and therefore captures market liquidity. It can be observed that λ is directly related to σ_V, therefore if the variance of V increases, this makes the market less deep. This finding is intuitive, since σ_V^2 captures the advantage that the insider has due to his fundamental information, and this is positively related to adverse selection costs. It can also be seen that a greater volume of uninformed trading (σ_z^2) will increase liquidity in the market, as well as the trading frequency of informed traders. This occurs because the presence of noise traders provides a camouflage of the insider's activities (from the market maker), and implies that insiders will make more profit in shares that are more frequently traded and commonly held.

Kyle (1985) thereafter extends the preceding model, to account for noise, which therefore potentially inhibits the signal received by the informed trader about the fundamentals of the asset, and creates uncertainty over its expected return. The model proves that when a perfect signal is given the information efficiency of the asset is equal to $\frac{1}{2}\sigma_V^2$. This therefore implies that half of the informed trader's information is captured in the price, and as noise trading increases, the informational efficiency of the asset price is reduced, whilst more noise trading encourages informed traders to trade more belligerently. Kyle (1985) also proves that as the variance of a security increases (as measured by the variance of the informed trader's information), the profit of the informed trader also increases. By combining different securities into a single basket security (ETF), the diversification effect will therefore result in diminished variance, thus implying that the liquidity traders in the model can reduce their losses against the informed traders, by trading in the ETF instead of the individual assets.

3.3.4. Contribution to ETF microstructure theories

The seminal theories of Grossman and Stiglitz (1980) and Kyle (1985) discussed previously have contributed greatly towards understanding of market microstructure, in their development of an equilibrium in which both informed and uninformed traders are present in the financial market. Both theories therefore provide evidence that even though, in the presence of both informed and uninformed/noise traders, prices are only partially informationally efficient, this still allows informed traders to earn a profit. Furthermore, Kyle's (1985) derivation of lambda (λ) is an extremely important one which revolutionised future studies of liquidity. Whilst both these theories have been developed with assumptions of single securities, their results have been extended by the literature surveyed in section 3.4, to encompass basket securities such as ETFs.

3.4. THEORIES OF LIQUIDITY AND INFORMATION EFFICIENCY

The literature examining the liquidity and informational efficiency aspects of speculative markets was pioneered by both Grossman and Stiglitz (1980) and Kyle (1985). Whilst the REE became the basis for the Investor recognition theory developed by Merton (1987), Kyle's (1985) dynamic model of efficient price formation, was the foundation for the theories developed by Subrahmanyam (1991), Gorton and Penacchi (1993), Cong and Xu (2016) and Bhattacharya and O'Hara (2018). It should be noted that the theories developed relative to basket securities (an in particular ETFs) all have implications on both liquidity, and information efficiency of the underlying assets, as these two microstructure elements are linked. These theories are therefore discussed relative to both concepts.

3.4.1. Merton (1987) Model

Merton's (1987) model begins with the assumption made of homogenous information being available to all informed traders of a particular security. However, whilst the REE incorporates game theory into the evaluation of trade by both informed and uninformed traders, Merton (1987) ignores the presence of uninformed investors, by postulating that only informed traders would want to trade in individual securities. He theorises that, if investors are not aware about a particular firm, they are unlikely to engage in any active analysis of that firm or try to trade in its shares (and this is particularly true for small unknown companies). Therefore, in order for fundamental information about a firm's shares to be transmitted to the market, there are two costs to acquiring this information that are borne:

- The actual cost of gathering pertinent fundamental data and using it to calculate intrinsic value, and
- The cost of spreading this information from the source to other parties in the market.

Whilst for a firm that is trying to gain traders, the cost of gathering information is low, the cost of transmitting this information would be high in a world where the agency issue exists, and the release of information sends some kind of signal to the market. Furthermore, the process is further exacerbated by the need for investors to actually be willing to receive signals on a previously unknown firm. The management of the firm therefore needs to spend resources on inducing investors who are unaware of the firm, to incur the necessary information costs in order to become aware of the firm, and trade in its shares.

Merton (1987) therefore suggests that the introduction of basket securities (such as unit trusts, and ETFs) attracts more investors as this instrument allows them to trade easily, at a low cost and with minimal expertise. This therefore leads to an increase in interest not only in the index which is being replicated by the ETF, but in its individual constituents, especially those with the lowest weighting in the index which tend to be traded less than the larger assets, and which are usually faced by the aforementioned issue of information cost. Due to this added level of investor participation, this therefore results in a greater level of information efficiency, and the liquidity of the overall market should increase, alongside a decrease in adverse selection. These effects are expected to be largest for the smallest companies in the index.

3.4.2. Subrahmanyam (1991) Model

Subrahmanyam (1991) attempts to model the effect of index formation on the underlying assets informativeness and liquidity, by extending the single asset analyse of Kyle (1985) to a market which includes multiple assets forming a basket of securities. His analysis begins by identifying two types of investors: informed traders, who choose to trade securities based on informed analyses, and liquidity traders, who trade for reasons other than their future payoffs, such as their desire for cash, or tax planning (and could be represented by individuals or institutions who trade on their behalf). These liquidity traders are assumed to trade due to their desire for immediacy, even though this would cause transaction costs due to the presence of the informed traders. Liquidity traders are then further subdivided into discretionary and non-discretionary traders as per Admati and Pfleiderer (1988). Whilst discretionary traders can choose, based on the associated costs, to either trade on the basket security or individual shares, non-discretionary traders are constrained by other circumstances to either trade in the basket security, or in the individual assets.

Subrahmanyam (1991) finds that, under the assumption that informed investors possess only asset-specific information, when these rational investors choose to trade in the basket security, the asset-specific component of adverse selection gets diversified away, which results in a reduction in the transaction costs for the basket security. Therefore, since the basket security represents the lowest cost market for discretionary liquidity traders, they choose to trade in this market. This result was found to be consistent even when informed traders who possess systematic information as well are introduced into the market. Furthermore, due to the migration of discretionary traders to the market for the basket security, this would result in decreased liquidity for the underlying assets, and therefore an increase in the adverse selection component of the individual securities. This increase is likely to be higher for securities with smaller weights in the ETF, than for those which hold a greater proportion of the ETF. As a result, one should find that the liquidity in individual assets varies in conjunction with the adverse selection – the higher the adverse selection present, the lower the liquidity in that security. It should also be noted that a reduction in adverse selection will also result in a greater degree of information efficiency.

3.4.3. Fremault (1991) Model

The work of Fremault (1991) is not explicitly based on basket securities like ETFs, but instead evaluates the role of stock index futures and the market impact of the arbitrage mechanism generated by this security. Since ETFs are similar in function to stock index futures – their value is derived from another asset, and there is a possibility of using this asset for arbitrage purposes – her study is therefore considered an influential one in the understanding of ETF impacts on market structure.

Index arbitrage is a trading strategy that aims to make arbitrage profits off any price differences between spot and futures markets. This process is therefore similar to the in-kind creation and redemption process of ETFs, which is designed to ensure that the market price of the ETF stays close to its NAV. The author asserts that the index arbitrage process allowed by stock index futures (vis a vis the creation and redemption process of ETFs) provides a mechanism through which prices are corrected to reflect their equilibrium value, and risks can be diversified. In addition, the presence of index arbitrageurs adds liquidity to the market, which thus reduces adverse selection costs as well as overall market volatility. This kind of result can be extrapolated to the ETF market, in which APs serve the same function as index arbitrageurs, and it can therefore be deduced that the creation and redemption arbitrage mechanism of APs results in lower adverse selection costs, which leads to higher information efficiency and greater liquidity.

3.4.4. Gorton and Pennacchi (1993) Model

Gorton and Pennacchi (1993) develop their rationale based on Kyle's (1985) model of microstructure. They begin their analysis by acknowledging that since basket securities are derivatives, theoretically, the same benefits should be obtained by investors who would be able to form the same portfolio by themselves, by investing proportionately in the underlying asset. However, their multi-asset model proves that basket securities are not actually as redundant as theory states it should be. This is because, as proven by Kyle (1985), when basket securities are created, the overall variance is reduced, which implies lower asymmetry of information, and lower trading losses for liquidity traders.

Gorton and Pennacchi (1993) develop their model by attempting to derive an optimal trading strategy for the uninformed traders in the market. The authors prove that the presence of a basket security reduces any information advantages that informed traders hold over uninformed traders, and it is through this channel that the uninformed traders' potential losses are limited. These traders would then actively choose to migrate away from the underlying securities, to the ETF, due to easier trade, lower transaction costs and lower adverse selection. This will therefore result in greater adverse selection risk in the underlying securities market, which will mean that prices become very responsive to the quantities traded, ie. Markets become less deep, thus reducing the liquidity of the underlying securities.

3.4.5. Malamud's (2016) Model

Whilst the theories of liquidity listed in 3.4.1 to 3.4.4 were all based on basket securities in general, or similar derivative securities, Malamud (2016) develops his theory of liquidity with the sole purpose of evaluating the market impact of ETFs given their distinctive structure. He asserts that the role of a primary market (facilitated by the Authorised Participant) and the creation and redemption mechanism of ETFs (discussed in section 2.4) makes this asset class unique, in which case the standard models of market microstructure need to be adjusted. Malamud (2016) begins his explanation with the assumption that there are N individual securities traded in the market *(n=1,.....N)*, alongside L physically replicated ETFs, where $f_w = (f_{w,n})_{n=1}^{N}$ denotes the vector of ETF portfolio weights used to create replicating ETF w. If $p_t = (p_{t,n})_{n=1}^{N}$ denotes the vector of individual security prices in the market, then ETF NAV can be expressed as $NAV_t = \boldsymbol{F}p_t$ where F is a matrix consisting of the ETF basket weights, and is equal to $\left(f_{w,n}\right)_{w,n=1}^{L,N}$. If P_t represents the vector of ETF prices at time t, then the difference between the price of the ETF and its NAV (also known as mispricing, or pricing gap) can be calculated as $P_t - \boldsymbol{F}p_t$.

Malamud (2016) also assumes that there are four main participants in the ETF market. The first participant is the ETF sponsors, who exist in the primary market, and provide liquidity to the APs. The second type of participants are dealers, who trade in the market for the underlying securities, supply liquidity to the secondary market and are susceptible to income shocks. The third and fourth participants are ETF traders, and APs respectively. ETF traders are similar to dealers, as they are also subject to income shocks, and they demand liquidity in the ETF market. Whilst APs supply liquidity to the ETF market, they also demand liquidity in the market for the underlying securities. In this way, APs act as both market makers and arbitrageurs. These APs are also assumed to be able to trade in both the ETF and the underlying securities, however since markets are segmented this is the only market participant that can trade in both markets. APs therefore play the integral role of maintaining ETF prices at their NAV, as these market participants can act on any mispricing to earn arbitrage profits. Information is also assumed to be symmetrical, and all trade is assumed to occur only for the purpose of sharing risk.

Since the purpose of an ETF sponsor is to supply liquidity, this implies that each AP in the market can contact an ETF sponsor at the end of each trading day $(t + \epsilon(t, t+1))$ to assist in the process of creation or redemption of ETF shares. The creation/redemption can take place either by the use of "in-kind" transactions, or cash transactions[33]. If the transaction is requested "in-kind" (I), this implies that an AP will be able to exchange his portfolio of individual securities $(Z_w(\left(f_{w,n}\right)_{n=1}^{N})$ for Z_w shares of ETF w. The anticipated cost of this transaction is the spread (λ) charged by the ETF sponsor, which is assumed to be quadratic in the number of ETF shares. It is important to note that the spread (λ) is directly associated with liquidity, and a higher level of liquidity will result in a lower cost (λ) and vice versa. The cost of the in-kind transaction can therefore be denoted as $0.5\lambda_{I,w}Z_w^2$.

[33] This process was discussed in detail in section 2.3.1.

If the transaction is requested in cash (C), the AP will be able to purchase Z_w shares of ETF w at its NAV at time t+1 (since the AP does not know at what price the ETF will trade at the time of transaction, this represents a friction or a limit to arbitrage in the primary market for the ETF). The cost of this transaction will therefore be equal to $0.5\lambda_{C,w}Z_w^2$. Whilst no specific action is necessary for an in-kind transaction, a cash transaction (Z_C) requires the ETF sponsor to purchase the corresponding number of shares in the underlying asset market($F^T Z_C$), for delivery to the AP sponsor. For both an in-kind and cash transaction however, the total replicating basket ($F^T(Z_I + Z_C)$) is held by the ETF sponsor and is no longer available for trade on the equity market.

An integral assumption of the Malamud (2016) model is that APs are the only market participant who is able to interact in both the ETF market, as well as the market for the underlying securities. Therefore, at any time t, the AP holds $x_t^A \epsilon \mathbb{R}$ amount of individual securities, and $y_t^A \epsilon \mathbb{R}$ amount of ETFs. When they contact the ETF sponsors at time t+ for the purpose of creation/redemption activity (either $Z_{I,t+}$ or $Z_{C,t+}$), their resultant portfolios get adjusted as follows:

$$x_{t+}^A = x_t^A - F^T Z_{I,t+}$$

$$y_{t+}^A = y_t^A + Z_{I,t+} + Z_{C,t+}$$

(3.11)

If the above equations are expanded, to obtain the aggregate supply available for the other three participants in the market, the following is equilibrium equations are obtained:

$$\bar{x}_{t+} = \bar{x}_{t-1} - F^T(Z_{I,t+} + Z_{C,t+})$$

$$\bar{y}_{t+} = \bar{y}_{t-1} + Z_{I,t+} + Z_{C,t+}$$

(3.12)

Under the assumption of the invariance law, the aggregate supply of the individual securities should remain constant, because these securities simply move between being traded inside the ETF, and being freely traded on the secondary market.

Malamud then attempts to obtain a Markov equilibrium after applying a demand shock in the underlying asset market (ε_t), and a demand shock in the ETF (ξ_t) market. The result models the prices of ETF and the underlying assets as follows:

$$P_t = \bar{P} + \beta_X^E \bar{X}_{t-1+} + \beta_\xi^E \xi_t$$

$$p_t = \bar{p} + \beta_X^D \bar{X}_{t-1+} + \beta_\xi^D \xi_t + \beta_\varepsilon^D \varepsilon_t$$

(3.12)

Where $\bar{P}, \bar{p}$ represent the price of the ETF and individual assets based on the present value of expected dividends, $\bar{X}_{t+}$ is a vector of $\begin{pmatrix}\bar{x}_{t+}\\ \bar{y}_{t+}\end{pmatrix}$, and β represents a sensitivity coefficient to the independent variable in question. The results from the equations above indicate that the price of an ETF(P_t) is independent of shocks to the individual asset, since these shocks are borne by the dealer, and thus only impacts the prices at which the AP can transact in the market for the underlying securities. In contrast, the price of the underlying securities (p_t) is affected by demand shocks to its own market ($\beta_\varepsilon^D \varepsilon_t$), as well as demand shocks to the ETF market ($\beta_\xi^D \xi_t$). This occurs through the creation/redemption process, where APs seek to hedge their demand shocks (ξ_t) by using this primary market mechanism, which thus results in the propagation of ETF demand shocks to the market for the underlying asset. This should therefore have an effect on both price and liquidity of the underlying asset. Malamud (2016) in his conference address, refers to the above equations as an ETF Capital Asset Pricing Model (CAPM), which can be used to capture the additional risk premium from creation and redemption activity.

The further implications of Malamud's (2016) model is that any reduction in costs in the primary market will serve to stimulate further creation and redemption activity, which will thus amplify the propagation of shocks from the ETF to the market for the underlying asset. This may then also result in an increase in volatility of the underlying assets. However, the author postulates that if new ETFs enter the market, these may serve as a substitute for existing ETF demand, which could thus reduce volatility, and improve liquidity in the underlying assets. This phenomenon is termed the "demand substitution effect".

3.4.6. Cong and Xu (2016) Model

Whilst the preceding theories discussed in sections 3.4.1 – 3.4.5 have their primary focus on liquidity, with extenuating implications for information efficiency, the discussions in sections 3.5.6 and 3.5.7 have their primary focus on information efficiency. In addition, alongside Malamud (2016) and Bhattacharya and O'Hara (2018), Cong and Xu's (2016) theory was developed with a specific focus on ETFs, and will now be detailed further.

Cong and Xu (2016) develop their theory of the informational effects of ETFs, by extending Kyle's (1985) analysis into a multi-asset framework, with the presence of a basket security (ETF). The inherent assumptions of their analysis is that there are two assets in the market, and each has a fundamental value that is linked to both a systematic factor (γ) that encompasses both market-specific and industry-specific information, as well as a firm-specific factor (ϵ_i). The value of asset i (V_i) is therefore expressed as follows:

$$V_i = \overline{V_i} + \beta_i \gamma + \epsilon_i \qquad\qquad i = 1,2 \tag{3.13}$$

Where $\overline{V_i}$ captures the expected payoff for each security and β_i represents the responsiveness of security i to factor γ. An important implication is therefore that information efficiency (which the authors also term as overall efficiency) can be further sub-divided into two components: systematic efficiency, which is the ability of the asset i to reflect systematic information (γ), whilst asset-specific efficiency refers to the ability of asset i to reflect asset-specific information (ϵ_i).

The model developed by Cong and Xu (2016) therefore expands on the analysis of Kyle (1985), which assumes the presence of an informed trader and an uninformed trader in the market. In Cong and Xu's (2016) study, this is further sub-divided, there are two different types of speculators (informed) and liquidity (uninformed) traders present in the market. Asset-specific speculators incur costs to acquire firm-specific information, and the asset-specific liquidity traders have exogenous requirements for a firm-specific factor. Likewise, a systematic speculator is an individual who incurs costs to obtain factor information (and is therefore also referred to as a factor investor), whilst the factor liquidity trader has an exogenous need for the common factor in question.

The simplest case of the ETF in this market, is termed a Composite Security by the authors, and consists of the two underlying assets (w_1S_1, w_2S_2) where w_1 and w_2 refer to the weights of assets 1 and 2, which sum to 1. Therefore the price of the ETF is derived based on the weighted sum of the individual stock prices. The model also assumes further that only the ETF sponsors can purchase both assets, and the remaining market participants can therefore only purchase one asset, which makes the ETF a non-redundant asset.

The market without an ETF is described by Kyle (1985), in which case, the profits earned by the speculators in the model increases with their relative (asset-specific) informational advantage, and is inversely related to their relative price impact (as measured by Kyle's (1985) λ). Similarly, the liquidity traders in the model face adverse selection risk from both types of speculator, and will therefore choose to trade in the asset market which has the lowest adverse selection cost, which is the ETF market (due to the diversification effect). Whilst the factor speculator in this type of market cannot trade both assets to fully exploit any informational advantages he holds, in a market with the ETF, this is possible due to the presence of the composite security. The ETF market is therefore expected to attract both factor speculators and factor liquidity traders according to the model. Cong and Xu (2016) therefore hypothesise that there is an optimal design of the ETF (composed of weightings w_i and w_j for assets i and j), which will ensure the maximum profit for factor speculators, whilst ensuring the lowest cost for liquidity traders.

$$w_1 = \frac{\beta_1 \lambda_2^{ETF}}{\beta_1 \lambda_2^{ETF} + \beta_2 \lambda_1^{ETF}} \tag{3.14}$$

The optimal design specified by the above equation therefore results in an ETF which places higher weightings on liquid assets (with low λ), and assets which are more responsive to systematic factors (high β). This kind of design is accepted by all the market participants, as it optimises their relative trading objectives, and therefore trading in the ETF is preferred for this reason.

The higher weighting assigned to high beta stocks therefore implies that the overweighting of assets which have a higher sensitivity to systematic factors thus increases the systematic efficiency of the asset. Asset-specific efficiency however, is hypothesised to decline due to asset-specific speculators no longer finding it beneficial to acquire firm-specific information, due to the prohibitive costs involved. The authors further hypothesise that even though asset-specific efficiency declines, for assets which were previously relatively illiquid, the systematic efficiency increase outweighs the firm-specific decline, and thus results in an increase of overall efficiency.

Cong and Xu (2016) also extend their theoretical application to other microstructure elements of the market, and postulate that the introduction of an ETF will also cause an increase in volatility in the underlying asset, through the variance of the systematic component of stock prices (invariably as the stock price reflects more systematic information, the variance of this component also increases). In addition, the authors find that the increase of this systematic component also leads to greater co-movement between the returns of assets, and synchronicity of returns, particularly for small and illiquid stocks. The authors also find support for an decrease in liquidity of the underlying assets, similar to the hypothesis of Subrahmanyam (1991).

3.4.7. Bhattacharya and O'Hara (2018) Model

The seminal work of Bhattacharya and O'Hara (2018) attempts to model the informational linkages between ETFs and their underlying assets, when the latter are hard-to-trade. The authors hypothesise that trading in such ETFs could lead to greater market instability, due to the propagation of shocks from the ETF to the market for the underlying asset. The study also aims to provide some direction on the presence of rational herding by ETFs, which also causes the delinking of prices from their fundamental values.

The derivation of their theory begins in the same token as Cong and Xu (2016), with the value of an asset depicted by equation 3.13, however in their case they assume *N* underlying assets in the individual ETF in their model. The individual assets and the ETF each trade simultaneously in their respective markets, and each market has a single designated market maker, in conjunction with Kyle's (1985) seminal auction market. As a result, the model developed involves N+1 assets, 2N informed traders, and (N+1) market makers. Bhattacharya and O'Hara (2018) attempt to model the impact of ETF trading on information flow, by demonstrating a simplified trade process over three time periods.

- On day 1, trade occurs based on orders from informed traders in both the ETF and underlying asset markets.
- On day 2, the market maker in the underlying asset market, and the AP in the ETF market, update their prices based on the transactions from day 1.
- On day 3, the AP eliminates any deviations in the price of the ETF and its underlying basket, by engaging in creation or redemption activity.

Whilst the afore-mentioned trade process is accurate if the underlying securities of the ETF are easy to trade, the process becomes more complicated if the underlying assets are not as easily accessible to investors and ETF APs. In this case, it is often the case that any trade in the ETF market carries information about its underlying assets, which is tracked by the market makers. Therefore whilst on day 1, trade in the ETF still occurs, on day 2, the market maker in the underlying security uses the change in ETF price from day 1, to surmise the order flow (q_{etf}) as $q_{etf} = \frac{P_{etf,1} - P_{etf,0}}{\lambda_{etf}}$ where $P_{etf,t}$ refers to the price of the ETF at time t, and λ_{etf} measures the price impact in the ETF market, and is reminiscent of both Kyle (1985) and Cong and Xu (2016). The market maker, upon observation of this order flow therefore revises the price of the underlying asset *i* as follows:

$$V_{i,2} = V_{i,1} + \lambda_{etf,i} w_i q_{etf} = V_{i,1} + \frac{cov\left(\epsilon_i + \beta_i \gamma w_i q_{etf}\right)}{var\left(w_i q_{etf}\right)} w_i q_{etf} \tag{3.15}$$

Where, $\lambda_{etf,i}$ refers to the impact of a price change in the ETF, on asset *i*.

Since the observed market flow is a subset of orders placed by both speculators and liquidity traders in the model, the market price offered by the market maker (as captured by $V_{i,2}$ above), combines the information from all ETF market participants. However, this therefore implies that $V_{i,2}$ captures a mix of different information, which is pertinent fundamental information that is relevant to the intrinsic value of asset i, information related to noise, and systemic information that is linked to the other underlying assets of the ETF. Bhattacharya and O'Hara (2018) therefore argue that it is through this channel, that non-fundamental shocks are propagated across the underlying assets in the ETF, thus leading to market instability, since it is virtually impossible for the market maker in the model to distinguish between irrelevant and fundamental information.

Bhattacharya and O'Hara (2018) go on further to capture an expression for the $\lambda_{etf,i}$ variable, as follows:

$$\lambda_{etf,i} = \frac{\lambda_{etf}(N+1)var(\epsilon_i) + 2\lambda_{etf}N\beta_i(\sum_{j=1}^{N} w_j\beta_j)var(\gamma)/w_i}{(N+1)\left(\sum_{j=1}^{N} w_j^2 var\left(\epsilon_j\right)\right) + 2N(\sum_{j=1}^{N} w_j\beta_j)^2 var(\gamma)} \tag{3.16}$$

The most important implication from equation 3.16 is that even though factors such as asset weight, the variance of the firm-specific factor ($var\left(\epsilon_j\right)$) and the betas of the other assets in the ETF are all relevant factors which influence the price impact factor, even though the intrinsic value of an asset is independent from these factors. Bhattacharya and O'Hara (2018) therefore postulate that this additional mechanism leads to the underlying assets being "coupled", which further facilitates the transfer of non-fundamental risk from ETFs, across the market. Therefore whilst the ETF market brings the important benefit of providing more information and conveying this easily to market participants, the associated disadvantage is that it also transmits irrelevant information (Bhattacharya & O'Hara, 2018).

3.4.8. Summary of ETF microstructure models

The models described in sections 3.4.1 to 3.4.8 are varied in their approach, and their ultimate conclusions, relative to liquidity and information efficiency. For ease of reference, the conclusions reached by each theoretical model reviewed, is summarised in table 3-1.

Table 3-1: Summary table of ETF microstructure theories

Study	Postulated impact on liquidity	Postulated impact on information efficiency
Merton (1987)	Increase	Increase
Subrahmanyam (1991)	Decrease	Decrease
Fremault (1991)	Increase	Increase
Gorton and Pennachi (1993)	Decrease	Decrease
Malamud (2016)	Increase or decrease	Increase or decrease
Cong and Xu (2016)	Decrease	Increase in systemic and overall efficiency, decrease in firm-specific efficiency
Bhattacharya and O'Hara (2018)	Decrease	Decrease

Source: Author's own construction

3.5. CHAPTER SUMMARY AND CONCLUSION

This chapter aimed to outline the theoretical literature surrounding market microstructure, with a specific reference to the associated impacts of ETFs. Whilst the market microstructure literature is vast and covers many volumes of textbooks, the focus in this chapter began with the seminal works of Grossman and Stiglitz (1980) and Kyle (1985), which attempted to model the informational effects of the trade activities from both informed and uninformed traders in the financial market. This analysis was later extended to the ETF market, to provide implications on the liquidity and informational efficiency of ETFs and their underlying assets.

The discussion produced in this chapter shows that even the theoretical literature is mixed on the proposed effects of ETF introduction on the liquidity and information efficiency of its underlying securities. This illustrates the possibility that the potential effects could vary based on the type of underlying asset and differing market conditions, and even the relative maturity of the ETF market as a whole. This therefore prompts the necessity of a study like this in the South African financial environment, and further motivates the central objectives of this study. The next two chapters therefore provide empirical investigations of both Liquidity and Informational Efficiency, which seek to answer the research questions posed in Chapter 1 (section 1.1.4).

CHAPTER FOUR: THE EFFECT OF ETFS ON THE LIQUIDITY OF THEIR UNDERLYING ASSETS

4.1. INTRODUCTION

Liquidity is an extensive concept, which has different meaning in varied types of financial markets, and when applied in different contexts. Lybek and Sarr (2002, p. 7) define equity market liquidity as "the ease with which, in the absence of new information altering an asset's fundamental price, large volumes of an asset can be disposed of quickly, at a reasonable price." This concept of liquidity is integral to the efficient functioning of equity markets, and has five different dimensions which encapsulate it, which are: tightness, immediacy, depth, breadth and resilience (Kumar & Misra, 2015; Lybek & Sarr, 2002). The first dimension, is that a market should be "tight", which means that the cost of entering into, or exiting from, a position quickly should be minimal (Kyle, 1985). This therefore implies that there should always be bid and ask prices available for investors who want to transact immediately, and there should be a very small difference between these spreads. This would be an indication that there are many competing offers to purchase/sell the share, which is what narrows the bid-ask spread. A liquid market, should therefore have infinite "tightness" (Black, 1971; Kyle, 1985). Immediacy is closely linked to tightness, and is an indication of the speed with which orders can be placed, executed, and settled (Lybek & Sarr, 2002).

The third facet of liquidity discusses "market depth", which refers to the existence of many orders, both above and below the price at which a stock is trading. A liquid market should not be infinitely deep (Black, 1971; Crockett, 2008; Kyle, 1985). Lybek and Sarr (2002) define a further dimension that is related to market depth, which is "breadth", and this implies that market orders should have high volumes, with minimal price impact. The final dimension to equity market liquidity infers that stock prices should be "resilient", which refers to the speed with which prices recover from a random shock. A liquid market should consist of prices which are resilient enough to trend towards their underlying intrinsic value (Black, 1971; Kyle, 1985).

The presence of the afore-mentioned five aspects therefore contributes to a stock market in which transaction costs are low, bid-ask spreads are narrow, and market efficiency can be maintained (Crockett, 2008). Whilst ETFs are traded on an exchange, like stocks, these instruments are also structured very differently, which leads to additional unique liquidity characteristics (Broman & Shum, 2018). In reality, the liquidity of ETFs are subject to the liquidity of their underlying securities[34]. Therefore, for ETFs which are made up of hard-to-trade assets which are not easily liquidated, the ETF is also likely to suffer from this illiquidity (Hammond & Lieder, 2015). A core advantage however, is the creation and redemption process used to create ETFs, which means that large enough investors (institutional investors) can bypass the secondary market and interact directly with the AP in the primary market, thus ensuring a guaranteed transaction, even if the secondary market is relatively illiquid (Hammond & Lieder, 2015). This provision thus ensures that for institutional investors, there will always be enough market breadth to ensure a transaction occurs, and it offers an additional layer of liquidity to the ETF market that is unique. This additional layer is termed "hidden liquidity" by Kittsley and Edrosolan (2008) and presents the opportunity for increases in ETF market depth, with minimal price impact.

Generally, the statistics produced indicate that the ETF market is fairly liquid, with ETF trading on US exchanges amounting to more than a third of total equities traded (Lim & Frankl-David, 2020), and the JSE recording approximately R600m worth of ETF transactions occurring on a daily basis (Liedtke, 2020). The possibility, however, is that these volumes are due to investors leaving the market for their underlying securities, and trading in the ETFs instead (Liebi, 2020). This resultant migration of investors could have negative consequences for the individual underlying securities, which rely on active analysis to ensure that their share prices efficiently reflect fundamental information timeously (Hegde & McDermott, 2004). Since liquid markets are required to sustain market efficiency, this chapter aims to evaluate what impact the introduction of ETFs has on the liquidity of their underlying assets.

There are many theories which aim to dictate how market liquidity should be affected upon inception of basket securities such as ETFs. This evidence is subdivided into two different streams. The first body of evidence is termed "adverse selection hypothesis", which postulates

[34] Studies such as Kittsley and Edrosolan (2008), Agrrawal and Clark (2009) and Roncalli and Zheng (2014) all find evidence that whilst there are other factors that could drive liquidity in ETFs, the predominant factor is the liquidity of its underlying securities.

that the introduction of ETFs would result in decreased liquidity in the component stocks. This argument is favoured by studies like Subrahmanyam (1991) as well as Gorton and Pennacchi (1993). The second body of evidence, termed "arbitrage hypothesis", develops its argument based on the assumption of imperfect markets (contrary to the adverse selection hypotheses, which assumed perfect markets), and studies like Fremault (1991) indicate that liquidity of these stocks should increase after ETF conception. Merton (1987) asserts that this increase in liquidity should be higher for the smaller companies in the ETF, which were previously thinly traded, but now benefit from the exposure of being indexed in the ETF. This theoretical framework is discussed comprehensively in Chapter 3, and the dearth of empirical evidence in the South African ETF market, leads to the necessity of this study. In particular, this chapter aims to evaluate the impact of ETF introduction on the liquidity of its underlying assets, which is sub-divided into the following research questions:

I. What is the effect of the introduction of Equity ETFs on the JSE on changes in liquidity for the stocks that constitute the EFT?
II. How does the weighting of a company in the Equity ETFs listed on the JSE affect the liquidity change experienced by the underlying firms?

The chapter begins with a coverage of the empirical evidence on the topic, followed by a discussion of the methodology employed as well as the results obtained.

4.2. EMPIRICAL EVIDENCE ON THE IMPACT OF ETFS ON LIQUIDITY

This section aims to review the empirical evidence surrounding ETF and its impacts on the microstructure component of liquidity. The discussion therefore seeks to link the theoretical models outlined in section 3.4 to the actual evidence produced from empirical analyses of ETF-based data. The discussion begins with a broad review of other closely related index-based products, after which the empirical evidence on ETFs in particular is reviewed.

4.2.1. Empirical studies on index-based products and liquidity

This discussion of the related literature begins with an analysis of studies which focus on other index-based products such as stock index futures and index funds. Whilst ETFs were only created in 1990, the creation of index-based products date back to 1975 (Bogle, 2016), and many of the initial theories on possible "index-effects" such as Subrahmanyam (1991) and

Gorton and Pennacchi (1993) were derived based on indexed products and only later applied to the ETF market. This sub-section will therefore review some of the earlier studies focused on the liquidity effects of index-based products, before reviewing the relevant literature on ETFs in sub-section 4.2.2.

Jegadeesh and Subrahmanyam (1993) were the first authors to test Subrahmanyam's (1991) theory on the S&P 500 stock index future market. They postulated that the introduction of the S&P 500 future should cause a migration of traders from both the underlying index assets, as well as non-index assets, but that the effect is likely to be more pronounced for the former than the latter. Their study therefore aimed to investigate the impact of the S&P500 future introduction on the adverse selection and liquidity of the individual S&P500 companies that constitute the index future. Their results found evidence that the introduction of the S&P500 future caused an increase in spreads due to the increase in adverse selection, and this therefore also resulted in a decrease in liquidity in the underlying assets.

A subsequent study by Liu (2009) also found evidence of diminished liquidity in the underlying assets of the S&P100 option. In contrast, Kan's (1999, 2004) evaluations of the Hang Seng index future contracts found evidence of increased liquidity in the underlying assets, with a specific increase in the resiliency component of liquidity, a result that was later confirmed by Jinliang, Yao, and Shujingi (2012). The only South African study to date on this subject (known to the author) is that of Swart (1998), who also found evidence of improved liquidity in the underlying assets after option introduction on the JSE. The differing results suggest that these assets may have different impacts on developed, and developing/emerging markets. In addition, it is noted by Swart (1998) that any study of liquidity impact is very sensitive to the measures of liquidity used, which could also be a source of the differing results.

A further subset of studies makes use of an event study methodology to evaluate the impact of addition or deletion of companies into an index. These studies hypothesise that inclusion into a broad-based index such as the S&P500, or the JSE ALSI results in more arbitrage activity in the share due to it now being included in index-based basket securities and derivatives. This should therefore result in a decrease in information asymmetry, an increase in informational efficiency and an increase in liquidity of the underlying asset. Erwin and Miller (1998) found results that were consistent with this hypothesis, although the increase in liquidity was greater for shares which were not exposed to any option or future activity previously. Similar results were also produced by Hegde and McDermott (2003), and Elliott, Van Ness, Walker, and Warr (2006) who found sustained liquidity increases in stocks that were added to the S&P500 index, with the former study also noting liquidity decreases in deleted stocks over three months after deletion. In contrast, Beneish and Whaley (1996) finds improved spreads only in the first few days after the S&P500 index change, which the authors attribute to index funds using limit orders to facilitate the rebalancing process. The differing results detailed above is noted by Hegde and McDermott (2003) to be due to the differing objectives of the respective studies. Whilst Erwin and Miller (1998), Hegde and McDermott (2003) and Elliott et al. (2006) aim to fully analyse the liquidity impacts of S&P500 index revisions, the focus of Beneish and Whaley's (1996) study is a risky arbitrage strategy based on the revisions, and therefore differs in terms of approach and method.

In their study of the Indian stock market, Narasimhan and Kalra (2014) found that, the introduction of options had no effect on the liquidity of underlying assets that were already liquid, but significantly increased the liquidity of shares which were previously infrequently traded. While Katzke and van Tiddens (2019) do not have a direct study of liquidity impacts, their evaluation on JSE indices also found evidence of volume increases (decreases) for index additions (decreases). The results reviewed in this section therefore largely concur that index additions positively impact liquidity for the underlying assets, particularly for assets which were previously not well known or frequently traded. This result is also found to be consistent across both developed and emerging markets.

4.2.2. Empirical evidence on ETFs and liquidity

The studies reviewed in this section form three basic branches. The first branch of analysis makes use of spread decomposition models[35] such as those developed by Glosten and Harris (1988) and Madhavan, Richardson, and Roomans (1997) to evaluate the adverse selection

[35] The bid-ask spread usually encompasses both order processing costs, and inventory holding costs. Spread decomposition models therefore aim to further decompose inventory costs into an information component (also known as adverse selection), and a non-information component (Gregoriou & Rhodes, 2017).

component of ETF spreads. The seminal works of Merton (1987), Subrahmanyam (1991), Fremault (1991) and Gorton and Pennacchi (1993) all predict a preference for the ETF market over the market for the underlying asset, for varied reasons discussed in section 3.4. This hypothesis suggests that the combination of different stocks into a single basket security reduces the ability of informed investors to benefit from the use of their firm-specific data, which thus reduces information asymmetries and adverse selection in the market for the ETF. This reduction in adverse selection thus leads to declining spreads and thus greater liquidity in the ETF. Whilst these studies provide important information on the relative liquidity of the ETF market and its underlying constituents, the key focus is not in determining possibility of a change in liquidity of the underlying asset, after ETF introduction.

The second branch of studies therefore extends these further, to evaluate the impact of ETF introduction on the liquidity of its underlying assets. This branch includes authors such as Hegde and McDermott (2004) and De Winne et al. (2014), who use event studies to investigate the impact of ETF inception. The main aim of these studies, is to evaluate whether the liquidity of the underlying assets increases or decreases subsequent to ETF introduction in the short-term. The third and final branch of studies evaluated, examines longer term effects on ETF liquidity by evaluating the proportion of each firm held collectively by ETFs (captured by ETF holdings/ETF ownership) over time. This variable is then studied alongside measures of liquidity, to provide insight into the way in which liquidity varies with ETF ownership. Each branch of empirical evidence is extremely important to the discussion on ETF liquidity, and thus will now be discussed further.

4.2.2.1. Empirical evidence on adverse selection in the ETF market

The evaluation of adverse selection in ETFs begins with the theoretical application by Kittsley and Edrosolan (2008) who find that the creation and redemption mechanism of ETFs creates what the authors term "hidden liquidity". Whilst traditional shares have a fixed supply of shares available, the depth of available shares at each bid and ask price represents an important determinant of the liquidity offered. However, with ETFs, there is a possible unlimited depth available for large enough market participants who are able to liaise with the ETF provider, and stimulate further creation of units if needed. This mechanism leads to the "hidden liquidity", which thus ensures that the ETF market is always more liquid than that off the underlying securities (Kittsley & Edrosolan, 2008).

The literature on adverse selection can take two different approaches to decomposing a stock's bid-ask spread; and the first method is known as trade indicator models, whilst the second method is commonly referred to as covariance models (Ivanov, 2016). The dominant literature on ETF adverse selection makes use of trade indicator models derived from Kyle (1985), whose model asserts that the bid-ask spread is adjusted by the market maker, in response to trading with informed participants in the market. These market makers therefore attempt to offset any losses made during trade with the informed traders, by adjusting the bid-ask spread, which is thus referred to as an adverse selection cost, and is borne by all market participants, including liquidity traders. Trade indicator models such as Glosten and Harris (1988), Lee, Mucklow, and Ready (1993) and Madhavan et al. (1997) therefore attempt to use high-frequency, transaction data to decompose the bid-ask spread of a stock or ETF into its order processing, inventory holding and adverse selection components (Small, Wansley, & Hood, 2012). The adverse selection costs of a basket security is likely to be significantly lower than the cost for individual securities, since pooling shares into a single portfolio greatly reduces the ability for informed traders to profit from any fundamental firm-specific information. The results from the studies in this section largely find support for this hypothesis, and is discussed further below.

The study by Chelley-Steeley and Park (2010) employs the Madhavan et al. (1997) model alongside the Glosten and Harris (1988) model, to evaluate if the presence of ETFs reduces the adverse selection issue. Their results confirm this hypothesis, as the authors find that the ETF securities display lower adverse selection costs than a representative sample of control securities. These results are confirmed by the further studies of Bennett and Kerins (2009), Zhou (2011), Small et al. (2012) and Ivanov (2016), all of whom find evidence of lower adverse selection and thus higher liquidity evident in the ETF market. This result suggests that the ETF market should offer a greater level of trading efficiency than the portfolio of underlying assets, and confirms the hypothesis that this would be the preferred market, especially for uninformed investors (Ivanov, 2016). A further result from Small et al. (2012) also indicats that, as the number of constituents in the ETF increased, the adverse selection decreases, and the liquidity increases proportionally. This suggests that larger ETFs have a greater diversification effect, which is found to be independent of whether the ETF was concentrated in one sector, or diversified across many sectors.

Overall, the evidence overwhelmingly suggests that the ETF market is more liquid than that of the underlying securities. Whilst this finding is a positive indication for the ETF market overall as a liquid market is a more efficient and stable market, the evidence of decreased adverse selection also suggests that more uninformed and short-term traders would be attracted to this market[36]. This therefore confirms the hypotheses of Merton (1987), Subrahmanyam (1991) and Gorton and Pennacchi (1993) that the ETF market is the preferred one for uninformed investors. However, their warning that this phenomenon could lead to negative effects for the constituents of the ETFs, needs to be evaluated further. The second branch of analysis studies this implicitly, and will now be discussed in detail.

4.2.2.2. Empirical evidence on impact of ETF introduction on the liquidity in the underlying assets

The first study which evaluates the impact of ETF introduction on the liquidity of its component securities was Hegde and McDermott (2004), who study the Nasdaq 100 (QQQ) ETF, and the Dow Jones Industrial Average 30 (DIAMONDS) ETF. These two ETFs were, at the time of the study, two of the most popular ETFs in the US market. The authors make use of a Seemingly Unrelated Regression (SUR) on transactional market volume and price data over an event window of 50 days prior, and post, introduction of the two ETFs, to evaluate its impact on spread and depth measures of the underlying shares. Overall, strong evidence is found in favour of the liquidity of the component stocks of the DIAMOND ETF increasing in liquidity subsequent to its introduction, whilst similar results are found for the QQQ ETF, although this the latter result is supported by weak evidence. Their use of the Madhavan et al. (1997) measure of spread allows them to also analyse if the decrease in spreads can be attributed to the decrease in adverse selection in the underlying stocks, which is confirmed for the DIAMONDS ETF.

[36] This finding is asserted by the authors reviewed in section 4.2.2.1, and is based on the liquidity clientele effect (developed by Amihud and Mendelson (1986)), which asserts that more liquid instruments will attract short-term traders.

This decrease in adverse selection costs is attributed to the diversification benefits offered by basket securities, where the firm-specific risk is diversified away.

Hegde and McDermott's (2004) second method of analysis makes use of a pooled regression reminiscent of Stoll (1978) and Jegadeesh and Subrahmanyam (1993). Their results indicate that over the first 50 days of its trading, the DIAMONDS and QQQ ETFs exhibit greater liquidity compared to their underlying portfolios, which confirms the results of their initial analysis. The authors further find that the presence of ETFs also contributes to greater liquidity in other derivative products based on the replicated indices.

A later study by Richie and Madura (2007) also uses the Jegadeesh and Subrahmanyam (1993) model in their evaluation of the QQQ ETF, by generating matched portfolios of the underlying securities for comparison. An important innovation to their study is the inclusion of a size variable, to proxy the proportion of an ETF invested in any particular company. The aim of this addition is to investigate whether the liquidity effect was impacted by the relative size of the stocks in the sample, which therefore tests Merton's (1987) hypothesis that small stocks in the ETF would be affected differently to large stocks. Similar to Hegde and McDermott (2007), they find an increase in liquidity of the underlying stocks of the QQQ ETF, but this effect is seen to be more significant for lower-weighted stocks in the ETF, consistent with the "investor recognition hypothesis" of Merton (1987).

De Winne et al. (2014) use a multivariate panel method on the CAC 40 ETF in order to evaluate the liquidity effect when the ETF market involves selected market makers. Their study is unique as the CAC 40 ETF is traded in a market which requires Liquidity Providers (LPs) to provide immediacy services. Since these LPs contribute greatly to the liquidity of the ETF market, their study stands in contrast to those based in other markets (De Winne et al., 2014). Their event study utilises 3 months of trading data prior and post-ETF inception, and the results produced concludes that the market for underlying stocks becomes more liquid after ETF introduction. However, the stock market is also found to become less deep for the stocks with large weights in the index, due to migration of some investors from the large stocks to the index. Whilst their liquidity results are consistent to those of the previously mentioned studies, their adverse selection tests find that the liquidity improvement is not due to decreased adverse selection, but is instead attributed to the decreased order processing, and order imbalance cost components of the bid-ask spread. The authors therefore report confirmation of Fremault's (1991) theory that the presence of ETFs increases arbitrage activity, which thus reduces order processing and order imbalance costs.

The preceding three studies all find evidence of increased liquidity in the underlying assets after ETF introduction. In contrast, Van Ness, Van Ness and Warr (2004) discover evidence to the contrary in their evaluation of the DIAMOND ETF. The authors make use of Feasible Generalised Least Squares (FGLS) on 30 days of pre-and post-trade data for both the underlying constituents to the DIAMOND ETF, as well as a matched sample of similar companies that are not included in the ETF. The aim of the matched sample is to control for other factors that might also affect liquidity of the stock market as a whole. They find that whilst their time period of evaluation is characterised by decreasing spreads for all assets in the stock market, relative to the matched sample, the introduction of the DIAMONDS ETF causes a smaller decrease in spreads for its underlying 30 stocks. This result indicates diminished liquidity in the underlying components, although the authors find no significant change in adverse selection.

Whilst the adverse selection results are attributed to the limited power of their test, the liquidity results are robust and stand in contrast to the results of Hegde and McDermott (2004) who get different results for the same ETF. The two studies differ in their approach however, with the use of different event study periods (Van Ness et al. (2005) uses 30 days, whilst Hegde and McDermott (2004) utilise 50 days), and different methods. In particular, the Van Ness et al. (2005) analysis makes use of multiple additional control variables to capture other common factors which were found to impact spread in the US market, such as the day of the week effect, holiday effect and market return; in addition to conducting the same analysis on a corresponding matched sample. The difference in results therefore suggests that the positive effect (captured by decreased spreads) noted in the Hegde and McDermott (2004) is actually due to other factors which were not controlled in their study, and reinforces the importance of an accurate control variable selection procedure.

The studies reviewed in this section (De Winne et al., 2014; Hegde & McDermott, 2004; Richie & Madura, 2007; Van Ness et al., 2005) make use of short term trading data (in the range of 30 days to 3 months) to evaluate the impact of a single event (ETF introduction) on the liquidity of the assets. Whilst these studies largely show increased liquidity in the constituent securities after ETF introduction, each of the studies are based on limited samples, with each author focussing on only one or two of the popular ETFs in the market. There is therefore the possibility that different effects would be found based on differing samples, and that factors such as ETF concentration and market capitalisation of the underlying constituents could have an effect on the results produced. The next section therefore reviews studies which have evaluated longer term impacts of ETF trading on the underlying securities, for large samples of US and International ETFs.

4.2.2.3. Empirical evidence on impact of ETF holdings on liquidity

The first comprehensive study which evaluates the impact of ETF trade on the relative illiquidity of its underlying stocks is conducted by Hamm (2014), who uses quarterly data on 8420 US firms between 2002 and 2008. Her study makes use of data on the proportion of each firm held by ETFs as the dependent variable in a cross-sectional regression with illiquidity (measured by Kyle's (1985) lambda), as the independent variable, alongside other control variables such as size and volume. Her results show a positive relationship between ETF holdings and illiquidity, which implies that as the proportion of ETF holdings in a firm increases, the liquidity of that firm's shares decreases. Hamm (2014) also finds that the introduction of ETFs tends to exacerbate the illiquidity of shares which exhibit low earnings quality, and thus high levels of adverse selection. This result is also found for index unit trusts, suggesting that the problem lies with all basket securities and not just ETFs. Hamm (2014) asserts that her result is consistent with Gorton and Penacchi's (1993) hypothesis that uninformed investors migrate to the market for basket securities (ETFs), after realising the informational disadvantage that they face in the market for the individual stocks.

Ben-David et al. (2018) conjecture that the popularity of ETFs and the migration of traders to the ETF market may cause a new layer of demand shocks to be transferred to their underlying securities, since the two markets are implicitly connected via arbitrage. The authors assert that this phenomenon (which they term the "liquidity trading hypothesis") may be exacerbated by the ability to trade ETFs intra-daily (at a low cost), as these products attract more high-frequency demand than other similar assets like unit trusts. This activity is therefore hypothesised to ultimately lead to the degradation of liquidity and increased volatility, in the market for the underlying assets (Ben-David et al., 2018). The use of the arbitrage mechanism for ETFs is also emphasised in the hypothesis developed by Evans et al. (2019). The creation/redemption mechanism of ETFs specifies that excess supply should result in APs redeeming ETF shares, whilst excess demand will lead to APs creating more shares of the ETF (Evans et al., 2019). However, current US regulation of ETFs allows APs to sell ETF shares that have not been created yet, which the authors term an "operational short" (Evans et al., 2019). The result of this allowance is that the APs can delay transacting in the market for the underlying securities, which therefore creates a liquidity mismatch between the ETF market, and the market for the underlying security. The operational shorting practice therefore has the potential to reduce volatility and liquidity shocks from being transmitted from the ETF market to the market for the underlying security, whilst also potentially negatively impacting the transmission of fundamental information between the two markets (Evans et al., 2019).

The Ben-David et al. (2018) study of 454 US ETFs over the period of January 2000 to December 2015 utilises both Ordinary Least Squares (OLS) and Instrumental Variables (IV) regressions to evaluate the impact of ETF ownership on common liquidity measures such as the bid-ask spread, and the Amihud illiquidity measure. The results from their study indicates that the ETF market is more liquid than the market for the underlying assets, and thus attracts more short-term traders. This result also causes an increase in the volatility of the ETFs, through the liquidity trading hypothesis. The results from the Evans et al. (2019) fixed effects panel regressions also find evidence of a positive relationship between ETF ownership and intraday spreads for the underlying securities, whilst operational shorting exhibits an inverse relationship to intraday spreads and volatility measures. The authors therefore conclude that the operational shorting mechanism actually acts as a "release valve", which removes arbitrage constraints and thus creates more liquid and efficient markets in the underlying securities (Evans et al., 2019). The study by Box, Davis, Evans, and Lynch (2019) also finds evidence that the ETF market might actually act as a shield for the underlying assets from demand shocks, and thus the presence of ETFs increases the liquidity of their underlying assets. However, in contrast to Evans et al. (2019) their OLS and dynamic panel regressions (estimated using GMM) indicates that this result is not due to the arbitrage mechanism, and is instead attributed to what the authors term the "liquidity buffer hypothesis".

The support found for the presence of the Amihud and Mendelson (1986) liquidity clientele effect by Ben-David et al. (2018) is echoed in an associated study of 167 domestic equity ETFs in the US market by Broman and Shum (2018). The authors use the quoted spread, Amihud and turnover liquidity measures to construct relative liquidity values for each underlying asset, by using the log-difference between the corresponding ETF measure, and the measure calculated for the underlying asset. Broman and Shum (2018) thereafter evaluate the impact of ETF ownership on the relative liquidity measures using fixed effect panel regressions. The results of the study indicate that institutional investors were found to be more active in the US ETF market than retail investors, as they utilise these investment vehicles for a variety of different purposes, such as hedging, transition and liquidity management, as well as tactical asset allocations. In addition, the results found 10 percent more short-term traders in the ETF market, than the market for the underlying securities, which confirms that it is the ease of trading in the ETF market which attracts short-term investors, and thus short term demand. This short-term demand was confirmed by findings that the holding period for very liquid ETFs was shorter than that of lower liquidity ETFs.

The result of ETFs attracting short-term demand, can be proven to be detrimental to overall market stability, based on the findings from the Cella, Ellul, and Giannetti (2013) study. The authors attempt to model long- and short-term demand from institutional investors with the aim of evaluating how institutional trade changes during periods of market turmoil. The central hypothesis of the study, is that even though the trading horizon of any market participant is not directly observable, it can still be observed through the trading behaviour. The authors therefore centre their study on the "churn ratio", which is a measure capturing institutional investor's trading horizons. The results from Cella et al. (2013) pooled regression analysis indicated that during periods of market distress, short-term institutional traders liquidate their holdings to a larger extent than those who are long-term traders, and this results in price volatility and liquidity drying up for those assets in which they were invested. As noted by the authors, this effect will therefore negatively impact market stability, and is a cause for concern for regulators. When evaluated in conjunction with Broman and Shum's (2018) results, this finding further confirms the concerns regarding the potential impact of ETFs on systemic risk, which was noted in Chapter 2 (section 2.4.2.4).

The recent study by Sağlam et al. (2019) focuses on the impact of ETF ownership on the index components of the S&P500 and Nasdaq 100 ETFs. Their analysis makes use of liquidity measured by spreads, as well as Implementation Shortfall (IS), which is meant to measure the cumulative impact of trading costs such as bid-ask spreads, market impact and commission (and is thus a measure of price impact. The results of their fixed effect panel regressions indicate that the ETF holdings variable displays a positive relationship with the spread measures, but a negative relationship with the IS measure. The authors conclude that the ETFs in their sample have increased the liquidity for the underlying securities, and this increase has been attributed more to the improved price impact and market depth, rather than lower spreads. In addition, the study finds evidence that shares with high levels of ETF ownership display increased trading opportunities with uninformed arbitrageurs. The final contribution of the Sağlam et al. (2019) is the analysis of these liquidity measures during the US debt ceiling crisis in 2011, which indicates that whilst shares with high levels of ETF ownership enjoy greater liquidity during normal market conditions, under conditions of market stress, the liquidity of these shares dries up significantly.

The working paper of Brogaard, Heath, and Huang (2019) attempts to further explore ETF liquidity, by theorising that the current ETF market and structure leads to a concept known as “bifurcation” of liquidity. The authors hypothesise that ETF initiation and trade leads to two different effects for large capitalisation firms, and small capitalisation firms. Their discussion concurs with Subrahmanyam’s (1991) theory that investors migrate to the ETF market due to its ease of trade, which is one source of the liquidity effects. The second source results from the replication strategies of ETFs, which do not employ 100 percent replication strategies[37] even for physically replicated ETFs.

[37] Lettau and Madhavan (2018) document that ETF providers have considerable discretion in determining their underlying basket of securities. In South Africa, CISCA dictates that a minimum of 90% of the portfolio should be physically replicated.

Their model therefore predicts that in the aim of minimising tracking error and costs, ETFs will underweight or omit shares that are less liquid in their replication strategies, whilst overweighting stocks with high liquidity levels. This effect therefore leads to already liquid shares becoming more liquid, whilst illiquid shares become even more illiquid. Brogaard et al. (2019) then utilise data on the Russell 3000 ETF and its constituents to empirically investigate the hypothesis, with the resulting evidence from their fixed effect panel regressions lending support to their theory. This consideration is particularly appropriate in the South African ETF market, where the market has already been documented to be very concentrated on a few large company listings on the JSE, as discussed in section 1.1.3 previously.

The findings of Ben-David et al. (2018) and Broman and Shum (2018) are both similar to Hamm (2014), as all three studies find evidence of diminished liquidity in the underlying securities. However, whilst Hamm (2014) attributes this to an increase of uninformed investors in the ETF market, the former two studies find evidence of institutional investors driving increased demand in the ETF market. An important reason for this observation can be found in Khomyn et al. (2020), which builds on the finding of a liquidity clientele by Ben-David et al. (2018) and Broman and Shum (2018). This finding implies that the easy tradability and inherent liquidity of ETFs that was noted in section 4.2.2.1, attracts short-term investors who require liquidity (ie. liquidity clientele). Khomyn et al. (2020) documents that institutional investors form a large proportion of this liquidity clientele, and that they are even willing to incur higher Total Expense Ratios (TER) for this advantage. As noted previously, whilst the presence of institutional investors in the ETF market might assist in promoting liquidity, one might also find that liquidity dries up quicker in these markets during periods of market distress (Cella et al., 2013; Sağlam et al., 2019). This therefore provides an indication that further research on the subject is necessary, especially in markets which are previously unexplored, as these results have important market stability implications, and are thus a cause of regulatory concern.

4.2.3. Summary and conclusion of the empirical evidence on ETF liquidity

The studies reviewed in this chapter take three main approaches to the study of ETF liquidity. The first approach makes use of spread decomposition models in order to evaluate the adverse selection component of ETF liquidity (Bennett & Kerins, 2009; Chelley-Steeley & Park, 2010; Ivanov, 2016; Small et al., 2012). The existing literature reviewed in this section (section

4.2.2.1) provided overwhelming evidence that the ETF market displays less adverse selection than the market for the underlying assets, and thus the ETF market can be considered more liquid. Whilst this result is expected, based on the inherent popularity of ETFs and its exponential growth since its first creation, the literature does not provide any further analysis of the underlying securities and their impacts. The second main approach however, does account for this, by using the date of ETF listing as the event date in their event studies, in which case the liquidity around the pre-and post-event periods is analysed to record any changes (De Winne et al., 2014; Hegde & McDermott, 2004; Madura & Richie, 2004; Van Ness et al., 2005).

The extant literature based on the second approach of analysis is largely mixed, with no consensus reached on whether ETF introduction impacts positively or negatively on the liquidity of its underlying assets. From the studies reviewed in this section, all of which apply the event study approach to its relative data, 75 percent indicate an increase in liquidity for the underlying assets. These studies therefore conclude that the introduction of ETFs has a positive impact on market function. However, the reason for this liquidity increase is mixed, with Hegde and McDermott (2004) attributing their finding to decreased adverse selection faced (in the US market), whilst De Winne et al. (2014) attribute their result in the French market, to a decrease in order processing costs. Nonetheless, this second branch of literature lays the foundation for further studies, and also introduces the possibility that small stocks in the ETF might benefit more from ETF introduction and trading, than large stocks (Merton, 1987; Richie & Madura, 2007).

An important note is that different results are reported by Hegde and McDermott (2004) and Van Ness et al. (2005) even though both authors evaluate the introduction of the DIAMONDS ETF. The notable differences however are in the authors' methodological approach. Whilst Hegde and McDermott (2004) use a 50 day event period and intraday data, Van Ness et al. (2005) use a 30 day event period, daily data, and they compare their analysis to a matched portfolio. In addition, Van Ness et al. (2005) make use of many more control variables in their multivariate regression, based on their findings that in the US market, spread is impacted by certain days of the week, holidays and the change in certain interest rate variables. This therefore indicates that the result of the analysis can be sensitive to the methodology applied.

It could also be an indication that the increased liquidity reported by Hegde and McDermott (2004) is falsely attributed to the introduction of the ETF, whereas in reality it was due to the other control variables which were accounted for in the Van Ness et al. (2005) study.

Whilst the preceding paragraphs detail a more short-term approach to evaluating liquidity, the final approach of analysis was employed in more recent years and took advantage of many years' worth of ETF trading data, to evaluate the longer-term liquidity impacts. All of the studies reviewed in this section make use of US-based data, which had the advantage of being varied in the number of ETFs, whilst ensuring that longer time periods were available for testing[38]. However, the literature here has also produced varied results, with some studies finding support for ETFs increasing liquidity and providing a buffer against liquidity shocks in the market for the underlying securities (Box et al., 2019; Sağlam et al., 2019); whilst others have found evidence of ETF decreasing liquidity in the underlying assets, and transferring an additional layer of demand shocks to the underlying securities via the arbitrage function (Ben-David et al., 2018; Hamm, 2014). Nonetheless, this stream of literature also provides a theoretical foundation for small and large firms reacting differently to ETF formation (Brogaard et al., 2019), which further motivates the second objective of this chapter.

4.3. RESEARCH METHODOLOGY FOR ETFS AND LIQUIDITY

The literature reviewed in section 4.2 illustrates the potential of ETFs to either aid in achieving overall market efficiency and stability, or to create fragility in the market and contribute towards the systemic risk discussed in section 2.4.2. This research is still in its infancy in South Africa, with no studies providing a clear and concise evaluation of ETFs on the microstructure of the JSE. The first research question of this chapter therefore aims to evaluate the impact of ETF introduction on the liquidity of its underlying constituents by employing an event study methodology on the introduction of 23 domestic, equity ETFs listed on the JSE between November 2000 and December 2018.

[38] Data from ETFGI (2020) indicates that the US currently has 2139 ETFs available for trade (as at 30 August 2020), with some ETFs like the SPDR ETF being listed and traded from its inception in 1991.

The second research question aims to expand on the findings of Richie and Madura (2007), Hamm (2014) and Brogaard et al. (2019) who find that market capitalisation of the underlying asset has a bearing on the liquidity impact from ETF introduction. The motivation of this additional objective in the South African environment comes from the relative concentration of the JSE, as noted by Bradfield and Munro (2017), Lambridis (2019), Mans-Kemp and Viviers (2019), Nogantshi (2019) (discussed previously in section 1.1.3), who find that a few large companies dominate the market in terms of size and trading volumes. The investigation of this second objective therefore allows the chapter to further analyse liquidity impacts in the context of the unique South African financial environment. This chapter therefore aims to investigate this further using an event study analysis of the 23 ETFs in the sample, reminiscent of the studies by Hegde and McDermott (2004), Madura and Richie (2004), and De Winne et al. (2014). This section provides a review of the research tools and methods used to evaluate the afore-mentioned two research questions of this study. The sample period and data collection is discussed first, after which the research methods used to evaluate the data is discussed.

4.3.1. Data description for ETF liquidity analysis

The description of data used in this chapter begins with a discussion of the sample period, and the resultant ETFs included in the analysis, after which the chosen data frequency and liquidity proxies will be further deliberated.

4.3.1.1. Sample period and data considerations for ETF liquidity analysis

The earliest ETF introduced in South Africa was the Satrix Top 40 ETF in November 2000, which is a passive ETF meant to replicate the JSE Top 40 index. The last twenty years has seen the ETF market grow to its current offering of 74 different ETF products, from 7 different ETF providers, which range from domestic equity ETFs, international ETFs, commodity ETFs, to the recent offering of smart-beta products[39] (ETFSA, 2020b). The Top40 index remains the most commonly benchmarked index, with 7 products from 4 different providers replicating this index (ETFSA, 2020b).

[39] Smart-beta ETFs are a new generation of ETFs which aim to improve investor returns, or reduce volatility, by investing according to a specific theme, such as value, quality of earnings or low volatility (iShares, n.d).

Whilst the liquidity effect has been investigated in other asset classes such as bonds (Pan & Zeng, 2019; Sultan, 2014), many of the previous studies in this field (surveyed in section 4.2) have been focused on equity ETFs only. The importance of the stock market in particular to the overall economy of a country has been documented in many international studies like Levine and Zervos (1998), Arestis, Demetriades, and Luintel (2001) and Bekaert, Harvey, and Lundblad (2005). Advocates of the stock market-based financial system argue that the stock market is superior to the banking system in propelling country growth, due to the ability of the stock market to offer alternative forms of financial services which thus mobilises savings towards different channels (Levine & Zervos, 1998). In addition, stock markets allow for risk diversification, greater liquidity as well as more readily available information about firm fundamentals (Levine & Zervos, 1996).

Adjasi and Biekpe (2006) find evidence of a positive relationship between stock market development and economic growth only for upper income African countries (their study considers South Africa to be an upper income country). The analysis of Odhiambo (2010) also finds support for the hypothesis that stock market development in SA spurs economic growth, a result which exists over both his short-and long-run analyses. The author concludes that this result is due to the development of the financial sector leading to growth in the real sector, and thus economic growth. This result is confirmed by Ngare, Nyamongo, and Misati (2014) whose panel data analysis of 38 African countries concludes that countries with stock markets develop quicker than those with no stock markets. These findings confirm the resolution by the studies reviewed in section 4.2, which only made use of equity market ETFs. In addition, the liquidity of the stock market has been found to be a determinant of stock market development (Adjasi & Yartey, 2007; Balogun, Dahalan, & Hassan, 2016; Garcia & Liu, 1999; Tsaurai, 2018), which thus impacts on overall economic growth. This further necessitates the use of the equity market only in the study of liquidity impacts, which is why the current study only makes use of equity ETFs in the sample.

On the JSE, equity ETFs are subdivided into domestic ETFs, which replicate purely domestic benchmarks, and international ETFs which replicate international benchmarks such as the S&P500 index, or the Morgan Stanley Capital Index (MSCI) World index. Since the constituents that make up these ETFs is the focus of this study, including international ETFs with varied benchmarks is considered complex and subject to many other factors which go beyond the scope of this study. Furthermore, the evaluation of this issue has been explored extensively in international financial markets, but is in its infancy in the South African market. The focus of this chapter therefore remains exclusively on domestic ETFs.

Within the JSE-listed domestic ETFs, there is a further subdivision into passive products (which aim to mimic a pre-selected benchmark and thus ensure index returns), and so-called smart-beta products (which aims to tilt the included securities towards a specific theme to ensure outperformance) (Du Preez, 2015). As such, the smart-beta products have the characteristics of actively managed products, which aim for outperformance, rather than the passive approach of accepting market- or index-returns (Malkiel, 2014). Whilst smart-beta products differ in their aim, their structure remains the same as passive ETFs. This chapter therefore includes both passive and smart-beta equity ETFs to ensure a large enough sample that is reflective of the ETF market. The sample period therefore covers any domestic, equity ETF introduced from November 2000 until December 2019, which meets the data requirements.

The foundation of this study is the evaluation of the underlying assets for each ETF included in the sample. Therefore, the full list of constituents and their weightings at ETF inception is necessary preliminary data, so that the relevant share data (discussed in section 4.3.1.3 and 4.3.1.4) can be collected for each underlying asset. This data is collected from the Bloomberg and S&P Capital IQ databases, however whilst both databases contain holdings information from recent years, the data at inception is missing for some ETFs in the sample (especially those listed in the initial few years of the sample period)[40]. As a result, any domestic equity ETFs for which their underlying constituents at inception could not be identified, are removed from the sample. As at 31 December 2019, there are 33 ETFs that meet this criteria (a full list of the ETFs listed on the JSE can be found in Appendix A-1 (page 222). However, after removing the ETFs with data missing and/or unavailable, the final sample consisted of 23 ETFs, and their underlying assets, as shown in table 4-1.

[40]Data on these ETFs portfolio constituents was also unavailable in the JSE Stock Exchange News Service (SENS), and could not be sourced from their respective websites and/or fact sheets.

Table 4-1: Summary of ETFs used in the liquidity analysis

ETF	Inception date	Number of viable constituents at inception	Market capitalization (Rm) as at 31 December 2019
Top 40 ETFs			
Ashburton Top40	16 October 2008	35	1 524,1
Satrix Rafi 40	August 2011	38	966,4
NewFunds Shariah Top40	6 April 2009	16	52,3
Newfunds SWIX Top40	26 January 2012	40	Delisted (27/12/2019)
Satrix SWIX 40	10 April 2006	37	371,0
Other diversified ETFs			
Coreshares Top 50	13 May 2015	52	1 424,1
NewFunds NewSA	1 December 2008	34	Delisted (27/12/2019)
NewFunds Equity Momentum	26 January 2012	18	219,7
Ashburton Midcap	15 August 2012	59	424,5
NewFunds Defensive Equity	25 February 2019	30	49,5
Coreshares DivTrax	14 April 2014	26	317,6
NewFunds Moderate Equity	25 February 2019	15	56,0
Satrix Momentum	24 October 2018	35	30,3
Satrix Quality	16 November 2018	26	119,7
Newfunds Low Volatility	26 March 2018	19	125,1
Newfunds Value Equity	31 December 2012	27	112,4
Newfunds High Growth	25 February 2019	15	60,6
Sector-based ETFs			
NewFunds S&P Givi Financials	15 June 2009	13	Delisted (27/12/2019)
NewFunds S&P Givi Resources	15 June 2009	17	Delisted (27/12/2019)
NewFunds S&P Givi Industrial	15 June 2009	23	Delisted (27/12/2019)
Coreshares PropTrax Ten	30 May 2011	10	Merged[41] (31/07/2019)
Satrix Property	24 February 2017	15	234,0
Satrix Resi	10 April 2006	13	411,6

Source: Own compilation (2020)

[41] This ETF was merged with the Coreshares Property SAPY ETF.

The number of viable constituents in the table 4-1 refers to the number of underlying assets which met the data requirements. Companies which are included in the composition of a particular ETF at listing, but which do not have at least 50 full trading days' worth of data before inception, are also excluded from the analysis[42]. Similarly, companies which have incomplete data (such as the bid-ask spread, or volume) are also excluded from the analysis. In total, the sample consists of 147 different JSE-listed companies, which are included in domestic equity, JSE-listed ETFs between 2006 and 2019. Many of these companies appear in multiple ETFs, especially the highest capitalisation companies. Some of the ETFs that are included in the analysis due to meeting the data criteria, are subsequently delisted after its inclusion in the sample. However, since the chapter aims to evaluate the liquidity around ETF listing, the subsequent delisting (long after the sample period of evaluation) was not deemed important enough to warrant an exclusion from the sample.

The ETFs sampled fall into three broad categories based on their benchmark index, which are: Top 40 ETFs, Other diversified ETFs, and sector-specific ETFs. The Top 40 ETFs replicate the Top 40 index and are therefore clustered together for analysis purposes as their underlying assets are mostly consistent. The Other diversified ETFs are funds which track benchmarks such as the midcap index (Ashburton Midcap ETF), or ones such as Satrix Momentum which is classified as a smart beta product. The final category of sector-based ETFs such as the Satrix Resi are based on specific industry sectors of the market, and cannot be considered diversified products as they are concentrated on one sector only. The results are therefore segmented into these categories, for ease of comparison.

4.3.1.2. Data frequency for the analysis of ETF liquidity

Current studies of microstructure have the option to employ much more granular data than earlier studies. The impact of high frequency trading has ensured that nanosecond-level data is available for both transactional as well as quote data (Bohmann, Michayluk, Patel, & Walsh, 2019). As a result, when embarking on studies of liquidity, the choice of what frequency of data to use is vast and has many implications. Whilst the increase in frequency of data presents

[42] These companies usually listed at the same time as the ETF, and therefore did not have enough historical data for the analysis.

a further opportunity to investigate microstructure changes, in emerging markets such as South Africa (where data availability might be an issue), this element must trade-off against lower computational resources, and ensuring longer sample periods (Lesmond, 2005). Studies such as Ma, Anderson, and Marshall (2016) postulate that for these reasons, the use of low frequency data (daily/weekly/monthly) is appropriate, as long as the accuracy of the chosen proxies is ensured.

This issue of liquidity proxy frequency prompted the research of Goyenko, Holden, and Trzcinka (2009), who test commonly used low frequency liquidity proxies against liquidity benchmarks to ascertain their efficacy. Their findings show that the low frequency measures can accurately proxy for high frequency benchmarks, with the authors concluding that "the effort of using high frequency measures is simply not worth the cost" (Goyenko et al., 2009, p. 179). A similar conclusion is reached by Fong, Holden, and Trzcinka (2017) and Bohmann et al. (2019), with the latter study also finding evidence that this relationship holds even during times of information asymmetry in the market. Bohmann et al. (2019) postulates that the reason for this finding is because once informed traders receive any private information about a firm, they have to act on the information timeously before it becomes publicly available. The limited time available for action therefore necessitates trade regardless of the current liquidity in the market (since they are unable to time their trade for times when liquidity may be high and costs may be lower). For this reason, both low and high-frequency trades are equally likely to capture the actions of informed traders in the market (Ahern, 2017). Therefore, whilst studies of the ETF market such as Hegde and McDermott (2004), Madura and Richie (2004) and Sağlam et al. (2019) all use intraday data in their studies of the US market, this chapter makes use of daily data, in alignment with the methods of Van Ness et al. (2005), De Winne et al. (2014) and Brogaard et al. (2019).

4.3.1.3. Liquidity proxies

A critical component of this chapter is the evaluation of liquidity in the underlying securities. To date, there have been multitude of liquidity studies, with many different measurement alternatives available. Each of these measures correspond to either the tightness, immediacy, breadth, depth or resilience components of liquidity (discussed in section 4.1), with some measures incorporating more than one component. The literature on liquidity measures is vast and there are constantly new proxies being developed. As noted by Ma et al. (2016), the choice of liquidity proxy for use in any study should be based on its accuracy and efficiency in that particular market, and for that type of security. This chapter therefore selects four liquidity proxies, based on their relevance in the South African context, as well as their applicability and ease of estimation under the current constrained data environment. The four proxies chosen are: quoted spread, percentage spread, quoted depth, as well as the Amihud Illiquidity ratio. Whilst quoted spread and percentage spread aim to capture trading costs, and thus the tightness of the market, quoted depth captures the depth of the market. The Amihud (2002) illiquidity measure captures price impact, which is the ability of a share to trade with minimal influence on share price, and can thus be considered a measure of depth and market tightness. Each measure now elucidated in further detail.

- **Quoted Spread**

Earlier studies of the subject such as Demsetz (1968) and Stoll (1978) simply measured the tightness and thus liquidity of the market by using bid-ask spreads. The bid-ask spread is the foundation of most liquidity studies, and is decomposed into two different components, which are the transaction cost, and the adverse selection cost (O'hara, 1997). Transaction cost refers to the costs incurred by the dealers, for inventory storage as well as the normal costs of conducting business (Biais et al., 2005). If all information was homogenous and known to every entity in the market, the transaction cost would be the only cost component in the bid-ask spread. However, in reality, due to information asymmetries, there is a possibility that dealers expose themselves to losses when providing liquidity for informed traders (who have a better idea of fundamental value than the dealers) (De Jong & Rindi, 2009). This cost is therefore recouped when dealers trade against uninformed traders, because if there was no option to recoup the losses made, dealers would eventually get pushed out of the marketplace entirely (Harris, 2003). This adverse selection component of the bid-ask spread is often an important determinant of liquidity. If adverse selection costs are low, the bid-ask spreads would also be low, which would stimulate a liquid market, and vice versa (Hegde & McDermott, 2004).

The bid-ask spread is termed Quoted spread in this chapter and allows for the capture of both implicit costs of trading, as well as the explicit costs of trade (Lybek & Sarr, 2002). The Quoted spread ($Qspread_{it}$) is equal to the ask price (Ask_{it}) less the bid price (Bid_{it}) (expressed in Rands), and is expressed in equation 4.1.

$$Qspread_{it} = Ask_{it} - Bid_{it} \tag{4.1}$$

This spread is simply the difference between the price an investor is willing to sell the security, and the price an investor is willing to pay to purchase it. The quoted spread represents an immediacy cost, since this is what is paid when investors want to trade immediately (Schmidt, 2011). The bid-ask spread is said to capture both explicit transaction costs, such as taxes and order processing costs, implicit costs such as execution cost, and the cost of adverse selection (Ahn, Cai, Hamao, & Ho, 2002). Aside from being easily available and relatively simply to compute, this is the most commonly used measure of liquidity in the empirical literature reviewed in section 4.2, and is used in Hegde and McDermott (2004), Van Ness et al. (2005), De Winne et al. (2014) and Box et al. (2019).

- **Percentage spread**

A weakness of using the bid-ask spread in its current form is that its comparability across different firms can become difficult, as the sample employed has multiple different sized firms, with varied price levels. The percentage spread therefore allows for the fact that a given spread will be less expensive for higher prices, and is easier than quoted spread to compare across markets (Sarr and Lybek, 2002). This measure is therefore calculated as follows:

$$Pspread_{it} = \frac{Ask_{it} - Bid_{it}}{(Ask_{it} + Bid_{it})/2} \tag{4.2}$$

In their evaluation of the applicability of multiple different liquidity proxies to global markets, Fong et al. (2017) found that the percentage spread is the best proxy of trading costs for daily data. This measure is used in Van Ness et al (2004).

- **Quoted depth**

Whilst spreads are commonly used in liquidity studies, a potential weakness of using these this measure is that closing prices can sometimes differ from the bid or ask quotes, since trades can occur outside the quoted spread (Lesmond, 2005). In addition, Lee, Mucklow and Ready (1993) find that use of this measure in isolation, is insufficient to evaluate liquidity of the market, and depth should also be included in the analyses. Subsequent studies, therefore, made use of both spread and depth in measuring market liquidity. This study therefore includes two volume based measures, which are quoted depth, and the Amihud illiquidity measure. Quoted depth is equal to the equally weighted average of the sum of volume at the bid ($Volume_{bid}$) and ask prices ($Volume_{ask}$), which is displayed in equation 4.3 below.

$$Qdepth_{it} = \frac{Volume_{bid} + Volume_{ask}}{2} \tag{4.3}$$

Measures of depth have been used in studies by Hegde and McDermott (2004), Richie and Madura (2007) and Small et al. (2012). However, the data required for this study could only be obtained for ETFs listed during or after August 2012, so this measure was calculated and interpreted for the 11 ETFs that met the data requirements.

- **Amihud Illiquidity measure**

Whilst the measures such as quoted spread and depth discussed above are intuitively appealing and simple to compute, the key disadvantage is that sometimes cross-sectional or time series comparison becomes difficult, as these estimates are not scalable (Lesmond, 2005). The Amihud (2002) measure was developed in the aim of providing a consistent liquidity measures for different stock markets, and since its inception, has proven to be the most widely used liquidity measure in studies of the stock market (Díaz & Escribano, 2020). This measure is based on Kyle's (1985) lambda (discussed in chapter 3), and is calculated as follows:

$$Amihud_{it} = \sqrt{\frac{\frac{1}{N}\sum_{1}^{N}\sum|R_{it}|}{(Price_{it\times}Volume_{it})}} \tag{4.4}$$

Where: R_t represents return of the asset, which is calculated as $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, and $Volume_t$ represents the daily trading volume of the asset. The numerator of the illiquidity ratio is the absolute value of the daily return for each stock in the ETF, and the denominator $(Price_{it\times}Volume_{it})$ represents the daily volume of the share, in Rands. The conventional form of this measure does not include the square root in the formula, and captures the daily price response associated with one Rand of trading volume, however it was found by Hasbrouk (2009) that when using daily data, the square root of this measure is more appropriate for use. A high value for this measure indicates that the stock price has moved a lot, on low volume, which indicates illiquidity. This illiquidity measure allows one to capture the linkages between price and volume, and evaluates the price change for a unit change in volume. A major advantage of this measure is that it is appropriate for an emerging market like South Africa, since the Amihud measure is expected to have a value even on days with no price changes (Lesmond, 2005).

The Amihud measure is a commonly utilized proxy which captures breadth as well as price impact in many liquidity studies, such as Hasbrouck (2009), Israeli et al. (2017), Broman and Shum (2018) and Box et al. (2019). In their 2017 study which evaluated the best liquidity proxies for use, Fong et al (2017) found that the daily version of the Amihud Illiquidity measure is the best proxy for cost-per-volume measures. In addition, in his study of liquidity in emerging markets, Lesmond (2005) found that the Amihud measure can be considered the best liquidity estimator for capturing effects within the same country (this was found to be the case for the South African market as well), a result that was confirmed by Goyenko et al. (2009) and Będowska-Sójka (2018).

4.3.1.4. Control variables for ETF liquidity analysis

The use of a multivariate method of analysis within the event study (this method is discussed further in section 4.3.2. alongside the univariate method of analysis), necessitates the selection of control variables. These variables are defined by Hünermund and Louw (2020) as variables that have some impact on the dependent variable, but are not the primary sources of interest in the study. Therefore, these control variables are factors which could influence the liquidity of the underlying assets, and failure to remove these effects from the multivariate analysis may result in biased estimates that are falsely attributed to the introduction of ETFs. Since this chapter has a focus on liquidity, identifying the determinants of the liquidity proxies used, such as the bid-ask spread, is an important step in identifying the control variables.

Initial studies such as Demsetz (1968), aimed to evaluate the determinants of the bid-ask spread, by understanding the information environment around trades. The bid-ask spread represents the compensation for the dealer of a security, who incurs inventory costs, costs of processing, as well as the cost of information asymmetries. The seminal work of Demsetz (1968), Stoll (1978) and Ho and Stoll (1983) therefore postulate that the bid-ask spread, and thus liquidity, is dependent on factors which influence the dealers' risk of holding inventory, or increase the information asymmetry faced. The first factor identified by these studies is the volatility of an asset. Since higher levels of risk in an asset results in higher inventory costs as well as information asymmetry costs, this should thus result in an increased bid-ask spread (Wyart, Bouchaud, Kockelkoren, Potters, & Vettorazzo, 2008), a phenomenon which is documented in studies by Madhavan (2000) and Chordia, Roll, and Subrahmanyam (2001).

The second factor that influences spreads is the price of the asset. Changing prices are hypothesised to impact the dealers' ability to adjust his inventory levels, which will thus result in changes to the bid-ask spread (Chordia et al., 2001). Similarly, Stoll (2000) argues that a larger volume of shares traded in a firm will increase the possibility of traders matching to a counterparty quicker, and this therefore decreases the inventory risk borne by the dealer, which decreases the bid-ask spread.

The extant literature is rich in other possible factors that could impact liquidity, such as interest rates, market return, holiday effects (Chordia et al., 2001), transaction rate and market competition (Demsetz, 1968), number of dealers (Stoll, 1978), firm size (Stoll, 2000) dividends and the risk-free rate (Song & Chen, 2016), analyst coverage (Iskandrani, 2016) and thin trading (Fathi, Jalali, Ajam, & Sadeghi, 2020). A study by Hearn and Piesse (2013) of the JSE, expanded the analysis further by postulating that corporate governance factors also impact the firm's liquidity. Whilst each of the afore-mentioned studies found varied levels of support for their hypothesised factors, the three factors that have garnered the most support in the literature are the price, volume and volatility measures discussed previously (Boehmer & Boehmer, 2003; Chordia et al., 2001; De Winne et al., 2014; Hearn & Piesse, 2013; Hegde & McDermott, 2004; Jegadeesh & Subrahmanyam, 1993; Madura & Richie, 2004; Stoll, 1978; Van Ness et al., 2005).

As a result, this chapter makes use of these three control variables in the multivariate analysis for the event study. The price of the asset ($Price_{it}$) is easily captured as the closing price of each firm *i* at time *t*, and the standardised trading volume of the asset ($Volume_{it}$) is calculated by subtracting the mean (over the sample period) from the daily trading volume, and dividing by the standard deviation of volume (over the sample period). The volatility of the assets included in this chapter is calculated using Parkinson's (1980) extreme value method and captured by the $StdDev_{it}$ variable . Whilst the usual method of calculating volatility in an asset applies the method of moments from daily returns, the approach developed by Parkinson (1980) makes use of the high and low prices from each day's trade to calculate the risk. This estimate of volatility is found to be more efficient than the traditional measure which makes use of closing prices, as it incorporates the range of prices over the trading day. The efficiency of this estimator is confirmed by Beckers (1983), Wiggins (1991), Pandey (2005), which thus confirms its use in Hegde and McDermott (2004), Wang, Xie, Zhao, and Jiang (2018) and Zainudin, Mahdzan, and Yet (2018). The volatility is therefore calculated as follows: $volatility^2 = \frac{[\ln(High) - \ln(Low)]^2}{4\ln(2)}$ where high and low are the daily high and low prices.

A full list of the variables utilised in this chapter, together with a summary of their definitions and computation is contained in table 4-2.

Table 4-2: Variable summary and definitions for ETF liquidity analysis

Variable	Definition
Quoted spread ($Qspread_{it}$)	= the quoted spread for each asset *i* at time *t* = ask price – bid price
Percentage spread ($Pspread_{it}$)	= the bid-ask spread of the share, expressed as a percentage $= \frac{Ask_{it} - Bid_{it}}{(Ask_{it} + Bid_{it})/2}$
Quoted Depth ($Qdepth_{it}$)	= the measure of volume depth at the bid and ask prices for each firm *i* at time *t* $= \frac{Volume_{bid} + Volume_{ask}}{2}$
Amihud illiquidity measure ($Amihud_{it}$)	= a measure of price impact $= \sqrt{\frac{\frac{1}{N}\sum_1^N \sum \lvert R_{it} \rvert}{(Price_{it} \times Volume_{it})}}$
Price of an asset ($Price_{it}$)	= the price of asset *i* at time *t* = ln (closing price)
Daily trading Volume ($Volume_{it}$)	= standardised trading volume of asset *i* at time *t* $= \frac{volume - average\ volume\ over\ sample\ period}{standard\ deviation\ of\ volume\ (over\ sample\ period)}$
Volatility ($StdDev_{it}$)	= standard deviation of asset *i* at time *t*, as measured by Parkinson's (1980) extreme value method $volatility^2 = \frac{[\ln(High) - \ln(Low)]^2}{4\ln(2)}$
Dummy ($Dummy_{it}$)	= a dummy variable which takes the value of 1 for the period post-introduction, and 0 otherwise
Weight in ETF ($Weight_{it}$)	= the proportion of the ETF represented by security *i* at time *t*. $= \frac{market\ capitalisation\ of\ firm\ i\ included\ in\ ETF\ j\ at\ time\ t}{total\ market\ capitalisation\ of\ ETF\ j\ at\ time\ t}$

Source: Own compilation (2020)

4.3.2. Research Methods to evaluate liquidity in ETFs

The dominant research methods used to evaluate liquidity in ETFs takes three routes. The first body of evidence (Bennett & Kerins, 2009; Chelley-Steeley & Park, 2010; Ivanov, 2016; Small et al., 2012) aims to evaluate the relative liquidity of the ETF to its underlying basket of securities, and was discussed in section 4.2.2.1. Whilst this research provides valuable evidence on ETF liquidity, it does not provide much indication on the impact faced by the underlying securities. The second body of evidence however, has a focus on the underlying assets, and thus uses event studies to evaluate whether the introduction of ETFs have a significant impact on the liquidity of the underlying assets (De Winne et al., 2014; Hegde & McDermott, 2004; Richie & Madura, 2007; Van Ness et al., 2005). In these studies, the list date of the ETF is considered the "event", and the liquidity of each underlying asset is examined in the immediate period before and after this event.

The third and final body of evidence examines the impact of continued ETF trading (captured by the ETF ownership variable) on the liquidity of the underlying assets, and aims to provide longer term conclusions than the second stream of evidence (Ben-David et al., 2018; Broman & Shum, 2018; Hamm, 2014; Sağlam et al., 2019). However, these studies require further data constraints to ensure that the liquidity of the ETF is established and stabilised before the study is conducted, which results in the studies eliminating the first few months/year of data after ETF/stock listing, and requires a minimum of 36 months consecutive trading data before inclusion in the sample (Broman & Shum, 2018). Whilst this method is valued and feasible in the US context which has thousands of ETFs listed[43], the use of this method in the South African context may place further restrictions on the overall dataset (there are currently only 33 domestic equity ETFs, and 342 listed companies on the JSE as at 30 August 2020). The adoption of the second method of analysis therefore ensures a larger dataset with fewer data restrictions, whilst still allowing for the analysis of liquidity in the underlying securities. This chapter therefore uses the event method to evaluate the first research question posed, which will now be discussed further.

[43] The average age of the ETFs in Broman and Shum's (2018) sample was 6.3 years, which ensures that the liquidity of these ETFs is already established.

4.3.2.1. Event Study: Univariate analysis

The first research question of this chapter aims to evaluate the impact of ETF introduction on the liquidity of its underlying shares. Since the date of ETF introduction constitutes a specific event, an event study is deemed necessary as the primary method of evaluation. This method, first introduced by Dolley (1933), gained popularity in financial studies after its usage by Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969). The rationale behind an event study, is that, given rational and efficient markets, the effect from an event will reflect in stock prices immediately, or over a short time frame, and therefore the financial impact can be measured using the observed stock prices during this time frame. The event study method therefore allows for the capture of the information flow into asset prices, or some other stock characteristic like liquidity or volatility (Kliger & Gurevich, 2014). Since its initial use, the event study methodology has become the standard approach to measuring stock market reaction to any firm announcements or events (Binder, 1998). Whilst the initial event studies were designed around the calculation of abnormal returns, subsequent studies such as Jegadeesh and Subrahmanyam (1993) and Hegde and McDermott (2003, 2004) have used this method to evaluate other microstructure elements such as volatility and liquidity, and attempt to pool the observations to allow analyses at both a portfolio-level, as well as at a firm-level (Cao & Petrasek, 2014).

The procedure for an event study is adapted from Campbell, Lo, and MacKinlay (1997) and MacKinlay (1997) as follows:

1. Definition of the event,
2. Identify the event window,
3. Identify selection criteria for study sample,
4. Define the estimation and testing procedure, and
5. Calculate and interpret the empirical results.

Whilst the first step has already been established as the day of ETF listing, the second step of an event study involves identifying the event window. According to Hegde and McDermott (2004), the use of a shorter window will minimise the possibility of an impact from other control variables (that were not included in the study). However, longer event windows also ensure that sustained changes in liquidity will be captured. A balance between these two factors is therefore necessary when choosing an event window. The extant literature makes use of a 101 day event window (50 days pre- and 50 days post- event) (Hegde & McDermott, 2004), a 61 day event window (30 days pre- and 30 days post- event) (Van Ness et al., 2005), and 121 day event window (60 days pre- and 60 days post- event) (De Winne et al., 2014). Richie and Madura (2007) make use of 3 months (which equals to 63 trading days) of data in the pre- and post- period, which equates to a 127 day event window in total.

In South Africa, the ETFs are rebalanced on a quarterly basis (which have on average 63 trading days), and this study postulates that by the time the ETFs are rebalanced, the effect should be already incorporated into the individual securities. Therefore, the shorter event windows of a 61 and 101 day event window was selected, to allow for 30 and 50 days pre- and post- ETF introduction respectively[44]. This time period satisfies the criteria of being long enough to identify the effect, and short enough to eliminate the impact of other factors, and to eliminate any changes in the structure of the ETF impacting on liquidity of the other components.

The third step of the event study method involves identifying selection criteria for the sample, which has already been discussed in section 4.3.1.1. Steps 4 and 5, which entail discussion of the estimation procedure, as well as the results will not be discussed further. This study employs the use of univariate as well as multivariate testing. Whilst a univariate approach is the simplest form of analysis, it aims to provide important information about the liquidity proxies used in the study, and attempts to provide a preliminary understanding of liquidity impacts.

The liquidity proxies discussed in section 4.3.1.3 are therefore used to calculate a liquidity ratio, as shown in equation 4.5 below:

$$Liquidity\ ratio_{it} = \frac{\overline{V_{it}^{Post}}}{\overline{V_{it}^{pre}}} \quad - \cdots \ldots . for\ i = 1 \ldots . n$$

(4.5)

[44] The event day (the day that the ETF lists on the JSE), is not included in the analysis

Where $\overline{V_{it}^{Post}}$ is the daily average of the liquidity variable of interest for security I in ETF j during the period after ETF introduction, and $\overline{V_{it}^{pre}}$ refers to the associated value in the period before ETF introduction (Hegde & McDermott, 2004). This ratio is calculated for each of the four liquidity measures specified previously, as well as for trading volume, which is a common simple measure of breadthe. A liquidity ratio which is greater than 1 indicates that the liquidity measure has increased after ETF introduction, whilst a ratio less than 1 indicates that the liquidity measure has decreased. Whilst increased liquidity is presented by a pre/post ratio of higher than 1 for the trading volume variable, a value of less than 1 for quoted spread, percentage spread and Amihud measure indicates lower spreads and lower price impact (and thus higher liquidity). The standard t-test is used to test the statistical significance of the liquidity ratio.

4.3.2.2. Event study: Multivariate analysis

The multivariate approach to testing will make use of the model introduced by Hegde and McDermott (2004) and later extended by Richie and Madura (2007) is motivated by Subrahmanyam's (1991) argument that liquidity traders would migrate to the ETF market as it serves as the lower cost market. This method therefore allows for a comparison of the market liquidity in the ETF against the market liquidity of a market-cap weighted portfolio of the constituent securities over the post-introduction period, in addition to evaluating whether the liquidity of the underlying assets increase after ETF introduction. The model expressed in equation 4.6 therefore allows for the testing of both objective 1 and 2 in this chapter.

Richie and Madura's (2007) pooled OLS model therefore combines the pre-and post-liquidity data from section 4.3.2.1 into a single pool[45], and accounts for pre-and post-ETF introduction periods by using a dummy variable. In addition, their pooled model allows for an additional component of asset weighting in the ETF, as shown by equation 4.6.

[45] For the data using a 30 day event, the panel will therefore consist of 61 days of observation data, whilst the 50 day event period will correspond to 101 daily observations for each cross-sections in the panel.

$$ln(liquidity\ measure_{it}) = \alpha_0 + \alpha_1\, ln(Price_{it}) + \alpha_2\, ln(Volume_{it}) + \alpha_3\, ln(Volatility_{it}) + \alpha_4 Dummy_{it} + \alpha_5 (Dummy_{\ it} \times Weight_{it}) + \varepsilon_{it},$$

$$i=1.....N,\ t=1....T \tag{4.6}$$

Where: $liquidity\ measure_{it}$ is the four measures used in this study, of Quoted Spread, Percentage Spread, Amihud measure and Quoted Depth, for each firm i, at time *t*.

$Price_{it}$ is the natural logarithm of the daily closing share price for each firm *i*, at time *t*.

$Volume_{it}$ is the natural logarithm of the daily standardized trading volume[46], for each firm *i*, at time *t*. This variable is omitted for the depth measure due to multicollinearity.

$Volatility_{it}$ is calculated using Parkinson's (1980) extreme value method, for each firm *i*, at time *t*.

Dummy is a dummy variable which takes the value of 1 for the period post-introduction, and 0 otherwise, and

$Weight_{it}$ is the proportion of the ETF represented by security *i* at time *t*.

The control variables of $Price_{it}, \%\Delta StdDev_{it}$ and $\%\Delta Volume_{it}$ were discussed in section 4.3.1.4. The volume variable is omitted in the equation for depth (4.9) however, as it displays a very high correlation with depth due to the construction of the variable. Studies such a Copeland and Galai (1983), Stoll (2000) and Hearn and Piesse (2013) have found that the measures of spread of stocks have a direct correlation with the variability of the stock, whilst the price and trading volume have an inverse relationship to the spread. This is because as stock volatility increases, dealers would be expected to increase the bid-ask spread to protect themselves from adverse movements, whilst higher priced securities are expected to have greater levels of liquidity. Similarly, a higher level of trading volume indicates greater liquidity in an asset, which thus allows for the dealer to narrow the spread (Richie & Madura, 2007). However, the depth variable is expected to be positively correlated to changes in volume, with

[46] This variable is included for the quoted spread, percentage spread and amihud liquidity measures, but is excluded for the quoted depth measure due to high correlation with the measure.

an inverse relationship expected for price and variability (Copeland & Galai, 1983; Hegde & McDermott, 2003).

A statistically significant, positive α_4 in equation 4.6 indicates that there is a significant increase in spreads, or depth experienced in the post-introduction period. Whilst an increase in spreads indicates diminished liquidity, an increase in depth indicates an increase in liquidity. These variables should therefore be interpreted together, and ideally, positive effects on liquidity in the underlying assets should be indicated by both decreasing spreads, alongside increasing depth. A statistically significant coefficient for α_5 indicates that higher weighted stocks in the ETF are positively correlated with the liquidity measure in question. In the case of the Quoted spread, percentage spread and Amihud measures, this indicates an increase in spreads and therefore a reduction in liquidity, whilst the opposite is true for the quoted depth measure.

A pooled OLS regression involves stacking the variables in equation 4.6 into vectors, and estimating using OLS. However, the drawback of this method is that it relies on the assumption that the relationships between the chosen variables remains constant over time and across all the companies used, which therefore implies that the resultant error terms are uncorrelated across observations, and it is known as unobserved heterogeneity[47] (Brooks, 2019). In the event that a variable which impacts both the left- and right-hand side of the above equation is omitted, the resultant independent variables will be found to be correlated with the residuals in the model (Arellano, 2003).

Studies by Petersen (2009) and Cochrane (2009) assert that if the assumption of uncorrelated residuals is violated, this would result in biased coefficient estimates, and incorrect standard errors and t-statistics, which would impair the inferences made, and ultimately result in an inefficient model. Gormley and Matsa (2014) note that there are many sources of unobserved heterogeneity when evaluating groups of observations, such as in this study, unobserved risk factors which impact on both liquidity and stock returns of the underlying assets of the ETF. The use of panel data modelling, therefore overcomes this issue as its modelling allows for the

[47] This concept will be discussed further in section 5.3.4.2.

incorporation of unobserved heterogeneity, and thus eliminates the issue of biased results. In addition, the use of panel data methods allows for the revelation of dynamics and complexities that may be unobservable in OLS methods (Baltagi, 2008). This method also allows for the reduction of collinearity among variables and therefore ensures increased efficiency of the estimators (Pesaran, 2015).

When dealing with panel data regression, there are two possibilities of estimation, Random effects (RE) or Fixed Effects (FE). A RE model assumes that the intercepts of a model are constant, therefore any variation in errors across time periods or cross section are due to changes in the variance of the error term (Brooks, 2019). Therefore, for a RE model, equation 4.6 can be rewritten as follows:

$$ln(liquidity\ measure_{it}) = \alpha_0 + \alpha_1\, ln(Price_{it}) + \alpha_2\, ln(Volume_{it}) + \alpha_3\, ln(Volatility_{it}) + \alpha_4 Dummy_{it} + \alpha_5 (Dummy_{\ it} \times\ Weight_{it}) + (v_i + u_{it}),$$

$$i{=}1 \ldots\ldots N,\ t{=}1 \ldots\ldots T \tag{4.7}$$

Where: $u_{it} \sim IID(0, \sigma_u^2)$ and Where: $v_i \sim IID(0, \sigma_u^2)$

In the preceding equation, the intercept for each cross-sectional unit is assumed to remain constant, whilst the error variable v_i will vary over cross-sections, but remain constant over time, and is meant to capture the unobservable firm-specific liquidity impacts that are unique to each company in the analysis. The variable u_{it} therefore captures the remaining error in the model, and it varies over time and with the cross-sections. The unobserved heterogeneity in the model is therefore captured by the error term$(v_i + u_{it})$, which relies on the condition that v_i is not correlated to the explanatory variables in the model (Barros, Bergmann, Castro, & da Silveira, 2020). A random effects model is considered most appropriate if the sample of the study draws random observations from a large population, and inferences are meant to be extended to the larger population (Baltagi, 2008).

In contrast to equation 4.7, a FE model allows for variation in the intercepts of the model across time periods or cross-sections (or both), and therefore any variation in the errors is assumed to be due to changes in the intercept term (Park, 2015). The estimation equations for a FE model, based on equation 4.6 is therefore expressed in equation 4.8 below.

$$ln(liquidity\ measure_{it}) = (\alpha_0 + v_i) + \alpha_1\, ln(Price_{it}) + \alpha_2\, ln(Volume_{it}) + \alpha_3\, ln(Volatility_{it}) + \alpha_4 Dummy_{it} + \alpha_5 (Dummy_{\ it} \times Weight_{it}) + \lambda_t + \varepsilon_{it},$$

$$i=1.....N,\ t=1....T \tag{4.8}$$

Where: $u_{it} \sim IID(0, \sigma_u^2)$

The fixed effect represented in equation 4.8 therefore examines the differences in intercept across cross-sections. The α_0 in equation 4.6 is considered time-invariant, therefore it is meant to capture any company-specific effect that is not included in the regressors of the model (Mundlak, 1978). The time-invariance of the intercept therefore allows for v_i to be correlated with the explanatory variables, in contrast to the random effects model. The variable λ_t in equation 4.12 accounts for a time-fixed effect, and is allowed to vary over time, but not within cross-sections (Brooks, 2019). This therefore captures the shocks in liquidity which simultaneously affect all the companies in the ETF (Barros et al., 2020). Both the RE model depicted in equation 4.7, and the FE model in equation 4.8 can be estimated by controlling for either cross-sectional effects or time effects (termed a one-way model), or both cross-sectional and time effects (termed a two-way model) (Park, 2010).

According to Baltagi (2008), the fixed effects model is most appropriate when the focus is on a specific sample of companies, and all inferences are restricted to those companies. The study by Gormley and Matsa (2014) shows that the FE estimator is efficient in controlling for unobserved heterogeneity between different cross-sectional groups. The decision on whether to use fixed or random effects could therefore revolve around a theoretical argument, or based on the data specified, however there are statistical means of evaluating the choice between the two effects. The Hausman test is one such statistical procedure available, which aims to compare the FE and RE specifications in order to evaluate which form is more suitable to fit the dataset.

As discussed earlier, the assumption of the RE model is that the explanatory variables of the regression should not be correlated to the residual v_i in equation 4.7. The Hausman test therefore evaluates the correlation between these variables, and suggests the use of FE if any correlation is found (Brooks, 2019). Stated formally, the null hypothesis of the Hausman test assumes that there is no correlation in the regressors and the error term, in which case the RE model is apt. The alternative is that there is statistically significant correlation present between the regressors and error variables, and therefore the FE model is apt. The resultant test critical values follow a chi-square distribution ($\chi^2(f)$) that has the degrees of freedom equal to f (where f is the number of factors in the model). If the test statistic produced is found to be greater than the critical values of the test, the null hypothesis can be rejected in favour of a fixed effects model (Sheytanova, 2015). Based on the superior model chosen, this chapter makes use of both one-way and two-way fixed or random effects for the purpose of evaluating the liquidity impact of ETF introduction.

4.3.2.3. Panel data diagnostic testing

When conducting a panel data analysis, there are two additional problems which could potentially occur, which require preliminary diagnostic testing before estimation is conducted. The first problem is the possibility that all the units in a single cross-section of panel data are correlated due to common shocks, which gets captured in the error term, and reflects as cross-sectional dependence (Henningsen & Henningsen, 2019). In the presence of cross-sectional dependence in the errors, which are correlated to the explanatory variables in the regression, the RE or FE estimators are found to be inconsistent (Pesaran, 2015). This issue is commonly tested using the cross-sectional test statistics developed by either Pesaran (2004), Frees (1995), or Friedman (1937). However, as noted in De Hoyos and Sarafidis (2006), these tests are only valid for cases where the number of time series in the panel, is less than the total number of cross-sections, which is not the case in this chapter. Therefore, whilst this test will be omitted, an important test that is necessary given the nature of the data used (which is, T>N), is the use of panel unit root tests.

The second diagnostic test is therefore a test of the data series used for the presence of unit roots. The use of non-stationary data in a panel analysis could result in a spurious regression, which thus leads to biased estimates (Phillips & Moon, 2000). There are multiple different tests which can be used to test for a unit root in panel data, such as the tests developed by Levin, Lin, and Chu (2002), Breitung (2001), Im, Pesaran, and Shin (2003) and Hadri (2000). Each of these tests have the null hypothesis of a panel unit root being present in the data, and they differ in their methodological approach to the approximation of a test statistic. As such, each of the above-mentioned tests also perform differently under different finite sample conditions. Pesaran (2015) notes that the Levin et al. (2002) test has superior small sample properties, and the simulation studies of Barreira and Rodrigues (2005) and Westerlund and Breitung (2009) concur with the finding of model superiority. Since this chapter makes use of smaller values for T (either 61 or 101 days' worth of data), this test is considered efficient for use. The Levin et al. (2002) test has the null hypothesis of a unit root being present in the data, with the alternative indicating stationarity, and the test makes use of a three step procedure to calculate the test statistic, which is based on asymptotic normality (Brooks, 2019).

4.4. DATA ANALYSIS AND RESULTS FOR ETF LIQUIDITY

This sub-section aims to display and explain the results produced from the methodological approach previously discussed in section 4.4. The analysis therefore begins with a univariate analysis of the data and variables used in the sample, after which the results from the multivariate analysis are deliberated.

4.4.1. Univariate Analysis of ETF liquidity

The first analysis of the data looks at the impact of trading volume in the 30/50 day period before introduction, and compares it to the 30/50 day period after introduction. An increase in average volume in the post-introduction period signals increased activity in the underlying securities, and a possible increase in liquidity. The post/pre ratio is also calculated, along with an associated t-statistic to indicate significance. If this ratio has a value greater than 1, it indicates increased trading volumes and thus increased liquidity, and this is in boldface in the tables provided. The last measure calculated the proportion of the ETF portfolio that had a post/pre ratio of greater than 1, and thus represents the proportion of the underlying securities that recorded increased liquidity after ETF introduction. Any proportions higher than 50 percent are italicised in the tables. The relevant information for the 30 day event period is contained in table 4-3, whilst the information pertaining to the 50 day event period is contained in table 4-4.

Table 4-3: Average Trading Volume of ETFs pre-and post-ETF introduction over 30 day event period

ETF	Pre-mean	Post-mean	Post/Pre ratio	Proportion > 1.0
Panel A: Top 40 ETFs				
Ashburton Top40	4 021 550	3,725,658.67	0.90***	22.86%
Newfunds Shariah Top 40	3 369 268	3,264,421.71	**1.00*****	43.75%
Newfunds SWIX Top 40	2 335 411	2,433,478.39	**1.16*****	*60.00%*
Satrix Rafi 40	2 939 356	3,135,771.57	**1.04*****	*50.00%*
Satrix Swix 40	2 565 851	2,457,172.35	**1.03*****	*56.76%*
Panel B: Other Diversified ETFs				
Ashburton Midcap	882 996	1165289.94	**1.48*****	*65.00%*
Coreshares Top50	2 406 628	2699357.21	**1.18*****	*58.82%*
Newfunds Defensive Equity	2 706 027	2700753.83	**1.04*****	*60.00%*
Coreshares DivTrax	1 461 270	1199797.93	0.90***	15.38%
Newfunds Moderate Equity	2 339 568	2512196.65	**1**.16***	*72.00%*
Satrix Momentum	2 247 051	2034553.06	0.97***	31.43%
Satrix Quality	1 556 259	1190561.79	0.92***	34.62%
Newfunds NewSA	3 397 992	2403898.91	0.74***	2.94%
Newfunds Low Volatility	3987865.03	2881298.09	0.85***	15.79%
Newfunds Value Equity	1837243.80	1861780.88	**1.05*****	*51.85%*
Newfunds High Growth	2611308.28	2767010.32	**1.19*****	*80.00%*
Newfunds Equity Momentum	2598753.92	2479158.92	**1.08*****	*55.56%*
Panel C:Sector ETFs				
Newfunds Givi Financials	3329332.59	3554597.79	**1.12*****	*76.92%*
Newfunds Givi Industrials	3160535.80	2283499.20	0.86***	17.39%
Newfunds Givi Resource	1559162.42	1391417.18	0.92***	29.41%
Satrix Resi	1595012.55	1599695.10	**1.13*****	*53.85%*
Coreshares Proptrax Ten	1455623.88	1734975.88	**1.26*****	*50.00%*
Satrix Property New	2505238.27	2804516.28	**1.07*****	*66.67%*

*'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance. Liquidity measures which indicate an improvement in liquidity (with pre/post ratio <1) are indicated in bold, whilst proportions greater than 50% are in italics. The average trading volume was calculated as an equally-weighted average of each of the ETF constituents.*

Source: Own estimation (2020)

Table 4-4: Average Trading Volume of ETFs pre-and post-ETF introduction over 50 day event period

ETF	Pre-mean	Post-mean	Post/Pre ratio	Proportion > 1.0
Panel A: Top 40 ETFs				
Ashburton Top40	3 506 051	3 397 719	0,95***	37,14%
Newfunds Shariah Top 40	3 121 803	3 217 491	**1,08*****	*50%*
Newfunds SWIX Top 40	2 272 670	2 527 484	**1,20*****	*77,5%*
Satrix Rafi 40	2 785 977	2 974 679	**1,05 *****	*55,26%*
Satrix Swix 40	2 435 475	2 688 703	**1,14*****	*72,97%*
Panel B: Other Diversified ETFs				
Ashburton Midcap	964 569	1 087 643	**1,15****	35,59%
Coreshares Top50	2 684 640	2 566 626	**1,05 *****	37,25%
Newfunds Defensive Equity	2 551 156	2 546 324	**1,03 *****	*53,33%*
Coreshares DivTrax	1 406 379	1 212 545	0,86 *	15,38%
Newfunds Moderate Equity	2 268 828	2 363 450	**1,10 ****	*56%*
Satrix Momentum	2 117 234	1 817 292	0,96*	25,71%
Satrix Quality	1 574 818	1 147 971	0,81*	15,38%
Newfunds NewSA	3 618 629	2 512 594	0,70 ***	0%
Newfunds Low Volatility	3 770 930	2 901 875	0,86*	26,32%
Newfunds Value Equity	1 850 912	2 026 082	**1,08****	*55,56%*
Newfunds High Growth	2 578 637	2 624 989	**1,10 *****	*53,33%*
Newfunds Equity Momentum	2 407 390	2 538 899	**1,16*****	*72,22%*
Panel C:Sector ETFs				
Newfunds Givi Financials	3 664 066	3 358 473	**1,02 *****	*53,85%*
Newfunds Givi Industrials	2 988 188	2 509 471	0,93 ***	34,78%
Newfunds Givi Resource	1 663 225	1 426 731	0,94***	35,29%
Satrix Resi	1 590 846	1 617 099	**1,07****	*61,54%*
Coreshares Proptrax Ten	1 557 108	1 612 585	**1,09 *****	40,00%
Satrix Property New	2 241 455	2 487 576	**1,13 ****	*73,33%*

*'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance. Liquidity measures which indicate an improvement in liquidity (with pre/post ratio <1) are indicated in bold, whilst proportions greater than 50% are in italics. The average trading volume was calculated as an equally-weighted average of each of the ETF constituents.*

Source: Own estimation (2020)

The results from Tables 4-3 and 4-4 are largely consistent, and indicate that all of the ETFs based on the Top 40 index, except for the Ashburton Top 40, found an increase in trading volume post the ETF introduction. This was further emphasised by a large portion of the underlying assets (all > 50 percent) exhibiting higher trading volumes. Whilst a similar result is found for the sector-based ETFs, with 4 out of the 6 reporting a statistically significant increase in volume, only 7 out of the 12 other diversified ETFs show increases in trading volume. Whilst 65 percent of the ETFs in the sample report increased trade after the ETF inception (both over the 30 day and 50 day period), the analysis of these results are preliminary and must be interpreted with caution, as an increase in volume could also be caused by an increase in volatility. It should be noted that in some instances, even though the pre/post ratio was greater than 1, the average trading volume between the pre- and post- period actually decreased. Since this average is an equally weighted average, this could be an indication that there are differing responses by different companies based on their relative size (market capitalisation). There is therefore a need to investigate the various liquidity measures chosen for this chapter; which are the quoted spread, percentage spread, Amihud Illiquidity measure, and Quoted depth; the results of which is contained in Tables 4-5 and 4-6.

Whilst the trading volume (in tables 4-3 and 4-4) was analysed to report the proportions that were higher than 1, for each of the liquidity measures used, a proportion lower than 1 would be indicative of increased liquidity, as this implies narrower spreads, and greater price impact. Table 4-5 shows the resultant quoted spread, percentage spread and Amihud values when computed over the 30 day event period, and table 4-6 shows the associated values over the 50 day event period. The results from tables 4-5 and 4-6 seem to be largely consistent, with the same result (either improved or diminished liquidity) being noted over both time periods of analysis. A notable difference in results is only found for the Coreshares Top 50 ETF, which notes an improvement in liquidity over the 30 day period, but diminished liquidity over the 50 day period of analysis. The results presented in both tables find that whilst most ETFs record improvements in liquidity for all three measures, there are a few discrepancies where one measure improved whilst the others did not.

Table 4-5: Pre/Post ratios of Quoted Spread, Percentage Spread and Amihud measures (30 day period)

ETF	Quoted Spread		Percentage Spread		Amihud measure	
	Post/Pre ratio	*Proportion <1.0*	*Post/Pre ratio*	*Proportion < 1.0*	*Post/Pre ratio*	*Proportion < 1.0*
Panel A: Top 40 ETFs						
Ashburton Top40	**0.94*****	*62.86%*	1.08***	37.14%	1.25***	17.14%
Newfunds Shariah Top 40	**0.97*****	*62.50%*	**0.94*****	*62.50%*	1.02***	*50.00%*
Newfunds SWIX Top 40	**0.88*****	*77.50%*	**0.82*****	*77.50%*	**0.89*****	*85.00%*
Satrix Rafi 40	1.11***	31.58%	1.09***	39.47%	1.09***	34.21%
Satrix Swix 40	1.01***	*56.76%*	**0.98*****	*62.16%*	**0.96*****	*56.76%*
Panel B: Other Diversified ETFs						
Ashburton Midcap	1.10***	46.67%	1.09***	*50.00%*	1.14***	40.00%
Coreshares Top50	**0.82*****	*56.86%*	**0.85*****	*54.90%*	**0.98*****	*66.67%*
Newfunds Defensive Equity	1.09***	30.00%	1.09***	33.33%	**0.97*****	*66.67%*
Coreshares DivTrax	**0.95*****	*61.54%*	**0.90*****	*69.23%*	1.02***	42.31%
Newfunds Moderate Equity	1.19***	28.00%	1.12***	32.00%	**0.98*****	*60.00%*
Newfunds Equity Momentum	**0.85*****	*77.78%*	**0.79*****	*94.44%*	**0.89*****	*88.89%*
Satrix Momentum	1.18***	28.57%	1.19***	25.71%	1.06***	34.29%
Satrix Quality	1.24***	34.62%	1.26***	30.77%	1.14***	26.92%
Newfunds NewSA	1.06***	41.18%	**0.97*****	*58.82%*	1.06***	41.18%
Newfunds Low Volatility	**0.82*****	*52.63%*	**0.85*****	*57.89%*	1.04***	31.58%
Newfunds Value Equity	1.03***	*51.85%*	**0.98*****	*59.26%*	**0.97*****	*51.85%*
Newfunds High Growth	1.26***	26.67%	1.15***	26.67%	**0.96*****	*66.67%*
Panel B: Sector ETFs						
Newfunds Givi Financials	**0.93*****	*84.62%*	**0.88*****	*84.62%*	**0.87*****	*76.92%*
Newfunds Givi Industrials	**0.92*****	*69.57%*	**0.89*****	*73.91%*	1.00***	*56.52%*
Newfunds Givi Resource	1.03***	*52.94%*	1.06***	*52.94%*	1.02***	*70.59%*
Coreshares Proptrax Ten	1.04***	*50.00%*	**0.99*****	*60.00%*	**0.92*****	*60.00%*
Satrix Property	1.03***	46.67%	1.03***	46.67%	1.01***	46.67%
Satrix Resi	1.21***	7.69%	1.10***	46.15%	1.01***	*53.85%*

*'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance. Liquidity measures which indicate an improvement in liquidity (with pre/post ratio <1) are indicated in bold, whilst proportions greater than 50% are in italics.*

Source: Own estimation (2020)

Table 4-6: Pre/Post ratios of Quoted Spread, Percentage Spread and Amihud measures (50 day period)

ETF	**Quoted Spread**		**Percentage Spread**		**Amihud measure**	
	Post/Pre ratio	*Proportion <1.0*	*Post/Pre ratio*	*Proportion < 1.0*	*Post/Pre ratio*	*Proportion < 1.0*
Panel A: Top 40 ETFs						
Ashburton Top40	1,02 ***	*54,29%*	1,30 ***	5,71%	1,18 ***	22,86%
Newfunds Shariah Top 40	**0,94*** **	*62,50%*	**0,93*** **	*75%*	**0,90*** **	*62,5%*
Newfunds SWIX Top 40	**0,88 *** **	*70%*	**0,85*** **	*92,5%*	**0,82*** **	*85%*
Satrix Rafi 40	1,20***	23,68%	1,11***	21,05%	1,18***	21,05%
Satrix Swix 40	1,17***	29,73%	1,04***	45,95%	1,16***	24,32%
Panel B: Other Diversified ETFs						
Ashburton Midcap	1,16**	*66,10%*	1,12**	*62,71%*	1,13**	*66,10%*
Coreshares Top50	1,09 ***	*64,71%*	1.21**	*60,78%*	1,05**	37,25%
Newfunds Defensive Equity	**0,96*** **	43,33%	**0,92*** **	*83,33%*	**0,93*** **	*53,33%*
Coreshares DivTrax	**0,92 * **	*73,08%*	**0,96* **	*61,54%*	**0,86* **	*84,62%*
Newfunds Moderate Equity	1,02**	36%	**0,90** **	*84%*	**0,91** **	48%
Newfunds Equity Momentum	**0,90*** **	*72,22%*	**0,84*** **	*100%*	**0,81*** **	*94,44%*
Satrix Momentum	1,24*	42,86%	1,11*	48,57%	1,27*	40%
Satrix Quality	1,20*	26,92%	1,36*	19,23%	1,24*	23,08%
Newfunds NewSA	**0,85 *** **	*82,35%*	1,05***	44,12%	**0,81 *** **	*85,29%*
Newfunds Low Volatility	**0,78* **	*84,21%*	1,03*	36,84%	**0,82* **	*78,95%*
Newfunds Value Equity	**0,99** **	37,04%	**0,95 ** **	*66,67%*	**0,93** **	29,63%
Newfunds High Growth	1,19***	20%	**0,90*** **	*80%*	1,06***	33,33%
Panel B: Sector ETFs						
Newfunds Givi Financials	**0,86*** **	*92,31%*	**0,82*** **	*84,62%*	**0,78*** **	*92,31%*
Newfunds Givi Industrials	**0,88*** **	*78,26%*	**0,87*** **	*82,61%*	**0,79*** **	*91,3%*
Newfunds Givi Resource	**0,98*** **	*64,71%*	**0,92*** **	*76,47%*	**0,93*** **	*52,94%*
Coreshares Proptrax Ten	1,09 **	*50%*	1,05 ***	40%	1,03 ***	*60%*
Satrix Property	**0,85 *** **	*86,67%*	**0,83*** **	*80%*	**0,84*** **	*86,67%*
Satrix Resi	1,36**	7,69%	1,12**	38,46%	1,30**	15,38%

*'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance. Liquidity measures which indicate an improvement in liquidity (with pre/post ratio <1) are indicated in bold, whilst proportions greater than 50% are in italics.*

Source: Own estimation (2020)

The results from the Top 40 ETFs are mixed, with the Newfunds SWIX 40 ETF showing the greatest improvement in liquidity from the 5 ETFs in the sample (the ratio of pre/post liquidity measures is less than 0,9 for all liquidity measures, across both time periods). A similar improvement was noted for the Newfunds Shariah Top 40, however, this was marginal. The remaining 3 Top 40 ETFs documented diminished liquidity after ETF introduction. This observation is notable as the constituents of these ETFs are largely the same, and the only difference between the ETFs is the time period in which they were listed. A further analysis of the remainder of the sample however, does not seem to indicate that ETFs which were listed more recently experienced improvements in liquidity, and that earlier ETFs all experienced diminished liquidity. The differing results produced in the sample could therefore be a direct result of the underlying constituents.

The remainder of the results for the different ETFs are largely mixed. In total, approximately 50 percent of the sample ETFs exhibit and improvement in spreads, and price impact after ETF introduction. The remainder report diminished liquidity. The contrasts are also equivalent, with some like the Newfunds SWIX 40 showing significant improvements in liquidity, whilst the Satrix Quality shows significant decreases in liquidity after ETF inception. The results of these two tables in comparison to the volume results, shows that whilst some ETFs indicated an increase in trading volume, this was actually accompanied by widening spreads (eg. Ashburton Midcap ETF). This further confirms that the increases in trading volume noted could be as a result of stock volatility after ETF introduction, and not due to an increase in liquidity of the underlying securities.

The figures estimated for the ETFs which had the data to calculate quoted depth are shown in table 4-7. In contrast to the spread and Amihud measures, an increase in liquidity would be represented by post/pre quoted depth ratios that are greater than 1. The results of table 4-7 show that only 7 out of a total of 11 ETFs displayed higher depth and thus increased liquidity, and of these an average of only 50 percent of the portfolio constituents showed an increase of liquidity (the exception is the Satrix Property ETF, for which 80 percent of the portfolio indicated depth improvements). The results from the quoted depth analysis only conform to the results from the spread analysis for 4 ETFs in the sample (Satrix Momentum, Satrix Quality, Newfunds Value Equity, Newfunds High Growth), which shows lower spreads accompanied by increased depth (therefore increased liquidity for all measures). The remaining 7 ETFs either show decreased spreads accompanied by lower depths, or increased spreads, accompanied by higher depth. These results are counter-intuitive, as the expectation is that spread and depths are correlated. The resultant de-correlation is often noted during a market crash, when market liquidity decreases despite increased trading volumes (Cella et al., 2013; Chordia, Roll, & Subrahmanyam, 2002), and this may be an indication of increased market volatility during the post-ETF period.

Table 4-7: Pre/Post ratios of Quoted Depth

ETF	**Quoted Depth (30 day)**		**Quoted Depth (50 day)**	
	Post/Pre ratio	*Proportion > 1.0*	*Post/Pre ratio*	*Proportion > 1.0*
Ashburton Midcap	**1.07*** **	43.33%	0,96 **	22,03%
Coreshares Top50	**1.18*** **	*58.82%*	**1,04** **	37,35%
Defensive Equity	**1.05*** **	*60.00%*	**1,03*** **	*53,33%*
Coreshares DivTrax	0.90***	15.38%	0,86*	15,38%
Newfunds Moderate Equity	**1.16*** **	*72.00%*	**1,10** **	*56%*
Satrix Momentum	0.97***	31.43%	0,96*	25,71%
Satrix Quality	0.92***	34.62%	0,81	15,38%
Newfunds Low Volatility	0.85***	15.79%	0,89*	26,32%
Newfunds Value Equity	**1.05*** **	*51.85%*	**1,08** **	*55,56%*
Newfunds High Growth	**1.19*** **	*80.00%*	**1,10 *** **	*53,33%*
Satrix Property	**1.22*** **	*80.00%*	**1,21*** **	*80%*

*'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance. Liquidity measures which indicate an improvement in liquidity (with pre/post ratio >1) are indicated in bold, whilst proportions greater than 50% are in italics.*

Source: Own estimation (2020)

Overall, the results from the univariate analysis are inconclusive on whether liquidity improvements or decreases should be expected after ETF introduction. Whilst this method of analysis provides an interesting window into the behaviour of each of the liquidity measures during the period of analysis, it provides no indication of the relationships or causation present in the data. The multivariate method of analysis is therefore expected to be much more informative, the results of which are detailed in the ensuing section.

4.4.2. Multivariate Analysis: Panel Data Results

The results from the panel data are used to statistically test the two objectives of this chapter. The results from the preliminary panel unit root tests are contained in Appendix A-2 (page 225), and all variables were found to be stationary at varying levels of significance (some at 1%, some at 5% and some at 10%). The results of the preliminary Hausman tests are also shown in Appendix A-3 (page 226) and the test results finds support for the use of FE, therefore the panel regressions conducted in this section are based on equation 4.8.

The first objective is to evaluate whether liquidity of the underlying securities changes after ETF introduction, which is evaluated by the sign and statistical significance of the dummy variable from equation 4.8. A positive coefficient for the spread and Amihud variables indicates an increase in spreads and illiquidity after the introduction of ETFs, which implies diminished liquidity in the underlying securities. On the contrary, a positive coefficient for the Depth variable indicates increased market depth which coincides with a liquidity improvement. The second objective aims to evaluate whether the market capitalisation of a firm affects its liquidity impact. The interpretation of the coefficient of the interaction variable (Dummy x weight) therefore allows one to analyse whether the observed change in liquidity is attributed more to the heavily weighted stocks in the index, or if there is an equal change observed for all stocks, regardless of size. Similar to the univariate analysis, these results are segmented based on the three categories of ETFs used in the analysis. Whilst both one-way and two-way FE models were estimated, the results were similar. The results displayed in tables 4-8 to 4-10 therefore show the results from the two-way model.

Table 4-8: Panel Data results for Top 40 ETFs

Table 4-8 contains the results from a two-way FE panel regression of the following equation: $ln(liquidity\ measure_{it}) = (\alpha_0 + v_i) + \alpha_1 ln(Price_{it}) + \alpha_2 ln(Volume_{it}) + \alpha_3 ln(Volatility_{it}) + \alpha_4(Dummy \times Weight_{it}) + \lambda_t + \varepsilon_{it}$. The coefficient on the time variable is excluded for brevity.

	30 day event period			50 day event period		
	Quoted Spread	**Percentage Spread**	**Amihud**	**Quoted Spread**	**Percentage Spread**	**Amihud**
Panel A: Ashburton Top 40						
C	-12.93	-10.02	1.974	-0.753	-0.786	-2.267***
Price	-0.660	-0.692	-1.912***	-0.753	-0.786	-2.267***
Volume	-0.0596	-0.0515	-0.374***	-0.0324	-0.0245	-0.316***
StdDev	2.372**	0.454	2.247**	2.531**	0.592	2.989***
Dummy	-0.117	-0.119	-0.0503	-0.187**	-0.191**	-0.0185
Dummy x Weight	0.0204	0.0210	0.0125	0.0213	0.0221	0.00766
Panel B: Newfunds Shariah Top 40						
C	27.66	37.32	-13.31	-3.849	1.234	25.12*
Price	-0.643	-0.551	-1.577**	-1.992*	-1.881*	-1.454**
Volume	-0.123**	-0.120**	-0.310***	-0.108**	-0.104*	-0.259***
StdDev	3.015	0.906	1.972	4.658**	2.463	1.771
Dummy	-0.0665	-0.0498	-0.145	-0.154	-0.148	-0.0482
Dummy x Weight	0.000966	0.000700	0.00700	0.00417	0.00401	0.00578
Panel C: Newfunds SWIX Top 40						
C	116.6***	121.3***	54.35**	16.34	19.89	40.46***
Price	-3.213	-3.195	-5.622***	-5.218***	-5.161***	-4.239***
Volume	-0.204***	-0.203***	-0.382***	-0.120***	-0.118***	-0.386***
StdDev	10.36*	8.391	10.42***	12.84***	10.75***	7.722***
Dummy	0.104	0.106	0.0889	-0.0931	-0.0930	0.000181
Dummy x Weight	-0.00967	-0.00984	-0.00342	-0.0111	-0.0113	0.0109
Panel D: Satrix Rafi 40						
C	-20.58	-17.95	-41.96	-16.84	-12.87	2.341
Price	-2.650	-2.613	-2.867**	0.130	-0.825***	-0.592***
Volume	-0.0755*	-0.0711*	-0.381***	-0.106***	-0.104***	-0.428***
StdDev	5.531	3.492	4.103*	0.256***	0.256***	0.504***
Dummy	0.0770	0.0738	-0.0953	0.0592	0.0567	-0.0799*
Dummy x Weight	-0.0123	-0.0124	0.0145	-0.0160	-0.0157	0.00109
Panel E: Satrix SWIX 40						
C	-63.57**	-60.71**	-9.835	-78.36***	-76.04***	-1.394
Price	0.183	0.204	-5.048***	-1.670**	-1.631*	-5.108***
Volume	0.0190	0.0227	-0.369***	0.0418	0.0460	-0.414***
StdDev	1.704	-0.293	7.507***	4.226**	2.156	7.306***
Dummy	-0.233**	-0.233**	0.0458	-0.262***	-0.264***	0.0657
Dummy x Weight	-0.00923	-0.00951	-0.0269***	-0.0113	-0.0115	-0.0235***

'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Source: Own estimation (2020)

The results in table 4-8 reveal that, when significant, the coefficients of standard deviation, price and volume all exhibit the expected signs (negative for price and volume, and positive for volatility). The results across the 30 day and 50 day analyses are found to be comparable for the Top 40 ETFs. The dummy variable was found to be statistically significant only for three of the ETFs in the Top40 category (Ashburton Top 40, Satrix Rafi 40 and Satrix SWIX 40). The sign of this variable, when significant, was consistently found to be negative, indicating that after ETF introduction, the spreads and illiquidity of the underlying securities for these three ETFs decreased, thus indicating improved liquidity. The dummy interaction variable (*dummy* × *weight*) was only found to be significant for the Amihud measure in the Satrix Swix 40 ETF. The coefficient of this variable is negative, which further confirms that the decline in illiquidity level, was driven by the improved liquidity of the higher weighted firms in the sample.

The results for the other diversified ETFs are displayed in table 4-9, and the results from the sector-based ETFs is contained in table 4-10. This table includes quoted depth for those ETFs in the sample for which the relevant data was available. The results in the table shows that most of the price coefficients are found to have the expected negative correlation, and volume is also found to be consistently negative. As noted before, whilst the spread and Amihud measures should display negative coefficients with price and volume, and a positive coefficient with standard deviation, the quoted depth is expected to be negatively correlated to both standard deviation and price. An analysis of the coefficients produced indicates that whilst statistically significant standard deviation values have the expected positive coefficient for measures of spread and illiquidity, its associated coefficient for depth is also positive (instead of the expected negative coefficient). This indicates that a rising trading volume in the underlying assets, increases the standard deviation, which could be an indication of noise trading on the JSE after ETF introduction, causing share volatility.

The dummy variable for the Ashburton Midcap ETF is found to be statistically significant and positive, over both the 30 and 50 day periods. However, the interaction variable is also found to be negative and significant over the 50 day period. This indicates that the underlying securities (which are the Top 41 to 100 stocks listed on the JSE) experienced diminished liquidity after the ETF introduction, which is persistent over both the 30 and 50 day periods, and is more severe for the smaller firms in the ETF. The result of diminished liquidity in the underlying securities is also found for the Satrix Momentum ETF, the Satrix Quality ETF and for the Newfunds Moderate Equity ETF over the 50 day period after ETF inception. The Newfunds Moderate Equity ETF however, has improved liquidity over the 30 day period (measured by the Amihud ratio), which is enjoyed more by the small firms in the sample. An interesting result is noted for the Satrix Momentum ETF, where the increase in spreads is accompanied by an increase in depth, rather than a decrease. The result of widening spreads despite high volume and market breathe could be due to the presence of noise traders in the market, who increase information asymmetries and induce greater volatility in the period post-ETF introduction (Easley & O'hara, 1992).

The dummy variable for the Coreshares Top 50 ETF is found to be statistically significant and negative, alongside an interaction variable that is statistically significant and positive. The same result is found for the Newfunds Value Equity ETF. This indicates that for these two ETFs, in the 30 day period after ETF inception, even though the higher weighted underlying assets enjoy greater levels of liquidity, the greatest improvement in spreads occurs for the smaller weighted firms. However, the lack of statistical significance (for both ETFs) over the 50 day period illustrates that these benefits were short lived. A similar improvement in liquidity is found for the Newfunds Defensive Equity ETF, which displays lower levels of illiquidity that is equally felt for both small and large firms in the sample. In contrast, there are no statistically significant liquidity changes after ETF introduction for the remaining ETFs in the sample. For the 11 ETFs in the other diversified ETF category, the results are largely mixed, with 4 ETFs showing diminished liquidity after ETF introduction, and 3 showing improvements in liquidity. A consistent result however, is that small firms are impacted differently from large firms, as they suffer more during periods of illiquidity, but also enjoy the benefits of liquid periods more. This could be an indication that the concentration issues of the JSE have a significant impact on the liquidity effects of the underlying securities, however, it requires further investigation over the remainder of the sample. It should also be noted that whilst improvements were mostly found only over the 30 day period, evidence of diminished liquidity seemed to be persistent across both time periods.

Table 4-9: Panel Data results for other diversified ETFs

Table 4-9 contains the results from a two-way FE panel regression of the following equation: $ln(liquidity\ measure_{it}) = (\alpha_0+v_i) + \alpha_1\, ln(Price_{it}) + \alpha_2\, ln(Volume_{it}) + \alpha_3\, ln(Volatility_{it}) + \alpha_4(Dummy \times Weight_{it}) + \lambda_t + \varepsilon_{it}$. The coefficient on the time variable is excluded for brevity. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

	30 day				50 day			
	Quoted Spread	**Percentage Spread**	**Amihud**	**Quoted depth**	**Quoted Spread**	**Percentage Spread**	**Amihud**	**Quoted depth**
Panel A: Ashburton Midcap								
C	24.14	28.24	-42.43	-64.02*	-9.636	-5.135	20.81	22.18
Price	0.779*	-0.150	-0.160	-1.176**	0.926***	-0.0598	-0.0492	-0.207
Volume	-0.0484**	-0.0484**	-0.389***	--	-0.0542***	-0.0540***	-0.369***	--
StdDev	0.207***	0.206***	0.102	0.0957	0.192***	0.192***	0.123	0.108*
Dummy	0.146*	0.148*	-0.0579	-0.232	0.178**	0.179**	0.0753	-0.0987
Dummy x Weight	-0.0203	-0.0208	0.0529	0.0284	-0.0695**	-0.0701**	0.0413	0.0467
Panel B: Coreshares Top 50								
C	-30.83	-24.24	7.321	-42.81**	-9.382	-5.776	-11.93	29.10**
Price	0.374	-0.579	-0.352	-0.343	0.749***	-0.219	-0.534***	-0.255
Volume	-0.119***	-0.119***	-0.407***	--	-0.102***	-0.103***	-0.437***	--
StdDev	0.133**	0.137**	0.187***	0.412***	0.145***	0.149***	0.188***	0.408***
Dummy	-0.149**	-0.143*	-0.0382	-0.0561	-0.0596	-0.0577	-0.0725	0.0450
Dummy x Weight	0.0238**	0.0234**	0.000874	-0.0129	0.0137	0.0135	-0.00170	-0.00619
Panel C: Newfunds Defensive Equity								
C	-56.08	-51.20	-39.47	11.95	32.02	36.15*	4.932	-0.129
Price	-0.179	-1.097*	-0.368	-0.0472	-0.152	-1.092*	-0.924***	0.0289
Volume	-0.122*	-0.122*	-0.351***	--	-0.182***	-0.180***	-0.444***	--
StdDev	0.106	0.109	0.0550	0.409***	0.176***	0.179***	0.0637*	0.366***
Dummy	-0.0862	-0.0762	-0.187***	0.0440	0.149	0.155	-0.124**	0.0363
Dummy x Weight	0.0299	0.0276	0.0183	-0.00935	0.00850	0.00669	0.0187	-0.00484

	30 day				50 day			
	Quoted Spread	***Percentage Spread***	**Amihud**	**Quoted depth**	**Quoted Spread**	**Percentage Spread**	**Amihud**	**Quoted depth**
Panel D: Coreshares DivTrax								
C	-2.317	2.555	29.28	-7.160	2.347	6.754***	16.10***	21.78***
Price	0.541	-0.390	-0.511	-0.328	0.586*	-0.381	-0.501*	-0.882*
Volume	-0.0634	-0.0642	-0.459***	--	-0.0665**	-0.0673**	-0.432***	--
StdDev	0.285***	0.286***	0.172***	0.367***	0.280***	0.281***	0.163***	0.358***
Dummy	-0.0482	-0.0503	-0.0522	-0.190	-0.0109	-0.0186	-0.0822	-0.175
Dummy x Weight	-0.00159	-0.00124	0.00267	-0.00577	-0.000269	1.42e-05	0.00911	-0.00508
Panel E: Newfunds Moderate Equity								
C	-51.22	-44.45	-53.57**	1.647	48.84**	53.05**	13.72	17.61
Price	0.458	-0.506	-0.421**	0.312	0.500	-0.468	-0.550***	0.492**
Volume	-0.148**	-0.152**	-0.383***	--	-0.185***	-0.186***	-0.414***	--
StdDev	0.157	0.157	0.0843**	0.399***	0.227***	0.229***	0.0956**	0.324***
Dummy	0.176	0.182	-0.138**	0.167	0.369***	0.370***	0.0129	0.197
Dummy x Weight	-0.0211	-0.0213	0.00721	-0.0346*	-0.0265	-0.0269	-0.00546	-0.0291
Panel F: Newfunds Equity Momentum								
C	162.5**	166.9**	57.16	--	-6.918**	-6.870**	-5.264***	--
Price	-10.58***	-10.58***	-5.410**	--	-6.918**	-6.870**	-5.264***	--
Volume	-0.194***	-0.192***	-0.400***	--	-0.105***	-0.103***	-0.393***	--
StdDev	23.56***	21.65***	11.81**	--	14.17*	12.11	10.06***	--
Dummy	0.172	0.172	0.0973		-0.104	-0.105	-0.120	
Dummy x Weight	0.00462	0.00467	-0.0284*	--	0.00491	0.00482	-0.00247	--

	30 day				50 day			
	Quoted Spread	***Percentage Spread***	**Amihud**	**Quoted depth**	**Quoted Spread**	**Percentage Spread**	**Amihud**	**Quoted depth**
Panel G: Satrix Momentum								
C	58.47	58.20	27.13	80.33***	3.514	5.652	36.49***	94.58***
Price	0.988***	0.0560	-0.941***	-0.739*	0.405*	-0.538**	-0.832***	-0.695**
Volume	-0.0187	-0.0212	-0.444***	--	-0.0883**	-0.0852**	-0.484***	--
StdDev	0.0690	0.0683	0.0999***	0.161	0.142***	0.145***	0.104***	0.318***
Dummy	0.312**	0.305**	0.0824	0.0642	0.200**	0.195**	0.0846*	0.111**
Dummy x Weight	-0.00749	-0.00838	-0.00541	0.000812	-0.00475	-0.00481	-0.00483	-0.00505
Panel H: Satrix Quality								
C	-118.8**	-114.2**	14.93	317.8***	-5.799	-1.677	19.29*	118.0***
Price	0.0149	-0.885*	-0.471	-1.132**	0.253	-0.690**	-0.520**	-1.106**
Volume	-0.157***	-0.157***	-0.526***	--	-0.141***	-0.140***	-0.505***	--
StdDev	0.215***	0.213***	0.0969***	0.395***	0.278***	0.278***	0.138***	0.409***
Dummy	-0.0579	-0.0523	-0.0203	0.414***	0.154	0.157	-0.0363	0.0237
Dummy x Weight	-0.0196	-0.0201	0.000753	-0.0119	-0.0239*	-0.0241*	0.00379	-0.00470
Panel I: Newfunds NewSA								
C	49.31	55.90	74.43**	--	6.636***	10.18***	20.89***	--
Price	-2.136***	-2.150***	-2.242***	--	-1.124**	-1.171**	-2.597***	--
Volume	-0.0853**	-0.0815**	-0.324***	--	-0.114***	-0.110***	-0.346***	--
StdDev	4.423***	2.488	2.831**	--	3.712***	1.845*	3.498***	--
Dummy	0.110	0.111	-0.0406		0.101	0.0976	-0.103	
Dummy x Weight	0.00372	0.00409	0.0178	--	-0.00628	-0.00535	0.0136	--

	30 day				50 day			
	Quoted Spread	*Percentage Spread*	Amihud	Quoted depth	Quoted Spread	Percentage Spread	Amihud	Quoted depth
Panel J: Newfunds Low Volatility								
C	106.5**	109.5**	51.13	50.30	34.64	37.41	43.08***	-16.54
Price	1.197	0.274	-0.151	0.736	0.669*	-0.297	-0.759***	0.552
Volume	0.108	0.108	-0.381***	--	0.0658	0.0662	-0.363***	--
StdDev	0.0498	0.0490	0.108	0.320***	0.0422	0.0411	0.0948	0.389***
Dummy	0.178	0.173	0.0429	0.0648	0.0111	0.00445	0.0277	-0.0678
Dummy x Weight	-0.00218	-0.00223	0.0132**	-0.00970	-0.000658	-0.000607	0.00995**	-0.0115*
Panel K: Newfunds Value Equity								
C	-40.96	-35.38	53.08**	-48.03	7.324	12.07	17.22	-27.72
Price	1.552**	0.624	-0.145	-0.922	0.709	-0.262	-0.0506	-1.055*
Volume	-0.190***	-0.190***	-0.478***	--	-0.172***	-0.171***	-0.473***	--
StdDev	0.274***	0.274***	0.161***	0.435***	0.251***	0.251***	0.148***	0.436***
Dummy	-0.166*	-0.166*	0.0738	-0.0933	0.0103	0.0105	0.00564	-0.0578
Dummy x Weight	0.0175**	0.0178**	0.00795	-0.00820	0.000920	0.00105	0.00247	-0.00947
Panel L: Newfunds High Growth								
C	-1.515	5.956	-57.60*	-3.438	39.73	43.96	19.07*	29.30**
Price	1.228**	0.269	0.0932	0.622	0.880	-0.0944	-0.433*	0.671***
Volume	-0.113	-0.117	-0.366***	-0.113	-0.189**	-0.191**	-0.424***	--
StdDev	0.174	0.173	0.177**	0.373***	0.249***	0.251***	0.198**	0.326***
Dummy	0.241*	0.241*	-0.189	0.178	0.424***	0.423***	0.0712	0.254
Dummy x Weight	-0.0131	-0.0124	0.00663	-0.0248	-0.0271*	-0.0270*	-0.00833	-0.0239

Source: Own estimation (2020)

Table 4-10: Panel Data results for Sector-based ETFs

Table 4-10 contains the results from a two-way FE panel regression of the following equation: $ln(liquidity\ measure_{it}) = (\alpha_0+v_i) + \alpha_1\ ln(Price_{it}) + \alpha_2\ ln(Volume_{it}) + \alpha_3\ ln(Volatility_{it}) + \alpha_4(Dummy \times Weight_{it}) + \lambda_t + \varepsilon_{it}$. The coefficient on the time variable is excluded for brevity. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

	30 day				50 day			
	Quoted Spread	Percentage Spread	Amihud	Quoted Depth	Quoted Spread	Percentage Spread	Amihud	Quoted Depth
Panel A: Newfunds Givi Financial								
C	5.898	9.032	14.51**	--	92.55***	98.16***	60.84***	--
Price	-0.191	-0.119	-1.270	--	-4.113**	-4.107**	-0.850	--
Volume	-0.168***	-0.166***	-0.431***	--	-0.163***	-0.161***	-0.421***	--
StdDev	3.689	1.731	7.688*	--	10.59***	8.721***	0.716	--
Dummy	0.438**	0.442**	0.719***		0.156	0.157	0.0767	
Dummy x Weight	-0.0187	-0.0189	-0.0320**	--	-0.00289	-0.00300	-0.00801	--
Panel B: Newfunds Givi Industrial								
C	66.47*	72.66*	142.1**	--	51.53**	57.17***	77.50***	--
Price	-2.819*	-2.855*	-2.777**	--	-3.816***	-3.892***	-2.001*	--
Volume	-0.0850**	-0.0838**	-0.403***	--	-0.131***	-0.129***	-0.432***	--
StdDev	5.110*	3.275	5.918**	--	8.458***	6.684**	4.285**	--
Dummy	0.0449	0.0493	0.219		-0.00148	0.00118	0.0648	
Dummy x Weight	-0.000572	-0.000747	0.00384	--	-0.000775	-0.000787	0.00376	--
Panel C: Newfunds Givi Resource								
C	-54.06***	-51.56***	2.074	--	43.79**	52.38***	54.40**	--
Price	-3.846**	-3.863**	-0.785	--	-4.139***	-4.162***	-0.329	--
Volume	-0.0324	-0.0245	-0.316***	--	-0.106***	-0.104**	-0.453***	--
StdDev	2.531**	0.592	2.989***	--	8.801***	6.980***	0.766	--
Dummy	-0.187**	-0.191**	-0.0185		0.0814	0.0978	-0.0430	
Dummy x Weight	0.0213	0.0221	0.00766	--	0.00297	0.00287	-0.00137	--

	30 day				50 day			
	Quoted Spread	Percentage Spread	Amihud	Quoted Depth	Quoted Spread	Percentage Spread	Amihud	Quoted Depth
Panel D: Satrix Resi								
C	-83.51*	-80.14*	-96.47	--	-53.09**	-50.07**	-39.41*	--
Price	1.382	1.534	-1.893	--	-0.0830	0.0664	-0.712	--
Volume	-0.0277	-0.0228	-0.318***	--	-0.0500	-0.0447	-0.248***	--
StdDev	-2.225	-4.457*	-0.463	--	1.273	-0.970	0.696	--
Dummy	-0.0472	-0.0437	-0.114		-0.0250	-0.0228	-0.0305	
Dummy x Weight	5.93e-05	-0.000156	0.00351	--	0.00288	0.00281	-0.00209	--
Panel E: Coreshares Proptrax Ten								
C	1.459	6.012	54.87	--	-27.65	-24.99	69.27	--
Price	0.122	-0.401	2.303	--	-3.779	-4.372*	-2.115	--
Volume	-0.0957***	-0.0951***	-0.542***	--	-0.110***	-0.110***	-0.619***	--
StdDev	13.00	12.43	18.89	--	13.77***	13.22***	16.81*	--
Dummy	-3.248***	-3.255***	2.937		-2.498***	-2.499***	1.691	
Dummy x Weight	0.304***	0.304***	-0.301	--	0.227***	0.227***	-0.160	--
Panel F: Satrix Property								
C	-46.41	-43.51	-22.40	-146.1*	5.597	10.19	-9.362	-51.57*
Price	0.588	-0.357	-0.705	3.323*	0.589	-0.346	-1.306*	1.937
Volume	-0.0822*	-0.0833*	-0.496***	--	-0.0956**	-0.0960**	-0.406***	--
StdDev	0.225***	0.225***	0.297**	0.190***	0.296***	0.295***	0.569***	0.210***
Dummy	-0.132	-0.134	0.0447	0.0908	-0.128	-0.126	-0.197	0.203
Dummy x Weight	0.00923	0.00927	-0.0212	-0.0322	0.0162	0.0161	0.00156	-0.0203

Source: Own estimation (2020)

The results for the sector-based ETFs is shown in table 4-10. The coefficients of the control variables are all found to be consistent with theory. Diminished liquidity is only noted for Newfunds Givi Financial Index in the sample, which documents positive and statistically significant dummy variables over the 30 day period. In contrast, evidence of improved liquidity is found for both the Newfunds Givi Resource ETF (over the 30 day period) and the Coreshares Proptrax Ten ETF, with the latter ETF displaying persistence in the results over the 50 day period as well. In addition, whilst the interaction variable for the former ETF is statistically insignificant, this variable is positive and significant for the Coreshares Proptrax Ten ETF. This indicates that, similar to the results noted for Table 4-8, the improvements in liquidity are enjoyed more by the smaller weighted firms in the ETF. The results for the remaining ETFs in this sub-sample indicate no change in liquidity after ETF inception (Satrix Resi, Newfunds Givi Industrial and Satrix Property).

4.5. DISCUSSION OF LIQUIDITY RESULTS

The results from the univariate and multivariate analysis conducted, whilst largely consistent with each other, were mixed in terms of providing an overall conclusion to the question of whether ETFs have a positive or negative impact on the liquidity of their underlying assets. The results from the multivariate analysis is summarised in table 4-11, which indicates that the liquidity of the underlying assets for both Top 40 and sector-based ETFs were improved after ETF introduction, albeit over different time intervals. However, the results from the other diversified ETFs is mixed, with 4 ETFs noting diminished liquidity, and 3 ETFs showing increased liquidity. In addition, one of the ETFs in this category noted improved liquidity in the shorter time period, but diminished liquidity over the longer period.

Overall, the results from the study found that 35 percent of the ETFs in the sample displayed improved liquidity after ETF introduction, in a result that confirms the hypotheses of Merton (1987), Fremault (1991) and Malamud (2016). In contrast, 21 percent of the ETFs surveyed displayed diminished liquidity after ETF introduction, and again, this decrease affected the smaller firms in the sample more. This confirms postulations by Subrahmanyam (1991), Gorton and Pennacchi (1993) and Cong and Xu (2016) that once ETFs are introduced, the liquidity of the underlying assets decreases. A notable result is that there are minimal impacts noted for the ETFs which replicate the Top 40 companies on the JSE, however there was a decrease noted the Ashburton Midcap ETF, which constitutes the companies of rank 41 to 100 in market capitalisation. Therefore whilst the results of the liquidity analysis cannot conclusively predict an increase or decrease in liquidity of the underlying assets after ETF introduction, the results show a definite impact on the lower weighted firms on the JSE ALSI, whose liquidity varies alongside that of the ETF. This is similar to the findings of Richie and Madura (2007) who found evidence of overall improved liquidity, which was higher for the lower weighted stocks in their sample of ETFs. In contrast however, De Winne et al. (2014) found that the larger stocks in their sample exhibited diminished liquidity, despite overall liquidity increasing for the remainder of the underlying assets.

From the total sample of 23 ETFs, 9 ETF showed no statistically significant change in liquidity after ETF introduction, and whilst 8 ETFs showed improvements in liquidity, 5 ETFs illustrated diminished liquidity (a single ETF showed diminished liquidity in one period, and improved liquidity over the other). The improvement or degradation in liquidity noted in the sample, was mostly indicated in the spread variables, which were the dominant liquidity measures found to be statistically significant in the analysis. Whilst the Amihud measure also displayed significance for a few ETFs, the quoted depth measure was only significant in two ETFs from the ten ETFs which had quoted depth data in the analysis. However, where depth was found to be statistically significant, the results produced important evidence that indicated the presence of noise trading in the assets underlying the Satrix Momentum ETF. Whilst the possible cause for noise traders being attracted to these assets at the time of its introduction is unknown, the resulting volatility proved detrimental for the liquidity of these assets, and resulted in spreads widening despite increased depth in the market. This finding contrasts to previous findings by Poterba and Shoven (2002), Ivanov (2016), Broman and Shum (2018) and Ben-David et al. (2018), who found evidence of noise traders in the ETF market rather than the market for the underlying asset. A similar result was also found in the study by Sağlam et al. (2019), who noted improved market depth amidst worsening spreads, which the authors also attribute to the presence of noise traders. However, this evidence was found for a single ETF only, and it cannot be ruled out that this is an anomaly that could have occurred due to other market occurrences at that time period.

Whilst the liquidity results were mixed, the results relevant to the second objective was more consistent. The results concluded, that liquidity improvements and diminished liquidity impacted smaller firms more than larger firms. This therefore implies that for large firms who are already fairly liquid, the introduction of ETFs does not make much change to their underlying microstructure. However, for smaller firms listed on the JSE, these firms are subject to the microstructure impacts, and their results vary with the underlying sample. This outcome provides partial support to Merton (1987), who postulates that the smaller firms in the ETF should experience greater benefits than the higher capitalisation firms, due to the increased popularity. However, it also provides an additional dimension that improvements are not always guaranteed, and that these small firms can also suffer more from ETF introduction, depending on the overall impact. This provides limited confirmation of Subrahmanyam's (1991) hypothesis that when liquidity decreases, this is felt more by lower weighted stocks in the ETF due to the high level of adverse selection in these assets.

Table 4-11: Summary of ETF liquidity study results

ETF	Inception Date	Improved liquidity /Diminished liquidity/No change (30 days)	Improved liquidity /Diminished liquidity/No change (50 days)	Observed effect greater for higher capitalisation firms	Observed effect greater for small capitalisation firms
Top 40 ETFs					
Ashburton Top 40	16 October 2008	No change	Improved	-	-
Newfunds Shariah Top 40	August 2011	No change	No change	-	-
Newfunds SWIX 40	6 April 2009	No change	No change	-	-
Satrix Rafi 40	26 January 2012	No change	Improved	-	-
Satrix SWIX 40	10 April 2006	improved	improved	x	--
Other Diversified ETFs					
Ashburton Midcap	13 May 2015	Diminished	diminished	--	x
Coreshares Top 50	1 December 2008	No change	Improved	--	x
Newfunds Defensive Equity	26 January 2012	Improved	improved	-	-
Coreshares DivTrax	15 August 2012	No change	No change		
Newfunds Moderate Equity	25 February 2019	Improved	Diminished	x (for improved liquidity only)	--
Newfunds Equity Momentum	14 April 2014	No change	No change	--	--
Satrix Momentum	25 February 2019	Diminished	Diminished	--	--
Satrix Quality	24 October 2018	Diminished	No change	--	--
Newfunds NewSA	16 November 2018	No change	No change	--	--
Newfunds Low Volatility	26 March 2018	No change	No change	--	--
Newfunds Value Equity	31 December 2012	Improved	No change	--	x
Newfunds High growth	25 February 2019	Diminished	Diminished	--	x
Sector-Based ETFs					
Newfunds Givi Financial	15 June 2009	Diminished	No change	--	x
Newfunds Givi Industrial	15 June 2009	No change	No change	--	--
Newfunds Givi resource	15 June 2009	Improved	No change	--	--
Satrix Resi	30 May 2011	No change	No change	--	--
Coreshares Proptrax Ten	24 February 2017	Improved	improved	--	x
Satrix Property	10 April 2006	No change	No change	--	--

4.6. CHAPTER SUMMARY AND CONCLUSION

This chapter provides an empirical review of the dominant literature surrounding ETF liquidity. The literature surrounding this topic takes three basic strands of evaluation, with each utilising different methods and approaches to understanding ETF liquidity. The focus of this chapter is therefore understanding the potential impact of ETF introduction on the liquidity of its underlying assets. This is achieved by applying an event study methodology to the introduction of 23 domestic equity ETFs listed on the JSE. The motivation for this evaluation stems from the seminal theories of Subrahmanyam (1991), Merton (1987), Fremault (1991), Gorton and Pennacchi (1993) and more recently Malamud (2016), all of whom assert different impacts of ETF introduction on its underlying assets (these are reviewed extensively in chapter 3, section 3.5).

The chapter therefore used an event study methodology to evaluate the liquidity of the underlying assets before and after ETF listing, in order to investigate the above-mentioned theories. The event window utilised, made use of both a 30 and 50 day pre- and post-period around the listing of 23 domestic ETFs which were listed on the JSE between 2006 and 2020. The chosen liquidity proxies for this chapter, quoted spread, percentage spread, Amihud illiquidity measure, and the Quoted depth measure; were computed and then included in both a univariate and multivariate method of analysis. Whilst the univariate method aimed to calculate post/pre ratios for evaluation, the multivariate analysis made use of FE panel data regressions to investigate any changes in the chosen liquidity measures after ETF introduction.

The results produced from the analysis finds that the largest portion of the sample (39 percent) documents no significant impact on liquidity after ETF introduction. The profiles of these firms are varied, with different underlying samples of firms, and different listing dates. Therefore, no inferences can be made about ETFs that were listed during a certain period, or even ETFs which have a common sample of underlying assets. Merton's (1987) hypothesis states that the underlying assets of an ETF should face positive impacts after ETF introduction, and that lower weighted firms in the ETF will benefit the most, due to these firms now becoming more popular and therefore getting more attention from analysts and investors. The results from this chapter found support in favour of this hypothesis, with 8 of the ETFs in the sample (35 percent) exhibiting improved liquidity after the event date. Furthermore, the small firms in these samples were found to benefit the most from the liquidity improvement, which lends further support for Merton's (1987) hypothesis.

However, the results from the sample provided also found evidence of 5 ETFs (21 percent) in the sample displaying diminished liquidity after the ETF introduction. This finding therefore provides limited support to Subrahmanyam's (1991) hypothesis that as investors migrate to the ETF market, this impacts negatively on the underlying assets by decreasing the trade and thus liquidity in the market for the underlying assets. Furthermore, the author hypothesises that the smaller firms in the sample will suffer the most from the diminished liquidity, which is a result that was confirmed for this sub-sample. The overall results therefore indicate that whilst the smaller firms listed on the JSE benefit from ETF liquidity improvements, these firms also face more detriment from ETF liquidity decreases. Therefore, the large firms on the JSE are largely found to be immune from any change in liquidity of the underlying assets, as these firms are already highly liquid, and display active trading environments due to the concentration issue on the JSE (noted in section 1.1.3). Smaller firms however, which in this case are any firm that is not part of the Top 40 index, display liquidity which fluctuates alongside the liquidity of the ETF overall.

CHAPTER FIVE: INVESTIGATING THE IMPACT OF ETFS ON INFORMATIONAL EFFICIENCY OF JSE-LISTED STOCKS

5.1. INTRODUCTION

The two primary aims of a financial market are to distribute risk, as well as effectively convey information to investors (Arrow, 1964; Debreu, 1959). In a perfectly efficient market described by Fama (1965), all investors have full (symmetric) access to all the information present on a security, and this information is fully reflected in the price of the asset. These efficient stock prices can therefore assist in the vital economic functions of the stock market, by ensuring the proficiency of risk allocation, and providing a feedback mechanism for financial managers who aim to monitor stock changes in response to their decisions (Durnev, Morck, Yeung, & Zarowin, 2003). Tobin (1984) terms this type of stock market as "functionally efficient" as it ensures that capital is directed to its most valued use, which leads to an efficient allocation of resources across companies.

In reality however, empirical studies such as Sarpong, Sibanda, and Holden (2016), Heymans and Santana (2018) and Chipunza, Muguto, Muguto, and Muzindutsi (2020) have all found evidence of market inefficiency on the JSE, particularly with the small firms listed on the exchange. This implies that the investors in financial markets often have asymmetric information, which means that the market price of securities often conveys important information to investors. In this kind of environment, the role of aggregation and transmission of private information takes on increased importance, a concept which was first introduced by the REE of Grossman and Stiglitz (1980) (this was discussed in detail in section 3.4.1).

The REE, which is a traditional microstructure model, makes use of two types of market participants: informed traders, who expend resources to attain information, and uninformed investors, who trade purely based on their observations of market price (Schmidt, 2011). In these microstructure models, the informed traders profit from their information, by trading with the uninformed investors, and it is through this process that information becomes incorporated into stock prices. Since informed traders bear a cost to obtaining their fundamental information, the equilibrium between this cost, and their potential profit from trading with the uninformed investors is reflected in the level of informational efficiency[48] of the stock prices in the market (Israeli et al., 2017). Therefore, the degree, to which an asset reflects new information, and the time taken to reflect it, refers to informational efficiency of an asset (Huang & Wang, 1997). Since the introduction of new securities alters market structure and thus overall information efficiency, it is necessary to evaluate the impact of ETF introduction on this market characteristic, which is the focus of this chapter.

5.1.1. Informational efficiency of ETFs

When basket securities such as ETFs are introduced into the market, they represent an important trading avenue for investors. In a world without ETFs, investors will have to weigh off the relative benefits and costs of trading on firm-specific information since aspects like asset illiquidity, and short constraints may act as a deterrent to trade (Glosten, Nallareddy, & Zou, 2020). The existence of a basket security such as an ETF, is often the cheaper and easier market to trade in, with the result that traders may choose to react on firm-specific information, by trading in the ETF, rather than the actual firm. ETFs therefore create an easier method in which traders can incorporate firm-specific information, with the result that the broad cross-section of stocks included in the ETF will also simultaneously reflect the relevant information (Glosten et al., 2016). Studies by Cong and Xu (2016) and Xu, Yin, and Zhao (2019) hypothesise that even though ETFs are technically passive products, their trading process is not passive, as investors still have to choose the amount to invest, the holding period, and what type of ETF will suit their needs (factor investing).

In addition, factors such as improved liquidity in the ETF market (as evidenced in chapter 4), and the continuous trading flexibility offered by these products often results in the ETF market being the preferred avenue for information processing. This is clearly evidenced by the finding of liquidity clienteles in the ETF market, by Broman and Shum (2018) and Ben-David et al. (2018). The net result of these factors is that the informed trade which occurs in the ETF market assists in transferring firm-specific to a broad subset of stocks, which therefore results in reduced adverse selection and increased informational efficiency in the market. The opposing effect that is hypothesised, is that acting on firm-specific information in the ETF market, as

[48] Informational efficiency is also known as "pricing efficiency". These two terms will be used interchangeably in this study

opposed to the firm in question, may generate an additional element of price movements that are not due to fundamental information in the other stocks that constitute the ETF, thus making prices less informationally efficient (Huang and Wang, 1997)[49].

Israeli et al. (2017) hypothesise that the inclusion of a share into an ETF should theoretically decrease its informational efficiency through two different avenues. Firstly, as the ETF grows in size, a proportionately higher amount of the available shares of a company get "locked up" by the fund sponsor which means there are less shares available to be traded by informed traders who wish to purchase or sell the share based on firm-specific information. Secondly, the ETF market provides a lower cost and easier market for uninformed traders, thus making them migrate away from the market for the underlying securities (Fremault, 1991; Gorton & Pennacchi, 1993; Subrahmanyam, 1991). Over time, this "cannibalises" the liquidity of the underlying stocks, and creates a disincentive for informed traders to utilize resources in order to obtain firm-specific information. The result is thus a decrease in the extent to which individual shares are able to adjust to new information. This also creates the possibility that the ETF market is capable of transmitting shocks that are attributed to non-fundamental factors (such as market sentiment), which will thus result in a disconnect between fundamentals and stock prices (Malamud, 2016). Since the market price of an asset is used to guide a variety of different financial and investment decisions in companies, the disconnection from fundamentals[50] creates important ramifications, which need to be considered.

Cong and Xu (2016) derive a model where they define three different types of informational efficiency: "Overall efficiency", which refers to how well prices reflect the intrinsic value of an asset, "systematic efficiency", which refers to how prices of assets reflect market-related (systematic) information, and "asset-specific efficiency" which captures how well firms reflect firm-specific information. The concept of systematic efficiency is usually captured as "Synchronicity" in the related literature, which was pioneered by Roll (1988), and measures the extent to which a firm's returns co-move with market and industry returns. The Cong and

[49] Studies such as Barberis et al. (2005), Basak and Pavlova (2013)and Da and Shive (2018) indicate this this effect also creates an "asset-class effect", where stocks become more correlated to their other index constituents, thus causing prices to delink from fundamental information.
[50] Many studies of informational efficiency usually use the earnings information (more specifically Earnings Per Share (EPS)) of a firm to capture fundamental information, which is also a proxy utilised in this study.

Xu (2016) article posits that overall; introduction of a basket security decreases asset-specific efficiency, increases systematic efficiency and increases the level of overall efficiency, an impact that is found to be greater for illiquid assets. An additional aim of this chapter therefore lies in capturing the change in synchronicity (systematic efficiency) in the underlying assets of the ETFs, a concept is discussed further in the ensuing section.

5.1.2. Systematic efficiency

The rationale of Grossman and Stiglitz (1980) that market frictions may inhibit information dissemination into asset prices, can lead to the inference that the presence of an easy-to trade, low cost ETF will thus cause investors to prefer the ETF market (Subrahmanyam, 1991). This migration to the ETF market will reduce the incentive for investors to obtain firm-specific information for individual assets, which will thus also result in the stock covarying more with market-related information. The seminal work of Roll (1988) established that a small proportion (20-30%) of variation in US-based stocks is attributed to changes in systematic (market and industry) information, with the remainder being attributed to private information, or noise-motivated trading. Roll's (1988) measurement of the extent to which stocks react based on market-specific information is referred to as synchronicity[51] (which is a measure of systematic efficiency), and has laid the foundation for many empirical studies on information efficiency.

The empirical literature on synchronicity however, predates the period in which ETFs gain popularity, and the initial studies all use this measure to proxy for the differing forms of market activity (from informed and uninformed traders), and thus measure their informational impact. The early empirical evidence on this subject therefore assumes that each market participant contributes different information to the price discovery process, and thus have differing effects on the information dissemination process. Piotroski and Roulstone (2004) find evidence that a higher concentration of institutional investors, and more analyst coverage of an asset contributes to lower levels of stock synchronicity. Morck, Yeung, and Yu (2000) find evidence of greater synchronicity in emerging market assets, and countries with poor corporate governance policies. In addition, Jin and Myers (2006) find the same result for firms which are

[51] The terms "synchronicity" and "systematic efficiency" will be used interchangeably in the remainder of this study.

not fully transparent about their information environment. In their study, Gassen, LaFond, Skaife, and Veenman (2014) find evidence of low synchronicity in countries with illiquid assets.

Whilst the above-mentioned articles are clear on their results, the actual interpretation of high/low stock synchronicity is more ambiguous, and differs among authors. Roll (1988) postulates that low stock synchronicity corresponds with a greater level of firm-specific variation in stock prices. This increase in variation is considered an indication that informed trading by arbitrageurs is present, which thus results in greater market efficiency (Durnev et al., 2003). This argument is supported by Wurgler (2000), Durnev et al. (2003), Piotroski and Roulstone (2004) and Dang, Moshirian, and Zhang (2015). In contrast, studies such as Pontiff (2006) argue that low synchronicity, and thus greater levels of firm-specific information, actually represents a limit to arbitrage due to the volatility of this information. This limit to arbitrage actually prevents market participants from acting to eliminate mispricing, which thus decreases market efficiency. Similar arguments by Mashruwala, Rajgopal, and Shevlin (2006), Teoh, Yang, and Zhang (2009), Dasgupta, Gan, and Gao (2010) and Kelly (2014) question whether stock synchronicity is due to information, or noise, and cast doubt on the use of synchronicity to capture the information content in prices. The later studies by Lee and Liu (2011) and Xing and Anderson (2011) attempts to reconcile these conflicting results, and find evidence that there is a U shaped relationship between stock synchronicity and price informativeness. This issue and its implications for this study is debated further in section 5.3.2.2.

Despite the ambiguity in the interpretation of the synchronicity measure, and even though it is meant to capture a subset of information, return synchronicity is still commonly used to capture informational efficiency in ETF studies, as noted by its use in Israeli et al. (2017), White (2018) and Glosten et al. (2020). It should be noted however, that both Israeli et al. (2017) and Glosten et al. (2020) utilise synchronicity as an additional measure of informational efficiency, and not the primary method of analysis. This chapter therefore aims to evaluate both information efficiency (as proxied by earnings information), as well as return synchronicity, and both these concepts are elaborated upon in section 5.3.

In addition to the measuring of information and return synchronicity, the research objectives for this chapter also aim to differentiate between ETF ownership and ETF activity as two separate variables which dictate ETF market activity. Whilst ETF ownership captures the current amount of free-floating shares that are held collectively by ETFs, the ETF activity variable captures the unique creation and redemption activity that defines ETF trading[52], and which facilitates the process of eliminating inefficiencies in the ETF market (Israeli et al., 2017). Whilst the role of ETF creation and redemption activity in creating/destroying market efficiency is clear, the role of ETF ownership is abstract and linked to the objectives identified in chapter 4 of this study.

The theories on ETF liquidity reviewed in chapter 3 (section 3.5) and chapter 4 (section 4.1) all dictate that the introduction of ETFs into the equity market either reduces trading costs in the underlying assets (by increasing liquidity), or increases transaction costs in the underlying assets (by reducing liquidity). Since the cost of trading is a direct market friction that inhibits arbitrage activity, it is hypothesised that as ETF ownership increases, this directly impacts on the trading costs for the underlying assets, which thus either inhibits or stimulates the action of obtaining fundamental information. It is therefore noted in Israeli et al. (2017), that in a market where frictions to trade result in market inefficiencies, the ETF ownership of a firm may constitute a significant economic event, which therefore has direct impacts on the informational efficiency of the underlying assets. Thus, a pivotal assumption in the study of Israeli et al. (2017), which is adopted in this chapter as well, is that an increase an ETF ownership significantly impacts the cost of obtaining and acting on information, and it is through this channel that information efficiency is affected.

These two definitions of ETF market activity, alongside the afore-mentioned descriptions of information efficiency therefore form the following research objectives for this chapter:

- To determine the impact of ETF ownership on the informational efficiency of the JSE-listed companies which are constituents of both international and domestic equity ETFs;

[52] This was discussed in detail in Chapter 2 (section 2.4).

- To determine the impact of ETF trading activity on the informational efficiency of the JSE-listed companies which are constituents of both international and domestic equity ETFs;
- To assess the impact of ETF ownership on stock synchronicity of the JSE-listed firms which underlie both domestic and international equity ETFs; and
- To assess the impact of ETF trading activity on stock synchronicity of the JSE-listed firms which underlie both domestic and international equity ETFs.

This chapter therefore introduces the empirical literature on the topic in section 5.2, after which the data and methodology used in this chapter is discussed in section 5.3. The results from the data analysis, and concluding comments are thereafter debated in sections 5.4 and 5.5 respectively.

5.2. EMPIRICAL EVIDENCE ON INFORMATIONAL EFFICIENCY

The literature on informational effects begins with an evaluation of price discovery in ETFs. Price discovery in the equity market refers to the manner in which transacting parties (buyers/sellers) determine the price of a stock, and is thus focused on how information is reflected in prices, as well as how long it takes for information to reflect (McCullough, 2017). This process is very dependent on external factors such as market structure and quality, investor sentiment, liquidity and volatility (Alan & Schwartz, 2013; McCullough, 2017). The dominant theoretical literature in this field of enquiry expects that asset markets which display greater liquidity, lower trading costs, and less restrictions to trade usually lead the price discovery process (Chen & Chung, 2012).

The current financial offerings available often have multiple derivative-type instruments based on a single index. The JSE Top 40 index for example, is the benchmark index for both equity options and index future contracts, as well as multiple exchange traded funds from different ETF providers. Whilst theoretically, all these different products are subject to the same information set and should thus reflect fundamental changes simultaneously, there are differences in their information transmission abilities (and thus efficiency), which thus leads to some assets leading the others in terms of information incorporation (So & Tse, 2004). This strand of literature (reviewed in section 5.2.1) is therefore often focused on determining whether the ETF market, the futures market or the spot market reflects information first, and makes use of high frequency data over smaller sample periods. The evaluation of this strand of literature is important, as it conveys information about the direction of information flow in the different assets.

The results from these price discovery studies provide insights into the flow of information that then allow for the development of hypotheses regarding the potential impact of ETFs on the informational efficiency of their underlying securities. Whilst informational efficiency in the ETF market could have a positive impact on the price discovery in its underlying securities, this could also be a channel through which non-fundamental shocks negatively impact the constituent assets (Ben-David, Franzoni, & Moussawi, 2017). The purpose of this second strand of literature, which is detailed in section 5.2.2, is therefore to investigate the issue further to provide overarching observations for the purpose of this chapter.

5.2.1. Empirical evidence on price discovery in the ETF market

The information-based models of microstructure discussed in Chapter 3 (section 3.3) postulate that it is the informed traders in the market who transmit fundamental information into security prices (Glosten & Milgrom, 1985). Studies of price discovery therefore typically make use of common factor models, such as Hasbrouck (1995) or Gonzalo and Granger (1995), which are often referred to as the Information Share (IS) approach, and the Permanent-Transitory (PT) approach respectively (Baillie, Booth, Tse, & Zabotina, 2002). Whilst both models base their methods on the Vector Error Correction Model (VECM), they differ in their approach to defining price discovery. Hasbrouck (1995) develops his IS model on the assumption that price discovery can be captured by the degree to which a market contributes to the variance of innovations in a common factor. The Gonzalo and Granger (1995) also measures the market's contribution to innovations in a common factor, however the authors focus on only permanent (and not transitory) changes in the market equilibrium.

Chu, Hsieh, and Tse (1999) make use of the Gonzalo and Granger (1995) method on intradaily data of the S&P500 ETF, to evaluate which market between the spot, futures and ETF market reflects information first. The authors predict that the preferred market for informed traders are markets with high leverage, lower costs, fewer restrictions on trading and basket securities which contain less adverse selection. This implies that whilst earlier discussions found evidence of the futures market leading the spot market[53], the introduction of the ETF should significantly impact the direction of information flows in the market. Chu, Hsieh and Tse's (1999) results finds that, even in the presence of an ETF, the futures market still dominates price discovery in the US market. The later study by Ivanov, Jones, and Zaima (2013) attempts to extend the analysis of Chu et al. (1999) by accounting for a longer time period, and both the IS and PT models of price discovery. Ivanov et al. (2013) theorise that the inception of an ETF will increase the price discovery in the spot market, while decreasing the price discovery in the futures market. This effect occurs due to the arbitrage activities from the ETF creation and redemption process, which serves as a quick link between the spot and ETFs market, and excludes the futures market (Ivanov et al., 2013). The authors therefore conclude that this should result in a shift in the origination of information from the futures market to the spot market, and their empirical analysis in on S&P500 data provides confirmation of this hypothesis.

An evaluation of the Hong Kong market by So and Tse (2004), who make use of both the IS and PT models, found that the futures market still led the price discovery process, with the ETF contribution to price discovery being very minimal. A similar evaluation of the Dow Jones Index by Liu, Fung, and Tse (2008) yielded the same result. Whilst their study is not directly focussed on price discovery, Deville, Gresse, and De Séverac (2014) also find evidence in their evaluation of the CAC 40 index, that the presence of ETFs does not increase the efficiency of the French market, and neither does it decrease the level of mispricing between the spot and futures markets. The additional literature on the topic is mixed. Whilst some studies have found that even in the presence of ETFs, futures still dominate the price discovery process (Chu et al., 1999; Deville et al., 2014; Liu et al., 2008; So & Tse, 2004), others have found evidence that price discovery shifts to the ETF market. In his study, Hasbrouck (2003) found that when an e-mini contract[54] was available for the indices in his sample, this instrument led the price discovery process despite the presence of ETFs. However, when there was no e-mini contract

[53] Studies by Bose (2007), Fedderke and Joao (2001), Kumar, Sarin, and Shastri (1998) and Yi and Liang (2014) all found evidence of the futures market leading the spot market in price discovery.
[54] E-mini contracts are futures contracts in the US market which are a fraction of the size of normal futures contracts, to allow easier accessibility for smaller traders (Hasbrouck, 2003).

present, the ETF led the price discovery process, a phenomenon which the author attributes to the ETF market consisting of mostly liquidity traders, which thus ensures that information is processed faster in this market[55].

In her study of the JSE Top 40 index, McCullough (2017) also found evidence that the futures market still dominated the price discovery process despite the presence of the Top 40 ETF. The author however notes that her results showed weak evidence that the presence of the ETF does contribute to the price discovery process, and that further research might be necessary. Similar inferences of the ETF contributing somewhat to the price discovery process through its arbitrage process is found in the studies by Park and Switzer (1995), Kurov and Lasser (2002), Tse, Bandyopadhyay, and Shen (2006) and Chen and Strother (2008). The study by Deville et al. (2014) also confirms an improvement in price discovery caused by ETFs, however the authors attribute this to the decrease of liquidity in the underlying securities after ETF introduction, which thus causes a structural shift of traders into the ETF market. The authors postulate that this shift of liquidity traders and hedgers into the ETF market thus leaves more arbitrageurs present in the other index markets. This finding further reinforces the link between the liquidity impacts discussed in chapter 4, and the rapid incorporation of information, which is the focus of this chapter.

5.2.2. Empirical evidence on informational efficiency and stock synchronicity in the ETF market

The link between ETF efficiency and the informational efficiency of the underlying assets can be found in the influential work by Ben-David et al. (2018), who postulated the presence of a "price discovery hypothesis". The authors theorise that since the ETF market reacts first to fundamental information, if there is a random shock, the price of the ETF will react immediately, whilst there will be a delay in the reaction of the underlying securities. The resulting mispricing between ETF market price and NAV will then result in arbitrage activity, which will thus adjust the stock prices to incorporate this new information. This therefore

[55] Recent studies by Broman and Shum (2018) and Ben-David et al. (2018) also find evidence of the ETF market attracting liquidity clienteles. These studies, alongside other studies of liquidity impacts are detailed in chapter 4, and are closely linked to the information efficiency discussion provided in this chapter.

implies that if ETFs are efficient, the process will occur quickly, whilst inefficient ETFs may inhibit the process. A similar theory was purported by Madhavan and Sobczyk (2016), who argue that the arbitrage mechanism of ETFs will accelerate price discovery for the underlying asset, as long as there are no limits to arbitrage.

The extant literature on informational efficiency differentiates between different types of relevant information to the firm, which are market information, industry-related information, and firm-specific information. Theories such as Cong and Xu (2016) confirm that the presence of ETFs will have different impacts on each type of information. Whilst market and industry related information may be more easily incorporated into firms due to the nature of trading, the reaction to firm-specific information may suffer proportionately. This implies that the informational effects in the ETF market are different for sector-based ETFs, and for broad-based ETFs. This section therefore divides the discussion of literature based on each type of ETF.

5.2.2.1. Empirical evidence on informational efficiency in Sector ETFs

Bhojraj, Mohanram, and Zhang (2017) hypothesise that the nature of ETFs, which allows for trade of a basket of securities simultaneously at low cost, facilitates the quick transfer of market- or industry-related information into the underlying securities. Therefore, informed traders in the ETF market would prefer to use sector-based ETFs in response to market or industry information, rather than the underlying asset, and the resulting arbitrage activity from the APs in the ETF market would transmit the information to the market for the underlying assets (Ben-David et al., 2018). Bhojraj et al. (2017) test their hypothesis by using data on the top five holdings in his sample of US ETFs, between the sample periods of 2002 – 2015. The authors thereafter term the first company to announce earnings changes as the "leader", while the remaining four firms are classified as "followers". The flow of information from the leader firm to the follower firms is thereafter investigated in event studies of both sector-based ETFs, as well as broad-based ETFs. The results from their analysis found that the flow of information from leader firms, to the follower firms, was three times greater for the sector-based ETFs (Bhojraj et al., 2017).

A recent study by Huang, O'Hara, and Zhong (2018) expands on the Bhojraj et al. (2017), by asserting that informed traders become more willing to act on firm-specific information in the market for individual securities, because they are able to use sector-based ETFs to easily hedge against market or industry risk[56]. This ease therefore incentivises more aggressive trading in the market for the underlying securities, as higher profits can be attained based on the firm-specific information advantage, which ultimately results in greater informational efficiency for the assets that constitute the sector ETFs. The authors use the Fama and MacBeth (1973) method of two-pass regression on a sample of US sector-based ETFs over the period of January 1995 to December 2016. Similar to Bhojraj et al. (2017), Huang et al. (2018) find support for their hypothesis in the data, with the authors concluding that industry ETFs are commonly used by informed traders as a way of hedging sector-specific risk, and that this ultimately results in sector-ETFs increasing the information efficiency of the market. The earlier analysis by Yu (2005) (whose research is discussed further in section 5.2.2.2), also found evidence of increased informational efficiency in her sample of sector SPDR ETFs. Yu's (2005) overall conclusion states that, even though ETFs are technically redundant assets from a hedging perspective as their payoff can easily be replicated in the underlying market, they facilitate both production and dissemination of information, which leads to increased efficiency in markets overall.

5.2.2.2. Empirical evidence on informational efficiency in broad-based ETFs

Theoretically, as discussed in section 5.1.1, the impact of ETFs on informational efficiency of its underlying assets could have two possible impacts. The first possibility is an increase in informational efficiency, hypothesised by Li, Liu, and Sun (2018), as well as Glosten et al. (2020), who assert that the low cost and easy trade offered by the ETF market ensures that it is the preferred trading venue for noise traders. As a result, the market for the underlying assets consists of mostly informed traders, who thus face fewer restraints to profiting from fundamental information, which results in stock prices that are informationally efficient (Li et al., 2018).

[56] This article fits in a broader academic theme, which evaluates the impact of financial innovations on the financial market. Studies in this field such as Chen (1995); Dow (1998) and Simsek (2013) all find evidence that financial innovations such as ETFs lead to more aggressive trading by informed investors due to the increased hedging ability, which thus leads to more complete financial markets.

Similarly, Glosten et al. (2020) asserts that including individual firms into an ETF can increase its visibility to the market, especially when an ETF is traded across multiple different platforms. This increase in visibility results in an increased opportunity to gather information on the firm in question, which ultimately leads to improved informational efficiency. The process of securities lending (this concept was discussed in detail in section 2.4.2.5) is also a conduit for increased information efficiency according to Glosten et al. (2020). If a firm is therefore added to an ETF, the number of shares that are available to be shorted increases, which reduces the cost of shorting these shares. This decrease in cost therefore encourages investors to act on fundamental information, as the costs are less prohibitive, which will thus also increase informational efficiency. This rationale is also supported by Li and Zhu (2018), who postulate that in some cases, where the underlying asset is hard to short, the ETF market provides an opportunity to create a "synthetic hedge" by shorting the ETF whilst simultaneously going long on other underlying constituents. This process is then able to create a more informationally efficient market, by creating an easier opportunity to short overpriced assets that would not have otherwise been possible without ETFs.

In reality however, the mechanical allocation of broad-based indices, which are often weighted by market capitalisation, may inhibit the level of firm-specific information incorporation (Bhojraj et al., 2017). Therefore, for example, if investors react to firm-specific information in the ETF market, the prices of all constituent securities will also adjust, regardless of whether the fundamental information had any relation to the firm or not. This results in constituent assets that remain mispriced, unless trading occurs in the underlying asset to eliminate the inefficiency (Israeli et al., 2017). Non-fundamental activities such as portfolio rebalancing, or liquidity-motivated trade could also result in price reactions for all the underlying securities of an ETF, thus further delinking these asset prices from their fundamental information (Da & Shive, 2018; Glosten et al., 2020). In addition, the increase of ETF ownership may act as a disincentive to traders conducting analyses on individual firms, which could lead to fewer traders in the market for the underlying securities, and thus greater levels of information inefficiency (Israeli et al., 2017). Bradley and Litan (2010, 2011) also argue that passive investors such as ETFs are inefficient in ensuring that individual firms align to corporate governance principles, which thus slows down the price discovery process, and even acts as a deterrent to private companies who are considering converting to public companies.

The first study to evaluate the element of price discovery in the underlying assets of an ETF was Yu (2005), who uses the broad-based SPDR ETF and sector SPDR ETFs to evaluate the informational efficiency of underlying asset prices. Her multi-asset Vector Autoregression (VAR) method uses tick data over a 58 day period after the ETFs began trading on the NYSE. She uses the multi-asset variance decomposition methodology to measure the "efficient" prices of an asset, after which the deviation between the market price and the efficient prices is calculated and analysed. The results produced indicate that the deviations between market and efficient price of the component securities are significantly smaller after the introduction of the ETF, which suggests that information efficiency is improved with the formation of ETFs. Yu (2005) also finds that innovation in the ETF market informs changes in the individual stock returns, with an almost equivalent weighting to changes in the stocks own fundamental information. Conversely, innovations in the market for the underlying asset has almost negligible contributions to ETF prices, a result which, according to the author, confirms the presence of informed traders in the ETF market.

A later study by Wermers and Xue (2015) postulates that when an ETF is introduced to the market, any increase in volatility in the underlying assets could be attributed to two possible sources: either an increase in price discovery (attributed to informed trading), or an increase in noise transmission. The authors therefore use the prices of the S&P500 ETF alongside the prices of its underlying assets to investigate which source is the dominant cause of price movements. Informed trading is defined in the study as trades based on private or public information, whilst all other trades (including trade based on hedging and speculation by both retail and institutional investors) are referred to as noise, or uninformed trades. Wermers and Xue (2015) hypothesise that informed trades dominate noise trades when the ETF market leads the market for the underlying security, whereas the opposite effect is found when the price is reflected in the market for the underlying asset first. Their VECM results indicate that compared to informed trades, noise trades have a small impact on volatility in the underlying index, which wears off after three minutes of trade. Therefore, the authors conclude that informed trades dominate the ETF market, and thus contemporaneous volatility in the market for the underlying assets is due to increased price discovery activity.

The study of Glosten et al. (2020)[57] is an influential one, which informed many other empirical analyses of informational efficiency in the ETF market. The authors test quarterly cross-sectional US ETF data using the Fama and MacBeth (1973) method of two-pass regression, over the period of 2004 – 2013, to test whether an increase in ETF trading leads to increased pricing efficiency in the constituent shares. They find evidence that the ETFs in their sample incorporate contemporaneous accounting information into asset prices, but not lagged or forecasted information, and only for firms with low analyst following, firms with imperfectly competitive markets, and the smaller stocks in the index. They attribute this observation to the possibility that information does not reflect timeously for these firms due to aspects such as illiquidity and short sale constraints, therefore the easily traded and liquid ETFs allow this information to be incorporated into these securities. Support for the rationale that ETFs facilitate short selling in firms which would otherwise face short selling constraints, is also found in Li and Zhu's (2018) evaluation of US ETFs between 2002 and 2013. The authors therefore conclude that this activity induces greater informational efficiency in the underlying assets, by facilitating arbitrage activity in overpriced assets.

Glosten et al. (2020) also hypothesise that the increase in informational efficiency should be accompanied by an increase in return synchronicity, since traders in the ETF market have no incentive to act on firm-specific information. The results from their further analysis therefore finds evidence in favour of positive return synchronicity (Glosten et al., 2020). The results from Glosten et al. (2020) and Li and Zhu (2018) provide an indication that the informational effects of ETFs may be felt differently for firms with different sizes, which prompted the study of White (2018) who implemented a firm-level study of large capitalisation US firms from the DJIA. White's (2018) analysis made use of the Israeli et al. (2017) method to analyse the impact of ETF ownership on ETF liquidity and informational efficiency as measured by synchronicity. The author finds evidence that an increase in ETF ownership coincides with higher spreads, and lower synchronicity levels, which the author attributes to greater informational efficiency being present in the constituent securities.

[57] Whilst this article was published in 2020, draft versions have been available to the academic community since 2015. As a result, this study has been used repeatedly for comparison and reference.

Israeli et al. (2017) use their study to evaluate the impact of ETF ownership on the informational efficiency, trading costs and synchronicity of their underlying assets. The authors theorise a decrease in liquidity in the underlying assets of an ETF, similar to Subrahmanyam (1991), which would result in an increase in trading costs. This increase will become prohibitive for informed investors to conduct analysis and trade on firm-specific information, which will therefore decrease the informational efficiency of the assets. The synchronicity measure was used as a proxy for the extent to which unsystematic information is reflected in stock prices. Their results found evidence of decreased informational efficiency and increased trading costs after ETF introduction, and the number of analysts researching a firm was also found to decrease after this event. The results of the Israeli et al. (2017) study stand in stark contrast to those produced by Glosten et al. (2020), however the authors attribute this to the differing objectives of each study. Whilst Israeli et al. (2017) aim to evaluate long term effects on pricing efficiency (and model previous ETF ownership against future earnings), the Glosten et al. (2020) study attempts to model contemporaneous ETF trading on current earnings and therefore does not aim to evaluate any long-term implications of ETF trade. Furthermore, whilst Glosten et al. (2020) makes use of the Fama and MacBeth (1973) approach, Israeli et al. (2017) make use of fixed effect panel data models.

The other difference noted in the two studies resulted from their expectations of the synchronicity factor. Whilst Glosten et al. (2020) record that they expect the synchronicity of the underlying assets to increase when informational efficiency increases, Israeli et al. (2020) hypothesise that synchronicity should decrease. This occurs due to the positive relationship between ETF ownership and the cost of information arbitrage, which imposes higher costs on investors and thus disincentives them from acquiring information about the underlying securities. According to the authors, this should result in lower systematic and firm-specific information being incorporated into the underlying assets after ETF inclusion. The results from the study confirm their hypothesis, and Israeli et al. (2020) therefore conclude that whilst ETF trade seems to improve contemporaneous price discovery (Glosten et al., 2020), this impact is short-lived as over the long term, ETF trade will decrease the amount of firm-specific and systematic information being impounded into the underlying assets.

The study by Li et al. (2018) attempts to expand the analysis on informational efficiency to what the authors term "real efficiency", which is the extent to which the informational efficiency of prices impacts real decisions in the firm. Their Fama and MacBeth (1973) analysis of data on US ETFs between the period of 2003 and 2013 provides evidence that the stock prices for the firms in their sample contain a higher level of systematic information than that reflected in the ETF prices, and this increases proportionately with the level of ETF ownership. The authors thereafter use their sample of data to replicate the tests of Glosten et al. (2016) and Israeli et al. (2017) as a robustness test. Their results find positive relationships between ETF ownership and informational efficiency, as well as stock synchronicity.

5.2.3. Conclusion of Literature review on information efficiency

The literature reviewed in this section is largely inconclusive on the issue of information efficiency in the underlying assets of an ETF. Whilst studies of sector-based ETFs unilaterally provide evidence of improved information efficiency for their underlying assets (Bhojraj et al., 2017; Huang et al., 2018; Yu, 2005), studies of broad-based indices have either found evidence of improved efficiency, or information inefficiency. The framing of these studies however, is largely different, with some authors focussing on the impact of ETF arbitrage trading activity (creations and redemptions) as the channel through which information efficiency of the underlying shares is impacted (Glosten et al., 2020; Li & Zhu, 2018; Wermers & Xue, 2015), whereas others use ETF ownership as the channel through which the underlying assets are affected (Bhojraj et al., 2017; Israeli et al., 2017; Li et al., 2018). This chapter deems both channels as important for analysis, and therefore evaluates the impact of both these variables on information efficiency of the underlying securities, with a further aim of assessing which channel impacts information efficiency more. The methods, variables and statistical testing procedures applied are discoursed further in section 5.3.

5.3. RESEARCH METHODOLOGY FOR INFORMATION EFFICIENCY ANALYSIS

The literature surrounding price discovery makes use of high frequency tick data, and the "information share" model developed by Hasbrouck (1995) to measure the influence of a selected market (future/ETF/spot) towards the variance of innovations in a common factor (Chen & Chung, 2012). In contrast, the informational efficiency studies on the constituents of ETFs have all used longer sample periods with lower frequency data (usually quarterly) to evaluate whether the presence of ETFs in the market contributes positively or negatively to the release of earnings information by their underlying firms. Furthermore, as mentioned previously, these articles focus on either ETF trading activity or ETF ownership as the channels through which information efficiency is impacted. Whilst the price discovery literature has an important implication and contribution to the literature, there are existing studies in the South African context which evaluate price discovery of ETFs (McCullough, 2017). The research gap therefore lies in identifying whether the contribution of ETFs towards price discovery noted by McCullough (2017) has an impact on the efficiency in the underlying assets. This section therefore commences with a discussion of the data and sample period, after which the chosen research method is detailed.

5.3.1. Sample description for information efficiency analysis

5.3.1.1. Sample period and data frequency for information efficiency analysis

The sample period of evaluation in this chapter, is the eleven year time period between January 2009 and September 2019. This time period coincides with the increased growth in ETF creation and usage after the subprime crisis (Borzykowski, 2018), which is also evidenced in the graph of South African ETF growth shown in figure 1-2 (page 3). As noted by Glosten et al. (2020), beginning the analysis in periods which exhibit low ETF growth (and thus also trading activity) is not helpful and provides limited additional value to the analysis. Given the necessity of obtaining ETF holdings data for the ETFs in the sample, this time period also ensured the maximum sample of ETFs, and conformed to the studies by Israeli et al. (2017) and Glosten et al. (2020). The usage of accounting data in this chapter means that the data could only be collected over a quarterly, or annual frequency. In order to ensure the maximum number of observations, the quarterly frequency is used, which thus ensures 43 quarterly observations for each underlying company of the sample ETFs utilised in the analysis.

5.3.1.2. ETF and underlying constituent sample for information efficiency analysis

The key variable of interest in this chapter, is the level of total ETF ownership exhibited in each JSE-listed firm. The first South African ETF was listed in November 2000 by the issuing company, Satrix. Whilst this ETF consists of only domestic equity, the current ETF environment has exposure to both domestic and international ETFs. Furthermore, there are many international ETFs that now have exposure to South African equities, through their global/country-based ETFs. As at December 2019, there are 37 listed domestic ETFs in SA which had exposure to JSE-listed companies, and 179 different foreign ETFs that also had some exposure to SA-listed companies (ETFDB, 2019). The array of ETFs which meet the criteria consists of both synthetically replicating portfolios, as well as physically replicated[58]. Since synthetic portfolios make use of derivatives to replicate their benchmark portfolios, only physically replicated ETFs are included in the study. Whilst all domestic (JSE-listed) ETFs that meet the data constraints are included in the study, the international ETFs are only considered if more than 2 percent of their assets under management is currently invested in JSE-listed firms[59]. This therefore eliminates ETFs with minimal exposure to South African assets and minimises the data intensity in the sample.

Furthermore, ETFs which do not coincide with the quarterly rebalancing period practiced in South Africa (March, June, September, and December) are also excluded from the analysis. In total, the sample therefore includes 91 ETFs, which were listed before or during the sample period, off which 33 are JSE-listed domestic equity ETFs. The remaining 58 ETFs in the sample are international ETFs which have exposure to South African listed companies traded on multiple different international exchanges. The full list of these ETFs can be found in Appendix B-1 (page 227).

The holdings for each of these ETFs is collected from the Bloomberg and S&P Capital IQ databases, over the sample period of 2009Q1, to 2019Q3. The use of quarterly data also coincides with the frequency of rebalancing of ETFs in the sample, therefore the sample is adjusted to include additions and exclude deletions from the ETF portfolios, for every quarter of the analysis. The underlying constituents are only selected for inclusion in the sample if they have fiscal-year ends in March, June, September and December (which coincides with the ETF rebalancing). The resultant number of underlying constituents to the chosen ETFs, which meet the data requirements is 94 JSE-listed companies. Each of the 94 companies are included in multiple ETFs over different periods of time, the full list of which is available in Appendix B-

[58] Whilst CISCA dictates that South African ETFs need to be physically replicating, the international ETFs were from varied geographical regions and were thus subject to that regions regulatory environment. In the US for example, synthetically replicating ETFs are allowed.
[59] The International ETFs consist of a wide range of different categories, from the iShares MSCI South Africa ETF, off which 92% of the portfolio consists of SA equity, to the iShares Core MSCI Pacific ETF, which invests just 0.02% of its overall portfolio in SA equity.

2 (page 230). The total sample therefore consists of 4042 (94 companies x 43 quarters) panel data observations.

5.3.2. Variable description for Information Efficiency analysis

This sub-section aims to detail the different variables utilised in this chapter. The discussion begins with a description of the variables which capture ETF ownership and ETF trading activity in the underlying assets, after which the central focus of the chapter (informational efficiency proxies) is discoursed further. This sub-section thereafter ends with an evaluation of the control variables included in the analysis.

5.3.2.1. ETF ownership and ETF trading activity

As mentioned previously, there are two main ETF market activity variables utilised in this chapter, which are ETF ownership[60], and ETF trading activity. The ETF ownership variable aims to capture the amount of shares in each firm that are being held collectively by ETFs, and is calculated as the number of a firm's shares held by the sample ETFs at the end of quarter *t*, divided by the total shares outstanding in the underlying asset at the end of quarter *t*.

$$\text{ETF ownership } (ETF_{it}) = \frac{total\ number\ of\ shares\ owned\ by\ sample\ ETFs\ at\ time\ t}{Total\ shares\ outstanding\ in\ firm\ i\ at\ time\ t} \tag{5.1}$$

The second ETF market activity variable is meant to capture the ETF stimulated trading activity for each share included in the analysis, and is calculated as the change in ETF ownership between quarter t and quarter t-1 (expressed in equation 5.2).

$$ETF\ trading\ activity = \Delta ETF_{it} = ETF_{it} - ETF_{it-1} \tag{5.2}$$

This proxy for ETF activity is used by Glosten et al. (2020), who postulate that the creation and redemption activity of ETFs accurately represents demand activity by investors, since if there is excess demand, the ETF sponsors will create more units of the ETF for sale on the secondary market. In this way, increases in the number of shares in ETFs implies that there has

[60] "ETF ownership" is used interchangeably with "ETF holdings" in this chapter, as both terms refer to the same concept.

been an increase in demand, which is why the change in ownership is an accurate proxy for ETF activity in the market. This chapter therefore adopts this method as well, to evaluate both ETF ownership and ETF trading activity on the information efficiency of the assets that underlie the ETFs.

5.3.2.2. Informational efficiency proxies

The informational efficiency framework presented by Grossman and Stiglitz (1980) suggests that when fundamental information is released, it is informed trading by investment professionals that aligns stock prices with the fundamental information, and mispricing can occur if transaction costs or other market frictions prevent the informed traders from trading in that asset. This tenet that prices adjust to order flow that arises out of information is one that is echoed in many subsequent microstructure theories such as Glosten and Milgrom (1985) and Kyle (1985). The seminal work of Ball and Brown (1968) aims to identify proxies for this information set, and their findings suggest that measures of accounting earnings accurately account for a portion of the information set that is relevant to stock returns. Studies on informational efficiency have therefore aimed to evaluate the speed of adjustment of firm prices to fundamental news, proxied by earnings information (Bhushan, 1994; Glosten et al., 2020; Israeli et al., 2017; Jennings & Starks, 1986; Skinner, 1997).

This relationship between stock return and earnings, has led to the commonly used Earnings Response Coefficient (ERC), and has been the subject of many empirical analyses based on the flow of information in the market. This concept aims to capture the market response to unexpected changes in earnings (Hasanzade, Darabi, & Mahfoozi, 2014), and is commonly measured as the coefficient from a regression with return as the dependent variable, and earnings as the independent variable[61] (Collins & Kothari, 1989). Kothari and Sloan (1992) postulate however, that using analyst forecasts of earnings provides a much better approximation, which thus leads to the development of the Future Earnings Response Coefficient (FERC). This measure aims to capture the predictive ability of stock prices with respect to prospective future earnings, and thus captures a richer information set than the ERC.

[61] In a regression of $R_{it} = \beta_{0t} + \beta_{1t} UE_{it} + \epsilon_t$, where R_{it} is the return on asset i, and UE_{it} represents the unexpected earnings component, the coefficient β_{1t} is known as the ERC (Collins & Kothari, 1989).

Support for the ERC/FERC measures as proxies for unanticipated information content is found in the studies of Huang and Zhang (2012), Mostafa and Dixon (2013), Patatoukas (2014) and Al-Baidhani, Abdullah, Ariff, Cheng, and Karbhari (2017). The use of the ERC and FERC to proxy for fundamental news which must be incorporated into stock prices, is therefore utilised to answer the first research question of this chapter, as per the studies of Israeli et al. (2017), Bhojraj et al. (2017) and Glosten et al. (2020).

The variable used to capture earnings can take various forms, and must consider the impact of effects such as seasonality in earnings. The time-series characteristics of quarterly earnings information was first evaluated by Griffin (1977), whose analysis of listed companies on the NYSE found that current estimates of earnings are reflective of the series of quarterly earnings for the same quarter, in previous years. This component is referred to as seasonality, which is attributed to seasonal changes in demand experienced by firms, and evidence of this phenomenon is also found in the studies of Peterson (1990), Alvarez (2004), Chang, Hartzmark, Solomon, and Soltes (2017) This chapter therefore makes use of seasonally adjusted earnings, as calculated in equation 5.3.

$$Earnings_{i,t} = \frac{EPS_{it} - EPS_{it-4}}{P_{it-1}} \tag{5.3}$$

Where: EPS_{it} measures the Earnings Per Share excluding extraordinary items[62] for firm i in quarter t, and P_{it-1} is the price per share for firm i at the end of quarter t-1. The Earnings variable is seasonally adjusted by deflating earnings by the beginning of quarter price (X_{it-4}).

The theoretical application by Cong and Xu (2016) (reviewed in section 3.4.6), asserts that there are three different forms of information efficiency in the market. Whilst overall efficiency refers to the extent of all fundamental information reflected in the price of an asset, this can be further sub-divided into systematic efficiency, and asset-specific efficiency. Systematic efficiency refers to the extent to which asset prices reflect market-wide information, and asset-specific efficiency refers to the extent to which asset prices reflect firm-specific information.

[62] Extraordinary items usually refers to reported profits or losses which are unusual and infrequent, such as the possibility that a natural disaster negatively impacts profitability drastically.

As discussed in section 5.1.2., the measure of synchronicity developed by Roll (1988) is commonly used to capture systemic efficiency, and is therefore the second proxy of choice for this chapter. The empirical method of estimating stock synchronicity requires estimating the market model, as per equation 5.4, after which the R^2 is collected for use in equation 5.5.

$$R_{i,d} = \beta_{0,i} + \beta_{1,i}MKTRET_d + \beta_{2,i}INDRET_d + \epsilon \tag{5.4}$$

Where $MKTRET_d$ is the return on the market portfolio, in this case the JSE ALSI (minus the effect of the firm); and $INDRET_d$ is the return on the industry sector to which the firm belongs (minus the effect of the firm). Due to the unique market structure and concentration issues in South Africa (detailed in section 1.1.2), where the top 40 companies occupy more than 80% of the market capitalisation in the ALSI (Mans-Kemp & Viviers, 2019), the firm effect had to be excluded from the MKTRET and INDRET variables to avoid spurious correlation in the regression (Gassen et al., 2014). Since the resultant R^2 from equation 5.4 has the undesirable property of being bounded between the values of 0 and 1, equation 5.5. therefore transforms this using natural log to create a more normally distributed series (Piotroski & Roulstone, 2004; White, 2018).

$$Sync_{i,t} = \log\left(\frac{R^2{}_{i,t}}{1 - R^2{}_{i,t}}\right) \tag{5.5}$$

Equation 5.5 is therefore calculated using daily data for each quarter of the analysis, in order to produce an associated synchronicity value for each quarter of firm information. In conjunction with Crawford, Roulstone, and So (2012), Li, Rajgopal, and Venkatachalam (2014), Israeli et al. (2017) and Glosten et al. (2020), the adjusted R^2 value from equation 5.4 is utilised in equation 5.5. This measure is preferred over the R^2 value, as it adjusts for the number of variables in the model, and is therefore considered a superior measure of goodness-of-fit (Brooks, 2019). A higher level of stock synchronicity in stock prices implies that the variation in stock returns for that firm is explained by a higher proportion of market- and industry-related data, and thus has a lower portfolio of firm-specific information in the underlying asset (Israeli et al., 2017). The interpretation of synchronicity relative to informational efficiency however, varies across authors.

The first body of evidence finds that high levels of firm-specific information (and thus low synchronicity), is an indication that stock prices have greater levels of information efficiency (Durnev et al., 2003; Jin & Myers, 2006; Morck et al., 2000; Piotroski & Roulstone, 2004). The second, conflicting body of evidence, finds that high levels of firm-specific information indicate more noise and higher levels of investor uncertainty[63], which thus infers lower information efficiency (Hou, Xiong, & Peng, 2006; Teoh et al., 2009; Zhang, 2006). To date, the literature on the interpretation of stock synchronicity remains split, and ensuing studies assume either the former or latter interpretation to be correct, before analysing their results. This study adapts the interpretation applied by the closest related studies which were also based on the ETF market, Israeli et al. (2017) and White (2018), who postulate that high levels of synchronicity indicate a disincentive for investors to procure firm-specific information, which thus leads to reduced information efficiency in the underlying asset.

5.3.2.3. Control variables for informational efficiency analysis

As noted in chapter 4 (section 4.3.1.4), control variables have some impact on the dependent variable, but are not the primary sources of interest in the study (Hünermund & Louw, 2020). The chosen control variables for this chapter were therefore selected based on evidence of their influence on an individual firm's information environment, and were found to impact either the earnings return relation in the stock, or the synchronicity of an asset (some control variables affect both these aspects).

The first variable utilised is the size of the firm ($S_{i,t}$), which is measured as the natural log of the market capitalisation of each firm in the sample (in R million), measured at the end of each quarter of analysis. The size of a firm is an important determinant of the information environment, as larger firms usually have higher levels of media exposure, richer information environments, and a higher numbers of analyst coverage/investor interest (Crawford et al., 2012). This variable is therefore employed by Kelly (2014) to proxy for the cost of information. The author hypothesizes that the cost of information for small firms is very high, because they

[63] All signals of information (i) contain a fundamental value (f) , plus some noise/error term (e). Since $i = f + e$, the variance off the signal can be characterised by: $var(i) = var(f) + var(e)$. The volatility of the firm's information is captured by $var(f)$, whilst $var(e)$ reflects the quality of the information, since there is a possibility that the information is poor and not relevant to the fundamental value of the asset. These two elements therefore contribute to the uncertainty faced by investors (Hirshleifer, 2001; Zhang, 2006).

are less well known by traders, who are less likely to even identify mispricing in the first place. This hypothesis is proven by their results which show much lower levels in firm-specific risk for the large firms in their sample. In addition, Banz (1981) documents evidence that small firms tend to outperform large firms on a risk-adjusted basis, in a result which is supported on the JSE by Rensburg and Robertson (2003), Pillay, Muller, and Ward (2010) and Strugnell, Gilbert, and Kruger (2011). These findings have therefore led to the size of the firm being commonly used as a control variable in related studies., as evidenced by its use in the studies of Bae, Kim, and Ni (2013), Haghighat, Farhangzadeh, and Haghighat (2015), Israeli et al. (2017) and Glosten et al. (2020).

The second control variable is the Market to Book ratio ($MTB_{i,t}$) which proxies for growth in the firm and is calculated as the ratio of market capitalisation, to the book value of equity of the firm at the end of each quarter (Bae et al., 2013). Studies such as Chun, Kim, Morck, and Yeung (2008) and Cao, Simin, and Zhao (2008) document that an increase in firm-specific variability is noted for higher growth firms. This is attributed to the higher expenditure of these firms on research and development projects which have higher levels of variance (Cao et al., 2008). The dummy variable ($Loss_{i,t}$) assumes the value of 1 if quarterly earnings for firm *I* is negative, and 0 otherwise. This variable is included as a further control, as the reporting of losses for a firm is considered a significant news event which will impact negatively on the company's stock returns (Hayn, 1995; Joos & Plesko, 2005; Skaife, Gassen, & LaFond, 2006).

The standard deviation of earnings ($STD_{i,t}$) is also included as a control variable, and is meant to capture the volatility in the underlying firm's fundamentals. This variable is usually calculated with 3 to 5 years of historical earnings data (Piotroski & Roulstone, 2004). The use of 5 years of historical earnings data posed a critical constraint to this objective, as many companies would have been eliminated from the analysis due to lack of data. Therefore, to ensure the largest sample, the former time period of 3 years (12 quarters) of historical earnings data (excluding extraordinary items) was utilised in order to calculate the $STD_{i,t}$ variable[64]. The use of this variable coincides with the tests of Glosten et al. (2020); Israeli et al. (2017) and

[64] As a result, whilst the sample for this chapter begins in 2009Q1, earnings data was collected from 2006Q1 in order to calculate *STDi,t*.

Crawford et al. (2012) all of whom found evidence that a greater level of variability in earnings will cause greater variability in stock returns and thus higher levels of synchronicity.

The final variable chosen as a control, is the level of institutional ownership in the firm ($INST_{i,t}$). The use of this variable is in conjunction with its usage by Hou et al. (2006), Israeli et al. (2017), White (2018) and Glosten et al. (2020). Institutional owners of a firm are regarded as the informed investors, and are generally considered in the literature to be much more sophisticated than retail investors (Chen, Hong, & Stein, 2002; Jennings, Schnatterly, & Seguin, 2002; Odean, 1999). Prior research such as Durnev et al. (2003), Chan, Hameed, and Kang (2013), Bae et al. (2013) and Kelly (2014) find that higher levels of institutional ownership often results in more disclosure of information, which reduces information asymmetry in the firm. This variable therefore proxies for the level of information already incorporated on the stock, and is measured as the cumulative number of shares held by institutional investors at the end of each quarter, divided by the total stock outstanding.

Since this study uses both ETF ownership and institutional ownership, these two variables overlap (ETF ownership is included in institutional ownership), which can result in a high correlation between the two variables. To isolate the institutional ownership effect, Glosten et al. (2020) suggest the following cross-sectional regression:

$$\Delta Inst_{i,t} = \gamma_{0t} + \gamma_{1,t}\Delta ETF_{i,t} + Residual_{i,t} \tag{5.6}$$

Where $\Delta Inst_{i,t}$ and $\Delta ETF_{i,t}$ refer to the change in institutional and ETF ownership respectively, from quarter t-1 to quarter t. The resultant $Residual_{i,t}$ series therefore captures the institutional ownership not related to ETFs, and this variable is henceforth used in all regression analyses (this variable is referred to as "Institution residual, or $IS_{i,t}$). The afore-mentioned variables are not an exhaustive list of control variables used in previous studies, however, this chapter needed to maintain a balance between including an extensive variable list, against the use of degrees of freedom. The variables used therefore constitute the ones used most in the literature, whilst drawing from information that is easily available/computed in the South African environment. The summary of these variables, and their description can be found in table 5-1.

Table 5-1: Variable summary and definitions for Information Efficiency analysis

Variable	**Definition**
ETF ownership (ETF_{it})	$= \frac{total\ number\ of\ shares\ owned\ by\ sample\ ETFs\ at\ time\ t}{Total\ shares\ outstanding\ in\ firm\ i\ at\ time\ t}$ = the number of shares in each firm held collectively by domestic and international ETFs.
ETF Trading Activity (ΔETF_{it})	$= ETF_{it} - ETF_{it-1}$ = the change in ETF ownership between quarter t and quarter t-1, that can be attributed to creation and redemption activity in new and existing ETFs.
Earnings$_{i,t}$	$= \frac{EPS_{it} - EPS_{it-4}}{P_{it-1}}$ = Seasonally adjusted Earnings (excluding extraordinary items) for firm i, during quarter *t*
Synchronicity ($Sync_{i,t}$)	$= \log\left(\frac{R^2{}_{i,t}}{1 - R^2{}_{i,t}}\right)$ from a regression of $R_{i,d} = \beta_{0,i} + \beta_{1,i}MKTRET_d + \beta_{2,i}INDRET_d + \epsilon$
Institutional Ownership ($Inst_{i,t}$)	$= \frac{total\ number\ of\ shares\ owned\ by\ all\ institutions\ at\ time\ t}{Total\ shares\ outstanding\ in\ firm\ i\ at\ time\ t}$ = the number of shares in each firm held collectively by institutions (both domestic and foreign).
Institutional residual ($IS_{i,t}$)	= the residual from the regression $\Delta Inst_{i,t} = \gamma_{0t} + \gamma_{1,t}\Delta ETF_{i,t} + Residual_{i,t}$ = the portion of institutional ownership that is attributed to all other categories except ETF ownership.
Size of the firm ($SIZE_{i,t}$)	= natural log of the market capitalisation of firm *i,* at the end of quarter *t* (measured in R millions)
Market-to-book ratio ($MTB_{i,t}$)	= market capitalisation e of firm *i* at the end of quarter *t*, divided by book value of equity at the end of quarter *t*. = a proxy for the growth in firm *i*
Standard deviation of earnings ($STD_{i,t}$)	= standard deviation of earnings over the previous 12 quarters = volatility of underlying earnings in firm *i*
Loss$_{i,t}$	= dummy variable which takes the value of 1 if quarterly earnings for firm *I* is negative, and 0 otherwise
Return ($R_{i,t}$)	$= = \ln(\frac{P_t}{P_{t-1}})$ = the natural log of the return for stock *I* during quarter *t*
Turnover ($TURN_{i,t}$)	= average volume traded of share *i* during the quarter divided by firm *i*'s total shares outstanding at the end of the quarter.

Source: Own compilation (2020)

5.3.3. Model Specification for informational efficiency analysis

The variables listed in section 5.3.2 are therefore combined into specific models for testing, which are detailed in the sections that follow.

5.3.3.1. The effect of ETF ownership and trade on FERC

The first regression equations used for this chapter makes use of the first informational efficiency proxy of FERC, which is discussed in section 5.3.2.2, and is expressed in equations 5.7 and 5.8.

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t}Earnings_{i,t} + \gamma_{2,t}(Earnings_{i,t} \times ETF_{i,t}) + \gamma_{3,t}Earnings_{i,t-1} + \gamma_{4,t}(Earnings_{i,t-1} \times ETF_{i,t}) + \gamma_{5,t}Earnings_{i,t+1} + \gamma_{6,t}(Earnings_{i,t+1} \times ETF_{i,t}) + \gamma_{7,t}\Delta ETF_{i,t} + \gamma_{8,t}SIZE_{i,t-1} + \gamma_{9,t}MTB_{i,t-1} + \gamma_{10,t}STD_{i,t-1} + \gamma_{11,t}Loss_{i,t} + \gamma_{12,t}\Delta IS_{i,t} + \gamma_{13,t}(Earnings_{i,t} \times Loss_{i,t}) + \gamma_{14,t}ETF_{i,t-1} + \gamma_{15,t}R_{i,t+1} + \varepsilon_{it},\ i=1.....N,\ t=1....T \tag{5.7}$$

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t}Earnings_{i,t} + \gamma_{2,t}(Earnings_{i,t} \times \Delta ETF_{i,t}) + \gamma_{3,t}Earnings_{i,t-1} + \gamma_{4,t}(Earnings_{i,t-1} \times \Delta ETF_{i,t}) + \gamma_{5,t}Earnings_{i,t+1} + \gamma_{6,t}(Earnings_{i,t+1} \times \Delta ETF_{i,t}) + \gamma_{7,t}\Delta ETF_{i,t} + \gamma_{8,t}SIZE_{i,t-1} + \gamma_{9,t}MTB_{i,t-1} + \gamma_{10,t}STD_{i,t-1} + \gamma_{11,t}Loss_{i,t} + \gamma_{12,t}\Delta IS_{i,t} + \gamma_{13,t}(Earnings_{i,t} \times Loss_{i,t}) + \gamma_{14,t}ETF_{i,t-1} + \gamma_{15,t}R_{i,t+1} + \varepsilon_{it},\quad i=1.....N,\ t=1....T \tag{5.8}$$

Where:

- Return ($R_{i,t}$) is the natural log of the return for stock *I* during quarter *t* = $= \ln(\frac{P_t}{P_{t-1}})$
- ETF ownership ($ETF_{i,t}$) is meant to capture ETF trade and is calculated using the description in section 5.3.2.1.
- $\Delta ETF_{i,t}$ represents the change in ownership from quarter t-1 to quarter t, and proxies for ETF activity as discussed in section 5.3.2.1.
- $Earnings_{i,t}$ represents the seasonally-adjusted EPS for each firm, in quarter t, as described in section 5.3.2.2.
- $SIZE_{i,t-1}$ is the natural log of the market capitalization for firm *i* at the end of each quarter *t-1* (which is also the beginning market capitalization for quarter *t*).
- $MTB_{i,t-1}$ is the market to book ratio for firm *I* at the at the end of each quarter *t-1.*

- $Loss_{i,t}$ is a dummy variable which assumes the value of 1 is quarterly earnings for firm I is negative, and 0 otherwise
- $STD_{i,t-1}$ is the standard deviation of earnings during the 12 quarters preceding quarter t.
- $\Delta IS_{i,t}$ refers to the change in the institutional residual, as calculated by equation 5.5 in section 5.3.2.3.

The models represented in equations 5.7 and 5.8 are identical, except that equation 5.7 uses ETF ownership $(ETF_{i,t})$ to capture the FERC, whilst equation 5.8 utilises ETF activity $(\Delta ETF_{i,t})$ instead. Equation 5.7 allows for the analysis of the first objective of this chapter, whilst equation 5.8 aims to test the second objective. The variable $\gamma_{1,t}$ captures the relationship between contemporaneous earnings and returns in quarter t, whilst $\gamma_{3,t}$ and $\gamma_{5,t}$ capture previous and future earnings, respectively. The interaction coefficients of $\gamma_{2,t}$, $\gamma_{4,t}$ and $\gamma_{6,t}$ capture the effect of ETF ownership or trade on the incorporation of current, previous and future earnings respectively. Whilst $\gamma_{1,t}, \gamma_{3,t}$ and $\gamma_{5,t}$ are the ERC of the model, the objective of this chapter is to ascertain whether ETF ownership or trade has an impact on the ERC, and therefore the interaction coefficients of $\gamma_{2,t}$, $\gamma_{4,t}$ and $\gamma_{6,t}$ are of particular interest. If these coefficients are positive, this indicates a greater level of informational efficiency brought about by ETF ownership or trade, whilst negative coefficients imply that ETFs have a detrimental impact on information efficiency.

The use of lagged variables for firm size, market to book ratio and standard deviation of earnings is meant to avoid the "look-ahead bias" that is commonly associated with accounting data. The "look-ahead bias" was first discovered by Banz and Breen (1986), and refers to the use of data in a model, which may not be known to market participants at the date of the observation in the dataset (Van Rensburg, 2001). When dealing with accounting data, it is often the case that financial statement information is indexed to the financial year-end of the company, even though most companies on the JSE are allowed up to three months after the financial year-end to release their final audited financial statements (Muller & Ward, 2013). This bias is therefore usually solved by making use of lagged accounting variables in the empirical models – in this case, 3 months accounts to one full quarter, which thus motivates the single lag used. The coefficients on these variables, as well as the $Loss_{i,t}$ and $(Earnings_{i,t} \times Loss_{i,t})$ variables are expected to have negative coefficients.

The use of actual earnings to proxy for future earnings could result in a measurement error in the model, due to the possibility that events which were not anticipated at time t, significantly impacted on earnings at time t+1. The use of $R_{i,t+1}$ as an additional proxy in the model therefore aims to control for this issue. The proportion of ETF ownership at the beginning of the quarter ($ETF_{i,t-1}$) is also included in equation 5.6 and 5.7, based on prior literature which indicates historical ETF ownership has an impact on volatility and liquidity of the underlying stocks, and the coefficient of this variable is expected to have a negative sign (Ben-David et al., 2017; Israeli et al., 2017).

5.3.3.2. The effect of ETF ownership and ETF trading activity on synchronicity

The third and fourth objectives of this chapter requires the usage of the synchronicity measure to capture information efficiency, and is expressed in equation 5.9 and 5.10 below:

$$Sync_{i,t} = b_{0t} + b_{1t}ETF_{i,t} + b_{2t}Size_{i,t-1} + b_{3t}MTB_{i,t-1} + b_{4t}STD_{i,t-1} + b_{5t}ETF_{i,t-1} + b_{6t}\Delta IS_{it-1} + b_{6t}\Delta TURN_{i,t} + \varepsilon \tag{5.9}$$

$$Sync_{i,t} = b_{0t} + b_{1t}|\Delta ETF_{i,t}| + b_{2t}Size_{i,t-1} + b_{3t}MTB_{i,t-1} + b_{4t}STD_{i,t-1} + b_{5t}ETF_{i,t-1} + b_{6t}\Delta IS_{it-1} + b_{6t}\Delta TURN_{i,t} + \varepsilon \tag{5.10}$$

Where:

- $Sync_{i,t}$ refers to the synchronicity of firm *i*, during quarter *t,* as measured by equation 5.5.
- $\Delta TURN_{i,t}$ refers to the change in turnover, measured by $TURN_t - TURN_{t-1}$, where $TURN_{i,t}$ captures the ratio of average volume traded of share *i* during the quarter, to firm *i*'s total shares outstanding at the end of the quarter.
- $ETF_{i,t}$, $Size_{i,t-1}, b_{1t}, \Delta IS_{i,t}$ and $ETF_{i,t-1}$ are defined as previously discussed in section 5.3.3.1.

Similar to the previous section, equations 5.9 and 5.10 only differ in their employment of ETF ownership (equation 5.9) or ETF trading activity (equation 5.10). The addition of the turnover variable ($\Delta TURN$) in equations 5.9 and 5.10, are in conjunction with the studies of Piotroski and Roulstone (2004), Crawford et al. (2012) and Israeli et al. (2017). The changes in synchronicity for any particular asset could be due to investor awareness that is brought about by some other factor, rather than fundamental information (Crawford et al., 2012). The Turnover variable therefore allows for the inclusion of this possibility in the analysis. The $Size_{i,t-1}$ and $\Delta TURN$ variables are expected to have a positive coefficients, whilst $MTB_{i,t-1}$ and $STD_{i,t-1}$ should have negative correlations to the synchronicity variable. If a positive b_{1t} coefficient is found in both equations 5.9 and 5.10, this would indicate that firms with higher ETF ownership/ETF trading activity exhibit higher synchronicity values, which would correspond to lower levels of information efficiency, as discussed previously in section 5.3.2.2.

5.3.4. Estimation Methods for informational efficiency analysis

The data contained in the regression equations of section 5.3.3 make use of both cross-sectional (firm) data, as well as time series. This therefore constitutes a panel of data, and is handled in the dominant literature using one of two ways. Whilst some studies such as Bhojraj et al. (2017) and Glosten et al. (2020) make use of the Fama and MacBeth (1973) method of two pass regression, the dominant method applies fixed effects panel data models to model the data (Huang et al., 2018; Israeli et al., 2017; Li et al., 2018; Li & Zhu, 2018; Wermers & Xue, 2015; White, 2018).

The two pass regression method has the advantage of allowing for beta-estimates to vary over time (Cochrane, 2009), and is also simple to implement, which results in it being widely used in financial literature. This method estimates cross-sectional regressions for each time period in the study in the first pass, in order to obtain the parameter estimates. These are then utilised in a time series regression in the second pass, to estimate the final parameters, alongside assessing their statistical significance. The key disadvantage of this method however, is the Error-in-variables (EIV) problem which arises, from making use of estimated coefficients from the first pass as inputs into the second pass regression, rather than making use of true betas (Kan, Robotti, & Shanken, 2013)[65].

The potential for measurement error in the first pass estimation thus results in potentially biased and inconsistent standard errors in the second pass, which inhibits statistical inference. This is off particular concern when residuals are potentially correlated across observations (either firm or time), which is often the case in panel data series. The study by Petersen (2009) finds that the Fama and Macbeth (1973) standard error estimates are only found to be unbiased when there are time effects present in the data, however with firm effects, these estimates are biased downward. In contrast, when accounting for firm effects in panel data, the resultant Newey-West standard errors produced were only slightly biased, and this was thus deemed a more suitable method to account for serial correlation.

The use of panel data estimation methods instead of the two pass regression avoids the errors in variables problem by estimating time-varying regressors in a single step, which are still observable (Skoulakis, 2008). The use of fixed or random effects thereafter assists in accounting for any correlation or serial correlation which exist, either in the cross-section or time-series, or both (Greene, 2001). The key advantages of both fixed and random effects have already been discussed previously in chapter 4 (section 4.3.2). The inherent usability of this model, alongside its extensive use in studies which have the same objective as this chapter, has led to the panel data method being chosen for use. Whilst there are various methods of application, this chapter makes use of both random or fixed effects, as well as Generalised Method of Moments (GMM) to estimate the specified models. This is discoursed further in the ensuing sections, which aim to debate each model and its application in further detail.

5.3.4.1. Random or Fixed effects

The extant literature based on the relationship between informational efficiency and ETF ownership makes use of a fixed effects estimation method (Glosten et al., 2020; Israeli et al., 2017; White, 2018), with studies focused on synchronicity also choosing fixed effects

[65] Fama and Macbeth (1973) and subsequent studies based on this method make use of beta-sorted portfolios to resolve the EIV problem.

estimation as the dominant method (Dong & Wilson, 2019; Gassen et al., 2014; Haghighat et al., 2015). Whilst the inclusion of a time fixed effect allows for the modelling of time trends in the sample (Glosten et al., 2020), the inclusion of a firm fixed effect allows for the modelling of firm-specific variation. The use of random or fixed effects in panel data has been discussed in detail, in section 4.3.2.2 and its merits will therefore will not be repeated. This method is the first estimation method to be applied to equations 5.6 – 5.10, and is consistent with the dominant literature as discussed above. In contrast however, instead of assuming fixed effects, this chapter adopts the approach of using a Hausman test (previously discussed in section 4.3.2.3) to first identify fixed or random effects, after which the preferred model is used in further analysis.

5.3.4.2. Panel GMM estimation

The fixed or random effects models discussed in section 5.3.4.1 are considered static models because they attempt to model contemporaneous relationships between the dependent variable, and the explanatory variables in the model (Brooks, 2019). These models are inference methods based on least squares estimation, and therefore assume strict exogeneity in the regressors. The exogeneity in a regression analysis infers that the explanatory variables are independent from both the dependent variable, as well as the random error component (Greene, 2003). If this assumption is violated, it could lead to inconsistent and biased regression estimates and standard errors, which thus result in incorrect inferences from the data (Baltagi, 2015). Endogeneity therefore exists when explanatory variables and random error term in a regression is correlated and, in firm-level studies, this endogeneity can arise from three possible sources: omitted variable bias, also known as unobserved heterogeneity, simultaneous equation bias and dynamic endogeneity (Abdallah, Goergen, & O'Sullivan, 2015; Wintoki, Linck, & Netter, 2012). A discussion on each of these sources, and its applicability to the objectives of this chapter now follows.

Omitted variable bias arises when certain explanatory variables should have been included in the estimation model, but are not, either due to lack of data availability, difficulty in quantifying the variable, or due to the trade-off between explanatory variables and degrees of freedom in a model (Roberts & Whited, 2011). The effect of these omitted (unobserved) variables is therefore captured in the random error term of the equation, however, there is then a possibility that this unobserved explanatory variable is correlated to one of the observed explanatory variables, which thus results in a correlation between the error term and the explanatory variables (Schultz, Tan, & Walsh, 2010). This issue is commonly referred to in the literature as unobserved heterogeneity (Wintoki et al., 2012).

Whilst the use of relevant control variables in the models is a possible way to avoid this bias, the number of variables to include should be moderated against the trade-off with degrees of freedom. In addition, sometimes variables are difficult to measure, or find proxies for, which leads to their omission (Barros et al., 2020). The discussion on the earnings-return relationship that is modelled in equation 5.7 and 5.8 has many different possible control variables in the literature, some of which could not be included in this chapter due to data availability. Thus, the possibility of this chapter suffering from omitted variable bias is acknowledged.

Simultaneous equations bias occurs when the independent variables in the equation cause changes in the dependent variable, but there is a possibility that the changes in the dependent variable also has an impact on the independent variables (Roberts & Whited, 2011). The estimation models represented in equations 5.7 and 5.8 present the contemporaneous and forecasted relationships between earnings and stock returns. Whilst the predominant literature finds evidence of earnings impacting stock returns (Ball & Brown, 1968; Ball, Kothari, & Robin, 2000; Dimitropoulos & Asteriou, 2009; Kothari & Zimmerman, 1995), there is some evidence that documents the possibility of stock returns impacting earnings as well (Akarim, Celik, & Zeytinoglu, 2012; Lopes & Procianoy, 2008; O'hanlon, 1991). This possibility of a bidirectional relationship therefore results in a further bias of utilizing least squares estimations of the panel data.

Dynamic endogeneity occurs when the current value of a particular variable, is influenced by its values in previous time periods (Schultz et al., 2010). Persistence in returns, which is the dependent variable in equation 5.7, has been documented by the studies of Chowdhury, Rahman, and Sadique (2017), Fusthane and Kapingura (2017), Rupande, Muguto, and Muzindutsi (2019) and Reschenhofer, Mangat, Zwatz, and Guzmics (2020). In addition, when evaluating firms and their information environments, there is a possibility that whilst a firm’s current actions affect its current control environment, and future returns, which also impacts on its future control environment. This is an additional source of dynamic endogeneity identified by Durlauf and Quah (1999) as well as Asada, Chen, Chiarella, and Flaschel (2006).

The simultaneous equations bias can be addressed empirically by the use of Two-stage Least Squares (2SLS), or Three-Stage Least Squares (3SLS), however these methods require the use of a large number of exogenous instruments which make the practicality of this approach questionable for certain studies (Abdallah et al., 2015). Greene (2001) documents that the panel data fixed effects model can be useful in accounting for individual heterogeneity between the different firms in the cross-section, a suggestion that is supported by Yermack (1996) and Himmelberg, Hubbard, and Palia (1999). However, this method only yields robust parameter estimates when the unobserved variable is constant over time for each individual firm, which is only feasible for panels which are wide in cross-section, but short in time series (Petersen, 2009). In addition, this method is only appropriate for datasets where the endogeneity is caused solely by the unobserved heterogeneity, and the sample is not subject to dynamic endogeneity or simultaneous equations bias (Ahn & Schmidt, 1999; Schultz et al., 2010). In this sample, where the endogeneity is likely due to multiple factors, as discussed previously, this method may not be sufficient to capture the dynamics of the data, and ensure correct statistical inferences. The dominant literature on ETF impacts on information efficiency make use of Fixed effects estimation techniques, however this may present a key disadvantage of ignoring the endogeneity issues in the data.

The Generalised Method of Moments (GMM) estimation method was developed by Hansen (1982) as a method of allowing for dynamic modelling, which is the inclusion of one or more lags of the dependent variable in the model (Barros et al., 2020). This approach is considered effective in controlling for all three sources of endogeneity (Abdallah et al., 2015), in contrast to the methods discussed previously which could only control for one source. A simplified linear dynamic model of equation 5.7, with p lags of the dependent variable, would take the following form:

$$R_{i,t} = \gamma_{0,t} + \alpha_p \sum_1^p R_{i,t-p} + \gamma_{x,t} X_{i,t} + (v_i + u_{it}), \ p>0 \tag{5.11}$$

Where: $X_{i,t}$ represents a (15x1) vector of explanatory variables as discussed in section 5.3.2, u_{it} represents an observed firm effect which varies across time and cross-sections, and v_i captures the time-invariance firm-specific effect.

By its very construction, the residual variable (ε_{it}) which aims to capture all unobserved panel effects in the model, will be correlated with the lagged return series, thus making estimation using standard estimators inconsistent. The solution presented by Anderson and Hsiao (1981, 1982) is to use additional lags of the dependent variable, or a differenced dependent variable as instruments in their IV estimation technique. Arellano and Bond (1991) therefore build on this idea, as well as the framework presented by Holtz-Eakin, Newey, and Rosen (1988) to include more instrumental variables under Hansen's (1982) GMM method.

The authors therefore indicate that the instruments variables in equation 5.11 can include lags of the return variable, lags of the independent variables, as well as lags of the endogenous variables in the model, alongside first differences of the variables which are strictly exogenous. Whilst the usage of first-differences allows for the elimination of unobserved firm-specific effects, the use of lagged variables in the differenced equations eliminates the impact of simultaneity bias (Blundell & Bond, 1998). These instrumental variables form a large matrix of instruments, which is then used by Arellano and Bond (1991) to develop a one-step and two-step GMM estimation procedure. The inherent design of this method has led to it also being known as GMM difference estimation. The inclusion of instrumental variables from within the system itself, without the need to identify further external instruments, provides a key advantage of this method (Wintoki et al., 2012).

The first-differenced form of equation 5.11 will therefore take the form of equation 5.12, which eliminates the impact of the time-invariant unobserved heterogeneity (v_i).

$$\Delta R_{i,t} = \gamma_{0,t} + \alpha_{pt} \sum_{1}^{p} \Delta R_{i,t-p} + \gamma_{x,t} \Delta X_{i,t} + \Delta u_{it}, \quad p > 0 \tag{5.12}$$

The weakness of the above approach however, is that there is generally a weak correlation between the variables in their level form, and the first-differenced version shown in equation 5.12 (Ahn & Schmidt, 1995; Blundell & Bond, 1998). This therefore results in weak instruments, and could decrease the explanatory power of the tests employed (Arellano & Bover, 1995). Blundell and Bond (1998) note that this issue is particularly important in samples where persistence in the series is noted. This then led to the development of System GMM by Blundell and Bond (1998), which aims to improve the GMM estimation procedure, by also including the instrument variables in levels in the differenced equation, which will take the form of equation 5.13 below:

$$\begin{bmatrix} R_{i,t} \\ \Delta R_{i,t} \end{bmatrix} = \gamma_{0,t} + \alpha_{pt} \begin{bmatrix} R_{i,t-p} \\ \Delta R_{i,t-p} \end{bmatrix} \gamma_{x,t} \begin{bmatrix} X_{i,t} \\ \Delta X_{i,t} \end{bmatrix} + \Delta u_{it} \tag{5.13}$$

The estimation of equations 5.11 and 5.13 can occur using a one-step or two-step estimation procedure (Arellano & Bond, 1991). The one-step estimation method assumes that the u_{it} are homoscedastic and independent across cross-section, and over time (Cole, Moshirian, & Wu, 2008). The two-step estimator however, allows for heteroscedasticity in the residuals, and instead uses the residuals from the first step to estimate a consistent variance-covariance matrix[66]. Theoretically, therefore, the two-step estimator is more efficient in the presence of heteroscedasticity, and its application generates more efficient estimates and increases the power of the accompanying statistical tests (Hwang & Sun, 2018). Simulation studies of the efficiency of the two estimators however, have found evidence that even in the presence of heteroscedasticity, the efficiency gains from a two-step procedure as opposed to a one-step is minimal. These studies also report that the standard errors produced in a two-step method is biased downward when there are a large number of instruments included in the analysis, and the sample size is small (Roodman, 2009).

This issue is resolved by Windmeijer (2005), who devised a method of correcting the resultant standard errors in a small sample, and thus improving the results from a two-step estimation. Furthermore, Roodman (2009) documents that if the recent observation for any variable in the model is missing, the use of a first difference transformation in the one-step estimation

[66] Whilst the one-step estimation utilises first-difference transformation, the two-step procedure makes use of second-order transformation (Ullah, Akhtar, & Zaefarian, 2018).

procedure will result in the loss of too many data points[67]. Arellano and Bover (1995) therefore suggest the use of the two-step GMM estimation, to avoid this loss of data in a balanced panel. The use of a two-step, system GMM estimation is therefore applied in this chapter, to the estimation equations specified in section 5.3.3, as this approach is largely considered superior, and is therefore favoured by empirical studies (Antoniou, Guney, & Paudyal, 2008; De Andres & Vallelado, 2008; Erickson & Whited, 2002).

The consistency of equation 5.13 is dependent on the condition that $E[\Delta u_{it}\Delta u_{it}] = 0$, therefore Arellano and Bond (1991) suggest an AR test for autocorrelation in the residuals. In addition, usage of the Sargan-Hansen test is necessary to test for the validity of the instruments used in the GMM analysis. These two tests are detailed in the ensuing sub-section.

5.3.4.3. Panel GMM Specification tests

There are two important tests to evaluate the validity of the GMM estimation, which are the Sargan-Hansen tests, as well as the AR test for autocorrelation of residuals. Each of these are now detailed further:

- Sargan-Hansen Test

The system GMM, as discussed previously, uses multiple lags of the included variables as instruments. A further critical assumption underlying the GMM estimation, is that each instrument selected is exogenous, and thus not correlated to the residuals. Each instrumental variable selected for a GMM estimation corresponds to a moment, or orthogonality condition (L) which must be satisfied (Baum, Schaffer, & Stillman, 2003). When L becomes greater than the number of endogenous variables in the system (K), the equation will be considered over-identified, as there are more equations in the system than unknown variables. The J statistic, which was first developed by Sargan (1958) and later extended to the GMM context by Hansen (1982), is the diagnostic test for over-identifying restrictions, and is a joint test of the orthogonality conditions, as well as the suitability of the model specification (Pesaran, 2015).

[67] The one-step GMM estimation procedure involves subtracting the lagged value of a variable from the current value, in an attempt to remove endogeneity. The two-step approach in contrast, subtracts the average of all future observations from the current value, and thus limits the loss of data observations.

The Sargan-Hansen test, therefore has a null hypothesis that the instruments in the system satisfy the orthogonality condition, and thus there is no correlation between the instrument variables, and the residuals in the estimation (Baltagi, 2015). This test follows a chi-square distribution ($\chi^2(m-k)$) that has the degrees of freedom equal to m-k (where m represents the number of instruments, and k represents the number of endogenous variables in the system) (Baum et al., 2003). A rejection of the null hypothesis suggests that the instrument variables included were not exogenous, and thus the correct specification of the model has been applied.

- Arellano-Bond test for autocorrelation

As noted previously, the residuals in the GMM estimation are assumed to be uncorrelated. This condition is necessary for the valid instrumentation of the GMM test, therefore Arellano and Bond (1991) suggest an autocorrelation test for the residuals (u_{it}). Whilst the Δu_{it}, by mathematical construction, has a relationship with its Δu_{it-1} as these values are linked by the shared u_{it-1} term, this first-order serial correlation is expected in the differences only (Roodman, 2009). Therefore, the test by Arellano and Bond (2001) ascertains first-order serial correlation in levels, by checking for second-order correlation in the differenced series. The null hypothesis of the Arellano-bond test therefore states that there is no second-order correlation in the first-differenced error terms, and, if the AR(2) coefficient is found to be significant, this implies that the moment conditions applied by the GMM estimation method are not valid (Roodman, 2009). This test therefore provides a further test of the accuracy of applying the GMM estimation method to the empirical model. In their simulation analysis, Arellano and Bond (1991) confirm that their test has greater power than the Sargan-Hansen test described previously. This chapter therefore makes use of both tests to assess the accuracy of the GMM specification.

5.4. DATA ANALYSIS AND RESULTS FOR INFORMATIONAL EFFICIENCY

This section aims to discuss the results from the methodological approaches described previously. The discussion therefore begins with a descriptive analysis, after which the results from the panel GMM estimations will be displayed and critically analysed.

5.4.1. Descriptive Analysis

The statistics in table 5-2 indicate the number of ETFs which were included in the sample over each of the years of the analysis. This table shows that whilst the earlier years of the analysis had fewer ETFs included in the sample, this number increased drastically to the current high of 88 ETFs in 2019. This is largely due to the proliferation, both in the South African ETF market, and in global markets, with an increase in appetite for emerging market assets. A full list of the companies which underlie these ETFs, and a description of how many ETFs each company was included in over the years of the analysis is contained in Appendix B-2 (page 230).This table indicates that whilst some companies in the sample, such as RCL Foods displayed marginal ETF ownership over time, with some periods indicating no ETF ownership at all, other stalwarts such as ABSA group maintained consistent ETF ownership over the years, with recent periods in the same indicating membership in a larger number of ETFs.

Table 5-2: Number of ETFs in the sample over time

Period	Number of ETFs included in the Sample
2008	14
2009	21
2010	25
2011	27
2012	36
2013	40
2014	48
2015	52
2016	61
2017	71
2018	82
2019	88

Source: Own estimation (2020)

Table 5-3: Sample descriptive statistics

Panel A: Univariate Statistics

Variable	**N**	**Mean**	**Std deviation**	**Min**	**Max**
Return	3994	0,0099	0,167	-2,558	1,224
ETF ownership	3994	0,7107	0,9793	-3,085	18
ETF trading activity	3994	0,0301	0,6276	-14,03	17,07
Institutional ownership	3994	52,28	0,2263	5,12	95,95
Synchronicity	3994	-1,669	0,566	-4,608	0
Earnings	3994	0,0077	0,0977	-1,816	1,463
ln(Size)	3994	23,66	1,539	0	28,29
ln(MTB)	3994	2,466	2,552	-3,766	60,289
ln(Std_dev)	3994	2,046	0,984	0,117	4,354

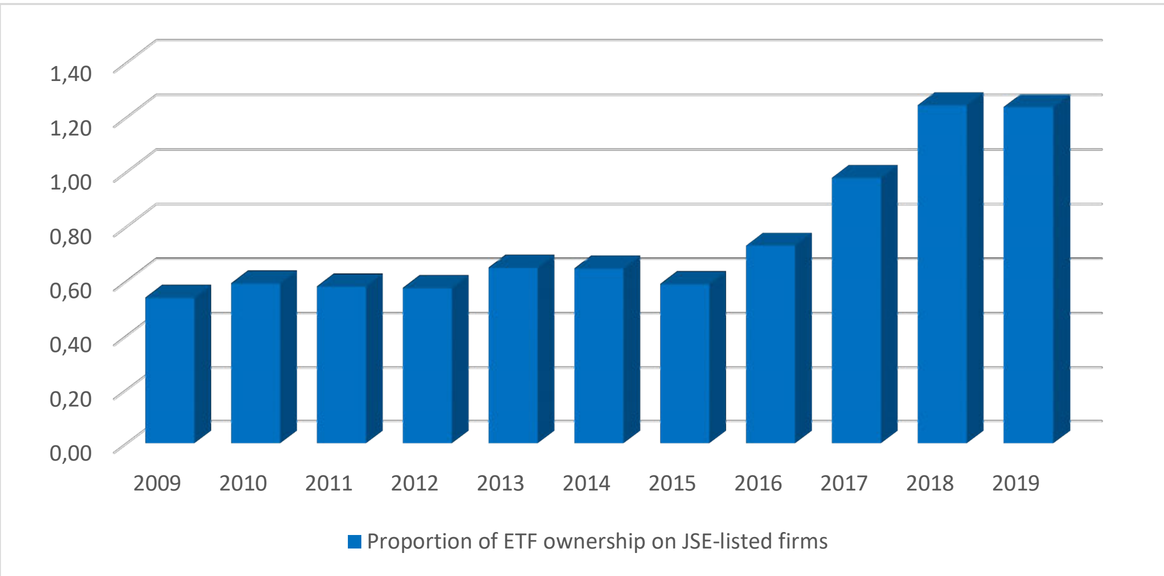
Panel B: Correlation matrix for level variables

	ETF own	**Synch**	**Size**	**MTB**	**Std dev**	**Return**	**Earnings**
ETF ownership	1.00						
Synch	0,0033	1.00					
Size	0,258***	0,0491**	1.00				
MTB	0,0996***	-0,012	0,2099***	1.00			
Std dev	0,101***	-0,018	-0,102***	-0,037	1.00		
Return	-0,0192	0,0187	0,0817***	0,1063	-0,0175	1.00	
Earnings	-0,0261*	0,0357**	0,0039	-0,0019	-0,0038	0,0789***	1.00

*'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.*

Source: Own estimation (2020)

Figure 5-1: Average percentage of ETF ownership for the sample of firms, over the period of 2009 - 2019



Source: Own construction (2020)

Table 5-3 indicates the descriptive statistics of the variables used in the sample, whilst Figure 5-1 shows the average ETF ownership represented in the sample of underlying firms. These statistics are also supported by Appendix B-3 (page 234), which contains a firm analysis of institutional and ETF ownership over the sample period. The results in table 5-3 (panel A) indicate that whilst the average institutional ownership of firms over the sample period is 52,28 percent, with one company exhibiting a maximum of 95,95 percent, the average ETF ownership in the sample is much lower, with an average of just 0,71 percent. This result is reinforced by the growth in ETF ownership shown in Figure 1-2, in which the proportion of ETF ownership in the sample firms displays levels below 1 percent before 2017, with ownership at the end of 2019 being a current level of 1,2 percent only. However, whilst the average is low, the highest proportion of a company at one point in time that was invested in ETFs, is 18 percent- which is 1/5th of the total shares of the firm, and represents a significant portion of a single firm, to be "locked up" in ETF ownership. These results are comparative to international studies, such as Israeli et al. (2017), whose average ETF ownership (in his sample of 4184 US firms between 2000 - 2014) amounts to 3,31 percent, whilst the associated value for institutional ownership is 57,78 percent. Similarly, Glosten et al. (2020) record an average ETF ownership of 3.6 percent over their sample period of 2004 – 2013. The relative youth of the ETF market is evidenced by these results, with the South African ETF market displaying ETF ownership levels that were noted in the early period of these authors' analysis (ETF ownership in the US market was approximately 1,2 percent in 2004 according to Glosten et al. (2020)).

The results in panel A of Table 5-3 further show that there is considerable variation of the size of the firm included in the analysis, which is reinforced by the firm-level statistics in appendix B-3 (page 234). The firms are also seen to exhibit considerable variation in returns earned over the sample period (with a range of -2.558 and 1,224), as well as synchronicity (with a range of -4,608 and 0). The latter result indicates that whilst some firms in the sample display high levels of co-movement with market returns, other firms have no co-movement at all. The correlation matrix in table 5-3 (panel B) indicates a very low correlation between ETF ownership and synchronicity, which is found to be statistically significant. In contrast, the ETF ownership variable displays positive, and statistically significant correlations with the size and MTB variables, and a negative, statistically significant correlation with the earnings variable.

5.4.2. Informational efficiency test results (as measured by FERC)

5.4.2.1. Impact of ETF ownership on FERC

The first objective of this chapter is an evaluation of the impact of ETF ownership on information efficiency of its underlying assets, as measured by FERC, which coincides with equation 5.7. The preliminary Hausman tests all indicate presence of fixed effects in the panel data, the results of which are tabulated in Appendix B-4 (page 238). Therefore, the fixed effects estimation method (with two-way effects) was estimated alongside the GMM estimation method for different specifications of equation 5.7, to provide results for the first objective of this chapter. The results of both estimation procedures are shown in tables 5-4 and 5-5 respectively.

The main variables in the regression are the interaction variables between ETF ownership and past, present and future earnings variables, and if a statistically significant positive coefficient is found, this indicates an improvement in information efficiency. These interaction terms are in boldface in the tables for ease of reference. Interestingly, none of the ERC or FERC coefficients are found to be statistically significant in both tables, which indicates no significant market response to earnings announcements. However, the interaction variables (between the ERC and ETF ownership) do display some level of statistical significance, which may indicate that any changes in earnings announcements for individual firms is captured first in the ETF. This result therefore lends support to the hypotheses of Glosten et al. (2020) and Li et al. (2018), who assert that the ETF market is the preferred market for trade.

The results produced for both estimation techniques (in table 5-4 and 5-4) provides evidence of no relationship between ETF ownership and contemporaneous earnings – as the interaction variables ($Earnings_{i,t}$ x $ETF_{i,t}$) are all statistically insignificant. In contrast the interaction variables which use both lagged and future earnings are found to be statistically significant and positive, in most equation specifications, for both estimation methods. Whilst one would expect that lagged earnings are already incorporated into the asset prices, the results for the future earnings response coefficient indicates that once a company is included in an ETF, the future earnings information will reflect quicker in current returns, which indicates a positive impact of ETF ownership on information efficiency. This finding is robust to both the fixed effects and GMM estimation methods, which indicates strong evidence that the ETFs in the sample have positively impacted on the informational efficiency of their underlying firms.

Table 5-4: Fixed effect panel regression of ETF ownership and FERC

VARIABLES	(1)	(2)	(3)	(4)	(5)
$Earnings_{i,t}$		0.0868			0.00223
		(0.106)			(0.113)
$Earnings_{i,t}$ x $ETF_{i,t}$	**-0.0320**	**-0.0540**			**-0.0868**
	(0.0493)	**(0.0888)**			**(0.0943)**
$Earnings_{i,t-1}$		0.00799	-0.0198		-0.0150
		(0.0451)	(0.0615)		(0.0406)
$Earnings_{i,t-1}$ x $ETF_{i,t}$	**0.0664****	**0.0855****	**0.0849*****		**0.0924****
	(0.0271)	**(0.0337)**	**(0.0308)**		**(0.0353)**
$Earnings_{i,t+1}$		0.0644		0.0586	0.0526
		(0.0824)		(0.0645)	(0.0856)
$Earnings_{i,t+1}$ x $ETF_{i,t}$	**0.222*****	**0.174**		**0.141*****	**0.172**
	(0.0685)	**(0.110)**		**(0.0504)**	**(0.110)**
$\Delta ETF_{i,t}$	0.0116	0.0135**	0.0115**	0.0156**	0.0129*
	(0.00882)	(0.00657)	(0.00495)	(0.00724)	(0.00708)
$Size_{i,t-1}$			-0.0498***	-0.0487***	-0.0475***
			(0.0155)	(0.0163)	(0.0155)
$MTB_{i,t-1}$			-0.00220	-0.00234	-0.00222
			(0.00223)	(0.00230)	(0.00203)
$STD_{i,t-1}$			-0.0112***	-0.0112***	-0.0107***
			(0.00308)	(0.00301)	(0.00296)
$Loss_{i,t-1}$			-0.0804***	-0.0765***	-0.0758***
			(0.0179)	(0.0183)	(0.0178)
$\Delta IS_{i,t}$	0.000135		0.000192	0.000170	0.000174
	(0.000236)		(0.000215)	(0.000226)	(0.000240)
$Earnings_{i,t}$ x $Loss_{i,t}$			0.161*	0.116	0.131**
			(0.0844)	(0.0911)	(0.0622)
$ETF_{i,t-1}$	-0.00379		-0.00138	-0.000981	-0.000951
	(0.00562)		(0.00360)	(0.00354)	(0.00383)
$R_{i,t-1}$		0.0795***			0.0278
		(0.0281)			(0.0339)
Constant	0.316***	0.00881***	1.283***	1.260***	1.221***
	(0.0585)	(0.000437)	(0.252)	(0.263)	(0.270)
Observations	3,990	3,990	3,992	3,990	3,990
R-squared	0.024	0.024	0.061	0.064	0.066
Number of id	94	94	94	94	94

Table 5-4 presents the results from a two-way fixed effects estimation of the following equation: $R_{i,t} = \gamma_{0,t} + \gamma_{1,t}Earnings_{i,t} + \gamma_{2,t}(Earnings_{i,t} \times ETF_{i,t}) + \gamma_{3,t}Earnings_{i,t-1} + \gamma_{4,t}(Earnings_{i,t-1} \times ETF_{i,t}) + \gamma_{5,t}Earnings_{i,t+1} + \gamma_{6,t}(Earnings_{i,t+1} \times ETF_{i,t}) + \gamma_{7,t}\Delta ETF_{i,t} + \gamma_{8,t}SIZE_{i,t-1} + \gamma_{9,t}MTB_{i,t-1} + \gamma_{10,t}STD_{i,t-1} + \gamma_{11,t}Loss_{i,t} + \gamma_{12,t}\Delta IS_{i,t} + \gamma_{13,t}(Earnings_{i,t} \times Loss_{i,t}) + \gamma_{14,t}ETF_{i,t-1} + \gamma_{15,t}R_{i,t+1} + \varepsilon_{it}$. All variables are defined in Table 5-1 (page 163). Robust standard errors are reported in parentheses. The coefficient on the time variable is excluded for brevity. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Source: Own estimation (2020)

Table 5-5: GMM estimation of ETF ownership and FERC

VARIABLES	(1)	(2)	(3)	(4)	(5)
$R_{i,t-1}$	0.0670***	0.0630***	0.0642***	0.0624***	0.0601***
	(0.0196)	(0.0206)	(0.0205)	(0.0209)	(0.0213)
$Earnings_{i,t}$ (ERC)		0.0519			0.0175
		(0.270)			(0.112)
$Earnings_{i,t}$ x $ETF_{i,t}$	**-0.0234**	**-0.0312**			**-0.0933**
	(0.0556)	**(0.196)**			**(0.0971)**
$Earnings_{i,t-1}$		0.00272	-0.0228		-0.0238
		(0.0732)	(0.0478)		(0.0329)
$Earnings_{i,t-1}$ x $ETF_{i,t}$	**0.0553****	**0.0679**	**0.0735****		**0.0859****
	(0.0263)	**(0.0674)**	**(0.0309)**		**(0.0357)**
$Earnings_{i,t+1}$ (FERC)		0.0738		0.0620	0.0530
		(0.123)		(0.0537)	(0.0764)
$Earnings_{i,t+1}$ x $ETF_{i,t}$	**0.211*****	**0.152**		**0.135****	**0.173**
	(0.0722)	**(0.166)**		**(0.0562)**	**(0.113)**
$\Delta ETF_{i,t}$	0.0157***	0.0162***	0.0147***	0.0184***	0.0154**
	(0.00581)	(0.00558)	(0.00440)	(0.00611)	(0.00611)
$Size_{i,t-1}$			-0.00623*	-0.00636*	-0.00591*
			(0.00336)	(0.00343)	(0.00318)
$MTB_{i,t-1}$			-0.00359***	-0.00349***	-0.00318***
			(0.00116)	(0.00116)	(0.00116)
$STD_{i,t-1}$			-0.00443	-0.00473*	-0.00444
			(0.00281)	(0.00280)	(0.00268)
$Loss_{i,t-1}$			-0.0732***	-0.0704***	-0.0683***
			(0.0153)	(0.0148)	(0.0141)
$\Delta IS_{i,t}$	5.59e-05		4.51e-05	3.57e-05	6.04e-05
	(0.000249)		(0.000245)	(0.000246)	(0.000241)
$Earnings_{i,t}$ x $Loss_{i,t}$			0.157*	0.108	0.122**
			(0.0842)	(0.0903)	(0.0505)
$ETF_{i,t-1}$	-0.00246		-0.000869	-0.000295	-0.000424
	(0.00333)		(0.00250)	(0.00284)	(0.00301)
$R_{i,t-1}$		0.0472			0.0251
		(0.0292)			(0.0290)
Constant	0.426***	0.403***	0.543***	0.547***	0.518***
	(0.0561)	(0.0463)	(0.0768)	(0.0773)	(0.0804)
Observations	3,897	3,897	3,899	3,897	3,897
Number of id	94	94	94	94	94
Hansen P-value	0.215	0.520	0.285	0.907	0.729
AR (2) P-value	0.844	0.250	0.830	0.256	0.345

Table 5-5 presents the results from Hansen's (1982) optimal two-stage GMM estimation of the following equation: $R_{i,t} = \gamma_{0,t} + \gamma_{1,t}Earnings_{i,t} + \gamma_{2,t}(Earnings_{i,t} \times \Delta ETF_{i,t}) + \gamma_{3,t}Earnings_{i,t-1} + \gamma_{4,t}(Earnings_{i,t-1} \times \Delta ETF_{i,t}) + \gamma_{5,t}Earnings_{i,t+1} + \gamma_{6,t}(Earnings_{i,t+1} \times \Delta ETF_{i,t}) + \gamma_{7,t}\Delta ETF_{i,t} + \gamma_{8,t}SIZE_{i,t-1} + \gamma_{9,t}MTB_{i,t-1} + \gamma_{10,t}STD_{i,t-1} + \gamma_{11,t}Loss_{i,t} + \gamma_{12,t}\Delta IS_{i,t} + \gamma_{13,t}(Earnings_{i,t} \times Loss_{i,t}) + \gamma_{14,t}ETF_{i,t-1} + \gamma_{15,t}R_{i,t+1} + \varepsilon_{it}$. All variables are defined in Table 5-1 (page 163). Standard errors are reported in parentheses. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Source: Own estimation (2020)

The control variables ($MTB_{i,t-1}$, $Size_{i,t-1}$, $STD_{i,t-1}$ and $Loss_{i,t-1}$) all exhibit the expected negative coefficients, and are consistent with the South African literature on the growth (Basiewicz & Auret, 2009; Rensburg & Robertson, 2003; Vermeulen, 2016) and size effects (Basiewicz & Auret, 2009; McKane & Britten, 2018; Rensburg & Robertson, 2003), as captured by the $MTB_{i,t-1}$ and $Size_{i,t-1}$ variables respectively. The negative coefficient on the interaction variable between Earnings and Loss is also consistent with previous literature (Basu, 1997; Hayn, 1995). In addition, the Lagged ETF ownership ($ETF_{i,t-1}$) variable is found to be statistically insignificant in the determination of returns, in a result which indicates that prior ETF ownership has no impact on current returns, and is consistent with the findings of Israeli et al. (2017) and Glosten et al. (2020). The $\Delta ETF_{i,t}$ variable however, which captures ETF trading activity during quarter t, is found to be statistically significant and positive, in both estimations. This indicates that the trading activity from ETFs is positively correlated to stock returns, and that an increase in ETF activity will also result in increased returns. This result, when viewed in conjunction with the statistically significant, positive interaction variables in the study, provides strong evidence in support of the hypothesis that fundamental firm-specific information-based trading is conducted in the ETF market first, after which arbitrage trading transfers the information to the actual underlying asset.

An interesting observation is that the $\Delta IS_{i,t}$ variable is found to be statistically insignificant, in all specifications, for both estimation methods. Whilst there is currently no research on the relationship between institutional ownership and returns in the South African market (to the authors knowledge), international studies such as Chuang (2020) have noted that the information flows from institutional investors are gradual, and thus whilst it may have a short-term impact on returns, this reverses in the long-term. In addition, whilst the dominant literature on this topic indicates a positive relationship between Institutional ownership and returns, some studies argue that this only occurs under certain circumstances, such as for shares which exhibit previous high values of return (Grinblatt, Titman, & Wermers, 1995), if a new institutional position is obtained in a share (Badrinath & Wahal, 2002), and for small capitalisation and growth firms (Yan & Zhang, 2009). The finding of an insignificant $\Delta IS_{i,t}$ variable therefore may be a confirmation of the hypothesis developed by Hong and Stein (1999), who assert that the entry or exit into a stock by institutional investors conveys greater information than rebalancing of their ongoing holdings, due to the constraints on short sales.

In addition, the results from the GMM equation in table 5-5 indicates a statistically significant lagged return variable, which provides evidence of dynamic endogeneity being present in returns. The resultant p-values from the AR(2) are all greater than alpha at the 1 percent level of significance, which indicates that there is no presence of serial correlation at the second lag, which satisfies the assumption of exogeneity. Furthermore, the p-values of the Hansen test is also greater than alpha at the 1 percent level of significance, which provides further evidence that the instruments implemented in the GMM estimation are valid, and reinforces the accuracy in the choice of a two-step system GMM model for this analysis.

The results thus far therefore provides preliminary evidence that the ETF market in South Africa may be the preferred one for investors, and that this ETF membership results in positive effects for the underlying assets. This result of improved market microstructure is consistent with the results of the US-based studies conducted by Yu (2005), Huang et al. (2018), White (2018) and Glosten et al. (2020). This result could lead to the expectation that changes in ETF trading activity also significantly impacts the ERC and FERC coefficients, which is investigated further in the ensuing section.

5.4.2.2. Impact of ETF trading activity on FERC

The second objective of this chapter aimed to evaluate the impact of ETF trading activity on information efficiency in the underlying assets (as measured by FERC). The results of the FE and GMM estimations of equation 5.8 are displayed in tables 5-6 and 5-7 respectively. The results produced indicate that, similar to the ETF ownership results, the control variables in the equation all display the expected signs. However, whilst the $MTB_{i,t-1}$ variable was significant in the previous analysis, this variable is found to be insignificant when modelled alongside ETF trading activity. In addition, the results from the AR(2) and Hansen test also indicate validity of the instruments in the GMM specification. Furthermore, table 5-7 also indicates statistically significant lagged returns, which finds further evidence in favour of the GMM estimation technique.

Table 5-6: Fixed effect panel regression of ETF activity and FERC

VARIABLES	(1)	(2)	(3)	(4)	(5)
$Earnings_{i,t}$		0.0804			-0.00619
		(0.0899)			(0.0969)
$Earnings_{i,t}$ x $\Delta ETF_{i,t}$	**0.0177**	**0.0428**			**0.0339**
	(0.0944)	**(0.104)**			**(0.106)**
$Earnings_{i,t-1}$		0.0264	0.000507		0.00497
		(0.0457)	(0.0608)		(0.0425)
$Earnings_{i,t-1}$ x $\Delta ETF_{i,t}$	**0.244**	**0.188**	**0.205***		**0.177**
	(0.149)	**(0.150)**	**(0.116)**		**(0.162)**
$Earnings_{i,t+1}$		0.103		0.0940	0.0902
		(0.0643)		(0.0586)	(0.0668)
$Earnings_{i,t+1}$ x $\Delta ETF_{i,t}$	**0.0259**	**0.0129**		**0.0143**	**0.00443**
	(0.0280)	**(0.0345)**		**(0.0209)**	**(0.0351)**
$\Delta ETF_{i,t}$	0.00789	0.0148**	0.0111**	0.0121**	0.0131*
	(0.00749)	(0.00667)	(0.00463)	(0.00608)	(0.00690)
$Size_{i,t-1}$			-0.0485***	-0.0486***	-0.0467***
			(0.0155)	(0.0158)	(0.0154)
$MTB_{i,t-1}$			-0.00229	-0.00233	-0.00222
			(0.00224)	(0.00227)	(0.00203)
$STD_{i,t-1}$			-0.0108***	-0.0110***	-0.0104***
			(0.00311)	(0.00302)	(0.00315)
$Loss_{i,t-1}$			-0.0809***	-0.0788***	-0.0766***
			(0.0177)	(0.0188)	(0.0177)
$\Delta IS_{i,t}$	0.000173		0.000235	0.000146	0.000200
	(0.000251)		(0.000229)	(0.000221)	(0.000248)
$Earnings_{i,t}$ x $Loss_{i,t}$			0.156*	0.113	0.114*
			(0.0854)	(0.0933)	(0.0665)
$ETF_{i,t-1}$	-0.0105***		-0.00582	-0.00319	-0.00502
	(0.00368)		(0.00440)	(0.00355)	(0.00512)
$R_{i,t-1}$		0.0628**			0.0274
		(0.0275)			(0.0341)
Constant	0.311***	0.309***	1.250***	1.255***	1.201***
	(0.0596)	(0.0493)	(0.254)	(0.256)	(0.272)
Observations	3,990	3,990	3,992	3,990	3,990
R-squared	0.019	0.032	0.061	0.062	0.065
Number of id	94	94	94	94	94

Table 5-6 presents the results from a two-way fixed effects estimation of the following equation: $R_{i,t} = \gamma_{0,t} + \gamma_{1,t}Earnings_{i,t} + \gamma_{2,t}(Earnings_{i,t} \times \Delta ETF_{i,t}) + \gamma_{3,t}Earnings_{i,t-1} + \gamma_{4,t}(Earnings_{i,t-1} \times \Delta ETF_{i,t}) + \gamma_{5,t}Earnings_{i,t+1} + \gamma_{6,t}(Earnings_{i,t+1} \times \Delta ETF_{i,t}) + \gamma_{7,t}\Delta ETF_{i,t} + \gamma_{8,t}SIZE_{i,t-1} + \gamma_{9,t}MTB_{i,t-1} + \gamma_{10,t}STD_{i,t-1} + \gamma_{11,t}Loss_{i,t} + \gamma_{12,t}\Delta IS_{i,t} + \gamma_{13,t}(Earnings_{i,t} \times Loss_{i,t}) + \gamma_{14,t}ETF_{i,t-1} + \gamma_{15,t}R_{i,t+1} + \varepsilon_{it}$, All variables are defined in Table 5-1 (page 163). Robust standard errors are reported in parentheses. The coefficient on the time variable is excluded for brevity. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Source: Own estimation (2020)

Table 5-7: GMM estimation of ETF activity and FERC

VARIABLES	(1)	(2)	(3)	(4)	(5)
$R_{i,t-1}$	0.0680***	0.0622***	0.0616***	0.0653***	0.0590***
	(0.0194)	(0.0218)	(0.0209)	(0.0211)	(0.0222)
$Earnings_{i,t}$		0.0748			0.00504
		(0.0916)			(0.0959)
$Earnings_{i,t}$ x $\Delta ETF_{i,t}$	**0.0406**	**0.0623**			**0.0240**
	(0.0980)	**(0.104)**			**(0.108)**
$Earnings_{i,t-1}$		0.0116	-0.00365		-0.00465
		(0.0397)	(0.0491)		(0.0351)
$Earnings_{i,t-1}$ x $\Delta ETF_{i,t}$	**0.204**	**0.156**	**0.199***		**0.180**
	(0.131)	**(0.130)**	**(0.108)**		**(0.153)**
$Earnings_{i,t+1}$		0.0979		0.0964*	0.0931
		(0.0619)		(0.0493)	(0.0583)
$Earnings_{i,t+1}$ x $\Delta ETF_{i,t}$	**0.0144**	**0.00281**		**0.0112**	**0.00471**
	(0.0327)	(0.0391)		(0.0265)	(0.0393)
$\Delta ETF_{i,t}$	0.0137**	0.0180***	0.0150***	0.0155***	0.0164**
	(0.00637)	(0.00603)	(0.00458)	(0.00540)	(0.00683)
$Size_{i,t-1}$			-0.00554*	-0.00607*	-0.00528*
			(0.00331)	(0.00328)	(0.00297)
$MTB_{i,t-1}$			-0.00353***	-0.00344***	-0.00318***
			(0.00120)	(0.00114)	(0.00120)
$STD_{i,t-1}$			-0.00435	-0.00459	-0.00411
			(0.00285)	(0.00277)	(0.00281)
$Loss_{i,t-1}$			-0.0747***	-0.0724***	-0.0706***
			(0.0153)	(0.0152)	(0.0144)
$\Delta IS_{i,t}$	8.12e-05		7.74e-05	8.72e-06	7.29e-05
	(0.000262)		(0.000258)	(0.000246)	(0.000251)
$Earnings_{i,t}$ x $Loss_{i,t}$			0.154*	0.106	0.109*
			(0.0840)	(0.0932)	(0.0555)
$ETF_{i,t-1}$	-0.00616*		-0.00355	-0.00168	-0.00326
	(0.00312)		(0.00291)	(0.00244)	(0.00343)
$R_{i,t-1}$		0.0460			0.0243
		(0.0293)			(0.0293)
Constant	0.431***	0.414***	0.531***	0.538***	0.499***
	(0.0575)	(0.0458)	(0.0781)	(0.0751)	(0.0815)
Observations	3,897	3,897	3,899	3,897	3,897
Number of id	94	94	94	94	94
Hansen P-value	0.219	0.266	0.273	0.848	0.655
AR(2) P-value	0.722	0.474	0.789	0.257	0.332

Table 5-7 presents the results from Hansen's (1982) optimal two-stage GMM estimation of the following equation: $R_{i,t} = \gamma_{0,t} + \gamma_{1,t}Earnings_{i,t} + \gamma_{2,t}(Earnings_{i,t} \times \Delta ETF_{i,t}) + \gamma_{3,t}Earnings_{i,t-1} + \gamma_{4,t}(Earnings_{i,t-1} \times \Delta ETF_{i,t}) + \gamma_{5,t}Earnings_{i,t+1} + \gamma_{6,t}(Earnings_{i,t+1} \times \Delta ETF_{i,t}) + \gamma_{7,t}\Delta ETF_{i,t} + \gamma_{8,t}SIZE_{i,t-1} + \gamma_{9,t}MTB_{i,t-1} + \gamma_{10,t}STD_{i,t-1} + \gamma_{11,t}Loss_{i,t} + \gamma_{12,t}\Delta IS_{i,t} + \gamma_{13,t}(Earnings_{i,t} \times Loss_{i,t}) + \gamma_{14,t}ETF_{i,t-1} + \gamma_{15,t}R_{i,t+1} + \varepsilon_{it}$, All variables are defined in Table 5-1 (page 163). Standard errors are reported in parentheses. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Source: Own estimation (2020)

The main aim of the results in tables 5-6 and 5-7 is to investigate whether ETF trading activity impacts on the informational efficiency of the underlying assets. In contrast to the results produced when evaluating ETF ownership, the results from both tables indicate limited statistically significant ERC/FERC coefficients, and interaction variables (just one specification displays a significant coefficient for the interaction variable between lagged earnings and ETF trading activity). These results therefore show very little indication of ETF trading activity having any impact on the transmission of earnings information. Similar to the results noted in the previous sub-section, the $\Delta ETF_{i,t}$ variable is found to be positive and statistically significant, which thus shows further, that whilst the trading activity of ETFs impacts the return of an asset, it has no bearing on the level of information transfer in the market for the underlying asset.

These results may be an indication that it is not the unique creation and redemption mechanism of ETFs which facilitates information transfer, but rather the ETF membership of the firms. Therefore, the evidence indicates that the inclusion of a firm into an ETF's membership serves to increase awareness about the firm, and it is through this channel that fundamental information is transferred quicker into stock returns. This evidence lends support to Merton's (1987) Investor Recognition hypothesis, which postulated that the introduction of ETFs creates increased awareness for the individual firms. This finding, alongside the insignificant institutional ownership ($\Delta IS_{i,t}$) variables in tables 5-6 and 5-7 may be an indication that the impact of ETF-motivated trade mirrors the associated impact of institutional investors' trade. Therefore, whilst only the initial entry and exit transactions of institutional investors conveys information to the market, any attempts at rebalancing portfolios using creation and redemption activity has no informational effect on the underlying assets.

Whilst the results from the first and second objective find support for ETF ownership increasing information efficiency, this result is produced relative to the FERC coefficient. The use of the synchronicity value was discussed previously as a further robustness test of the results, as this measures captures the systematic portion of information efficiency. The results from the synchronicity tests will therefore be discussed further in section 5.4.3.

5.4.3. Results from Tests of Synchronicity

The third and fourth objective of this chapter aims to analyse the systematic portion of information efficiency, as measured by the synchronicity variable. Whilst the initial intention was to utilise both Fixed effects and GMM estimation techniques, the GMM results produced for this section did not pass the specification tests, and no statistical significance was reported for the lagged values of synchronicity (these results are shown in Appendix B-5 and B-6 (page 238/239). Therefore, only the FE results are indicated here. The results from equation 5.9, which evaluates the impact of ETF ownership on synchronicity, is contained in table 5-8. The results from equation 5.10, which evaluates the impact of ETF trading activity on synchronicity, is reported in table 5-9.

Table 5-8: FE panel estimation of ETF ownership and stock synchronicity

VARIABLES	(1)	(2)	(3)	(4)
$ETF_{i,t}$	**-0.00393**	**0.00193**	**-0.00352**	**-0.00128**
	(0.0138)	**(0.0131)**	**(0.0139)**	**(0.0145)**
$Size_{i,t-1}$		-0.0139	-0.00652	-0.0140
		(0.0175)	(0.0160)	(0.0176)
$MTB_{i,t-1}$		0.000543		0.000641
		(0.00305)		(0.00305)
$STD_{i,t-1}$		-0.0130		-0.0130
		(0.00849)		(0.00860)
$\Delta TURN_{i,t}$		0.262**	0.265**	0.258**
		(0.115)	(0.115)	(0.115)
$ETF_{i,t-1}$	0.00207		0.00309	0.00442
	(0.0112)		(0.0112)	(0.0115)
$\Delta IS_{i,t-1}$	0.000913		0.000864	0.000857
	(0.000818)		(0.000810)	(0.000806)
Constant	-1.669***	-1.317***	-1.515***	-1.317***
	(0.00835)	(0.417)	(0.378)	(0.418)
Observations	3,992	3,992	3,992	3,992
R-squared	0.000	0.001	0.001	0.002
Number of id	95	95	95	95
F-stat	0.420	1.448	1.509	1.258
P-value	0.739	0.215	0.194	0.280

Table 5-8 presents the results from a two-way fixed effects estimation of the following equation: $Sync_{i,t} = b_{0t} + b_{1t}ETF_{i,t} + b_{2t}Size_{i,t-1} + b_{3t}MTB_{i,t-1} + b_{4t}STD_{i,t-1} + b_{5t}ETF_{i,t-1} + b_{6t}\Delta IS_{it-1} + b_{6t}\Delta TURN_{i,t} + \varepsilon$. All variables are defined in Table 5-1 (page 163).. Robust standard errors are reported in parentheses. The coefficient on the time variable is excluded for brevity. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Source: Own estimation (2020)

Table 5-9: FE panel estimation of ETF trading activity and stock synchronicity

VARIABLES	(1)	(2)	(3)	(4)
$\|\Delta \boldsymbol{ETF_{i,t}}\|$	**-0.00747**	**-0.00352**	**-0.00699**	**-0.00810**
	(0.00850)	**(0.00638)**	**(0.00814)**	**(0.00816)**
$Size_{i,t-1}$		-0.0135	-0.00763	-0.0152
		(0.0169)	(0.0159)	(0.0173)
$MTB_{i,t-1}$		0.000517		0.000706
		(0.00303)		(0.00304)
$STD_{i,t-1}$		-0.0127		-0.0133
		(0.00826)		(0.00854)
$\Delta TURN_{i,t}$		0.260**	0.262**	0.255**
		(0.114)	(0.115)	(0.115)
$ETF_{i,t-1}$	0.00249		0.00372	0.00684
	(0.0109)		(0.0110)	(0.0122)
$\Delta IS_{i,t-1}$	0.000918		0.000869	0.000875
	(0.000812)		(0.000803)	(0.000798)
Constant	-1.671***	-1.325***	-1.491***	-1.289***
	(0.00675)	(0.404)	(0.375)	(0.412)
Observations	3,992	3,992	3,992	3,992
R-squared	0.000	0.001	0.001	0.002
Number of id	95	95	95	95
F-stat	0.687	1.456	1.495	1.284
P-value	0.562	0.212	0.199	0.267

Table 5-9 presents the results from a two-way fixed effects estimation of the following equation: $Sync_{i,t} = b_{0t} + b_{1t}|\Delta ETF_{i,t}| + b_{2t}Size_{i,t-1} + b_{3t}MTB_{i,t-1} + b_{4t}STD_{i,t-1} + b_{5t}ETF_{i,t-1} + b_{6t}\Delta IS_{it-1} + b_{6t}\Delta TURN_{i,t} + \varepsilon$. All variables are defined in Table 5-1 (page 163). Robust standard errors are reported in parentheses. The coefficient on the time variable is excluded for brevity. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Source: Own estimation (2020)

Whilst a negative b_{1t} coefficient in table 5-8 would confirm the results of the previous information efficiency analysis (by indicating lower synchronicity levels and therefore increased information efficiency), the results produced indicate no statistically significant relationship between ETF ownership (or ETF trading activity) and return synchronicity. An analysis of the control variables in tables 5-8 and 5-9 indicates that only the Turnover variable exhibits any statistical significance in the model. Since this variable is meant to capture the changes in stock synchronicity which occur due to non-fundamental information, the positive coefficient therefore indicates that non-fundamental information drives increased co-movement between the underlying asset, and the market index. However, this non-fundamental information cannot be attributed to changes in ETF ownership or ETF trading activity, and even though this may be an indication of noise trading in the market for the underlying assets, further analysis is necessary to analyse the sources of this information, which is beyond the scope of this study.

The results found in this chapter are therefore in contrast to the findings of Glosten et al. (2016) and Israeli et al. (2017) who found evidence of a positive relationship between synchronicity and ETF ownership, and White (2018), whose quarterly analysis of large capitalisation US stocks found evidence of negative coefficients. All three of these studies are based in the US market however, with this study being the first one of its kind on the South African market. This therefore indicates, that the indexing of firms into basket securities such as ETFs, has not had any impact on its co-movement with the market, which stands in contrast to previous hypotheses by Wurgler (2010) and Da and Shive (2018), who assert that firms which are included in ETFs, are more correlated to each other as well as the market index. This result, when interpreted in the context of Cong and Xu's (2016) hypothesis, and the results from section 5.4.2, also indicates that whilst the information efficiency of the assets underlying the ETF increases, this is not due to any change in systemic efficiency, and is therefore most likely to be due to increased asset-specific efficiency in the market for the underlying asset.

5.5. DISCUSSION OF INFORMATION EFFICIENCY RESULTS

The results from the analysis conducted, indicates that ETF ownership increases the informational efficiency of the underlying assets, whilst ETF trading has no effect. In addition, the results from the synchronicity analysis indicate that this increase in information efficiency is due to increased asset-specific efficiency, rather than systematic efficiency. The overall results are consistent with the empirical findings of Yu (2005), Huang et al. (2018), Li et al. (2018) and Glosten et al. (2020), all of whom find evidence of improved information efficiency in the market for the underlying asset. In particular, evidence is found in favour of the postulations by Li et al. (2018) and Glosten et al. (2020), who assert that since the ETF market represents the lower cost and easier trade market, the noise traders are attracted to the ETF market, which leaves more informed traders in the market for the underlying asset. Since these informed traders face fewer restrictions to profiting from fundamental information due to the absence of noise traders, this results in greater information efficiency for the underlying assets.

These results are found to be consistent with the theoretical expectations of Merton (1987), Fremault (1991) and Cong and Xu (2016) (these theories were all discussed in detail, in section 3.4). However, Fremault (1991) postulates that this increase in information efficiency is due to an increase in index arbitrage activity, which found no support in this analysis, where ETF trading was found to display insignificant results. In addition, Cong and Xu (2016) postulate that the increase in efficiency is due to increased systemic efficiency, and diminished firm-specific efficiency in the underlying asset. Again, no support was found for this channel of information flows, as the synchonicity (systematic efficiency) results were also found to be insignificant.

The results found in this chapter therefore can be attributed to Merton's (1987) investor recognition hypothesis, which postulates that the introduction of ETFs, increases investors awareness of the firm's underlying assets, and thus increases both liquidity and information efficiency. These results are therefore consistent with the increased liquidity results found in chapter 4, and in particular provides conclusive evidence that the benefits enjoyed after ETF introduction, in the South African market, arise from ETF membership, rather than from the creation and redemption activity of these ETFs. The results from the synchronicity analysis also provide further support for Merton's (1987) hypothesis, as the results indicate that the increase in information efficiency is attributed to more traders acting on firm-specific information, in the market for the underlying asset, rather than being attributed to greater levels of systematic efficiency. The inclusion into an ETF, therefore seems to increase South African investor's awareness of these underlying assets, which thus increases firm-specific activity in the firm. This could be due to the concentration issues noted on the JSE (Bradfield & Kgomari, 2004; Lambridis, 2019; Nogantshi, 2019), which usually causes the most trading activity in the largest constituents of the index, and leads to greater restraints to trade in any assets which fall outside of the Top 40 index. The introduction of ETFs therefore seems to improve the concentration-related issues on the JSE, by removing the trade restrictions that may usually present in the smaller firms on the index, and thereby inciting greater interest in these lower weighted constituents which underlie the ETF.

5.6. CHAPTER SUMMARY AND CONCLUSION

This chapter aims to discuss the second microstructure element included in this study, which is the information efficiency of the assets that underlie ETFs. Whilst the information efficiency of an asset would not be an important consideration in an efficient market, the current financial markets display evidence of market inefficiency, which implies that ETF formation and subsequent trade represent significant events that convey information to the market. This notion is closely linked to the theoretical justification of liquidity impacts noted in chapter 4, and therefore the two microstructure elements discussed in this study are inevitably linked.

The theoretical foundation of this chapter postulates that there could be two possible impacts of ETFs on the information efficiency of its underlying assets. The first potential impact is an increase in efficiency for the underlying asset, which is caused by investors reacting to firm-specific information by trading in the ETF market (which represents a lower cost market with less frictions to trade). As a result, information is simultaneously reflected in many different assets thus leading to an increase in information efficiency. The second potential impact however, is that this same process results in firms' stock prices reacting to non-fundamental information, which thus creates inefficiency in the stock prices. This postulation has been the subject of many recent empirical studies, which aim to evaluate the positive or detrimental impact of this financial innovation on existing market structure. The literature reviewed however, is largely mixed and inconclusive on the market impact of ETFs.

The results from this chapter, provide no evidence of detrimental impacts on the JSE, in terms of information efficiency. Instead, robust findings indicate that ETF ownership increases the informational efficiency of its underlying constituents, particularly with respect to future earnings information. In addition, studies of synchronicity, find that ETF ownership and trade do not impact at all on the level of co-movement that stocks exhibit with the market index. However, it is noted based on the results that the positive impacts on information efficiency arise from the inclusion of firms into domestic/international ETFs, and not from the creation and redemption activity within each ETF. This conclusion is important, as it infers that JSE-listed firms benefit just from being included in ETFs, regardless of whether the ETF is active in the arbitrage market.

CHAPTER SIX:CONCLUSION AND RECOMMENDATIONS

6.1. INTRODUCTION

The constantly changing financial environment means that investors are continually being introduced to new financial products, for which the benefits are always widely advertised, to attract new investors. However, the disadvantages of these products are not always known, as these impacts sometimes only reveal themselves as impediments to market microstructure elements, which is only found once empirical analysis is conducted on the asset class in question. An ETF is one such investment vehicle available today, which has grown exponentially in popularity since its inception, and in its current format, provides various uses for both institutional and retail investors. The potentially damaging effects however, of this asset on market quality and function marks a growing trend in the literature, with new and confounding effects being found constantly.

The dearth of literature in the South African environment led to the justification of this study, which aims to evaluate the impact of ETF introduction and trading on both liquidity of its underlying assets, as well as the informational efficiency. The overarching objective of the study is therefore to provide important information on ETF market impacts, both to ETF providers as well as market regulators. In particular, the research objectives developed are as follows:

I. To examine the effect of the introduction of Equity ETFs on the JSE on changes in liquidity for the stocks that constitute the ETF;
II. To identify the impact of the weighting of a company in the Equity ETFs listed on the JSE on the liquidity change experienced by the underlying firms;
III. To determine the impact of ETF ownership and trading activity on the informational efficiency of the JSE-listed companies which are constituents of both international and domestic equity ETFs; and,
IV. To assess the impact of ETF ownership and trading activity on stock synchronicity of the JSE-listed firms which underlie both domestic and international equity ETFs.

The uniqueness of this study in the South African ETF market, lies in the current concentration levels of the JSE, which was documented in Chapter 1 (section 1.1.3). At present, the Top 40 companies listed on the JSE, make up 80 percent of the total market capitalisation, which is a statistic that has remained more or less constant in recent years (Mans-Kemp & Viviers, 2019). As a result, whilst studies of international markets provide important information on those markets, a study of ETF impacts in the South African environment is necessary, and aims to inform both investors who procure these ETFs, as well as market regulators. This chapter attempts to conclude the study by summarising the theoretical and empirical arguments proposed and cohesively discussing the findings found for each objective alongside the conclusions reached. The chapter thereafter ends with recommendations for future study in this field.

6.2. SUMMARY OF THEORETICAL AND EMPIRICAL LITERATURE

Chapters Two and Three of this study aims to outline the theoretical foundation, by first providing a background and critical analysis of the ETF as an asset class (Chapter Two), and thereafter conducting a review of the microstructure theories regarding the potential impact of ETFs on its underlying securities (Chapter Three). Thereafter each of the chapters addressing Liquidity (Chapter Four) and Information efficiency (Chapter Five) outline the empirical analysis related to each microstructure aspect, alongside the study's own empirical analysis based on SA data.

6.2.1. Theoretical foundations of Liquidity and Information Efficiency

Much of the microstructure literature begins with the foundational studies of Grossman and Stiglitz (1980) and Kyle (1985), who develop an equilibrium model in which the actions of both informed and uninformed traders in the market can coexist amidst asymmetric information environments. These authors therefore form the basis of understanding information flows in the equity market and their potential impacts on microstructure elements of trade. These theories were therefore the foundations for the previous theoretical literature on basket securities, and the more recent theoretical applications to the ETF market in particular. The concepts of liquidity and information efficiency are both based on the flow of information in the marketplace, and are closely linked in their theoretical foundations and applications. Whilst liquidity broadly refers to the ease with which assets can be transferred with minimal market impacts, information efficiency refers to the degree with which assets reflect their fundamental information, and both are strongly impacted by the level of adverse selection/information asymmetry in the market. There is therefore a bi-directional relationship between the two concepts, with each having an influence on the other.

Authors such as Merton (1987), Fremault (1991), Malamud (2016) and Cong and Xu (2016) postulate that the introduction of ETFs into financial markets has positive potential benefits for overall market function, as these securities cause an increase of both liquidity and information efficiency in their underlying securities. The channels through which these benefits accrue, is the increased visibility of these firms by virtue of its inclusion in the ETF (Merton, 1987), the increase in arbitrage activity stimulated by the creation and redemption process (Fremault, 1991) and the demand substitution effect of new ETF market entrants which reduces volatility, and thus improves liquidity (Malamud, 2016). In addition, Cong and Xu (2016) hypothesise that ETF inclusion increases the asset's sensitivity to systematic information, which is therefore the driving factor for overall increased efficiency.

On the contrary, Subrahmanyam (1991), Gorton and Pennacchi (1993) and Bhattacharya and O'Hara (2018) all postulate a detrimental impact on the underlying securities after ETF introduction. The diminished liquidity and lower information efficiency in the underlying assets, is due to the migration of investors away from the market of the underlying security towards the ETF market (Gorton & Pennacchi, 1993; Subrahmanyam, 1991), an increase in sensitivity to systematic factors alongside diminished sensitivity to firm-specific factors (Cong & Xu, 2016), and the transfer of non-fundamental information from the ETF market to the market for the underlying assets (Bhattacharya & O'Hara, 2018). In addition, whilst Malamud's (2016) hypothesis predicts information and liquidity benefits, he expects this result only for an expanding ETF market. Malamud's (2016) theory also postulates that the ETF market transfers demand shocks to the underlying asset market, thus creating potential negative impacts.

6.2.3. Empirical findings on Liquidity and Information efficiency impacts

The first microstructure element surveyed in this study, is the liquidity of the underlying constituents from ETFs. The empirical literature surveyed, finds support for the presence of "hidden liquidity" in the ETF market, which leads to the ETF security always displaying greater levels of liquidity than the market for the underlying assets, and indicates the presence of a greater proportion of short-term, or noise traders in this market. Whilst some authors find that the presence of more noise traders increases liquidity in the underlying assets, these studies also find that in times of market distress the liquidity dries up quicker (Cella et al., 2013; Khomyn et al., 2020; Sağlam et al., 2019). This observed increase in liquidity is postulated to be caused by the ETF market serving as a barrier in the transmission of shocks to the underlying asset market (Box et al., 2019; Evans et al., 2019).

In contrast, studies which have found evidence that a higher proportion of noise traders degrades the liquidity of the underlying assets, attribute this to these traders creating an additional layer of demand shocks, which then get transferred to the underlying asset market through arbitrage trade (Ben-David et al., 2018). Whilst the evidence on liquidity impacts is largely mixed, a common theme which emerged from the studies reviewed, is that the size of a firm may significantly affect the potential impact, especially since ETFs tend to overweight large firms in their replication procedure (Brogaard et al., 2019), which is an issue that has greater importance in the concentrated South African market which has already been documented.

The second microstructure element which was the focus of this study, is the information efficiency of the ETF constituents. Some of the studies which evaluate the contribution of ETFs to price discovery, find evidence that ETFs contribute positively to the price discovery process, thus allowing prices to become more efficient, quicker. However, the studies on the impact of ETF introduction on its underlying assets finds increased information efficiency for the constituents of sector ETFs, but mixed evidence for broad-based, or diversified ETFs. Studies that have found evidence of increased information efficiency advocate that the increased presence of noise traders in the ETF market documented previously, results in a higher proportion of informed traders in the market for the underlying asset, who face fewer adverse selection costs and are therefore able to arbitrage away any mispricing easily (Glosten et al., 2020; Li et al., 2018). In addition, the ETF market is postulated to create new methods of arbitrage which were previously not available, thus also increasing efficiency (Li & Zhu, 2018). In contrast however, authors who find evidence of diminished information efficiency in the underlying assets after ETF introduction, attribute this to the trading process of ETFs transferring non-fundamental information to the basket constituents, as well as the ease of trade in the ETF market providing a disincentive for research on individual firms (Israeli et al., 2017).

6.3. SUMMARY OF RESEARCH FINDINGS

The research findings are discussed relative to their overarching objective, which is either the impact of ETFs on liquidity, or information efficiency of its underlying assets. The first sub-section therefore begins with a discussion of the two research objectives linked to the liquidity analysis, and the second sub-section debates the remaining four research objectives, which focus on informational efficiency.

6.3.1. The impact of ETF introduction on liquidity

The first objective of this chapter, was to evaluate whether the introduction of an ETF on the JSE, results in an improvement or degradation of liquidity for the constituent assets of the ETF. This was achieved by evaluating the change in four chosen liquidity measures (quoted spread, percentage spread, Amihud illiquidity measure and quoted depth); over two event windows of 30 and 50 days pre- and post- ETF introduction. The sample consisted of 23 purely domestic, JSE-listed ETFs, which were introduced between the period of 2006 and 2019. Whilst the univariate method of analysis simply analyses the post/pre ratios for each of the liquidity measures used, the multivariate analysis makes use of a fixed effects panel data analysis, which attempts to use a dummy variable to capture the liquidity effects post-ETF introduction. The results of both the univariate and multivariate analyses conducted are consistent with each other, however, neither test provided conclusive evidence in terms of answering the research question posed. Overall, the greatest support was found for the hypothesis that ETFs improve liquidity in their underlying assets, in a result that confirms the hypotheses of Merton (1987), Fremault (1991) and Malamud (2016). In contrast, fewer ETFs favoured Subrahmanyam’s (1991) hypothesis of diminished liquidity, with only 21 percent of the sample reporting lower liquidity after ETF introduction.

The second research objective of this chapter aims to evaluate whether the weighting of the assets in the ETF, has any impact on their liquidity changes. This objective resulted from the necessity of including the unique concentration issues noted on the JSE, in the analysis. The results produced indicates that the large firms on the JSE, which occupy a majority of the market, have existing high levels of liquidity driven by the active trade in these firms, and this liquidity level does not seem to be impacted by the introduction of ETFs. The smaller firms in the sample however, which in this study does not refer directly to small capitalisation firms, but simply firms which are not included in the JSE Top 40 index, do not enjoy this same benefit, and as a result their relative liquidity fluctuates alongside the liquidity of the ETF. In particular, if the introduction of the ETF resulted in improved liquidity for the underlying assets, this benefit was enjoyed most by the lower weighted firms in the ETF, whereas a degradation in liquidity was noted more for the lower weighted firms as well.

6.3.2. The impact of ETF ownership on informational efficiency

The study of information efficiency impacts coincides with the third and fourth research objectives, and uses both fixed effects and GMM panel estimations to evaluate 94 different JSE-listed underlying firms, from a sample of 90 international and domestic ETFs. This analysis made use of both ETF ownership and ETF trade variables to infer whether the information efficiency effects of JSE-listed firms results solely from ETF membership, or from the ETF creation and redemption trading activity. In addition, the study applied two proxies for information efficiency, the FERC and the measure of synchronicity. The results produced indicates that ETF ownership positively impacts on the FERC, whilst no relationship is found to ETF trade. In addition, no statistically significant changes in synchronicity were found after ETF introduction. These results therefore coincide with the hypothesis of Merton (1987) only, who postulates that improvements in information efficiency arise from investors becoming more aware of the underlying assets after ETF introduction. Whilst both Fremault (1991) and Cong and Xu (2016) also hypothesise an increase in information efficiency, this is attributed to greater arbitrage activity and greater levels of return synchronicity respectively, however the results from this study find no evidence of either of these impacts.

6.4. CONCLUSION

As mentioned, the primary goal of this study is to evaluate whether the presence and trade of ETFs in the South African financial market impacts positively or negatively on the microstructure elements of the assets that underlie this product, most notably the liquidity and information efficiency. The results from the study finds evidence in favour of Merton (1987), who postulates that the inclusion of assets into an ETF increases the market's visibility of these assets, which facilitates greater interest and trading in these assets. It is through this channel that fundamental information is reflected faster into the assets (thus resulting in greater efficiency), and the asset's liquidity also increases. The findings from both the liquidity and information efficiency analyses therefore find evidence of improvements in liquidity and information efficiency, which in the latter study is proven to be due to ETF membership. In addition, the study finds that where there are improvements in the microstructure elements, the lower weighted companies in the ETF enjoy these benefits the most.

Therefore, the study finds evidence that the concentration level of the JSE (where the firms with the highest market capitalisation constitute a large portion of the overall listed market) has resulted in these large capitalisation firms being mostly immune from any microstructure impacts of ETF introduction. By virtue of their relative weighting on the JSE, these firms seem to already have entrenched liquidity and evidence of information efficiency, as these firms also tend to be the most actively traded on the JSE anyway. Instead, the significant impacts lie in the smaller weighted firms on the JSE, which in this instance are the firms which lie outside of the Top 40 firms on the JSE. Whilst these firms are by no means small capitalisation firms (the firms included in the current ETFs offered are all from the top 160 firms which constitute the JSE ALSI), by virtue of the concentration issues noted on the JSE, these firms occupy a smaller weighting in the broad-based index. The results find in favour of these firms benefitting from an increase in liquidity and information efficiency and therefore provides an indication that the formation of ETFs do benefit financial market microstructure.

However, the results of the study also provides some indication that certain ETFs (which are unpredictable in nature and benchmark) can also cause a decrease in liquidity and thus information efficiency in their underlying assets, which is felt particularly by the smaller weighted firms in the ETF. This case of decreasing liquidity has more extenuating conclusions which need to be examined. As the ETF market in South Africa expands to mirror different sectors of the equity market, the possibility of investing in firms beyond the top 160 firms on the JSE (which constitute the JSE ALSI) increases, and so too does the possibility of adversely impacting on these underlying securities microstructure effects. An increase in indexing for this smaller sector of the JSE might assist market quality by increasing the visibility of these firms and thereby creating more liquid and efficient markets. However, based on the results from this study it could also have the opposite effect, of decreasing efficiency and liquidity, thereby causing already illiquid firms to become even more illiquid. This presents a challenge to the traders who hold these assets, and will be unable to liquidate them easily and thus stand to suffer losses. As a result, a growing ETF market could unintentionally push smaller firms off the JSE platform due to decreased demand for their shares, which could further exacerbate the current concentration issue faced in South Africa. In addition, the inability to accurately predict which firm and ETF could potentially face these issues, poses an additional risk factor to domestic investors.

6.5. PRACTICAL IMPLICATIONS AND RECOMMENDATIONS

The overall results of this study imply that whilst globally, there is an observation of detrimental ETF impacts, and a growing concern on the destabilisation of the market by these assets, this concern is not mirrored in the South African environment. If anything, given the level of concentration observed on the JSE, the introduction of ETFs has facilitated greater market activity in the smaller capitalisation portion of the market, by increasing awareness of these firms, and reducing the restrictions to trade in these assets. Based on these findings, the study therefore aims to provide relevant recommendations to the market regulator, ETF providers, and the investment community at large.

- The growth in the South African ETF market should be encouraged, however regulatory constraints on this sector still need to play an active role. The definite benefits associated with the introduction of ETFs has served to limit the potential adverse effects that investors face due to the concentration level of the JSE, and thus as the ETF market grows, and the benefits strengthen, this may also further reduce the concentration risk faced by investors, by increasing the investment universe to include more assets, and increasing the stability of the underlying asset market. However, whilst a relaxation of the regulations that preclude the introduction of synthetic, leveraged or inverse ETFs may spur this growth in the ETF market, this may also have the unintended consequences of increasing volatility and destabilization of the underlying asset market, in the same manner this has occurred in international markets. Therefore regulators still need to play an active role in facilitating growth, whilst restricting the potential for market abuse and instability.

- The active asset management industry at current dwarves the size of the ETF market in South Africa, despite the extensive benefits offered by ETFs. It may be the case that the brand recognition of actively managed products is far greater than that of ETFs, given the age and maturity of this industry relative to ETFs, alongside extensive marketing campaigns being initiated by the main asset management providers in the country. The investor awareness and activity in the ETF market could therefore be improved by increased spending on marketing, advertising and investor roadshows by ETF sponsors. This increased market presence may further increase the amount of financial advisors who recommend these clients to include this asset class into a combined portfolio of assets, and thus recognize the vast advantages that they bring.
- A further reason why the active asset management industry is so prominent in South Africa, relative to the size of the ETF market, is due to the current tax legislation, which treats both unit trusts and ETFs in the same manner, and thus does not extend the tax benefits enjoyed by international ETF investors, to their South African cohorts. Whilst the introduction of the Tax-Free Savings Account has incited certain tax benefits for ETF investors, these benefits are small. A change to the taxation legislation by authorities may therefore spur the growth in this market and thus further positively impact market efficiency and liquidity.
- The current regulations defined in Regulation 28 of the Pension Funds Act imply that certain types of ETFs are precluded from possible investment from this sector. Since a large portion of South African wealth is housed in these funds, the re-evaluation of the ETF sector is necessary, and a relaxation of these guidelines will further enhance growth in this market.

6.6. LIMITATIONS AND AREAS FOR FUTURE RESEARCH

The limitations of this study arise from the lack of available data, which constrained the study to the use of selected liquidity proxies in particular. In addition, the current South African ETF market, differs from the US and European markets where most of the microstructure literature is based, in that many ETFs on the JSE have only been initiated in recent years, thus resulting in a short history of data. In addition to providing fewer data points for observation, this also results in a relatively young ETF market in which the full microstructure effects are not yet felt completely. This also negatively impacts on the study's ability to evaluate changes in liquidity or information efficiency under conditions of market stress. Therefore, whilst the results of the study aim to provide useful conclusions for the future of ETF development and regulation in the South African market, the issue of market microstructure should be revisited at a later stage when the ETF market is more mature, and has expanded to encompass more areas of the equity market.

Aside from the afore-mentioned limitations, there are various matters for future research which have fallen beyond the scope of this study, but nonetheless provide interesting avenues for future research:

- The evaluation of liquidity found varying results for the lower weighted firms in the ETF, with some indicating improved liquidity after ETF introduction, whilst others noted diminished liquidity. Further research in this area can therefore aim to identify further firm characteristics, market conditions or time periods, which aim to predict under which conditions an ETF will improve liquidity in its underlying assets.
- The study of liquidity and information efficiency impacts can be extended beyond the market for equity ETFs to bond ETFs, or commodity ETFs listed on the JSE, the latter of which is extremely liquid and popular with both domestic and international investors.
- The study of liquidity can be extended to evaluate each stock addition and deletion to an ETF over the life of the ETF, rather than simply at inception. This may allow one to view changes in liquidity as the ETF matures, and could also provide a further firm-based analysis which will aid in the understanding of the concentration issue on the JSE, and its impacts on the other listed shares.
- The results from the Information efficiency chapter provided some evidence of no information flows arising from institutional and ETF traders rebalancing their

portfolios. However, there is a lack of research in the South African environment which further evaluates the trading behavior of these market participants, and their resultant impact on the information flows to the market. Further research into this field may lead to greater inferences in the ETF market, and a greater understanding of the flow and importance of information in the South African financial market.

- There are many microstructure elements that extend beyond liquidity and information efficiency, yet are strongly linked to them. Whilst Matarutse and Sibanda (2014) find evidence of a reduction in volatility after ETF introduction, their study is limited to the Satrix Top 40 ETF, which is likely to behave differently from ETFs based on other benchmarks, as evidenced by this study. Therefore, opportunities for further research lie in evaluating the volatility impacts of ETF introduction and trading for the entire sample of ETFs listed on the JSE. In addition, studies such as Wurgler (2010), Da and Shive (2018) and Agarwal, Hanouna, Moussawi, and Stahel (2018) provide evidence that ETFs have the potential to increase the co-movement in prices between unrelated stocks, as well as a co-movement in the liquidity of stocks. This process is postulated to occur through the ETF trading process, which incorporates any new fundamental information into a broad-subset of shares simultaneously, regardless of whether the fundamental information is related to the share or not. The issue of asset and liquidity correlation, and its resultant impacts on stock diversification as well as portfolio risk is therefore a further area for research.

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APPENDIX

APPENDIX A

Table A-1: ETFs listed on the JSE as at 31 December 2019

ETF product	Region	Benchmark tracked	JSE Ticker	Inception date
EQUITY ETFS				
1nvest SA Property	Domestic	FTSE/JSE Africa SA Listed Property Index	ETFSAP	14 February 2013
1nvest SWIX 40	Domestic	FTSE/JSE Africa SWIX 40 Index	ETFSWX	18 October 2010
1nvest Top 40	Domestic	FTSE/JSE Top40 Index	ETFT40	18 October 2010
ABSA NewFunds Equity Momentum	Domestic	Absa Wits Risk-Controlled SA-Momentum Index	NFEMOM	27 January 2012
ABSA NewFunds Low Volatility Equity	Domestic	Absa Wits Risk-Controlled SA Low Volatility Index	NFEVOL	26 March 2018
ABSA NewFunds MAPPS Growth	Domestic	MAPPS Growth Index	MAPPSG	25 May 2011
ABSA NewFunds MAPPS Protect	Domestic	MAPPS Protect Index	MAPPSP	25 May 2011
ABSA NewFunds S&P GIVI SA Top 50	Domestic	S&P GIVI SA Top 50	GIVISA	23 June 2008
ABSA NewFunds S&P Namibia Bond	Domestic	S&P Namibia Sovereign Bond 1+ year Top 10 Index	NFNAMB	28 November 2019
ABSA NewFunds Shariah Top 40	Domestic	FTSE/JSE Shari'ah Top 40	NFSH40	06 April 2009
Sygnia Itrix SWIX Top 40	Domestic	FTSE/JSE Swix Top 40	SYGSW4	30 October 2017
Sygnia Itrix Top 40	Domestic	FTSE/JSE Top 40	SYGT40	30 October 2017
ABSA NewFunds Value Equity	Domestic	Absa Wits Risk-Controlled SA Value Index	NFEVAL	26 March 2018
ABSA NewFunds Volatility Managed High Growth Equity	Domestic	NewFunds/Absa Volatility Managed SA High Growth Equity Index	NFEHGE	25 February 2019
ABSA NewFunds Volatility Managed Moderate Equity	Domestic	NewFunds/Absa Volatility Managed SA Moderate Equity Index	NFEMOD	25 February 2019
ABSA NewFunds Volatility Managed Defensive Equity	Domestic	NewFunds/Absa Volatility Managed SA Defensive Equity Index	NFEDEF	27 February 2019
Ashburton MidCap	Domestic	FTSE/JSE Mid Cap Index	ASHMID	15 August 2012
Ashburton Top 40	Domestic	FTSE/JSE Top 40	ASHT40	15 October 2008
Satrix SWIX Top 40	Domestic	FTSE/JSE Swix Top 40	STXSWX	10 April 2006
CoreShares SA Property Income	Domestic	SA Property Income Index	CSPROP	30 October 2019
CoreShares SciBeta M-FI	Domestic	Scientific Beta Coreshares SA Six-Factor Equal Weighted Index	SMART	10 July 2019
CoreShares Top 50	Domestic	S&P SA 50	CTOP50	03 June 2015
Satrix Top 40	Domestic	FTSE/JSE Top 40	STX40	27 November 2000
Satrix DIVI	Domestic	FTSE/JSE Dividend Plus	STXDIV	30 August 2007

ETF product	Region	Benchmark tracked	JSE Ticker	Inception date
Satrix FINI	Domestic	FTSE/JSE Financial 15	STXFIN	15 February 2002
Satrix INDI	Domestic	FTSE/JSE Capped Industrial	STXIND	15 February 2002
CoreShares DivTrax	Domestic	S&P SA Dividends Aristocrat	DIVTRX	14 April 2014
CoreShares PrefTrax	Domestic	FTSE/JSE Preference Share Index (J251)	PREFTRAX	28 March 2012
Satrix Momentum	Domestic	Satrix Momentum Index	STXMMT	16 November 2018
Satrix Property	Domestic	S&P SA Composite Property Capped	STXPRO	03 March 2017
Satrix Quality SA	Domestic	S&P Quality South Africa Index	STXQUA	26 September 2017
Satrix RAFI	Domestic	FTSE/JSE RAFI 40	STXRAF	16 October 2008
Satrix RESI	Domestic	FTSE/JSE Capped Resources 10 Index	STXRES	10 April 2006
1nvest Global REIT	Foreign	FTSE EPRA/NAREIT Global REIT Index	ETFGRE	15 March 2018
1nvest MSCI World	Foreign	MSCI World Index	ETFWLD	15 March 2018
1nvest S&P 500	Foreign	S&P 500 Index	ETF500	15 March 2018
1nvest S&P 500 Info Tech	Foreign	S&P500 Info Tech Index	ETF5IT	15 March 2018
Ashburton Global 1200 Equity Fund of Funds	Foreign	S&P Global 1200	ASHEQF	06 October 2017
Cloud Atlas AMI Big50 ex-SA	Foreign	AMI BIG50 ex-SA	AMIB50	20 April 2017
Cloud Atlas AMI Real Estate ex-SA	Foreign	AMI Real Estate ex SA Index	AMIRE	01 June 2018
CoreShares S&P 500	Foreign	S&P 500	CSP500	04 November 2016
CoreShares Global Dividend Aristocrats	Foreign	S&P Global Dividend Aristocrats Blend Index (Custom)	GLODIV	22 February 2018
CoreShares Global Property	Foreign	S&P Global Property 40	GLPROP	09 November 2016
Satrix MSCI China	Foreign	MSCI China Index	STXCHN	22 July 2020
Satrix MSCI EM ESG Enhanced	Foreign	MSCI EM ESG Enhanced Focus Index	STXEME	10 September 2020
Satrix MSCI Emerging Markets	Foreign	MSCI Emerging Market Index	STXEMG	24 July 2017
Satrix MSCI World	Foreign	MSCI World	STXWDM	24 July 2017
Satrix MSCI World ESG Enhanced	Foreign	MSCI World ESG Enhanced Focus Index	STXESG	10 September 2020
Satrix Nasdaq 100	Foreign	iShares NASDAQ 100 UCITS ETF	STXNDQ	10 April 2018
Satrix S&P 500	Foreign	S&P 500	STX500	24 July 2017
Sygnia Itrix 4th Industrial Revolution Global Equity	Foreign	S&P Kensho New Economies Composite Index	SYG4IR	06 December 2017
Sygnia Itrix EuroStoxx 50	Foreign	Euro Stoxx 50 Equity	SYGEU	10 October 2005
Sygnia Itrix FTSE 100	Foreign	FTSE 100 Equity	SYGUK	10 October 2005
Sygnia Itrix Global Property	Foreign	S&P Global Property 40	SYGP	30 October 2017
Sygnia Itrix MSCI Japan	Foreign	MSCI Japan Equity	SYGJP	31 March 2008
Sygnia Itrix MSCI US	Foreign	MSCI US Equity	SYGUS	01 April 2008
Sygnia Itrix MSCI World	Foreign	MSCI World Equity	SYGWD	01 April 2008

ETF product	Region	Benchmark tracked	JSE Ticker	Inception date
Sygnia Itrix S&P 500	Foreign	S&P 500	SYG500	30 October 2017
COMMODITY ETFS				
1nvest Gold	Domestic	Gold Spot	ETFGLD	07 April 2014
1nvest Palladium	Domestic	Palladium Spot	ETFPLD	26 March 2014
1nvest Platinum	Domestic	Platinum Spot	ETFPLT	07 April 2014
1nvest Rhodium	Domestic	Rhodium Spot	ETFRHO	04 December 2015
ABSA NewGold	Domestic	Gold Spot	GLD	01 November 2004
ABSA NewPalladium	Domestic	Palladium Spot	NGPLD	02 April 2014
ABSA NewPlatinum	Domestic	Platinum Spot	NGPLT	26 April 2013
FirstRand Krugerrand Custodial Certificates	Domestic	Krugerrand	KCCGLD	17 July 2015
BOND AND MONEY MARKET ETFS				
Satrix Global Aggregate Bond	Foreign	Bloomberg Barclays Global Aggregate	STXGBD	19 August 2020
1nvest Global Government Bond	Foreign	FTSE G7 Government Bond Index	ETFGGB	15 March 2018
1nvest SA Bond	Domestic	S&P SA Sovereign Bond 1+ Year Index	ETFBND	05 June 2019
Satrix SA Bond Portfolio	Domestic	S&P South Africa Sovereign Bond 1+ Year Index	STXGOV	07 May 2020
Satrix ILBI	Domestic	S&P SA Sovereign Inflation-Linked Bond	STXILB	03 March 2017
FirstRand Dollar Custodial Certificates	Foreign	10 year US Treasury Bond	DCCUSD	24 January 2017
FirstRand 2-year Dollar Custodial Certificates	Foreign	2 year US Treasury Bond	DCCUS2	24 January 2017
ABSA NewFunds GOVI	Domestic	SA Government Bond Index (Total Return)	NFGOVI	27 January 2012
ABSA NewFunds ILBI	Domestic	Absa South African Government Inflation-Linked Bond Index	NFILBI	27 January 2012
Ashburton Inflation	Domestic	Government Inflation Linked Bond Index (GILBx)	ASHINF	20 May 2009
ABSA NewFunds TRACI 3 Month	Domestic	Absa Capital ZAR Tradable Cash Index 3 Month	NFTRCI	27 January 2012
Ashburton World Government Bond	Foreign	FTSE World Government Bond Index	ASHWGB	12 March 2018

Table A-2: P-values of unit root tests conducted for each of the ETFs used in the liquidity analysis

ETF	Quoted spread	Percentage spread	Amihud	Quoted depth	Volume	Price	Std deviation
Ashburton Top40	0.0000	0.0000	0.0886	0.0876	0.0876	0.0432	0.0906
Satrix Rafi 40	0.0002	0.0005	0.0001	--	0.0000	0.0647	0.0310
NewFunds Shariah Top40	0.0001	0.0003	0.009	--	0.0001	0.091	0.0885
Newfunds SWIX Top40	0.0001	0.0000	0.0001	--	0.0000	0.0992	0.0971
Satrix SWIX 40	0.0058	0.0056	0.0002	--	0.0000	0.0999	0.0998
Coreshares Top 50	0.0000	0.0000	0.0000	0.0000	0.0000	0.0763	0.0000
NewFunds NewSA	0.0000	0.0000	0.0000	--	0.0020	0.0037	0.0263
NewFunds Equity Momentum	0.0000	0.0000	0.0031	--	0.0000	0.0948	0.0817
Ashburton Midcap	0.0000	0.0000	0.0000	0.0000	0.0000	0.0043	0.0000
NewFunds Defensive Equity	0.0257	0.0238	0.0535	0.0000	0.0000	0.0305	0.0000
Coreshares DivTrax	0.0909	0.0003	0.0257	0.0002	0.0002	0.0039	0.0000
NewFunds Moderate Equity	0.0153	0.0145	0.0366	0.0135	0.0135	0.0688	0.0000
Satrix Momentum	0.0000	0.0021	0.0721	0.0000	0.0000	0.0378	0.0000
Satrix Quality	0.091	0.092	0.0047	0.0002	0.0015	0.0646	0.0000
Newfunds Low Volatility	0.009	0.0077	0.0995	0.0044	0.0044	0.0227	0.003
Newfunds Value Equity	0.0000	0.0000	0.0019	0.0000	0.0000	0.0927	0.0001
Newfunds High Growth	0.0166	0.0130	0.0214	0.0226	0.0226	0.0223	0.0000
NewFunds S&P Givi Financials	0.042	0.035	0.0083	--	0.0000	0.0952	0.091
NewFunds S&P Givi Resources	0.0003	0.0002	0.0013	--	0.0000	0.0967	0.0974
NewFunds S&P Givi Industrial	0.0000	0.0000	0.0000	--	0.0007	0.084	0.083
Coreshares PropTrax Ten	0.0612	0.0598	0.0036	--	0.0053	0.0105	0.0162
Satrix Property	0.0014	0.0011	0.0000	0.0002	0.0000	0.0026	0.0002
Satrix Resi	0.0000	0.0000	0.0002	--	0.0003	0.0557	0.0723

Table A-3: Chi-square statistics of Hausman tests for ETF liquidity analysis

ETF	Quoted spread	Percentage Spread	Amihud	Quoted depth
Ashburton Top40	41.73***	44.62***	19.92**	--
Satrix Rafi 40	20.91***	20.28***	9.78*	--
NewFunds Shariah Top40	32.31***	33.09***	32.94***	--
Newfunds SWIX Top40	18.17***	18.26***	17.56***	--
Satrix SWIX 40	26.79***	28.03***	34.01***	--
Coreshares Top 50	44.31***	44.10***	35.91***	37.71***
NewFunds NewSA	50.20***	96.28***	18.42***	--
NewFunds Equity Momentum	33.13***	33.11***	33.36***	--
Ashburton Midcap	205.57***	205.25***	12.39**	5448.71***
NewFunds Defensive Equity	76.69***	75.37***	20.34***	9.59***
Coreshares DivTrax	24.25***	24.79***	16.88**	22.30***
NewFunds Moderate Equity	59.94***	59.45***	21.56***	33.19***
Satrix Momentum	45.65***	16.68***	26.91***	17.45***
Satrix Quality	14.69**	14.40**	28.56***	22.66***
Newfunds Low Volatility	38.48***	38.38***	25.55***	21.37***
Newfunds Value Equity	23.18***	23.20***	47.31***	14.00***
Newfunds High Growth	151.37***	152.55***	12.18**	31.35***
NewFunds S&P Givi Financials	16.50***	16.54***	10.79*	--
NewFunds S&P Givi Resources	36.10***	36.40***	17.24***	--
NewFunds S&P Givi Industrial	101.12***	122.60***	50.01***	--
Coreshares PropTrax Ten	25.40***	25.83***	37.17***	--
Satrix Property	20.82***	20.76***	22.05***	10.18***
Satrix Resi	13.14**	13.35**	12.86**	--

*'***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.*

APPENDIX B

Table B-1: Sample of International and Domestic ETFs included in informational efficiency chapter

ETF	CODE
Domestic ETFs	
1nvest SA Property ETF	JSE:ETFSAP
1nvest Swix 40 ETF	JSE:ETFSWX
1nvest Top 40 ETF	JSE:ETFT40
Ashburton Mid Cap Exchange Traded Fund	JSE:ASHMID
Ashburton Top 40 Exchange Traded Fund	JSE:ASHT40
CORESHARES PropTrax Ten	JSE:CSPROP
CoreShares S&P South Africa Dividend Aristocrats Exchange Traded Fund	JSE:DIVTRX
CoreShares S&P South Africa Low Volatility Exchange Traded Fund	JSE: LVLTRX
CoreShares S&P South Africa Top50 Exchange Traded Fund	JSE:CTOP50
CoreShares Scientific Beta Multi Factor ETF	JSE: CSSBTCA
NewFunds Collective Investment - Low Volatility Equity ETF Fund	JSE:NFEVOL
NewFunds Equity Momentum ETF	JSE:NFEMOM
NewFunds NewSA Index Exchange Traded Fund	JSE:NEWFSA
NewFunds S&P GIVI SA Financial 15 ETF	JSE:GIVFIN
NewFunds S&P GIVI SA Industrial 25 ETF	JSE:GIVIND
NewFunds S&P GIVI SA Resource 15 ETF	JSE:GIVRES
NewFunds S&P GIVI SA Top 50 ETF	JSE:GIVISA
NewFunds Shari'ah Top 40 Index Exchange Traded Fund	JSE:NFSH40
NewFunds SWIX 40 ETF	JSE:NFSWIX
NewFunds Volatility Managed Defensive Equity ETF	JSE:NFEDEF
NewFunds Volatility Managed High Growth Equity ETF	JSE:NFEHGE
NewFunds Volatility Managed Moderate Equity ETF	JSE:NFEMOD
Satrix 40 ETF	JSE:STX40
Satrix Capped INDI ETF	JSE:STXIND
Satrix DIVI ETF	JSE:STXDIV
Satrix FINI ETF	JSE:STXFIN
Satrix Momentum ETF	JSE:STXMMT
Satrix Property Portfolio	JSE:STXPRO
Satrix Quality South Africa ETF	JSE: STXQUA
Satrix RAFI 40 ETF	JSE:STXRAF
Satrix Resi ETF	JSE:STXRES
Satrix SWIX Top 40 ETF	JSE:STXSWX
Sygnia Itrix SWIX 40 ETF	JSE:SYGSW4
Value Equity ETF Fund	JSE:NFEVAL

ETF	CODE
International ETFs	
AAM S&P Emerging Markets High Dividend Value ETF	NYSE: EEMD
AdvisorShares Trust AdvisorShares Dorsey Wright ADR ETF	AADR: PCQ
ALPS Emerging Sector Dividend Dogs ETF	ARCA:EDOG
ALPS ETF Trust ALPS Emerging Sector Dividend Dogs ETF	NYSE: EDOG
Amplify Advanced Battery Metals and Materials ETF	ARCA:BATT
Cambria Emerging Shareholder Yield ETF	BATS:EYLD
Davis Select International ETF	NasdaqGM:DINT
Davis Select Worldwide ETF	NasdaqGM:DWLD
DBX ETF Trust - Xtrackers FTSE Emerging Comprehensive Factor ETF	ARCA:EEMD
DBX ETF Trust - Xtrackers MSCI Emerging Markets ESG Leaders Equity ETF	ARCA:EMSG
DeltaShares S&P EM 100 & Managed Risk ETF	NYSEARCA: DMRE
Emerging Markets Equity Select ETF	NasdaqGM:RNEM
ETFis Series Trust I - Virtus Glovista Emerging Markets ETF	ARCA:EMEM
Exchange Traded Concepts Trust - EMQQ The Emerging Markets Internet & Ecommerce ETF	ARCA:EMQQ
Fidelity Targeted Emerging Markets Factor ETF	BATS:FDEM
FlexShares Currency Hedged Morningstar EM Factor Tilt Index Fund	ARCA:TLEH
Franklin LibertyQ Emerging Markets ETF	ARCA:FLQE
Global X MSCI Next Emerging & Frontier ETF	ARCA:EMFM
Goldman Sachs ActiveBeta Emerging Markets Equity ETF	ARCA:GEM
Hartford Multifactor Emerging Markets ETF	ARCA:ROAM
Invesco Emerging Markets Revenue ETF	BATS:REEM
Invesco FTSE RAFI Emerging Markets ETF	ARCA:PXH
Invesco Global Listed Private Equity ETF	ARCA:PSP
Invesco PureBeta FTSE Emerging Markets ETF	BATS:PBEE
Invesco S&P Emerging Markets Low Volatility ETF	ARCA:EELV
Invesco S&P Emerging Markets Low Volatility ETF	ARCA:EELV
iShares Core MSCI Emerging Markets ETF	ARCA:IEMG
iShares Edge MSCI Multifactor Emerging Markets ETF	BATS:EMGF
iShares Emerging Markets Dividend ETF	ARCA:DVYE
iShares MSCI Emerging Markets ex China ETF	NasdaqGM:EMXC
iShares MSCI Emerging Markets Small-Cap ETF	ARCA:EEMS
iShares MSCI Global Gold Miners ETF	NasdaqGM:RING
iShares MSCI South Africa ETF	ARCA:EZA
iShares, Inc. - iShares ESG MSCI EM ETF	NasdaqGM:ESGE
iShares, Inc. - iShares MSCI Emerging Markets ETF	ARCA:EEM
JPMorgan Diversified Return Emerging Markets Equity ETF	ARCA:JPEM
KraneShares Emerging Markets Consumer Technology Index ETF	ARCA:KEMQ

ETF	**CODE**
KraneShares MSCI Emerging Markets ex China Index ETF	ARCA:KEMX
Nuveen ESG Emerging Markets Equity ETF	BATS:NUEM
PIMCO RAFI Dynamic Multi-Factor Emerging Markets Equity ETF	ARCA:MFEM
Schwab Emerging Markets Equity ETF	ARCA:SCHE
Schwab Fundamental Emerging Markets Large Company Index ETF	ARCA:FNDE
SPDR MSCI Emerging Markets Fossil Fuel Reserves Free ETF	ARCA:EEMX
SPDR Portfolio Emerging Markets ETF	ARCA:SPEM
SPDR S&P Emerging Markets Small Cap ETF	ARCA:EWX
Sprott ETF Trust - Sprott Junior Gold Miners ETF	ARCA:SGDJ
Sprott Gold Miners ETF	ARCA:SGDM
U.S. Global GO GOLD and Precious Metal Miners ETF	ARCA:GOAU
VanEck Vectors Coal ETF	ARCA:KOL
VanEck Vectors Gold Miners ETF	ARCA:GDX
VanEck Vectors Rare Earth/Strategic Metals ETF	ARCA:REMX
VanEckVectors Junior Gold Miners ETF	ARCA:GDXJ
Vanguard FTSE Emerging Markets UCITS ETF	LSE:VFEM
VictoryShares Emerging Market Volatility Wtd ETF	NasdaqGM:CEZ
WisdomTree Emerging Markets Consumer Growth Fund	NasdaqGM:EMCG
WisdomTree Emerging Markets Dividend Fund	BATS:DVEM
WisdomTree Emerging Markets High Dividend Fund	ARCA:DEM

Table B-2: List of the JSE-listed companies which underlie the ETFs as listed in Table B-1, over the sample period of the study

Company	Ticker	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Absa Group Limited	JSE:ABG	0	15	15	20	22	25	29	29	33	42	46
Adcorp Holdings Limited	JSE:ADR	0	1	1	2	2	2	3	3	1	1	1
ADvTECH Limited	JSE:ADH	0	0	0	1	1	1	1	3	4	6	3
AECI Ltd	JSE:AFE	0	3	5	6	7	9	8	12	13	17	10
African Oxygen Ltd	JSE: AFX	2	2	3	2	3	3	2	2	0	0	0
Alviva Holdings Limited	JSE:AVV	0	0	0	2	2	2	0	0	0	0	0
ArcelorMittal South Africa Ltd	JSE:ACL	0	13	12	12	7	8	7	2	4	3	1
Aveng Limited	JSE:AEG	0	9	10	11	10	10	6	2	2	2	1
Adcock Ingram Holdings Limited	JSE:AIP	0	3	4	5	5	7	9	6	6	7	6
Steinhoff International Holdings N.V.	JSE:SNF	0	14	14	21	22	24	28	26	25	15	8
Massmart Holdings Limited	JSE:MSM	0	10	9	12	14	12	13	13	15	12	11
Capitec Bank Holdings Limited	JSE:CPI	0	2	2	4	8	9	19	20	32	33	45
Cashbuild Limited	JSE:CSB	0	0	0	1	3	3	2	3	3	6	4
AVI Limited	JSE:AVI	0	4	5	5	6	12	13	17	20	26	23
Aspen Pharmacare Holdings Limited	JSE:APN	0	11	12	18	16	18	22	29	32	36	35
Assore Limited	JSE:ASR	0	0	1	10	13	13	11	10	12	15	14
Astral Foods Limited	JSE:ARL	0	1	2	2	2	2	4	5	4	8	10
Anglo American Platinum Limited	JSE:AMS	0	15	15	19	18	18	16	16	12	28	36
Anglo American plc	JSE: AGL	0	10	10	12	11	11	12	13	12	19	21
AngloGold Ashanti Limited	JSE:ANG	0	15	15	20	20	21	23	28	29	33	42
African Rainbow Minerals Gold Limited	JSE:ARI	0	12	12	13	13	12	11	12	16	23	21
Barloworld Limited	JSE:BAW	0	6	8	11	13	14	19	18	19	23	25
Blue Label Telecoms Limited	JSE:BLU	0	0	0	1	1	1	2	4	6	7	6
Brait SE	JSE:BAT	0	3	4	6	8	11	19	21	14	13	9
BHP Billiton	JSE: BHP	8	10	10	12	12	14	13	12	14	19	21
British American Tobacco p.l.c.	JSE: BTI	0	2	4	10	12	14	15	16	16	19	20

Company	Ticker	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
City Lodge Hotels Limited	JSE:CLH	0	1	2	2	2	3	4	3	4	4	3
Coronation Fund Managers Limited	JSE:CML	0	2	4	6	7	13	14	20	20	24	15
Datatec Limited	JSE:DTC	0	1	3	3	4	7	10	7	8	6	4
Discovery Limited	JSE:DSY	0	9	9	11	15	21	22	23	30	33	32
DRDGOLD Limited	JSE:DRD	0	1	1	3	4	4	0	0	0	0	1
Emira Property Fund Limited	JSE:EMI (Inactive)	0	1	3	6	6	7	5	5	6	7	6
EOH Holdings Limited	JSE:EOH	0	0	0	1	2	3	9	10	11	13	5
Exxaro Resources Limited	JSE:EXX	0	13	13	16	17	18	16	14	26	30	35
Famous Brands Limited	JSE:FBR	0	0	1	3	3	5	7	7	8	11	6
FirstRand Limited	JSE:FSR	0	14	15	21	24	27	31	31	38	42	46
Gold Fields Limited	JSE:GFI	0	13	14	15	17	15	18	26	30	32	34
Grindrod Limited	JSE:GND	0	7	6	7	7	8	9	7	7	8	5
Growthpoint Properties Limited	JSE:GRT	0	11	13	18	19	23	27	29	34	42	45
Harmony Gold Mining Company Limited	JSE:HAR	0	11	12	13	11	11	11	16	16	17	17
Hosken Consolidated Investments Limited	JSE:HCI	0	2	2	2	4	5	5	5	5	6	5
Hudaco Industries Limited	JSE:HDC	0	1	1	1	1	2	3	3	4	3	3
Hyprop Investments Limited	JSE:HYP	0	0	1	2	4	7	15	17	21	27	22
Impala Platinum Holdings Limited	JSE:IMP	0	13	12	17	17	18	17	22	22	16	29
Imperial Logistics Limited	JSE:IPL	0	9	9	13	16	21	21	23	27	37	17
Intu properties P.L.C	LSE:INTU	0	7	7	9	9	11	11	11	9	8	6
Investec Group Limited	JSE:INL	0	21	23	30	29	31	35	35	42	54	57
Invicta Holdings Limited	JSE:IVT	0	1	1	1	1	2	2	1	2	3	3
JSE Limited	JSE:JSE	0	2	2	7	5	8	11	11	12	16	16
Kumba Iron Ore Limited	JSE:KIO	0	15	17	22	22	25	22	7	23	28	30
Lewis Group Limited	JSE:LEW	0	4	5	6	8	9	8	8	8	4	2
Merafe Resources Limited	JSE:MRF	0	2	2	1	1	1	1	1	1	1	0

Company	Ticker	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Metair Investments Limited	JSE:MTA	0	0	0	1	1	1	2	2	3	5	2
Mondi plc	JSE: MNP	0	6	6	13	11	11	14	14	15	19	22
Mr Price Group Limited	JSE:MRP	0	5	6	12	12	21	25	28	34	40	41
MTN Group Limited	JSE:MTN	0	15	16	22	24	29	30	31	37	39	45
Murray & Roberts Holdings Limited	JSE:MUR	0	10	10	8	7	7	6	5	6	5	4
Nampak Limited	JSE:NPK	0	4	5	9	11	14	14	14	11	12	5
Naspers Limited	JSE:NPN	0	15	15	19	19	21	23	28	38	42	45
Nedbank Group Limited	JSE:NED	0	15	15	21	23	25	30	29	32	42	48
Netcare Limited	JSE:NTC	0	8	10	14	15	23	28	34	35	43	41
Northam Platinum Limited	JSE:NHM	0	6	6	8	8	8	8	8	10	11	12
Oceana Group Limited	JSE:OCE	0	1	2	0	3	3	3	4	7	6	7
Octodec Investments Limited	JSE:OCT	0	0	0	0	1	1	1	1	2	2	1
Omnia Holdings Limited	JSE:OMN	0	0	1	3	5	6	7	8	7	12	5
Peregrine Holdings Limited	JSE:PGR	0	0	0	0	0	1	1	1	2	4	3
Pick n Pay Stores Limited	JSE:PIK	0	13	13	12	13	12	14	22	22	27	29
Pioneer Food Group Ltd	JSE:PFG	0	0	0	1	1	2	14	16	16	15	12
PPC Ltd	JSE:PPC	0	12	14	14	13	11	11	9	5	6	5
Raubex Group Limited	JSE:RBX	0	1	1	1	0	0	0	1	4	5	1
RCL Foods Limited	JSE:RCL	0	0	0	1	1	1	1	1	1	3	2
Redefine Properties Limited	JSE:RDF	0	0	1	2	3	10	27	27	35	41	46
Resilient REIT Limited	JSE:RES	0	0	1	2	3	9	15	21	30	26	20
Reunert Limited	JSE:RLO	0	8	10	9	9	9	8	9	11	16	16
RMB Holdings Limited	JSE:RMH	0	14	14	17	16	18	27	25	32	38	42
Sanlam Limited	JSE:SLM	0	16	16	21	22	24	26	29	36	41	44
Santam Ltd	JSE:SNT	0	4	3	4	1	4	5	7	8	13	8
Sappi Limited	JSE:SAP	0	7	9	10	12	13	17	27	36	40	42
Sasol Limited	JSE:SOL	0	15	16	23	24	28	27	30	35	46	48
Shoprite Holdings	JSE:SHP	0	13	14	20	21	27	29	31	36	40	41

Company	Ticker	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Steinhoff International Holdings N.V.	JSE:SHF	0	14	14	21	22	24	28	26	25	15	8
Sun International Limited	JSE:SUI	0	3	5	8	9	10	10	9	6	4	5
Super Group Limited	JSE:SPG	0	1	2	3	4	6	7	12	12	13	13
Telkom SA SOC Limited	JSE:TKG	0	12	12	11	8	14	17	19	23	29	35
The Bidvest Group Limited	JSE:BVT	0	14	14	19	20	23	28	34	36	42	45
The SPAR Group Ltd	JSE:SPP	0	7	9	9	13	17	21	29	31	41	45
Tiger Brands Limited	JSE:TBS	0	14	14	20	22	25	28	33	39	44	43
Tongaat Hulett Limited	JSE:TON	0	2	3	3	4	6	9	11	12	15	6
Truworths International Limited	JSE:TRU	0	6	8	13	16	15	22	25	29	37	35
Vukile Property Fund Limited	JSE:VKE	0	0	0	1	2	2	7	8	10	17	15
Wesizwe Platinum Limited	JSE:WEZ	0	1	1	0	0	0	0	0	0	0	0
Wilson Bayly Holmes-Ovcon Limited	JSE:WBO	0	2	3	4	5	8	6	5	5	8	5
Woolworths Holdings Limited	JSE:WHL	0	9	11	18	19	22	30	33	39	41	43
Zeder Investments Ltd.	JSE:ZED	0	0	0	1	1	2	4	4	5	6	4

Table B-3: Firm-level descriptive statistics for Size, Institutional ownership and ETF ownership variables

Company	Average size of the firm over sample period (R million)	Institutional Ownership (Mean)	ETF ownership (Mean)	ETF ownership (Max)	ETF ownership (Min)
Absa Group Limited	118 975,34	35,97%	0,87%	2,27%	0,21%
Adcock Ingram Holdings Limited	9 863,18	57,39%	0,28%	0,82%	0,002%
Adcorp Holdings Limited	2 154,55	84,48%	0,16%	0,92%	0,02%
ADvTECH Limited	4 920,79	63,33%	0,36%	1,41%	0,003%
AECI Ltd	11 572,55	95,93%	0,49%	1,75%	0%
African Oxygen Ltd	6 937,53	41,64%	0,03%	0,14%	0%
African Rainbow Minerals Gold Limited	31 137,75	42,11%	0,55%	1,18%	0,22%
Alviva Holdings Limited	2 320,57	48,13%	0,01%	0,12%	0%
Anglo American Platinum Limited	126 581,86	10,91%	0,33%	0,49%	0,10%
Anglo American plc	316 959,12	10,91%	0,10%	0,14%	0,016%
AngloGold Ashanti Limited	83 651,57	86,65%	1,71%	8,69%	0,85%
ArcelorMittal South Africa Ltd	17 825,30	22,47%	0,49%	1,65%	0,008%
Aspen Pharmacare Holdings Limited	90 638,87	52,51%	0,89%	2,03%	0,19%
Assore Limited	32 897,13	11,41%	0,31%	1,10%	0%
Astral Foods Limited	5 989,50	70,10%	0,53%	3,57%	0,002%
Aveng Limited	7 848,57	82,53%	0,24%	0,59%	0,001%
AVI Limited	22 625,29	78,07%	0,67%	1,68%	0,12%
Barloworld Limited	19 899,22	76,42%	1,22%	1,98%	0,12%
BHP Billiton	1 462 610,75	43,57%	0,08%	0,12%	0,01%
Blue Label Telecoms Limited	6 520,55	38,10%	0,23%	1,01%	0%
Brait SE	25 327,36	36,95%	0,73%	1,45%	0%
British American Tobacco p.l.c.	1 091 237,66	78,23%	0,02%	0,03%	0%

Company	Average size of the firm over sample period (R million)	Institutional Ownership (Mean)	ETF ownership (Mean)	ETF ownership (Max)	ETF ownership (Min)
Capitec Bank Holdings Limited	52 642,62	24,67%	0,28%	0,92%	0%
Cashbuild Limited	5 269,27	49,73%	0,33%	1,19%	0%
City Lodge Hotels Limited	4 887,60	59,93%	0,44%	1,48%	0%
Coronation Fund Managers Limited	17 419,90	48,82%	1,09%	2,28%	0,04%
Datatec Limited	8 587,08	68,12%	0,44%	1,00%	0,01%
Discovery Limited	58 116,84	31,80%	0,58%	1,26%	0,08%
DRDGOLD Limited	1 974,83	47%	0,08%	0,69%	0%
Emira Property Fund Limited	7 056,75	59,49%	0,46%	1,65%	0%
EOH Holdings Limited	8 417,86	47,59%	0,24%	1,11%	0%
Exxaro Resources Limited	44 925,11	28,14%	1,13%	2,02%	0,68%
Famous Brands Limited	8 437,90	38,61%	0,28%	1,12%	0%
FirstRand Limited	221 626,67	31,80%	1,07%	1,43%	0,80%
Gold Fields Limited	54 026,91	79,39%	1,95%	14,48%	0,89%
Grindrod Limited	9 527,83	35,59%	0,47%	0,95%	0,23%
Growthpoint Properties Limited	52 559,53	68,71%	1,11%	2,50%	0,33%
Harmony Gold Mining Company Limited	21 936,85	87,51%	3,69%	18%	0,06%
Hosken Consolidated Investments Limited	12 379,53	51,25%	0,50%	1,09%	0,005%
Hudaco Industries Limited	3 531,05	93,08%	0,55%	2,02%	0%
Hyprop Investments Limited	19 042,39	74,01%	0,75%	2,68%	0%
Impala Platinum Holdings Limited	68 609,42	72,01%	1,20%	1,63%	0,85%
Imperial Logistics Limited	30 777,94	75,68%	1,81%	3%	1,16%
Intu properties P.L.C	48 938,68	57,59%	0,10%	0,17%	0,03%
Investec Group Limited	68 787,41	77,34%	2,61%	3,63%	1,42%

Company	Average size of the firm over sample period (R million)	Institutional Ownership (Mean)	ETF ownership (Mean)	ETF ownership (Max)	ETF ownership (Min)
Invicta Holdings Limited	5 054,38	25,66%	0,07%	0,35%	0,02%
JSE Limited	9 204,95	74,77%	0,74%	1,58%	0,009%
Kumba Iron Ore Limited	103 572,07	10,09%	0,49%	0,92%	0,05%
Lewis Group Limited	5 426,26	88,64%	1,33%	3,18%	0,25%
Massmart Holdings Limited	27 319,09	51,12%	0,64%	1,00%	0,33%
Merafe Resources Limited	2 835,05	28,87%	0,14%	0,35%	0%
Metair Investments Limited	4 059,68	60,88%	0,28%	1,61%	0%
Mondi plc	92 132,03	57,97%	0,10%	0,25%	0,02%
Mr Price Group Limited	39 115,65	62,14%	1,14%	2,54%	0%
MTN Group Limited	270 261,55	63,36%	1,58%	2,73%	1,00%
Murray & Roberts Holdings Limited	9 352,39	90,21%	0,72%	1,61%	0,19%
Nampak Limited	15 968,47	82,89%	0,74%	1,44%	0,10%
Naspers Limited	633 073,27	71,8%	1,54%	2,24%	1,08%
Nedbank Group Limited	97 950,26	35,35%	1,03%	2,05%	0,64%
Netcare Limited	33 454,17	70,17%	1,69%	2,54%	0,94%
Northam Platinum Limited	18 139,15	64,61%	0,56%	1,03%	0,25%
Oceana Group Limited	9 136,22	26,80%	0,29%	1,35%	0%
Octodec Investments Limited	3 584,53	25,99%	0,01%	0,04%	0%
Omnia Holdings Limited	8 259,75	74,65%	0,23%	0,93%	0%
Peregrine Holdings Limited	4 072,95	49,06%	0,05%	0,42%	0%
Pick n Pay Stores Limited	26 103,70	43,58%	1,46%	2,12%	0,67%
Pioneer Food Group Ltd	21 905,26	32,19%	0,33%	1,16%	0%
PPC Ltd	13 917,14	61,43%	1,04%	1,49%	0,44%
	29 104,83	26,26%	0,34%	1,54%	0,01%
Raubex Group Limited	3 699,39	55,46%	0,04%	0,28%	0%
RCL Foods Limited	10 520,25	50,33%	0%	0,02%	0%

Company	Average size of the firm over sample period (R million)	Institutional Ownership (Mean)	ETF ownership (Mean)	ETF ownership (Max)	ETF ownership (Min)
Redefine Properties Limited	37 698,89	39,52%	0,75%	2,35%	0%
Resilient REIT Limited	23 892,11	28,74%	0,56%	1,63%	0%
Reunert Limited	12 484,77	70,71%	1,62%	2,71%	0,58%
RMB Holdings Limited	70 890,72	23,73%	0,66%	1,33%	0,30%
Sanlam Limited	113 224,12	41,46%	1,48%	2,00%	0,91%
Santam Ltd	23 298,36	24,64%	0,14%	0,41%	0,002%
Sappi Limited	8 768,52	76,48%	0,64%	1,66%	0%
Sasol Limited	257 912,44	61,53%	1,48%	2,21%	0,94%
Shoprite Holdings	86 504,47	60,97%	1,73%	4,15%	0,97%
Steinhoff International Holdings N.V.	109 692,07	26,80%	0,84%	2,17%	0,35%
Sun International Limited	9 606,27	91,92%	0,31%	1,04%	0,004%
Super Group Limited	8 401,82	77,96%	0,41%	1,41%	0,002%
Telkom SA SOC Limited	25 485,57	35,68%	0,82%	2,48%	0,12%
The Bidvest Group Limited	68 160,20	83,35%	1,60%	2,49%	1,21%
The SPAR Group Ltd	25 569,67	78,12%	1,58%	2,83%	0%
Tiger Brands Limited	52 854,73	76,62%	1,61%	2,36%	1,10%
Tongaat Hulett Limited	12 554,04	55,50%	0,36%	1,16%	0%
Truworths International Limited	33 916,52	77,07%	2,31%	4,07%	1,49%
Vukile Property Fund Limited	9 804,07	37,55%	0,38%	1,26%	0%
Wesizwe Platinum Limited	1 220,51	5,12%	0%	0,02%	0%
Wilson Bayly Holmes-Ovcon Limited	8 359,97	60,11%	0,49%	1,52%	0,01%
Woolworths Holdings Limited	51 849,18	78,80%	2,06%	3,37%	1,12%
Zeder Investments Ltd.	6 223,89	29,98%	0,39%	1,09%	0%

Table B-4: Hausman test results for Information efficiency analysis

Test equation	Chi-square test statistic
ETF ownership and FERC	66.15***
ETF trading activity and FERC	85.35***
ETF ownership and synchronicity	27.95***
ETF trading activity and synchronicity	27.27***

Table B-5: GMM estimation of the relationship between ETF ownership and synchronicity

VARIABLES	(1)	(2)	(3)	(4)
$Synch_{t-1}$	0.116*	0.0146	0.00796	0.0869
	(0.0631)	(0.0814)	(0.0575)	(0.0722)
$ETF_{i,t}$	**-0.00935**	**-0.00833**	**-0.00796**	**-0.0134**
	(0.0104)	**(0.0126)**	**(0.0130)**	**(0.0113)**
$Size_{i,t-1}$		0.0207	0.0214*	0.0210
		(0.0140)	(0.0122)	(0.0141)
$MTB_{i,t-1}$		-0.00548		-0.00557
		(0.00533)		(0.00486)
$STD_{i,t-1}$		-0.000312		-0.00172
		(0.0103)		(0.00985)
$\Delta TURN_{i,t}$		0.290**	0.284**	0.286**
		(0.137)	(0.124)	(0.142)
$ETF_{i,t-1}$	0.0118		0.000467	0.00865
	(0.0129)		(0.0125)	(0.0122)
$\Delta IS_{i,t-1}$	0.000888		-0.00181	0.00100
	(0.000890)		(0.00393)	(0.000873)
Constant	-1.475***	-2.115***	-2.155***	-2.001***
	(0.104)	(0.351)	(0.287)	(0.328)
Observations	3,899	3,899	3,899	3,899
Number of id	94	94	94	94
Hansen P-value	0.850	0.456	1	1
AR (2) P-value	0.0287	0.0189	0.0378	0.0960

Table B-5 presents the results from a GMM estimation of the following equation: $Sync_{i,t} = b_{0t} + b_{1t}ETF_{i,t} + b_{2t}Size_{i,t-1} + b_{3t}MTB_{i,t-1} + b_{4t}STD_{i,t-1} + b_{5t}ETF_{i,t-1} + b_{6t}\Delta IS_{it-1} + b_{6t}\Delta TURN_{i,t} + \varepsilon$. Robust standard errors are reported in parentheses. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

Table B-6: GMM estimation of the relationship between ETF trading activity and Synchronicity

VARIABLES	(1)	(2)	(3)	(4)
$Synch_{t-1}$	0.116*	0.0149	0.0267	0.0927
	(0.0627)	(0.0808)	(0.0491)	(0.0744)
$\lvert\Delta \boldsymbol{ETF_{i,t}}\rvert$	**-0.00996**	**-0.00510**	**-0.000577**	**-0.00406**
	(0.00890)	**(0.00804)**	**(0.00999)**	**(0.00958)**
$Size_{i,t-1}$		0.0190	0.0213*	0.0239
		(0.0125)	(0.0118)	(0.0158)
$MTB_{i,t-1}$		-0.00562		-0.00647
		(0.00551)		(0.00570)
$STD_{i,t-1}$		-0.00150		-0.000602
		(0.00956)		(0.01000)
$\Delta TURN_{i,t}$		0.292**	0.282**	0.255*
		(0.136)	(0.126)	(0.139)
$ETF_{i,t-1}$	0.00760		-0.00496	-0.00261
	(0.0105)		(0.0118)	(0.0127)
$\Delta IS_{i,t-1}$	0.000926		-0.00143	0.000926
	(0.000861)		(0.00384)	(0.000885)
Constant	-1.480***	-2.077***	-2.123***	-2.055***
	(0.104)	(0.320)	(0.280)	(0.372)
Observations	3,899	3,899	3,899	3,899
Number of id	94	94	94	94
Hansen P-value	0.846	0.450	1	1
AR (2) P-value	0.0287	0.0188	0.0345	0.0890

Table B-6 presents the results from a GMM estimation of the following equation: $Sync_{i,t} = b_{0t} + b_{1t}\lvert\Delta \boldsymbol{ETF_{i,t}}\rvert + b_{2t}Size_{i,t-1} + b_{3t}MTB_{i,t-1} + b_{4t}STD_{i,t-1} + b_{5t}ETF_{i,t-1} + b_{6t}\Delta IS_{it-1} + b_{6t}\Delta TURN_{i,t} + \varepsilon$. Robust standard errors are reported in parentheses. '***', '**' and '*' represent statistical significance at the 1%, 5% and 10% levels respectively, using a two-tailed test of significance.

ETHICAL CLEARANCE

23 June 2020

Mrs Faeezah Peerbhai (206514321)
School of Accounting, Economics & Finance
Westville Campus

Dear Mrs Peerbhai,

Protocol reference number: HSS/1693/017D
Project title: The impact of Exchange Traded Funds on the microstructure of their constituent shares: A South African case

Approval Notification – Recertification Application

Your request for Recertification dated 19 June 2020 was received.

This letter confirms that you have been granted Recertification Approval for a period of one year from the date of this letter. This approval is based strictly on the research protocol submitted and approved in 2017.

Any alteration s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study must be reviewed and approved through the amendment /modification prior to its implementation. Please quote the above reference number for all queries relating to this study.

PLEASE NOTE: Research data should be securely stored in the school/department for a period of 5 years

All research conducted during the COVID-19 period must adhere to the national and UKZN guidelines.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Professor Dipane Hlalele (Chair)

/dd

Cc Supervisors: Dr Muhammad Hoque
Cc Academic Leader Research: Dr Colette Muller
Cc School Administrator: Ms Seshni Naidoo

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