UNIVERSITY OF KWAZULU-NATAL

THE TRACKING PERFORMANCE OF EQUITY EXCHANGE TRADED FUNDS: A CONSIDERATION OF FUND REPLICATION STRATEGY, FUND DOMICILE, AND CRISIS PERIOD

By

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"Every act can be an act of prayer. Whatever you do, do it with a spirit of devotion." – (v. Lord Krishna, Bhagavad Gita).

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Abstract

An Exchange Traded Fund (ETF) is an investment vehicle that issues securities that are essentially claims on an underlying pool of assets. Tracking error measures, the ability of traditional passive ETFs to replicate the returns of their respective underlying index accurately. This measure is commonly reported for all funds with a mandate to replicate some benchmark index. Despite the primarily passive nature of ETFs, fund managers can apply active investment management techniques to them. The application of active management to these funds may include the respective index holding an actively selected basket of securities or entering derivative contracts that deliver the performance of an index, or some mixture of the two.

The importance of looking at the passive and active characteristics of funds corresponds to the replication strategies followed by ETFs. Here replication refers to the concept of mirroring the returns of a benchmark index with the returns of an ETF. Bloomberg Professional's categorisation of replication strategies shows that ETFs replicate their benchmark indices using the following strategies: full physical, stratified sampling, optimization, synthetic and leveraged replication. This study analyses the tracking performance of 52 equity-backed ETFs, focusing on replication strategies, fund domicile, and crisis period.

Four methods of tracking error estimation are applied to the ETF sample which have an inception date before 1 January 2006 or 1 January 2012 for the fund replication and domicile analyses due to the observed lack of ETFs following certain replication strategies and domiciled in emerging markets with an inception before 2006. For the crisis analysis the research period spans 18 years to account for the documented price impacts the 2008/2009 Global Financial Crisis (GFC) and the COVID-19 pandemic had on various indices and their replicating funds.

We find that overall partial physically replicated ETFs provide superior tracking performance. Full physically replicated ETFs exhibit the highest level of tracking error. Synthetic ETFs demonstrate superior tracking performance in comparison to full physical ETFs. Considering the same underlying benchmark index, leveraged ETFs with lower

leverage multipliers exhibit lower levels of tracking errors than their counterparts. ETFs domiciled in developed markets limit tracking errors to a greater extent than emerging market ETFs and synthetic ETFs show superior tracking performance when tracking emerging market indices. All fund replication strategies (noting that leveraged ETFs are excluded in this section of the analysis) for both emerging and developed market ETFs show increases in tracking error during the GFC and the COVID-19 pandemic. Optimized ETFs exhibited the highest increase in tracking error during the GFC while full physically replicated ETFs exhibited the highest increase during the pandemic. Synthetic ETFs showed the most resilience to the effects of the pandemic. Emerging ETFs exhibited higher increases in tracking error during both crises in comparison to those in developed markets.

This study provides both institutional and individual investors with valuable knowledge on the consideration of fund replication strategy, fund domicile and the performance effects of documented crisis periods when selecting an appropriate ETF. Investors and portfolio managers are provided with relevant insights on which type of ETF replication to follow in countries with different development levels and during volatile market periods. Partial physical replication provides superior tracking performance when focusing solely on replication strategy. Synthetic ETFs are recommended when investing in emerging market indices and aiming to minimize exposure to volatile markets marked by crises.

Keywords

ETF, Tracking Performance, Equity, Replication Strategy, Fund Domicile

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1. Introduction

1.1. Introduction and Background

An Exchange-Traded Fund (ETF) is a publicly traded and open-ended index-tracking fund continuously traded during an exchange's trading hours (Khan, Bacha and Masih, 2015). The creation of the Exchange Traded Fund, or ‘ETF’, came into play as an adaption to traditional index and mutual funds. The inception of the ETF occurred when a recurrent observation was made in connection with tracking the market. This observation was the need to take positions in and out of the entire market expeditiously, with the use of just one order. At inception, the primary purpose of an ETF was to replicate the returns of an underlying benchmark index. Hence, ETFs can provide investors with an investment alternative that has an almost identical risk-return profile to that of the basket of underlying assets, creating the ultimate passive investment instrument.

Passive investor's interest in ETFs as an investment vehicle grew extensively due to their unique characteristics that combine the advantages of conventional mutual funds with those of ordinary corporate stocks while maintaining a relatively low-cost structure. Advantageous properties of the ETF process include lowered transaction costs and tax burdens. Their increased flexibility in investment strategies enables them to easily diversify away from higher levels of portfolio risk (Rompotis, 2009). Therefore, the development of ETFs has contributed to an increase in various adaptions to their structure and replicating abilities within a significantly short period (Agapova, 2011).

ETFs have risen in popularity in terms of their trading volumes and market capitalization rates over the last decade (Bahadar, Gan and Nguyen, 2020). Statista (2024) provides a statistical introspection of the growth of the US ETF market, which remains one of the largest and most valuable equity markets globally. They found that the number of ETFs in the US had steadily increased over the last two decades, from 123 ETFs in 2003 to 3243 actively traded ETFs as of 2023 (Statista, 2024). The value of assets under management (AUM) allocated to US-domiciled ETFs experienced a rampant increase from 151 billion USD in 2003 to roughly 8 trillion USD in 2023. ETFs demonstrate spectacular growth in trading volume, variety, and contribution to the market capitalization values of various stock exchanges. For example, ETFs represented more than 10% of the market capitalization value of securities traded on the US's stock exchanges in the fourth quarter of 2016 and more than 30% of intraday trading volume on the US’s securities exchanges (such as the New York Stock Exchange).

The most recent data measured during the first quarter of 2023 has shown that while the market capitalization level of ETFs in the US is at around 12.7%, their daily trading volume constituted nearly 40% of the total US stock market trading volume as measured by the CBOE Volatility Index (VIX), a proxy for US equity market volatility (Cohen, 2023). Further, 2022 data shows that ETF shares comprise an average of 16.4% of overall short interest in US markets, with an average cost to borrow of 1.02% (Fidelity, 2022). These various figures provide a snapshot of the growth in ETFs' trading volume and market capitalization levels as investment vehicles (Rompotis, 2015; Bahadar, Gan and Nguyen, 2020).

Since the Global Financial Crisis, the introduction of ETFs as hybrid investment vehicles (with hybrid referring to a combination of active and passive management in this case) remains one of the most revolutionary innovations in financial markets. Despite ETFs being launched on American and Canadian exchanges in the early '90s, their dynamic development began in the last decade (Charupat and Miu, 2013; Miziolek and Feder-Sempach, 2019). As per ETFGI (2018), by the end of July 2018, it had been reported that ETFs, together with Exchange Traded Products (ETPs), have been listed on 70 platforms across 57 countries globally, with assets invested in 5649 ETFs, reaching a total level of approximately USD 4.96 trillion (Miziolek and Feder-Sempach, 2019).

The first ETFs were launched exclusively on the stock exchanges of developed countries with exposure to equity markets within this group of economies. However, the desire of international investors to diversify their investment portfolios globally, resulted in the launch of the first two equity-backed ETFs with exposure to single emerging market economies. ETFs that tracked Mexican and Malaysian equities were first listed on the American Stock Exchange (AMEX) in the late 90s. In more recent years, country-specific ETFs have been launched on various exchanges, such as in the USA, Hong Kong, India and South Africa, resulting in increased emerging market exposure for international investors. The popularity of ETFs and ETPs with exposure to fast-growing emerging economies has increased rapidly since the first broad emerging market exposure ETF, BLDRS Emerging Markets 50 ADR Index, which was listed on the NASDAQ in 2002. This enabled institutional asset managers to invest internationally without the added difficulty of meeting the requirement of foreign investor status in multiple emerging markets (Miziolek and Feder-Sempach, 2019).

Before the launch of emerging market tracking ETFs, a limited selection of futures contracts offering exposure to these markets were available. The rise of these ETFs has led to more investors enjoying the returns received from investing in indices that track the rapid development and economic growth of emerging market countries (Miziolek and Feder-Sempach, 2019). The iShares MSCI ETF (now called the iShares MSCI Emerging Markets ETF) became a trailblazer in the emerging market passive fund space. First launched in 1988, it has become a widely recognized benchmark for emerging market economies and a basis for the creation of ETFs globally, including Europe and the United States. This fund offers investors the opportunity to obtain broad market exposure to twenty-four emerging market countries with a single transaction. The global market exposure offered by this fund has positioned it as one of the most popular ETFs among investors. Due to most developed investment markets, such as those in Europe and the US, needing to be more cohesive, asset managers could not justify the costs of offering passive funds based on individual emerging market benchmarks (Miziolek and Feder-Sempach, 2019). The existence of ETFs that replicate the MSCI Emerging Markets Index addresses this issue. Their structure allows them to become some of the most vastly represented financial instruments of their type globally (Miziolek and Feder-Sempach, 2019).

The imminent rise of ETFs and the synonymous increase in passive investment trading volume suggests that the increased use of ETFs results in favourable investor sentiment in markets (Strydom, Charteris and McCullough, 2015; Ben-David, Franzoni and Moussawi, 2018). In recent periods of study, many researchers have attributed the increase in the use of ETFs as passive investment vehicles to an increase in the efficiency of financial markets. Other studies suggest that price efficiency plays a more significant role in ETF use rather than the increased efficiency of financial markets (Ben-David, Franzoni and Moussawi, 2018). Researchers have also observed that passively managed ETFs have encapsulated a more substantial market share than conventional indices and mutual funds (Ben-David, Franzoni and Moussawi, 2018).

The passive nature of ETFs aligns with the principles of efficient markets. Efficient markets and the Efficient Market Hypothesis (EMH) provide one of the foundational tenets within the scope of investment management. The EMH assumes that all available information has been considered in the valuation of a financial instrument at a specific moment (Fama, 1970). In adapting the EMH to the ETF environment, we understand that, based on all available trading information, it will not be possible to achieve abnormal rates of return when investing in actively managed funds. The use of financial investment vehicles that reflect the stock market index reinforces the argument presented by the EMH (Debski, 2010; Chlebisz, 2018; Zawadski, 2020). It is a widely recognized position that the most effective investment strategy to follow when markets are efficient is a passive investment strategy. A corollary that follows from passive investing is the advantage of the minimization of portfolio selection costs by replicating an existing index.

The inception of the ETF came at a time in the investment industry when the distinction between passive and active investing was clear. The idea was to select a one-size-fits-all, low-cost market index fund, or alternatively invest in a higher-alpha and higher-cost portfolio of assets (Easley, Michayluk, O'Hara and Putnins, 2021). Under this paradigm, the distinction between passive and active investing is based on the relative costs associated with investment products and the cost and availability of the information needed to generate above-market returns (Easley *et al.*, 2021).

Advancements in the ETF industry have undermined the simplicity of this depiction. While the historical debate between passive and active schools of thought provides a principal underlying basis for portfolio management strategy, research has found that the passive versus active discourse has also spilled into the ETF realm (Meziani, 2015). This discourse remains prevalent despite the structure of ETFs designed as a passive investment instrument. The structure of an ETF, however, enables it to provide a variety of cost-minimizing advantages, which give it the ability to generate alpha-seeking portfolios that appeal to more active investors (Easley *et al.*, 2021). Developments within the ETF space have resulted in the creation of ETFs that follow replication strategies based on the tenets of active investing, thus creating a new subgenre within this space.

ETFs can be deemed theoretically active in two ways, either active-in-form or active-in-function. An ETF that is active-in-form, suggests that the underlying benchmark of an ETF, which is made up of a portfolio of selected assets that the ETF is designed to track, is chosen to generate alpha. Active-in-function ETFs are used by investors as foundational constituents for creating active portfolios (Easley *et al*., 2021; Malhotra, 2023).

This study focuses on ETFs' replication strategies, which as a result looks at ETFs that are active-in-form, with replication strategy subsets such as swap-based synthetic replication, leveraged replication and optimization showing characteristics of actively curated benchmark indices. In considering a cross-section of active-in-form ETFs, findings have recently shown that they have positive performance sensitivity and high within-portfolio turnover due to holdings that are concentrated to a lesser extent (Easley *et al.*, 2021).

Further into the passive versus active argument we find that existing research and academic arguments favour the use of passive ETFs over newly found active paradigms (Meziani, 2015). The curation of this academic opinion is due to efficient markets and the follow-through of asset prices being intrinsically unpredictable (Meziani, 2015). Brinson, Hood and Beebower (1995) emphasized the extent to which asset allocation, security selection and market timing affect asset performance, where their study showed that approximately 90% of a fund's return over time can be explained by investment policy; thus, establishing a firm argument in favour of the EMH.

Contrary to studies such as Brinson, Hood and Beebower (1995), which have implicitly favoured traditional passive ETFs, our study focuses on the inclusion of a wide variety of ETFs, some of which deviate from their traditional passive nature. The inclusion of ETFs such as the ProShares Ultra S&P500 (Ticker: SSO), which aims to amplify the returns of the S&P500 (Ticker: SPX) by a multiplier of two, is an example of the activeness of the leveraged ETFs included in this study.

Several existing studies have focused on ETFs as passive investment instruments that are designed primarily to mimic the returns of their underlying benchmark index through full/physical replication (Rompotis, 2011; Strydom, Charteris and McCullough, 2015; Broby and Spence, 2020). However, there is a scarcity of research that unpacks the effect of an ETF's replication strategy on its tracking performance. Given the gap in understanding how replication strategies affect tracking performance, this study seeks to quantify this relationship by computing the tracking error of 52 ETFs that follow five different replication strategies as per Bloomberg classification. The replication strategies focused on in this study are full physical, stratified sampling, optimization, synthetic and leveraged replication.

The research is then furthered to consider emerging and developed market perspectives, which consider whether a difference in tracking performance arises depending on a fund's domicile. Finally, considering crisis periods, we will look at significant deviations in tracking error during the crisis periods to gauge a more accurate picture of the effect of the Global Financial Crisis and COVID-19 pandemic on the equity ETF market. Additionally, it allows us to further analyse the recovery of the equity ETF market post-crisis. This will be done through a comparative analysis of the changes in the tracking error levels of the ETF sample during 2010-2011, 2012-2013, 2014-2015, 2016-2017, 2018-2019 and 2022-2024.

In order to address the scarcity in ETF research surrounding the effect of factors such as fund replication strategy, fund domicile, and crisis periods, the main objective of this study is to investigate the relationships between these distinguishing factors and tracking performance on a sample of 52 ETFs. Using tracking error quantification methods, we will be able to determine how the tracking error levels of each respective ETF differ based on the replication strategy they follow and their country of domicile. Further to that, we will find how the tracking performance of ETFs behaved during the Global Financial Crisis and COVID-19 pandemic, and whether ETFs following specific replication strategies or domiciled in specific markets show more stability in their performance.

This study aims to clarify observations from previous studies that have found the following:

I. Naumenko and Chystiakova (2015) found that synthetic ETFs demonstrate higher levels of tracking error in comparison to physical ETFs, which contradicts the findings of Mateus and Rahmani (2017) and Meinhardt, Mueller and Schoene (2015).

II. Blitz and Huij (2012) and Zawadzki (2020) suggested that developed ETFs demonstrate lower levels of tracking error, with emerging ETFs being more predisposed to higher levels of tracking error.

III. Khan, Bacha and Masih (2015) stated that overall, the mean tracking error of ETFs for the period of 2007 to 2014, irrespective of their domicile, was higher during periods of increased volatility. Malhotra and Sinha (2023) and Ehnes, Norman and Rahman (2024) found that COVID-19 had a negative impact on stock market liquidity, returns and underlying volatility. Therefore, this resulted in observably higher levels of ETF tracking error. Both papers looked at country-specific ETFs and found that the level of tracking error worsened for ETFs depending on their country's economic outlook during the pandemic.

Three key research questions are posed from the preceding findings, namely:

I. How does the tracking error of ETFs under each of the five categories of replication strategy (as classified by Bloomberg) differ?

II. How does the tracking error of ETFs domiciled in countries of differing development levels (i.e. Developed or Emerging) differ?

III. How did the Global Financial Crisis and COVID-19 pandemic affect ETF tracking performance?

The subsequent sections 1.2, 1.3 and 1.4 of this study provide a theoretical framework discussing the surrounding literature and implications associated with tracking performance, fund replication, fund domicile, and the impact of crisis periods on ETF performance dynamics.

1.2. Tracking Performance

The ETF research undertaken in this study looks primarily at tracking performance. The tracking performance of ETFs is evaluated by the analysis of tracking errors, which refer to the difference between the movement of the fund price and that of the underlying benchmark (Miziolek and Feder-Sempach, 2019). Essentially, tracking error is a measure of the volatility of the difference in return between the fund and its underlying benchmark (Charteris and McCullough, 2020). Tracking error is one of the most common determinants of an ETF's performance (Lin and Mackintosh, 2010). The popularity of quoting tracking errors when comparing ETF performance is no surprise since ETFs perform quite similarly to index funds (Lin and Mackintosh, 2010). Roll (1992), Johnson, Bioy, Kellett and Davidson (2013) and Charteris and McCullough (2020) justify the measurement of tracking performance as volatility by the fact that it accounts for the observation that security returns are noisy. Therefore, the consistency with which investment performance differs from index performance is appropriate (Charteris and McCullough, 2020). As volatility is a measure of risk, tracking error essentially measures the tracking performance of the fund as the relative risk (Charteris and McCullough, 2020).

Investors who purchase ETFs want to be aware of how closely they follow an index in actual market conditions. Therefore, by analysing the tracking error of an ETF, the investor can gauge how closely the ETF is replicating its benchmark index (Tsalikis and Papadopoulos, 2019). Traditional passive investors will consider investment fees and tracking errors instead of abnormal returns when selecting their ideal investment vehicle. They are likely to prioritize investment in funds that minimize both. Therefore, the criteria used to assess the quality of a passive investment vehicle, such as an ETF, is their ability to simultaneously minimize tracking error and transaction costs (Strydom, Charteris and McCullough, 2015).

This study aims to quantify tracking performance by computation of tracking error by four well-established methods, which are further discussed in the data and methodology sections. The analysis focuses on determining if the tracking performance of ETFs differs when differing replication strategies and differing fund domiciles are applied. Further, we will deduce whether ETFs suffer from an increase in tracking error magnitude during periods of market volatility by considering the sample tracking errors during periods surrounding the Global Financial Crisis and COVID-19 pandemic.

Research shows that the returns of the fund and its benchmark index are typically correlated because of market frictions and new information (Cutler, Poterba and Summers, 1990; Rhee and Wang, 1997; Antoniou, Koutmos and Pericli, 2005; Charteris and McCullough, 2020). This finding is suggestive of the observation that tracking errors may be persistent in funds. For this reason, this study aims to measure the magnitude of a fund's tracking error as an indicator of tracking performance instead of the presence or absence of tracking error. Considering the preceding statement, a fund that demonstrates lower levels of tracking error will be regarded as depicting better tracking performance than a fund with higher tracking error.

Studies such as Osterhoff and Kaserer (2015) explored existing sources of tracking error, which looked at the relationship between stock market liquidity and the tracking ability of ETFs. Findings from Osterhoff and Kaserer (2015) suggest that tracking error is dependent on the liquidity of its underlying benchmark. This is due to liquidity costs significantly affecting portfolio adjustments and events that trigger market transactions. Other significant factors that have been shown to affect tracking error levels include the Total Expense Ratio (TER) (Elton, Gruber, Comer and Li, 2005), which is inclusive of management and administrative fees (Charteris and McCullough, 2020). These factors were shown only to affect tracking error if there is an observed fluctuation in the TER over time, deviations in the composition of an index or the index replication strategy (Gastineau, 2002) and dividend payments (Blitz and Huij, 2012).

With all other factors considered equal, management fees have the most prominent effect on tracking error measures (Osterhoff and Kaserer, 2015). The total expense ratio (TER) of an ETF is essential in explaining tracking errors, as the higher the TER, the higher the level of observed tracking error (Charupat and Miu, 2013). Chu (2011) initially found a positive relationship between the TER of a fund and its tracking error and a negative relationship between tracking error and fund size. However, in their later work, Chu (2013) found a negative relationship between tracking error and TER. Chu (2013) explained that these conflicting results arose from not differentiating between physically backed and synthetic ETFs. Therefore, Chu (2013) finds that neglecting to include the potential effect of replication strategy on tracking performance affects the results. The effect of the replication strategy on the TER arises from the increased transaction costs and management fees, that are consistent with the application of more complex replication strategies (Chu, 2013). These costs inflate the TER, thereby changing the way it affects the fund's tracking error (Chu, 2013).

This study classifies each ETF in the sample by its replication strategy and then categorizes them to ensure tracking errors are observed within the subgroups of differing replication techniques. While it can be justified that the increased costs associated with differing replication techniques may amplify variations in the absolute magnitude of tracking error, it does not provide a substantial basis for the negativity between the two variables (Chu, 2013).

The liquidity-tracking error magnitude argument had been dismissed by Gastineau (2004). Gastineau (2004) justified this claim by stating that ETFs' creation and redemption processes prevent them from bearing any liquidity costs. Therefore, liquidity costs should not affect the tracking performance of an ETF (Gastineau, 2004). Additionally, Gastineau (2004) stated that through the fees charged by ETF creators to asset providers, any liquidity or other transaction cost should be covered, thus removing it from being a determinant of tracking error.

In an ideal world, the tracking error of an ETF will be zero. However, the findings from existing research, such as Frino and Gallagher (2015) and Kanuri and McLeod (2015), suggest that this is not possible. Frino and Gallagher (2001) identified that tracking errors will almost always arise due to factors such as dividend payments, expenses and the size and timing of index rebalancing. In the case of international ETFs (in this case, this refers to ETFs domiciled outside of the US), Kanuri and McLeod (2015) found that the magnitude of tracking error significantly affected the diversification benefits of an ETF. If an investor seeking global market exposure as a means of portfolio diversification decides to invest in an ETF with a high tracking error, the benefit of diversification relative to the benchmark index will be lessened (Kanuri and McLeod, 2015).

Investors are encouraged to attain international diversification through indirect investment instruments such as ETFs (Huang and Lin, 2011). Earlier studies have emphasized the importance of portfolio diversification through low correlations between markets by allocating some of their funds to foreign investment funds (Huang and Lin, 2011). However, more recent studies have shown that during turbulent markets and periods of financial distress, the correlations between indirect foreign funds increase, resulting in higher levels of tracking error (Kanuri and McLeod, 2015). It has also been observed that foreign-indexed funds provide lower levels of excess return during market turmoil and restrictive monetary policy periods (Kanuri and McLeod, 2015).

Tracking error is a crucial risk measure for asset managers (Vardharaj, Fabozzi and Jones, 2004). It is influenced by factors such as portfolio composition, market capitalization, style differences and benchmark volatility (Vardharaj, Fabozzi and Jones, 2004). The relationship between tracking error constraints and fund performance can be visualized as an elliptical locus, with changes in its main axis slope serving as an early indicator of performance (Gunning and Van Vuuren, 2019). Investors who use tracking errors to guide decisions may exhibit greater risk-taking behaviour and accumulate more wealth compared to mean-variance investors (Berg and Lien, 2003). However, estimation risk in asset means and covariances can lead to poor out-of-sample performance for funds optimized to minimize tracking error (Woodgate and Siegel, 2015). Theoretical bias adjustments can help reduce this estimation risk, potentially improving fund performance and reducing portfolio rebalancing costs (Woodgate and Siegel, 2015).

Frino, Gallagher, Neubert and Oetomo (2004) and Dorocakova (2017) state that the existence of tracking error is unavoidable and a necessary component of a fund's performance, as the benchmark is measured as a paper portfolio with the assumption that perfect copying can be achieved instantaneously and without costs. Dorocakova (2017) found that endogenous and exogenous components of tracking error exist. While portfolio managers can influence the endogenous component, they cannot control exogenous components, which refer to the index design and maintenance procedures (Dorocakova, 2017). The main factors that influence tracking error are the number of index revisions, share issuances, share repurchases, spin-offs, index replication strategy, fund size, dividend policy, premium and discount to net asset value (NAV) and season in a year (Dorocakova, 2017).

While tracking error is popularly used as a guide to investment decision-making by portfolio managers, it is still a relatively foreign concept to investors. In academic literature, a significant amount of research on tracking errors exists. However, there is a gap in the literature that focuses on how factors such as replication strategy affect the tracking performance of ETFs. Therefore, in this study, we seek to amplify the available literature on tracking error in the context of differing replication strategies, fund domiciles, and crisis periods to provide valuable information to investors. This study will provide information on the tracking error differences among a wide variety of ETFs that investors may choose to add to their portfolios.

1.3. Replication Strategies

The two main classifications of fund replication are physically backed and synthetic. However, stratified sampling, optimized and leveraged fund replication strategies are provided as separate classifications under the Bloomberg Classification System. Technically, stratified sampling and optimized replication are forms of physical replication as they involve holding the physical assets of the underlying benchmark index, and leveraged replication represents a form of synthetic replication as it uses derivatives to replicate its underlying benchmark index. However, as this study aims to determine whether varying replication strategies and ETF construction methods affect the tracking performance of equity ETFs, the Bloomberg classification of replication strategies is used to draw a suitable data sample. There is substantial evidence in existing research that the replication strategy and construction method of an ETF inherently affects its tracking performance (Maurer and Williams, 2015).

Physical ETFs directly hold the underlying assets, while synthetic ETFs use derivative contracts, such as total return swaps, to replicate index performance (Fassas, 2014). Research comparing their relative performance has yielded mixed results. Some studies found that physical ETFs outperform synthetic ETFs in terms of tracking ability (Fassas, 2014). However, synthetic ETFs may offer advantages in certain market conditions. They demonstrate enhanced tracking performance during liquidity shocks and within high-liquidity groups (Kim, Cho and Seok, 2023).

While synthetic ETFs are theoretically expected to provide better tracking, some studies found no significant difference in tracking errors between the two types of equity ETFs (Mateus and Rahmani, 2014; Meinhardt, Mueller and Schoene, 2015). Contrary to this, Naumenko and Chystiakova (2015) reported higher tracking errors for synthetic equity ETFs. Tripathi and Sethi (2022) found that ETFs following full replication techniques exhibited lower tracking errors than those following statistical replication. However, synthetic ETFs were found to increase the returns of tangency portfolios compared to physical ETFs, suggesting that they may be more suitable for risk-tolerant investors (Broby and Spence, 2020). The choice between physical and synthetic ETFs is dependent on an investor's risk tolerance and specific market conditions (Mateus and Rahmani, 2017).

The performance impact of the "cash drag", caused by holding large cash reserves, and which may reduce returns during market upswings but mitigate losses during downturns, suggests that it is integral to consider the size of a fund's cash reserve when choosing between physical and synthetic ETFs (Maurer and Williams, 2015, p.134). This is because ETFs that hold more liquidity such as synthetic ETFs, will underperform their less liquid counterpart in times of up markets, and outperform their rival funds during periods of down markets (Maurer and Williams, 2015). This characteristic of synthetic ETFs enables them to act as a hedge against market downturns (Maurer and Williams, 2015). However, it also predisposes the investor to higher risk levels during market upswings (Maurer and Williams, 2015). Gallagher and Segara (2005) state that liquidity within the fund domicile and size have an integral effect on their replication strategy. Therefore, the observed variance in the magnitude of tracking errors across funds can be explained by the funds following different replication strategies (Gallagher and Segara, 2005).

Gallagher and Segara (2005) explained that an inverse relationship exists between tracking error accuracy and the cost of investing. Hence, a passive investor should recognize that perfect replication is unachievable. Tracking error is dependent on numerous external factors, such as the structural design of an index, the liquidity of underlying stocks in the benchmark, the size of the investment portfolio being managed and the replication strategy that has been adopted (Gallagher and Segara, 2005). These findings highlight the complexity of ETF performance and the importance of considering replication strategy in investment decisions.

Continuous innovations within the ETF space have led to the creation of leveraged synthetic ETFs, which act as reverse funds with double or triple exposure to an index (Yiannaki, 2015). While Elia (2012) found that both traditional and synthetic ETFs are affected by significant levels of tracking error, evidence showed that if ETFs followed synthetic replication, they would have lower levels of tracking error. Synthetic ETFs were also discovered to show better tracking ability in the context of emerging market indices (Elia, 2012). However, it should be noted that neither physical nor synthetic replication can guarantee perfect index replication; consequently, a level of tracking error is always present (Elia, 2012). Jaakkola (2022) found significant levels of tracking error across all ETFs, irrespective of whether they followed full or statistical replication methods.

A commonly made observation in existing research is that synthetic ETFs demonstrate higher transaction costs (Yiannaki, 2015). Synthetic ETFs include additional transaction costs, such as swap spreads, which are not reflected in their Total Expense Ratio (TER) (Maurer and Williams, 2015). The higher management fees included in the swap spreads are an example of a contributing factor to higher tracking error due to an ETF's adopted replication strategy (Gastineau, 2004; Maurer and Williams, 2015). A further observation is that higher volatility comes from indirect replication. Since the ETF and index are not identical in structure, higher tracking errors are observed (Yiannaki, 2015). However, with physical replication, lower tracking errors are observed since the securities within the index and the ETF are identical (Yiannaki, 2015). Synthetic replication also leads to higher tracking errors when the compounding of daily returns is not adjusted for exposure by the end of the day (Yiannaki, 2015). Physically backed ETFs also exhibit unique factors, such as index revisions and fund rebalancing processes that affect the magnitude of tracking errors (Maurer and Williams, 2015).

Existing research has also found that synthetic replication carries additional risks. Ramaswamy (2011) stated that synthetic replication may transform tracking error into significant counterparty risk. Risks inherent to synthetic replication include increased liquidity risk (Kim, Cho and Seok, 2023), counterparty exposure and reduced transparency (Aggarwal and Schofield, 2014). The creation of systematic risks threatens financial systems' stability (Ramaswamy, 2011). Regulators have expressed concerns about systematic risk, excess volatility and suitability for retail investors (Aggarwal and Schofield, 2014). To mitigate these risks, the industry has implemented measures such as multiple counterparties, over-collateralization and improved disclosure of collateral and index holdings (Johnson, Bioy and Rose, 2012; Aggarwal and Schofield, 2014). Understanding the mechanics of swaps and sources of risks is crucial for investors considering synthetic ETFs (Johnson, Bioy and Rose, 2012).

The findings in this section of the study have provided sufficient evidence that the replication strategy of a fund has significant implications for the fund's performance. Therefore, this study provides a basis for investigating how the magnitude of a fund's tracking error differs based on its replication strategy. This will enable us to undertake a comparative analysis to determine which replication strategy subset exhibits the highest level of tracking performance.

1.4. Fund Domicile: Developed and Emerging Markets

An important concept related to ETF tracking performance is the linkages between returns and volatilities across international financial markets. The growth in the global integration of financial markets has resulted in many studies considering the interlinkages between equity market movements across different economies (Yavas and Rezayat, 2016). Existing studies have proved that real economic conditions and equity market performance are related. However, the performance of financial markets is also dependent on localized factors within a specific country. This suggests that market performance will only be perfectly correlated across some countries (Yavas and Rezayat, 2016). This section looks at the reasoning behind why fund performance differs between emerging and developed markets.

Research on emerging and developed market ETFs reveals significant differences in performance and characteristics. Emerging market ETFs generally exhibit higher tracking errors and less efficient index replication compared to developed market ETFs (Khan, Bacha and Masih, 2015; Blitz and Huij, 2012). However, emerging market ETFs tend to provide better risk-adjusted performance (Khan, Bacha and Masih, 2015) and offer potential diversification benefits due to low correlation with developed markets (Hilliard and Dat Le, 2022). Emerging market ETFs are typically smaller, younger and have higher fees than their developed market counterparts (Hilliard and Dat Le, 2022). These factors have led to them being significantly underutilized as a method of international diversification by developed market investors (Hilliard and Dat Le, 2022).

Despite the absence of long-term cointegration, return correlation and flow sensitivity to volatility between emerging and developed markets, several risk factors that are inherent to emerging markets deter investors away from diversification opportunities (Hilliard and Dat Le, 2022). Instabilities and greater risks within emerging markets, such as political uncertainty, currency risk and various macroeconomic factors, lead to investors being reluctant to invest in them (Hilliard and Dat Le, 2022). The extent of the presence of political uncertainty and susceptibility to economic downturns in emerging markets inform the investment decisions of international investors (Hilliard and Dat Le, 2022). As a result, ETFs domiciled in Central and Eastern Europe may perform better than those in Latin America and Asia, of which the latter are more predisposed to economic uncertainty (Hilliard and Dat Le, 2022).

The popularity of emerging market ETFs has risen significantly in recent years, offering investors easier access to these markets (Mistry, 2013). The growth is evident in both developed markets, where investors gain exposure to emerging economies and within emerging markets themselves, where ETFs are increasingly being listed on local exchanges (Luhr, 2013). The increase in emerging market ETF creation can be attributed to the economic liberalization of various countries, particularly in Central and Eastern European countries, such as Poland, the Czech Republic and Slovakia, becoming members of the European Union (Hilliard and Dat Le, 2022). This has led to an increase in the attraction of foreign investors and equity market participation to these newly globally integrated countries (Hilliard and Dat Le, 2022).

Another example of global market integration is the BRICS coalition, which has allowed member nations Brazil, Russia, India, China and South Africa, which represent some of the fastest-growing emerging market economies, to integrate themselves within global equity markets and gain international exposure to attract foreign investment. This has led to increased interest in ETFs that are domiciled within these emerging markets, such as the iShares country-specific MSCI ETFs. The trend of investing in emerging markets through ETFs is expected to continue growing, driven by factors such as increased accessibility and potential for diversification (Luhr, 2013; Mistry, 2013).

Research indicates that emerging market ETFs generally exhibit higher tracking errors compared to developed market ETFs (Neto, Klötzle and Pinto, 2021; Khan, Bacha and Masih, 2015). The increased tracking error is attributed to various factors, including less efficient index replication in emerging markets (Khan, Bacha and Masih, 2015) and higher cross-sectional dispersion in stock returns (Blitz and Huij, 2012). Trading emerging market equities involves higher transaction costs and increased risk compared to developed markets, contributing to higher tracking errors (Fenty and Constantine, 2015). Additionally, emerging market stocks show higher volatility, greater uncertainty in liquidity and less stable correlations, making it more challenging to predict and manage tracking errors (Fenty and Constantine, 2015). Fund managers focusing on emerging markets face higher levels of tracking error, which can lead to lower performance if not accompanied by information about fund concentration in multiple market segments (Galloppo and Aliano, 2018).

Factors contributing to superior tracking performance in developed markets include lower bid-ask spreads, smaller price-to-net asset value deviations and potential fund age and size (Tripathi and Sethi, 2022). Asset size positively impacts ETF performance (Khan, Bacha and Masih, 2015). Fund age has been identified as a primary factor influencing tracking performance in some cases (Tripathi and Sethi, 2022). American ETFs, which have been around significantly longer than ETFs domiciled in other markets, exhibit lower tracking errors compared to European ETFs (Tsalikis and Papadopoulos, 2019). Additionally, ETFs with lower expense ratios and larger asset bases tend to attract more investors (Narend and Thenmozhi, 2016).

Regional diversity is integral to ETF performance, with tracking errors varying across different geographical locations and market development levels (Zawadzki, 2020). The geographical location and market development stage influence tracking error values (Zawadzki, 2020; Dobson, 2020). Emerging ETFs using statistical index replication techniques are particularly prone to higher tracking errors, especially during periods of high return dispersion (Blitz and Huij, 2012). However, synthetic ETFs demonstrate lower tracking errors and higher tax efficiency, particularly when tracking emerging market benchmarks (Elia, 2012).

A further observation has been that European emerging market ETFs predominantly follow synthetic or swap-based replication (Hilliard and Dat Le, 2022). As of 2022, more than 60% of European emerging market ETFs follow synthetic replication, in comparison to the 15% of synthetically replicated developed European ETFs (Hilliard and Dat Le, 2022). In this context, it can be deduced that the replication strategy of the emerging market ETFs predisposes them to higher levels of tracking error. However, some studies have found that emerging market ETFs generally offer better risk-adjusted performance than developed market ETFs, despite being less efficient in index replication and having higher tracking errors (Khan, Bacha and Masih, 2015).

Market conditions also influence tracking performance, with emerging market ETFs showing higher tracking errors in bullish conditions, contrary to developed market ETFs (Neto, Klötzle and Pinto, 2021). Illiquidity in emerging market bonds can increase tracking error, with diversification benefits diminishing during crisis periods (Darolles, Dudek and Le Fol, 2016). During the 2008-2009 financial crisis, ETF tracking performance was negatively impacted across all markets (Mateus and Rahmani, 2017). Notably, US ETFs outperformed international ETFs in terms of returns, risk and risk-adjusted performance during and after the crisis period (Kanuri and McLeod, 2015). US ETFs also demonstrated the lowest tracking errors during this period (Kanuri and McLeod, 2015).

The tracking performance of emerging market ETFs followed a different trajectory during the COVID-19 pandemic in comparison to the Global Financial Crisis. International markets showed increased correlation and cointegration, thereby decreasing their ability to act as diversification agents (Hilliard and Dat Le, 2022). The sensitivity of emerging market equities to global cycles has become much more prominent in recent years (Levy-Yeyati and Williams, 2020). Emerging market ETFs domiciled in countries with large holdings of equity shares exhibited increased sensitivity to worldwide financial market conditions (Levy-Yeyati and Williams, 2020). This suggests that emerging market ETFs have become significantly more influenced by international capital flows and global economic cycles, which have resulted in increased cointegration and correlation between emerging and developed markets.

However, Hilliard and Dat Le (2022) found that ETF flows in specific emerging markets, such as that of Central and Eastern Europe, are not significantly susceptible to changes in the volatility indices of developed nations. Therefore, this implies that some emerging market ETFs can retain their ability to diversify international portfolio offerings during periods of market crisis (Hilliard and Dat Le, 2022). The findings in this section have highlighted the complexity of ETF tracking performance and the importance of considering regional diversity and market conditions in ETF evaluation. Thereby providing a basis for this study as we look at how the development status (categorised as emerging or developed) of a fund's domicile affects its tracking performance.

1.5. Crisis Periods: The Global Financial Crisis and COVID-19

The Global Financial Crisis and the COVID-19 pandemic are two of the most significant economic disruptions of the 21st century, each profoundly affecting financial markets and investment instruments, including ETFs. Part of the research objectives of this study deals with the effect of the Global Financial Crisis of 2008/2009 and the COVID-19 pandemic on the tracking performance of equity ETFs. This section provides an overview of the crises and their impact on equity markets and investment funds.

The Global Financial Crisis (GFC) was the most severe financial shock since the Great Depression, causing widespread economic damage and market turmoil (Barma and Vogel, 2020). Originating in the credit market of the United States, it led to a significant shift from easy credit conditions to tight credit and dysfunctional markets (Edey, 2009). The crisis exposed major flaws in the capitalist financial system, including the destabilizing effects of financial deregulation, hedge funds and regulatory laxness (Razin and Rosefielde, 2010). The aftermath saw millions of people losing their homes and wealth, financial market losses, credit market crashes and a global recession (Barma and Vogel, 2020). Governments and central banks responded with various measures to mitigate the crisis' effects (Edey, 2009).

The GFC had significant impacts on investment markets worldwide. Equity markets experienced a sharp decline, with broad market averages falling approximately 40% from their end-2006 levels (Bartram and Bodnar, 2009). The crisis led to increased clustering and interconnectedness among equity markets, particularly along geographical lines

(León, Kim, Martinez and Lee, 2016). Strong evidence of contagion effects from the US to both international developed and emerging markets was observed, explaining a large portion of the variance in stock returns (Gajurel and Dungey, 2013).

Interestingly, the crisis positively affected Latin American stock markets, leading to improved efficiency, reduced volatility and increased investor preference for the post-crisis period (Zhu, Bai, Vieto and Wong, 2018). The global nature of the crisis was evident from high correlations between markets and investment styles, which further increased during the crisis, limiting the benefits of diversification when it was most needed (Bartram and Bodnar, 2009).

The GFC significantly impacted the tracking performance of ETFs across various replication types and geographical regions. Both physical and synthetic ETFs experienced increased tracking errors during the 2007-2009 crisis period (Mateus and Rahmani, 2017). For leveraged ETFs, management factors and reduced liquidity often outweighed compounding effects, leading to substantial premiums/discounts and distorted performance (Shum and Kang, 2013). The crisis also facilitated contagion effects, with shocks transmitting from global financial ETFs to regional and sectoral ETFs, although some remained relatively unaffected (Thomaidou and Kenourgios, 2020). Research indicates that tracking errors in Indian ETFs increased during the GFC and COVID-19 pandemic, with pricing and inefficiencies shifting from discount to premium (Malhotra and Sinha, 2023). Greek index funds experienced substantial losses and increased volatility during the GFC (Rompotis, 2013a).

The GFC and subsequent market volatility had significantly impacted the equity ETF market. While ETF assets under management (AUM) grew substantially, reaching $1.5 trillion by 2011 (Mazza, 2012), concerns arose about their effect on market functioning. However, research suggests that macroeconomic factors, as opposed to ETF proliferation, were primarily responsible for increased volatility and correlations (Mazza, 2012). The crisis created a divide in the ETF market, with standard asset-class ETFs remaining stable while alternative asset-class ETFs faced challenges (Goltz and Schroder, 2011).

Despite these challenges, ETFs generally maintained their ability to replicate benchmark returns, although modest tracking errors occurred (Rompotis, 2013a). Investors continued to view ETFs favourably, particularly for their liquidity and transparency (Goltz and Schroder, 2011). The crisis impact varied across regions and sectors, with some ETFs remaining relatively unaffected or even immune to the shocks (Thomaidou and Kenourgios, 2020).

The COVID-19 pandemic significantly impacted global investment markets, causing high volatility and negative returns (Shaikh, 2022; Jain, 2020). The outbreak disrupted investor sentiment worldwide, leading to unprecedented negative returns and increased volatility (Shaikh, 2022). Investor sentiment analysis revealed a mix of fear and negativity alongside hopeful attitudes, potentially influencing market behaviour (Jain, 2020). The pandemic's impact varied across time scales, with strong co-movements observed in short-term markets during the first and second waves (Karamti and Belhassine, 2021). Longer-term investors initially showed optimism about the pandemic's eventual end (Karamti and Belhassine, 2021). During crises, such as the COVID-19 pandemic, the withdrawal of high-frequency traders from large stock ETFs can significantly increase intraday volatility, by over 30% (Aggarwal and Huang, 2021). This withdrawal slows arbitrage activities and reduces market-making functions when most needed (Aggarwal and Huang, 2021).

The pandemic significantly impacted global equity markets, with emerging markets experiencing larger negative effects than developed markets (Harjoto and Rossi, 2023). The pandemic had a more significant impact on European countries compared to East Asian economies (Hui and Chan, 2022). Studies found evidence of contagion through equity market tail risk in early 2020, followed by widespread contagion across multiple channels from the US to the G20 equity markets after the pandemic announcement (Fry-McKibbin, Greenwood-Nimmo, Hsiao and Qi, 2021). The energy and financial sectors were particularly affected in both emerging and developed markets, while healthcare, telecommunications and information technology (IT) sectors showed positive impacts in some markets (Harjoto and Rossi, 2023). Notably, equity markets recovered faster from the COVID-19 pandemic compared to the Global Financial Crisis (Harjoto and Rossi, 2023).

The faster recovery was attributed to several factors. Governments responded more rapidly with larger-scale interventions during the COVID-19 crisis compared to the GFC (Zaimovic and Dedovic, 2021). Fiscal stimulus measures were strongly associated with higher market recovery, suggesting that targeted fiscal support for real sector firms helped restore investor confidence (Seven and Yilmaz, 2020). The recovery pattern for the S&P500 index was “V-shaped” during COVID-19, contrasting with the “U-shaped” recovery during the GFC (Zaimovic and Dedovic, 2021, p.1149). In the context of financial market behaviour, V-shaped patterns suggest a quick rebound in economic recovery and asset price behaviour, whereas U-shaped recoveries suggest a longer period of stagnation before improvement (Yao and Zhang, 2011).

Regarding the performance of the ETF market during the pandemic, ETFs demonstrated resilience (Nguyen, 2023). However, tracking errors increased, and pricing inefficiencies shifted from discount to premium (Malhotra and Sinha, 2023). The pandemic’s effect varied geographically, with China experiencing a greater impact than Taiwan (Liu and Lee, 2022). Despite challenges, ETFs showed improved short-term disequilibrium corrections and increased co-integration between ETF returns and benchmark performance during COVID-19 (Malhotra and Sinha, 2023). The pandemic also increased systematic risk for some ETFs, particularly those with higher exposure to severely affected markets (Liu and Lee, 2022).

The findings in this section provides valuable insights for investors and portfolio managers navigating economic shocks. Further to that, it provides a basis for the research objectives of this study, enabling us to further study the effects of notable economic crises on the tracking performance of equity ETFs. Building on the insights gained from the discussion on relevant crises, the subsequent section outlines the structure of this study and details how each chapter addresses the research issue.

1.6. Conclusion and Plan of Study

This chapter has provided the general history of ETFs, their rise to popularity and their tracking performance dynamics, along with how the success of ETFs in delivering on this goal is measured. The research question of this study considers tracking performance across fund replication strategy, fund domicile and critical global crisis periods. The remainder of this study is organized as follows: Chapters two and three provide the theoretical framework and a review of existing literature on various characteristics and subsections of ETFs, respectively. Chapter four outlines the data and methodology. Chapter five presents the results and the implications drawn thereof. Finally, chapter six provides the conclusions and discusses limitations and suggestions for future research.

2. Theoretical Framework

This chapter begins by examining the empirical literature around ETFs, focusing on equity ETFs (these being the focus of this dissertation). This chapter aims to fully explore the theoretical foundations of and empirical research on equity ETFs. In line with the research questions of this study, the first section explores equity ETFs in general, discussing their characteristics, advantages and disadvantages. We will then discuss the chosen replication strategies. Finally, we consider the findings of studies that discuss tracking performance and their implications.

2.1. Exchange-Traded Funds

The late 1970s mark the origins of passive investing through index-tracking funds such as ETFs (Gastineau, 2001). However, ETFs had evolved to become a more noticeable passive investment instrument in the early 1990s (Gastineau, 2001). Despite the early creation of ETFs, various kinds of index-tracking funds have been populated throughout various stock markets (Gastineau, 2001). The Toronto Index Participation (TIP) was launched on the Toronto Stock Exchange (TSE) in 1989 and represented one of the first ETFs that were formally publicly traded (Gastineau, 2001). Broms and Gastineau (2006) justify this claim by stating that the TIPs possess all the characteristics of ETFs, unlike the tracker funds that came before them. The TIPs tracked the performance of the Toronto Stock Exchange's top 35 and 100 indices (Gastineau, 2001; Broms and Gastineau, 2006).

More popularly discussed with respect to the creation of the modern ETF is the Standard and Poor Depository Receipt ETF (commonly referred to as the SPDR), which was formed in 1993 by AMEX in partnership with State Street Global Advisors (Daswa, 2016). Since the formation of the SPDRs, the creation of ETFs soared phenomenally, resulting in exorbitant levels of growth across various asset classes, assets under management (AUM) and across international borders with the creation of country-specific ETFs (Daswa, 2016).

The evolution of the ETF is remarkable, with the first ETFs being introduced in Asian markets at the latter end of 1999, as documented by Chu (2011). Within just a year from that point, in 2000, ETFs reached both European and African equity markets (Daswa, 2016). The first emerging market country in the African continent to introduce an ETF product was South Africa with the launch of the Satrix 40, a fund created to replicate the performance of the FTSE/JSE Top 40 index (Cairns, 2014). Since then, ETFs have gained popularity among both retail and institutional investors in South Africa (Kunjal and Peerbhai, 2021). Studies have shown that the South African ETF market is reasonably efficient, with prices generally aligning with Net Asset Values (NAVs) in the long run (Charteris, Chau, Gavriilidis and Kallinterakis, 2014). One of the latest emerging market ETFs to be introduced is the Invesco S&P China A 300 Swap UCITS ETF, which was incepted in 2022 and tracks the net total return performance of the S&P China A 300 index (Invesco, 2024). Research has indicated that the Chinese and Asian ETF markets have shown significant growth and impact on global financial markets, specifically after the 2015 Chinese Stock Crisis which increased volatility and strengthened linkages between Chinese and US markets (Rompotis, 2016).

In more recent times, country-specific emerging market ETFs have gained further traction, with the results of a study conducted by ETF Stream and Amundi showing that 40% of investors would like to be more country-specific with their allocations (Andrew, 2022). With, China positioning itself as a global economic powerhouse we have seen the inception of various equity ETFs that focus on tracking indices comprised of Asian and Chinese securities to meet investor demand (Andrew, 2022). In 2019, Lyxor introduced the Lyxor MSCI Emerging Markets ex China UCITS ETF (EMXC) (Andrew, 2022). Following that, in 2022 Amundi launched the Amundi MSCI EM ex-China ESG Leaders Select UCITS ETF (EMXG), which encouraged buyers to invest in China while prioritizing sustainable investing, via a single-country ETF (Andrew, 2022).

ETFs have become a significant force in modern capital markets, managing trillions of dollars in assets (Fisch, Hamdani and Solomon, 2020). ETFs offer investors diverse investment options, from simple to complex strategies, through a nearly frictionless portal (Hu and Morley, 2018). The growth of ETFs reflects a broader shift towards passive, index investing (Madhavan, 2014). New adjustments to ETF creation have led to various forms of ETFs which deviate from traditional passive investing. Since the modernization of ETFs, leveraged and inverse leveraged ETFs have been coined as short-term trading instruments. Studies have shown that ETFs can provide abnormal returns through various trading strategies (Dimkpah and Ngassam, 2013). The creation of active ETFs allows investors to generate excess returns by beating the benchmark index using active management strategies such as security selection and market timing.

However, concerns about potential liquidity risks during market turbulence have been raised, as ETFs rely on intermediaries for arbitrage and price discovery (Ben-David, Franzoni and Moussawi, 2018; Clements, 2019). While managing index-tracking funds is relatively simple as an investment strategy, the practical implementation is quite complex. Frino and Gallagher (2001, p.19, 2002, p.5) stressed that an index represents a "paper portfolio". This follows the assumption that a passive investment strategy is instantaneously implemented with little to no cost incurred (Frino and Gallagher, 2002). However, with the presence of market frictions, in practice, it is nearly impossible for ETFs to deliver investors with returns that are identical to their underlying benchmark index, thus resulting in the existence of a differential metric known as tracking error (Frino and Gallagher, 2002).

Passive investment managers have the sole purpose of creating and applying an investment strategy that will minimize tracking error, enabling investors to earn returns that are as closely approximated to the target benchmark as possible while incurring minimal transaction costs (Frino and Gallagher, 2002). ETF managers employ various strategies, including dynamic risk-budgeting techniques for absolute return funds and tactical asset allocation (Amenc, Goltz and Grigoriu, 2010). They focus on diversification, return prediction and risk management while making allocation decisions (Amenc, Goltz and Grigoriu, 2010). ETFs offer liquid access to diverse financial markets, allowing both large and small investors to build institutional-level portfolios with lower management fees compared to mutual funds (Hill, Nadig and Hougan, 2015). ETF managers must evaluate potential returns and risks using the high levels of transparency provided by ETFs' structure (Hill, Nadig and Hougan, 2015).

The following section looks at the various defining features of the traditional ETF and the factors that have contributed to reimagining these classic passive investment instruments to either hybrid investment vehicles or ones that dwell more on the active side of investment management through different replication strategies.

2.1.1. Characteristics of Equity ETFs

Gallagher and Segara (2005), suggest that ETFs have three distinguishing characteristics. The first is that ETFs are open-ended funds. This means that the number of units on issue, which represents the number of ETF shares available to be traded on the stock exchange, is driven by the market forces of supply and demand (Gallagher and Segara, 2005). The second characteristic is that since ETFs are open-ended funds they feature a continuous primary market which facilitates ETF creation and redemption processes. Since ETF units are tradeable on stock exchanges, their primary market operates simultaneously within a secondary market (Gallagher and Segara, 2005). The ongoing primary market is operated by the ETF issuer and handles the increase/decrease in the number of ETF units on issue, thereby controlling the balance between the supply and demand pressures in the market (Gallagher and Segara, 2005). The control processes also aid in preventing investors from capitalizing on arbitrage opportunities when the market price of the ETF deviates from its NAV.

The secondary market provides an active and liquid space where investors can trade ETFs. The third characteristic of ETFs is that they are price efficient (Gallagher and Segara, 2005). The price efficiency of ETFs is based on the main objective of the fund, which is to ensure that the trading price remains close to the NAV of the ETF (Golub, Ferconi, Madhavan and Ulitsky, 2018). Arbitrage between the primary and secondary market, and creation and redemption processes ensure that ETFs remain price efficient (Gallagher and Segara, 2005).

Creation and redemption refer to the simultaneous process in which new ETF units are created and current ETF units are terminated (Gastineau, 2004). The creation and redemption processes are crucial to ETF functionality, allowing authorized participants to create and redeem ETF shares by exchanging them for a basket of underlying securities (Antoniewicz and Heinreichs, 2014). However, most ETF trading occurs in the secondary market, with only about 10% of activity involving creations and redemptions (Antoniewicz and Heinreichs, 2014). The transaction costs involved with creation and redemption processes are relatively small. As a result, if a market-on-close order is applied, the impact on the market is not significant. If this process is carried out effectively, the ETF will be able to track the index performance precisely before fund expenses and after adjustments to the index have been made (Gastineau, 2004). Empirical research also attributes the supremacy of ETFs over mutual and index funds to their ability to acquire and redeem their shares throughout the trading day (Ben-David, Franzoni and Moussawi, 2018).

ETFs contain a combination of properties that are common to both open- and close-ended funds (Lin, Chan and Hsu, 2006). The similarities of ETFs to both open- and close-ended funds enable them to better replicate their underlying index therefore reducing price discrepancies between the ETF market price and NAV (Lin, Chan and Hsu, 2006; Ben-David, Franzoni and Moussawi, 2018). This results in the creation of a greater opportunity for arbitrage (Lin, Chan and Hsu, 2006).

The process of creation occurs in response to investor demand for ETF shares. To meet this demand, authorized market investment participants will create additional ETF shares (Gastineau, 2004). The creation process deals with the creation of a basket of securities inclusive of a cash-balancing amount being exchanged for ETF shares (Gastineau, 2004). If the authorized participant has accumulated an excessive amount of ETF shares in their inventory, the redemption process is undertaken. The redemption process involves the authorized participant returning the ETF share and receiving a basket of securities and the cash-balancing amount in exchange for it (Gastineau, 2004). The subsequent figure 2-1 simplifies ETFs' creation and redemption processes, which shows the transactional flow between market participants and ETF issuers.

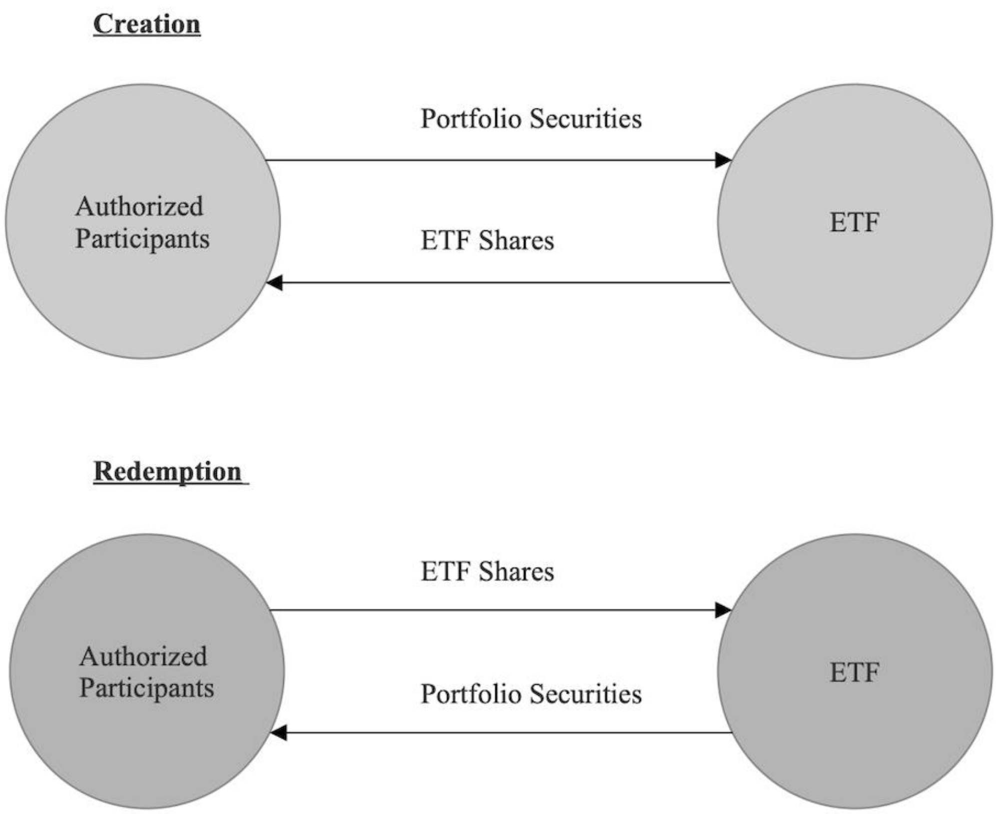

Figure 2-1: The Creation and Redemption Strategy of ETFs

(Author's own construction (2024); Adapted from Gastineau (2004))

The process of creation and redemption is cost-effective and simple. The ETF itself does not incur any transaction or other variable costs associated with the process (Gastineau, 2004). Therefore, shareholders of the fund are not predisposed to increased transaction costs when the size of the fund's composition is either increased or decreased (Gastineau, 2004). Since indices do not change their composition and weightings frequently, creation and redemption processes do not attract market attention or complications (Gastineau, 2004). When an index composition/weighting change occurs, the portfolio manager is required to decide how the portfolio of the fund will have to be adjusted to reflect the changes in the index accurately. The way in which the portfolio manager adjusts the fund in response to the index composition/weighting change has significant implications for how the fund will perform from that moment forward (Gastineau, 2004).

An ETF's underlying benchmark index can change its composition in three commonly observed ways:

(i) The addition of a new stock to the index;

(ii) Removing the stock of a company, that has been deemed no longer eligible for membership in the benchmark index;

(iii) And the reweighting of existing stock components in the index, since the addition and/or exclusion of components that have entered and/or left the index are not the same size (Gastineau, 2004).

When an index composition or weighting change occurs at the close of a trading day, the fund manager adjusts the portfolio accordingly at the beginning of the following trading day (Gastineau, 2004). This practice ensures the matching of the creation and redemption baskets to the revisions of the index (Gastineau, 2004). The most effective way for an ETF manager to adjust their fund composition, is to post the newly constructed creation and redemption baskets on the morning of the day that the index change will become effective (Blume and Edelen, 2002; Gastineau, 2004). The baskets of shares that the ETF contains will reflect what the composition of the index portfolio looks like after all the necessary changes have been implemented (Gastineau, 2004). The addition or removal of the security from the index, will be included/excluded in both the creation and redemption baskets, and all positions in the basket will be reflected at their present weight post-adjustments that occur at the market close on that specific date (Gastineau, 2004).

The objectives and undertakings of creation and redemption processes allow for the preservation of the passiveness of ETFs (Gallagher and Segara, 2005). In considering a situation in which a particular ETF trades at a premium to its NAV (the market price exceeds the NAV), the issuers in the primary market will create more ETF units and sell them in the secondary market (Gallagher and Segara, 2005). An arbitrageur will capture the value of the mispricing that arises from the market price deviating from the NAV. The increase in the supply of ETF units in the secondary market then moves closer to the mispricing opportunities, thus restoring the balance between the fund's NAV and its traded market price and keeping it close to fair value (Gallagher and Segara, 2005).

A redemption process occurs when the market price of the ETF is below its NAV. In this instance, authorized participants purchase ETF shares and redeem them in exchange for the underlying security. Selling pressures are then applied to the underlying ETF shares to eliminate price discrepancies in the ETF market (Ben-David, Franzoni and Moussawi, 2018). Creation and redemption processes are based on price manipulation and the elimination of price discrepancies (Ben-David, Franzoni and Moussawi, 2018). However, Tse and Martinez (2007) found that the use of creation and redemption strategies may directly indicate the presence of noise trading in the ETF market due to higher observed differences between returns on price and NAV returns.

Engle and Sarkar (2006) found that the presence of pricing inefficiency in international ETFs is significantly higher and more persistent than domestic funds. Therefore, they are harder to eliminate through creation and redemption strategies. Levy and Lieberman (2013) found that deviations between the market price and NAVs are significantly more persistent and occur at higher levels in equity ETFs than in other types of ETFs. Further studies such as Ackert and Tian (2008); Levy and Lieberman (2013) and Bahadar, Gan and Nguyen (2020) observed that international ETFs trade at higher premiums than domestic (US based) ETFs. The price deviations observed in international funds persist for more than one day and are mainly driven by their NAVs during synchronized trading hours (Bahadar, Gan and Nguyen, 2020). These observations result in a dominant effect on ETF pricing that may not necessarily be eliminated by creation and redemption strategies (Bahadar, Gan and Nguyen, 2020). Levy and Lieberman (2013) observed that during asynchronized trading hours the underlying index of international equity ETFs has a more dominant effect on the ETF's pricing than its NAV.

The introduction of the ETF as an instrument for short-selling strategies occurred because of the deviation between the market price and NAV due to the asynchronous trading of ETFs and their underlying index (Ben-David, Franzoni and Moussawi, 2018). When the differential between the ETF market price and NAV exceeds the associated transaction costs, an arbitrage opportunity arises. This occurrence attracts bullish market participants and secondary market arbitrageurs who possess the potential to benefit from the price discrepancy (Ben-David, Franzoni and Moussawi, 2018).

Stambaugh and Yuan (2017) looked at the effect of investor sentiment on ETF pricing, flows and returns in the long run. Stambaugh, Yu and Yuan (2015) and Stambaugh and Yuan (2017) deduced from their study on the arbitrage symmetry and idiosyncratic volatility flows within the ETF market, that investor sentiment has independent explanatory power on stock returns. Findings from Stambaugh, Yu and Yuan (2015) and Stambaugh and Yuan (2017) followed through from Baker and Wurgler (2006), who found that smaller, newer, less profitable and non-dividend paying stocks tend to be overpriced when investor sentiment is high and underpriced when investor sentiment is low. There has been a noticeable conflict in results surrounding studies on the effects of investor sentiment on ETF pricing and performance. Glosten, Nallareddy and Zou (2021) found that since the objective of an ETF is to replicate a benchmark index, they should be unaffected by investor sentiment. Glosten, Nallareddy and Zou (2021) justified this statement by stating that if investor sentiment is in fact an idiosyncratic pricing factor, it should only influence individual stocks and not a diversified portfolio of multiple stocks.

Contrary to the findings of Glosten, Nallareddy and Zou (2021), Kadiyala (2022) suggests that ETFs might be affected by investor sentiment if there is a market-wide component included in the measure of investor sentiment. Therefore, Kadiyala (2022) finds that investor sentiment could be one of the characteristic factors of the equity markets that affect ETF performance and pricing. Kadiyala (2022) states that due to the difference in the type of investors attracted to the ETF market versus those interested in direct investment in the underlying assets, there exists a significant differential in the response to sentiment between the ETF and underlying markets. This deviation in sentiment is a key component of the deviation between an ETF's market share price and NAV (Kadiyala, 2022).

The differential in investor sentiment between the ETF and the underlying markets arises from the differing objectives of their investors. Investors who favour investment in ETFs are mostly institutional investors who crave liquidity and immediacy (Kadiyala, 2022). Conversely, investors who are attracted to the underlying markets are retail investors who seek the ease of investment strategy and increased returns (Kadiyala, 2022).

2.1.2. Advantages and Disadvantages

Since being propelled into the equity markets, ETFs have become one of the most favoured and recommended passive investment products by investment professionals. A study in 2018 found that approximately 81% of financial investment professionals prefer ETFs over mutual funds, individual stocks and other alternative passive investment vehicles (Sherrill and Stark, 2018).

The increasing attraction to the ETF market has not only been contained to passive investment managers but has gained traction amongst actively managed mutual fund portfolios. Agapova (2011), found that ETFs are one of the best substitutes for traditional index mutual funds. The widespread interest in the ETF market has resulted in the largest increase in the number of available ETFs on offering as of 2006 with the number of live available funds on offer soaring to 1629, and their total assets under management (AUM) being stated at $2.8 trillion as of late 2016 (Qin and Singal, 2015). The driving factors behind the tremendous growth in ETF offerings are the advantageous properties they hold, from having low transaction costs to being easily liquidated, as well as their ability to closely replicate a variety of indices and earn investors substantial returns while remaining risk averse.

One of the key advantages of ETFs is their ability to be traded throughout the trading day, which places them as the superior investment instrument when compared to index funds, which can only be traded at the end of the day (Charteris, Strydom and McCullough, 2015). DeFusco, Ivanov and Karels (2011) and Strydom, Charteris and McCullough (2015) state that because of the creation and redemption processes, ETFs can avoid the accumulation of capital gains from the adjustment of portfolios therefore providing them with significant tax advantages. Kostovetsky (2003); Rompotis (2009) and Strydom, Charteris and McCullough (2015) have also found that in recent times, ETFs tend to be more popular among investors over traditional mutual and index funds. The popularity of ETFs is a result of their ability to have active trading strategies applied to them whereas index funds are exclusively passive investment vehicles. ETFs allow investors to purchase on the margin, use limit and stop-orders and engage in short-selling opportunities (Rompotis, 2009). Rompotis (2009) states that unlike index funds, ETFs enable institutional investors to make use of arbitrage opportunities that arise from ETF mispricing.

ETFs are considerably more cost-effective than other investment instruments. Dellva (2001) performed a comparative analysis of the costs associated with an iShares ETF and a Vanguard index fund that both track the Standard and Poor's (S&P) 500 Index. The results indicated that despite the inclusion of transaction costs and commissions to brokerage firms, ETFs offer significant cost benefits over index funds due to lower expense levels (Dellva, 2001). Further findings indicate that the cost-benefit of ETFs is amplified when investors take on hold positions for long periods of time (Dellva, 2001). A further benefit of ETFs is their ability to maintain their full or close to full portfolio holdings during liquidation and right until the closure of the fund (Sherrill and Stark, 2018).

Existing research indicates that while ETFs hold significant tax advantages, these may not always hold up in all investment environments (Bernstein, 2002; Rompotis, 2009). Bernstein (2002) and Rompotis (2009) argued that the tax and cost advantages of ETFs can be limited and sometimes eliminated by the behavioural fallacies that investors portray. The behavioural biases of investors entice them to frequently cash out their positions and liquidate their shares (Bernstein, 2002; Rompotis, 2009). Gastineau (2004) and Sherril and Stark (2018) found that despite the tax efficiency of ETFs, when the fund is in the process of liquidation, investors are predisposed to unexpected and significant tax costs. During normal conditions, investors will be exposed to a capital gains tax liability when they sell ETF shares if the ETF is held in a taxable account (Gastineau, 2004; Sherril and Stark, 2018). However, the unpredictability of the timing of when an ETF will go into liquidation predisposes investors to tax implications that they do not have control over (Gastineau, 2004; Sherril and Stark, 2018).

Bernstein (2002) and Elton *et al*. (2005) observed that shorter holding periods offset the cost-effectiveness of ETFs. This was observed through the regressive analysis of the Standard and Poor's Depositary Receipt (SPDR) and the Invesco QQQ ETFs. Bernstein (2002) and Elton *et al*. (2005) found that the average holding period of the ETFs for the first five months of 2001 was significantly shorter than expected, with values of ten and four days for each respective ETF. Gastineau (2004) and Rompotis (2009) found that the creation and redemption processes of ETFs might hamper the maximization of returns. Due to it causing a barrier to the accurate and immediate tracking of benchmark indices and the adjustments that occur. This ultimately results in lower returns being achieved (Gastineau, 2004; Rompotis, 2009).

In circling in on the liquidity argument that surrounds the ETF market, we find that despite the prominent growth in the number of ETF offerings and the increase in the total amount of assets invested within the ETF market, not all funds in the market experience success. With that in mind, in 2012, it had been recorded that there were 93 ETF liquidations, and 25.5% of all ETFs that were created had been liquidated (Sherrill and Stark, 2022). The recurrence of fund failures in the recent climate of financial markets because of widespread crises has resulted in an immediate need for investors, practitioners, and academics alike to understand the driving factors behind ETF failures to be able to find strategies to mitigate them.

Gastineau (2004) highlights that while ETFs are tax efficient, their pre-tax performance has been observed to lag in comparison to other conventional passive investment funds that track the same index. Mazzilli and Kittsley (2003) and Gastineau (2004) found that ETFs that track less commonly used indices demonstrate higher levels of tracking performance than those that track more prominent indices. Gastineau (2004) observed that ETFs that track the Russell 2000 index and the S&P500 index suffer from performance weaknesses. The observed weakness in performance is justified by a lack of aggressiveness in strategy by the fund members. The performance weaknesses can be easily corrected by increased determination from ETF managers and the application of structural changes to the underlying indices (Gastineau, 2004). Gastineau (2004) suggests that performance weaknesses can be mitigated by employing portfolio management processes to ETFs that mimic those applied to conventional index funds that better replicate their underlying index.

The portfolio management processes of conventional funds include changing the structure and weightings of indices to mimic those that gauge higher returns (Gastineau, 2004). A further contributor to the benchmark index ETF performance problem is that fund managers are not made aware of when creation and redemption processes will occur until the end of the trading day. To address this issue, Gastineau (2004) suggests that authorized market participants should be given a cut-off time of 2:30 pm on any trading day to create or redeem shares.

The cut-off time enables the portfolio manager to gauge the necessary information needed to determine the number of ETF shares that need to be traded within a portfolio to implement structural changes such as the switching of the underlying index on that specific day (Gastineau, 2004). This will ensure that on the day the portfolio manager decides to implement a change of indices, no repurchasing of sold positions will occur prematurely, and no simultaneous sales of positions will be acquired due to the creation processes being dealt with on the day of index change (Gastineau, 2004).

A theoretical barrier to ETF trading arises in the form of the provisions of the Securities and Exchange Commission (SEC) Rule 22c-1, which states that ETFs:

Cannot sell, redeem, or repurchase [their shares] except at a price based on the current net asset value of [their shares] for redemption or of an order to purchase or sell [their shares].

This rule inhibits ETF managers from being aware of what creation or redemption baskets they will face on a given trading day in advance of it occurring. Hence, they are unable to adjust their trading plans accordingly. However, to mitigate the impact this rule has on ETF trading, ETF issuers can follow the playbook of index funds, which have built policies with provisions that allow for effective protection from the disruption arising from late-arriving orders. These provisions include not accepting inter-fund transfer instructions after 2:30 pm on a trading day and while they do accept purchase instructions up until 4:00 pm on a trading day, they reserve the right to refuse orders that may result in the disruption of fund operations (Gastineau, 2004). These provisions provide a significant amount of flexibility for index funds (Gastineau, 2004). Therefore, if ETFs can achieve the same form of insulation against delayed fund instructions, they will be able to increase performance and place themselves on a level playing field with conventional passive investment instruments in terms of performance capability (Gastineau, 2004).

Ultimately, the overview is that ETFs offer several advantages over traditional mutual funds (Birdthistle, 2008; Gastineau, 2001). They provide diversification, low-costs, intraday trading and high tax efficiency without significant premiums or discounts to their NAV (Gastineau, 2001). They use a novel pricing mechanism that leverages arbitrage to offer investors accuracy, efficiency and a range of investment choices (Birdthistle, 2008). ETFs are considered a positive market response to the shortcomings of mutual funds, particularly during crisis periods (Birdthistle, 2008). However, they do have potential drawbacks, such as brokerage fees and vulnerability to harmful short-term trading (Birdthistle, 2008). Despite these concerns, ETFs are in general viewed as superior investment vehicles in terms of taxes, lower management fees and portfolio risk management (Mazumder, 2014). Therefore, investors are strongly advised to consider their objectives, risk attitudes and investment time horizons when deciding whether to invest in ETFs (Mazumder, 2014).

2.1.3. Passive versus Active ETFs

While traditional large passive index products continue to grow in leaps and bounds, more specialized characteristic-based ETFs have simultaneously entered the market. These ETFs provide exposure to a variety of underlying benchmarks and are characterized by factor investing and smart beta strategies (Easley *et al*., 2021). These specialized ETF products demonstrate a shift from the passive nature of ETFs to more active characteristics as they introduce fluctuating constituent index weightings and active rebalancing (Easley *et al.*, 2021).

When passive investing was considered synonymous with indexed mutual funds, the distinction between passive and active investing had been clear cut, with a choice between two simplified strategies. The first is selecting a one-size fits all low-cost market index fund, and the alternative is investing in a high alpha but a higher cost portfolio of assets (Easley *et al*., 2021). The equilibrium size of passive and active investing in those times were easily determined by the relative costs involved and the availability of information required to determine alpha (Easley *et al*., 2021). However, in recent times, the simple depiction of passive and active investment in the ETF space has been undermined.

Easley *et. al*, (2021) in conjunction with Berk and Green (2004), have determined that the proposed activeness of ETF's is a direct result of their ability to be easily and cheaply traded. While the activeness of ETFs has implications on a range of different factors, such as the evolution of investment management and the level of price discovery in a market, this study places special focus on the linkage between activeness and synthetic and leveraged fund replication. Cheng, Massa and Zhang (2019) proposed that there exists a linkage between the synthetic replication and active investment of ETFs. This linkage is demonstrated by the deviation of ETFs from their benchmarks when using synthetic replications with affiliated bank sponsors, which were proven to increase the returns to the ETF investor (Cheng, Massa and Zang, 2019). Therefore, this observation points out that ETFs can possibly function in an opposing manner to passive investment instruments.

The passive versus active debate has existed within equity markets for decades. However, only in recent years has it filtered through to the ETF market (Cheng, Massa and Zhang, 2019). Academics are insistent that ETFs will follow the EMH, as they exist in a market where all relevant information is reflected in the stock price (Cheng, Massa and Zhang, 2019). Investment practitioners have met this with a counterintuitive argument that markets have been perceived to be inefficient with a strong stance for the active management of ETFs, suggesting that they can in fact use ETFs to beat the benchmark (Cheng, Massa and Zhang, 2019). However, the SEC's stance on transparency has since slowed down the creation and progress of active ETFs.

The transition of ETFs into the active management space, has significant implications for both the growth and transformation of equity investment products and the nature of active investment in the global economy. The ability of ETFs to be traded with ease and minimal transaction costs being involved puts them at an advantage to traditional mutual funds and it is what enables their activeness in function (Berk and Green, 2004; Easley *et al.*, 2021). Easley *et al*. (2021) and Berk and Green (2004) have found that ETFs are able to fill the void in the market between active and passive products, as they can take on both characteristics. To identify the activeness of ETFs, Easley *et al*. (2021) proposed an empirical metric called the Activeness Index, which provides a magnification of the evolution of ETFs from traditionally passive investment products to its modernization into more advanced complex investment products that can be active in nature or in the way it functions.

The Activeness Index yielded results that showed that most ETFs do have an active nature embedded within them and with this practice increasing, active ETFs will gain more market share over less active ETFs (Easley *et al.*, 2021). Additionally, and as expected, it was found that passive ETFs are observed to be larger, have higher levels of assets under management (AUM) and charge significantly lower fees than those that are more active. However, it was also deduced that passive ETFs were less popular and less traded on security markets on an average basis compared to ETFs that have an active strategy imbedded in them (Easley *et al*., 2021). The spread of the fee discrepancy between active and passive ETFs has been shown to decrease significantly over longer periods of time (Easley *et al*., 2021).

However, surrounding the growth of active ETFs is the SEC's stance on transparency, which has played a significant role in mitigating their growth. While the SEC has approved the launch of active ETFs, the strict regulations governing them such as the transparency rule which requires all ETFs to disclose their holdings daily, Act 15 US.C. 80a-6(c), titled "Exemption of persons, securities or any class or classes of persons as necessary and appropriate in the public interest" has inhibited their growth (Legal Information Institute, 2015). Transparency is integral to the public's interest, and the SEC has stipulated that the transparency rule needs to be fulfilled before an exemptive order is issued to a fund issuer to launch a new ETF (Meziani, 2015). While the transparency provisions put into place by the SEC safeguard the interests of the public, it also hinders the active ETF market. ETF practitioners have stated that the transparency clause requires fund managers to reveal the underlying holdings of a fund, which is essentially openly disclosing their buying and selling intentions to the market, therefore diminishing their ability to beat the market by using active investment techniques (Meziani, 2015). ETF practitioners have, therefore, formed the opinion that the transparency clause hampers the productivity of active funds.

There exists ongoing debate within the ETF space as passive investment practitioners are of the opinion that active ETFs should also abide by the transparency laws that govern traditional passive funds (Rompotis, 2013a; Meziani, 2015). Their argument is based on their observation that a lack of transparency results in a source of undue risk for investors (Rompotis, 2013a; Meziani, 2015). This discourse has been the prime cause for the lagged issuance of active ETFs in the market.

Considering the rise of active investing, the SEC granted exemptive orders to actively managed ETFs in 2008. However, full transparency was still required. They required obligatory declarations by ETF issuers for the posting of their daily NAV calculation before the opening of each trading day (Easley *et al.*, 2021). Since active ETF managers did not get their desired outcome to protect their holdings from disclosure, actively managed ETFs did not gain massive traction after the 2008 SEC exclusionary announcements (Easley *et al*., 2021). However, the SEC's adoption of Rule 6c-11 in 2019 streamlined the regulatory process for transparent active and index ETFs, promoting innovation and competition (Moriarity, 2020). However, the rule does not provide a comprehensive framework for all ETFs, leaving room for improvement in areas such as disclosure requirements (Hu and Morley, 2019).

The impact of daily portfolio disclosure on active ETFs' pricing efficiency remains debatable. While US active ETFs that are subject to daily disclosure show lower premium levels compared to Canadian counterparts with quarterly disclosure, they also exhibit higher spreads and adverse selection components (Iaksaci, 2023). However, despite ongoing concerns, the 2019 "ETF Rule" better governs ETF construction, inception and trading than its predecessors (Meziani, 2015, p.87-88). It has strengthened the inception of both passive and active funds, with the growth of the US ETF market quadrupling from 2.0% in 2019 to 8.5% as of March 2024. Additionally, it has been reported that over the last five years, active ETFs have generated $375 billion in inflows (Armour, 2024).

As of 2024, there are currently 1255 active ETFs across all asset classes traded on US markets, which shows a phenomenal increase from 2019 which recorded merely 350 active ETFs being traded (Armour, 2024). While active ETFs still represent a small fraction of an almost $7 trillion ETF market, they were shown to have grown at a rate of 14% in the first two quarters of 2023, which is more impressive than that of passive ETFs (Morgan Stanley Research, 2024). Passive ETFs showed a minimal growth rate of 3% across the same period (Morgan Stanley Research, 2024). Despite, active ETFs holding only 5% of AUM globally, at the end of 2023 they were reported to have taken 20% of ETF net flows (JP Morgan Asset Management, 2024). The active ETF market had grown at a 51% compounded annual growth rate (CAGR) at the end of the first quarter of 2024, surpassing the total ETF market CAGR of 24% across the same period (JP Morgan Asset Management, 2024).

A report by Blackrock which focused on their vision for explosive growth in the active ETF market, stated that they project a monumental surge in actively managed ETFs (Hajric, 2024). Blackrock predicts that assets will increase exponentially from $920 billion (2024) to $4 trillion by 2030. The asset manager's bullish prediction is based on several factors, such as US regulatory updates, an increase in advisor portfolios, a rise in self-directed investors and higher market volatility (Hajric, 2024). These observations demonstrate the increased trajectory of active ETFs into the global equity markets over the last few years with 29% of EMEA ETF investors stating that the utilization of active ETFs adds value and diversification to their fixed income and equity portfolios (Trackinsight Global ETF Survey, 2024).

Active and passive funds have very clear-cut structural differences. One of the most notable differences is that passive ETFs are designed to track a specific index or basket of assets, while active ETFs employ various strategies to achieve their goal of beating the market (Rompotis, 2013a). Active ETFs are structured and created to track top-performing securities derived from an underlying index and that are picked by the investment manager (Rompotis, 2013a). The investment manager will either mirror an existing mutual fund or apply a specific investment strategy to earn above-market returns (Rompotis, 2013a). Other differences between passive and active ETFs include the following, passive funds require at least one market maker, whereas an active fund requires a minimum of two market makers (Rompotis, 2013a). The market maker and fund manager for an active fund needs to belong to the same investment company whereas they do not for passive funds (Rompotis, 2013a). Active funds require a minimum investment size which is dependent on the fund issuer and/or the security exchange it is being traded on, while passive funds do not require a minimum investment size (Rompotis, 2013a).

During their early proliferation into the equities market, active ETFs did not initially enjoy the same levels of growth and popularity as their passive counterparts. This was largely due to the arbitrage opportunities that are offered by passive ETFs, which do not exist within the active space (Rompotis, 2013b). The arbitrage opportunities of passive ETFs are based on their creation and redemption in-kind processes, which enable the elimination of deviations between the market prices of the ETF and the value of its underlying index. This is achievable by passive funds due to their holdings of the underlying benchmark index being available as public information throughout the trading day (Rompotis, 2013b). Whereas active ETFs only publish their holdings information at the end of the trading day (Rompotis, 2013b). The reason for this practice is so that active ETF managers can take advantage of mispricing opportunities and identify the stocks that need to be picked to generate active returns (Rompotis, 2013b).

Despite that, even if active ETFs regularly published their holding information, so that arbitrage processes could occur, their ability to beat the market would diminish. Since more investors would rely on fund managers to perform research on mispricing opportunities, it would cause an influx in the buying pressures on those selected securities. This would then cause price adjustments while avoiding the relevant management fees, which would, as a result, return the market back to its passive nature (Rompotis, 2013a). One of the foundational tenets of active investing is to contradict the EMH and make use of information that may not be directly reflected in the trading price (Rompotis, 2013a). Therefore, it is essential that the publishing of active ETF holding information is controlled so that fund managers are still able to exploit mispricing opportunities.

Regarding the performance differences between passive and active ETFs, Rompotis (2011) found that active ETFs that track the S&P500 index, seem to fail to successfully outperform the index. Rompotis (2009) found that active ETFs were shown to underperform their underlying benchmark index and their passive competitors, specifically those that tracked the same underlying index. In agreement, Schizas (2014) found that while active ETFs have significantly higher volatility levels than passive ETFs, they did not outperform the passive funds. Rompotis (2013a) found through a single-factor and multi-factor regression analysis using a sample of active and passive ETFs that track the same underlying index, that while active ETFs demonstrate higher levels of risk as expected due to their activeness in nature, they do not show higher levels of positive risk-adjusted excess returns over passive ETFs. While active ETFs continue to be a topic of interest amongst academics and investment practitioners, there has been no consensus as to which type of fund is better than the other in terms of performance. It is rather left to the investor, based on their risk profile and desired expectations from ETF investment, to determine which ETF will be more in line with their investment goals.

This study uses ETFs that are active-in-form due to the use of varying replication strategies, some of which have more active characteristics. The following sections look at the various replication strategies employed by ETFs and the predisposition of ETFs to tracking errors. A comprehensive overview of existing literature is provided to show how an ETF's adopted replication strategy either amplifies or constrains its level of tracking error.

2.2. Replication Strategies

Replication strategies may use slightly different terminology depending on the market and norms of different regulations. As such, this section uses the classification system for fund replication strategy provided by Bloomberg Professional, where it is possible to sort funds by one of five stated replication strategies, namely: physical (full), stratified sampling, optimization, synthetic and leveraged replication. Stratified sampling and optimization are subcategories of physical replication as they also refer to holding the actual securities of the underlying benchmark index. In contrast to full physical replication, the stratified sampling and optimization approaches hold only a subset of the benchmark index's securities (Vanguard, 2023). While we consider five different types of ETF replication strategies in this study, it is integral to note that there exist two broad structures of ETF replication under which these categories fall. Under the physical ETF structure, we consider full physical replication, stratified sampling and optimization. Synthetic ETF structures include derivative-based and more commonly swap-based methods of index replication. Leveraged (and inverse leveraged) ETFs represent a sub-category of synthetic ETFs that are more active in nature.

Research has shown that the type of structure an ETF follows has significant implications on its level of tracking performance. In recent years, the complexity of ETF structures and the strategies they implement have increased significantly (Fassas, 2014). While the findings from existing literature have yielded mixed results regarding the performance dynamics of physical and synthetic ETFs, this study aims to determine which replication strategy, and as a result ETF structure has the lowest predisposition to tracking error.

2.2.1. Physical (Full) Replication

Full physically replicated ETFs mirror the returns of their benchmark index by directly holding all the underlying securities contained in that index (Kim, Cho and Seok, 2023). For example, an ETF tracking the S&P500 through physical replication will hold all the constituent stocks of the S&P500. During the early development of the ETF market, index replication was achieved through simplified structures that involved purchasing all the securities comprising the benchmark index (Fassas, 2014). The advantages of physical replication include greater transparency of the ETF's holdings and improved investor certainty in the event of ETF liquidation (Kosev and Williams, 2011).

The creation process of full physically backed ETFs begins with the ETF issuer selecting an index that they would like the ETF to track. The type of index could vary from broad market indices to sector specific indices, or alternatively customized indices, which refers to a personally curated index that is created to suit a type of client's unique requirements and/or investment strategies (Blackrock ETF Course Materials, 2024). This process can be done through a facilitator such as the S&P Dow Jones Indices: S&P DJI Custom Indices platform. Subsequently, the ETF issuer will create a basket of securities that will closely imitate the composition of the selected index. This is achieved through the basket of assets, including the same stocks, bonds, or other assets in similar proportions as the reference index (Blackrock ETF Course Materials, 2024).

The securities in the basket will then be purchased by the ETF issuer, who will either acquire the individual securities by directly purchasing them on the open market or through authorized participants (APs) (the APs are required to carry out the creation and redemption processes of the ETF units). The ETF issuer will then aggregate the purchased securities into large blocks referred to as creation units (Blackrock ETF Course Materials, 2024). These creation units contain a specified number of shares. The ETF creation units will then be registered with regulatory authorities such as the Securities and Exchange Commission (SEC) in the United States (Blackrock ETF Course Materials, 2024). Registering the ETFs with these institutions ensures compliance with the relevant regulations and provides transparency to investors.

After gaining regulatory approval from the necessary commission, the ETF will be listed on the stock exchange, where investors can trade them throughout a trading day. Market makers represent key players in providing liquidity for ETFs by continuously quoting bid and ask prices on the exchange. Market makers also play a crucial role in ETF liquidity provision, with their risk aversion and inventory management affecting ETF spreads (Riva, Calamia and Deville, 2013). They are responsible for the facilitation of the buying and selling of ETF shares and ensuring that investors can trade them efficiently. ETF market makers can engage in "operational shorting" to meet excess demand, which improves liquidity and price efficiency in underlying securities but may also increase counterparty risk to investors (Evans, Moussawi, Pagano and Sedunoy, 2018, p.37-38).

Through the creation and redemption processes, an arbitrage mechanism is created that assists in keeping the ETF's market price in accordance with its net asset value (NAV) to minimize the occurrence of mispricing (Borio, Claessens, Schrimpf, Shin and Todorov, 2021). This differential being kept as small as possible is a sign of efficient tracking performance and low tracking error. While the arbitrage mechanism plays a crucial role in aligning ETF prices with their underlying assets, it can also lead to unintended consequences. Research shows that ETF arbitrage can propagate liquidity shocks between markets, potentially increasing volatility in underlying assets (Ben-David, Franzoni and Moussawi, 2012). This mechanism can also transmit US economic shocks to international markets, limiting diversification benefits for investors in country ETFs (Flippou, Gozluklu and Rozental, 2024). Additionally, ETFs attract high-turnover investors, potentially amplifying liquidity shocks (Ben-David, Franzoni and Moussawi, 2012). The arbitrage mechanism's impact was notably observed during the 2010 Flash Crash, where ETFs may have facilitated shock transmissions between futures and equity markets (Ben-David, Franzoni and Moussawi, 2012).

ETFs expose investors to counterparty risk through securities lending and total return swaps (Hurlin, Iseli, Pérignon and Yeung, 2019). Counterparty risk of ETFs is defined as the risk that the value of the collateral drops below the NAV of the fund when the counterparty of the fund defaults (Hurlin *et al.*, 2019). Issuers of physically backed ETFs achieve increased revenues by partaking in securities lending (Blocher and Whaley, 2014). As a result, there exists the possibility that the securities being loaned will not be returned in due time; that is, short sellers may default on the loan (Hurlin *et al.*, 2019).

The probability of fund counterparty default, therefore, exposes physical ETF investors to a significant level of counterparty risk. Hurlin *et al*. (2019) found that almost all ETF issuers have a provision in their prospectus for the loaning of their securities temporarily for revenue generation. Blocher and Whaley (2014) found that the revenues generated by ETFs from securities lending are comparable in size with their management fees. Since physical ETFs directly hold the underlying securities of their benchmark index, they generally carry a lower level of counterparty risk in comparison to synthetic ETFs, which use total return swaps (Hurlin *et al.*, 2019). Contrary to concerns raised by international agencies, empirical evidence suggests that collateral risk in ETFs is not as high as alleged and can be effectively controlled through the collateralization of securities lending (Hurlin *et al.*, 2019).

To mitigate counterparty risk, ETFs require collateral from their counterparties (Hurlin *et al.*, 2019). Optimal collateral portfolio construction can significantly reduce counterparty risk exposure in ETFs (Hurlin *et al*., 2019). Physical ETFs generally exhibit higher liquidity risks than synthetic ETFs, which offer additional returns in low-liquidity groups (Kim, Cho and Seok, 2023). The liquidity of ETFs depends on their benchmark index's liquidity, but size and trading volumes also matter, with larger and more heavily traded ETFs displaying tighter spreads (Riva, Calamia and Deville, 2013). This suggests that since physical ETFs are generally larger and demonstrate higher trading volumes than other replication strategies, they are predisposed to more liquidity concerns, specifically in times of market crisis (Riva, Calamia and Deville, 2013). ETFs operate in a complex ecosystem reliant on intermediating financial institutions, potentially creating liquidity illusions during crises (Clements, 2019).

Research on the performance of ETFs following different replication strategies across regions show mixed results, with some studies indicating that tracking errors vary depending on the region and market development (Zawadzki, 2020; Dobson, 2020). However, other research suggests that certain ETFs can outperform market indices consistently. For example, iShares MSCI country-specific ETFs which all follow physical replication techniques, were found to beat the US market index based on risk-adjusted performance measures and showed evidence of performance persistence (Mateus and Kuo, 2008). Conversely, the physically backed Lyxor PSI 20 (DR) UCITS ETF which tracks the Portuguese stock index, PSI20 did not exhibit significant abnormal returns compared to the market, unlike ETFs tracking major European and US stock indices (Pinheiro & Varela, 2018). These conflicting findings suggest ETF outperformance may be market-specific rather than consistent across regions, highlighting the need to carefully consider geographical factors when selecting ETFs of differing replication strategies for investment portfolio construction.

The use of physical replication allows for close tracking of the index's performance by directly holding the underlying securities, thereby reducing tracking error. Physically replicated ETFs can almost perfectly replicate the returns of their underlying benchmark index prior to the consideration of transaction costs. While the tracking error of physically replicated ETFs is generally low, it does exist. Sources of tracking error for physical ETFs include factors such as transaction costs, differences in dividend timings, higher expense ratios, lower liquidity and higher management fees (Chu, 2011; Osterhoff and Kaserer, 2016). However, dividends received from the underlying securities are reinvested back into the ETF, which may enhance returns over time (Broby and Spence, 2020).

Physically replicated ETFs are best suited to investors who are seeking direct exposure to the underlying index with increased transparency and lower counterparty risk (Broby and Spence, 2020). Physical ETFs are also more appropriate for investors who are risk-averse (Broby and Spence, 2020). Investors should note, however, that these ETFs may be predisposed to higher levels of operating costs due to the need to buy and sell the underlying securities, which can result in observably higher expense ratios in comparison to ETFs that follow other replication strategies (Huang and Guedj, 2009). Physically backed ETFs offer significant tax advantages over other investment vehicles. These tax advantages are especially pertinent to long-term investors, as they typically have lower portfolio turnover in comparison to actively managed funds (Broby and Spence, 2020).

Physical ETFs can distribute appreciated assets during in-kind redemptions without recognizing any gains, potentially reducing future tax burdens for shareholders (Colon, 2017). This tax treatment gives ETFs an edge over other investments, with some ETFs providing better after-tax returns than certain individual retirement arrangements (IRAs) (Colon, 2017). The arbitrage mechanism appears to work better for physically replicated ETFs than for futures-backed ETFs, which tend to be smaller and less liquid (Travis and Fulkerson, 2023).

Despite the subsequent modifications that have been made in recent years to the ETF market, physically backed ETFs remain one of the most popular types of ETFs. In 2020, US$ 6.23 trillion out of US$ 6.49 trillion in global ETF assets belonged to physically replicated ETFs (Corsi, Hussain and Hsu, 2020). The lion's share of global ETF assets belonging to physical ETFs is due to the stringent regulations in the US regarding the use of derivatives in funds; therefore, almost all the ETFs that track fixed income or equity securities in US markets are physically replicated (Corsi, Hussain and Hsu, 2020; Fassas, 2012). While research on the tracking performance comparison between physical and synthetic ETFs has yielded mixed results, physical ETFs are still considered an investor favourite. This is due to physical ETFs being more widely available and having lower levels of risk (Blackrock ETF Course Materials, 2024). The subsequent figure 2-2 shows the cash flows and asset transfers that occur during the physical replication process of ETFs.

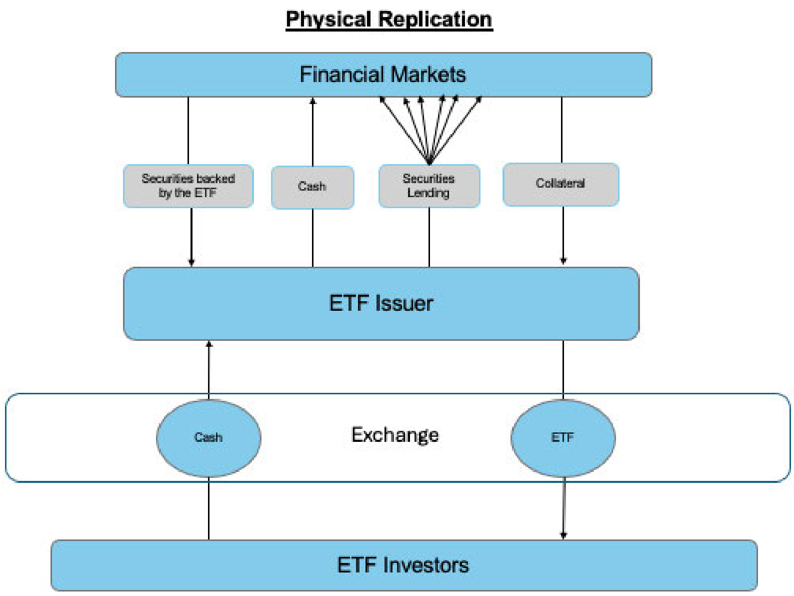

Figure 2-2: The Physical Replication Model

(Author's own construction (2024); Adapted from Hurlin et al. (2019))

2.2.2. Stratified Sampling

Stratified Sampling refers to a form of physical replication of ETFs that aims to match the risk and return profile of a benchmark index and is typically used in ETFs that offer exposure to broad fixed-income indices (Vanguard Asset Management, 2023). Stratified sampling is applied to ETFs when full physical replication may not be practical or cost-effective, as it minimizes trading and operational costs (Vanguard Asset Management, 2023). When using stratified sampling, the ETF manager aims to replicate the index's returns by holding a representative sample or subset of the index's constituents, rather than all of them (Fidelity Investments, 2024).

In the context of equity-backed ETF replication, most of the processes behind stratified sampling are the same as full physical replication. However, the differences arise in the index security selection process. In stratified sampling, the index is divided into different segments based on specified characteristics such as, sector, industry, market capitalization and geographic region (Blackrock ETF Course Materials, 2024). Each factor represents a subset of the index's constituents that share similar attributes. The ETF manager then selects a representative sample of securities from each sector of characteristics to create a portfolio that closely resembles the overall index (Blackrock ETF Course Materials, 2024).

Stratified sampling is commonly used by ETFs that track indices with a large holding size or less liquid securities (Vanguard Asset Management, 2023). For example, fixed-income benchmarks generally contain a broader basket of securities than equity indices. In addition, many of the bonds in fixed-income indices may be illiquid because many investors hold bonds until maturity (Vanguard Asset Management, 2023). For these reasons, stratified sampling is more commonly applied to fixed-income ETFs than equity ETFs. Despite incurring lower trading and transaction costs than full physical replication, ETFs that use sampling techniques are often shown to suffer from higher tracking errors than fully replicated ETFs (Vanguard Asset Management, 2023).

The primary purpose of stratified sampling is to achieve a close approximation of the benchmark index's performance while reducing the number of securities that need to be held (Gastineau, 2010). Fabozzi and Markowitz (2011) highlight that stratified sampling is commonly applied to ETFs that track large and diverse indices, such as the S&P500 and the Russell 2000. These indices contain hundreds of securities, making full physical replication costly and complex. Stratified sampling offers a practical alternative that balances the need for accurate index tracking with the necessity of cost minimization (Fabozzi and Markowitz, 2011). Stratified sampling provides an effective way to manage tracking errors. When proper stratification of the index and selection of securities is achieved, the ETF can maintain low tracking error while managing the risks associated with individual securities or sectors (Poterba and Shoven, 2002).

While existing research on the performance of stratified ETFs during market crisis and across different regions remains scarce. A corollary that should follow from sampled ETFs is that since they are cost-effective and demonstrate a reduced reliance on volatile stocks included in the benchmark index, they should show resilience during periods of market crisis. In contrast to the prior statement, research has shown that in general some ETFs that were not cointegrated with their indexes before a crisis become cointegrated during and after the crisis period (Ivanov, 2012; Saini, Sharma and Verma, 2023). This may poise an issue for ETFs following sampling techniques, as the ETF may no longer be cointegrated with the initial stock selection from the benchmark index resulting in increased tracking error. Studies have shown that partially replicated ETFs are more sensitive to downside risk and local market conditions, with their tracking ability varying significantly across different regions and market types (Thanakijsombat and Kongtoranin, 2018). This study seeks to address this gap in literature by looking at how the tracking performance of each replication strategy differs during crisis periods and across regions.

While stratified sampling may introduce some degree of tracking error compared to full replication, the trade-off is often worthwhile in terms of cost savings and operational simplicity (Poterba and Shoven, 2002). Gastineau (2010) suggests that careful security selection and ongoing management of the sampled securities can act as a key mitigating factor to the increased tracking error introduced by stratified sampling. The key steps involved in the stratified sampling of equity ETFs are summarised in the subsequent figure 2-3.

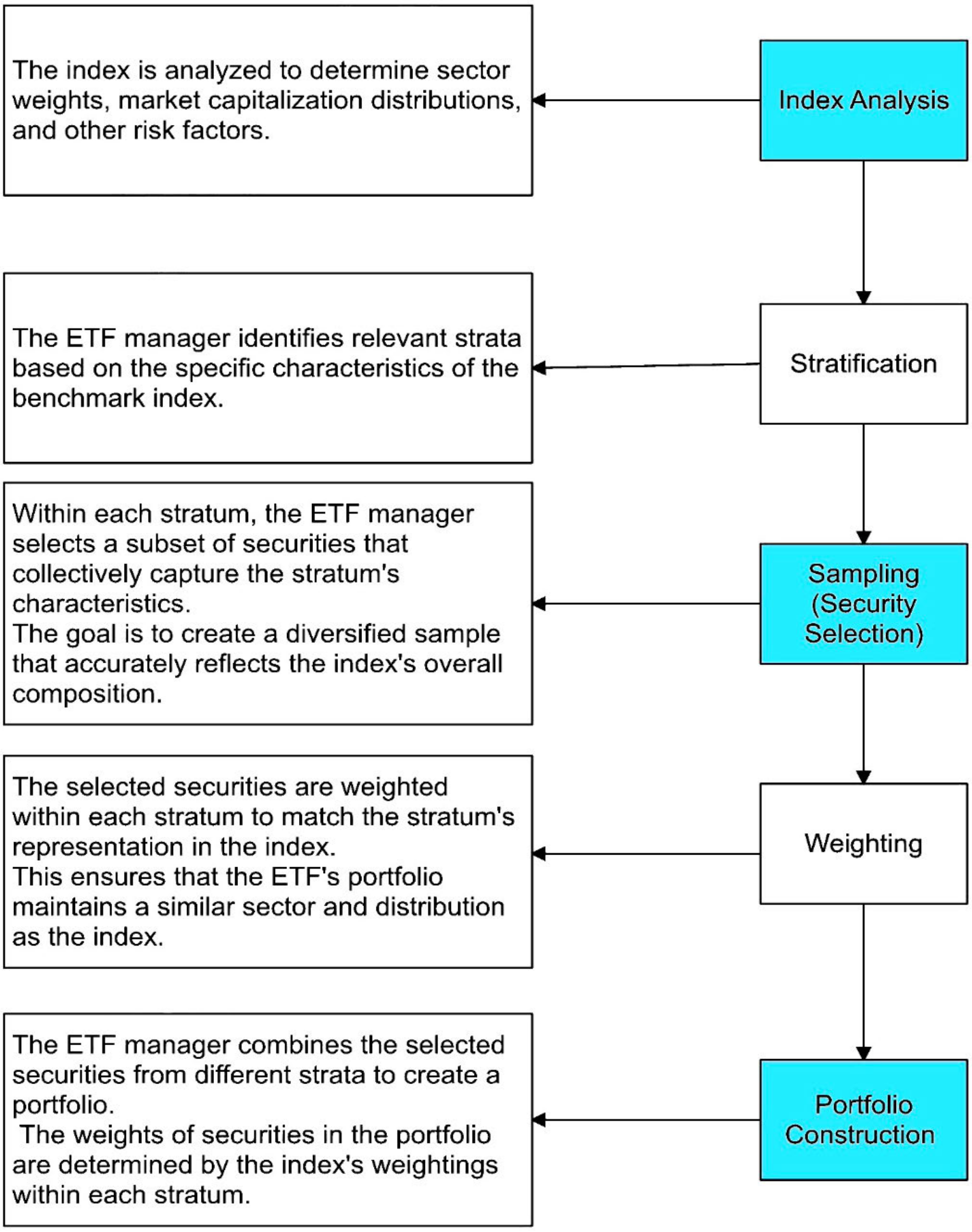

Figure 2-3: Security Selection Process of Stratified Sampling

(Author's own construction (2024); Gastineau (2010) and Fabozzi and Markowitz (2011))

Benefits of stratified sampling include cost efficiency, diversification, tracking accuracy and flexibility. Stratified sampling can significantly reduce trading and operational costs in comparison to full replication of the index (Gastineau, 2010). By focusing on selected securities, the ETF manager minimizes turnover and trading expenses (Gastineau, 2010). The selected securities within each stratum provide diversification benefits, allowing the

ETF to capture the overall index's performance while managing risk (Fabozzi and Markowitz, 2011). When executed effectively, stratified sampling can closely replicate the index's returns with a lower number of holdings. ETF managers can adjust the sample periodically to account for changes in the index's composition or market conditions (Gastineau, 2010; Fabozzi and Markowitz, 2011). Stratified sampling also enhances tax efficiency. By carefully selecting which securities to hold and sell, ETFs can minimize capital gains distributions (Poterba and Shoven, 2002). Stratified sampling improves the ETF's overall liquidity and ease of trading as it allows ETF managers to focus more on liquid securities within each stratum (Gastineau, 2010).

While stratified sampling aims to minimize tracking error, there may still be discrepancies between the ETF's performance and the index due to factors such as, rebalancing frequency, market movements and sampling choices (Gastineau, 2010; Fabozzi and Markowitz, 2011). The effectiveness of stratified sampling depends on the index's characteristics and methodology. Highly diversified and complex indices might be more challenging to replicate accurately through stratified sampling (Gastineau, 2010). However, recent technological advances and data analytics have improved the precision of stratified sampling, improving its viability for a wide range of ETFs (Gastineau, 2010). Periodic rebalancing is necessary to ensure that the ETF's holdings continue to reflect changes in the index. Rebalancing introduces trading costs, which need to be managed effectively to minimize tracking errors (Gastineau, 2010).

ETFs employing stratified sampling are required to provide transparency regarding the sampling methodology and the securities held in the portfolio (Gastineau, 2010). Stratified sampling is a practical approach for ETF managers seeking to replicate the performance of an equity index while minimizing costs and maintaining diversification (Fabozzi and Markowitz, 2011). However, it is advised that investors conduct due diligence to understand how the strategy is implemented and its potential impact on tracking performance.

2.2.3. Optimized Replication

Optimized replication of ETFs involves selectively including or weighting assets from the benchmark index by applying various optimization techniques (Roll, 2013). Commonly used optimization techniques include mean-variance optimization (MVO), tracking error minimization techniques and factor models such as the Fama-French Model (1993) (Kim, Lee, Kim and Fabozzi, 2021). Optimized funds are designed to minimize tracking error and are generally used for ETFs that track large global equity benchmarks (Vanguard Asset Management, 2023). As with full physical replication, optimization techniques hold the actual securities of the underlying benchmark index. Like stratified sampling, optimized funds will hold only a subset of the benchmark index's securities (Vanguard Asset Management, 2023). Certain subsets of optimized ETFs follow active management strategies, enabling investors to bet on price deviations, while some follow rules-based methodologies that systematically allocate assets based on predefined criteria (Braun, 2018).

Roll (2013) introduced a mean-variance optimization framework specifically designed to minimize tracking error as opposed to maximizing return for a given level of risk. The optimization involves selecting a portfolio of assets that closely match the returns of the target index while considering constraints such as limited available assets and transaction costs (Roll, 2013). Roll (2013) found that their methodology on portfolio optimization was specifically applicable to ETF replication strategies where full replication of an index may be deemed impractical due to transaction costs and liquidity issues. By using a subset of securities and optimizing their weights, portfolio managers can achieve a balance between tracking the index closely and minimizing the costs associated with frequent rebalancing (Roll, 2013).

Jorion (1992) and Chiang (2001) discussed the optimization problem where the objective is to maximize a portfolio's return subject to a constraint on tracking error. This approach is most relevant to portfolio managers who need to adhere to stringent benchmark tracking requirements while still seeking to generate excess returns (alpha). The optimization problem is formulated as a quadratic programming problem, where the objective function includes the expected return of the portfolio and a penalty for tracking error (Jorion, 1992; Chiang, 2001). While traditionally, optimization focuses on the trade-off between risk and return, Jorion (1992) introduces a second trade-off between return and tracking error, which is crucial for ETFs aiming to replicate a benchmark. By imposing a constraint on tracking errors, the portfolio manager can effectively manage the risk of underperformance relative to the index (Jorion, 1992; Chiang, 2001). This approach allows for some degree of active management within the constraints of tracking errors. Therefore, it is particularly useful for ETFs that aim to outperform their benchmark modestly while remaining largely passive (Jorion, 1992).

Recent research on the optimized replication of ETFs highlights various factors influencing tracking error and replication quality. Total costs, benchmark volatility and bid-ask spread are identified as significant determinants of replication quality for both equity and bond ETFs (Cox and Lehrbass, 2018). Different optimization techniques show varying effectiveness for equity and fixed-income ETFs, with Levenberg-Marquardt performing best for fixed-income and Nelder-Mead Simplex for equity benchmarks (Avdiu and Unger, 2023). Studies reveal that most optimized ETFs closely track their indices, managing tracking errors at acceptable levels (Kompalli, 2018). However, an ETF's optimal index replication strategy often involves underweighting or omitting illiquid index assets, leading to heterogeneous effects on asset markets depending on preexisting liquidity (Brogaard, Heath and Huang, 2020).

Kempf and Memmel (2006) developed the Global Minimum Variance Portfolio (GMVP), which represents a portfolio that has the lowest possible variance among all possible portfolios that can be formed from a given set of assets. In the context of ETF optimization, the GMVP can be used to create a portfolio that minimizes risk while maintaining exposure to the underlying index (Kempf and Memmel, 2006). Minimum Variance ETFs will use optimization techniques to select a subset of stocks that demonstrate low historical volatility or low levels of correlation, to reduce downside risk (Kempf and Memmel, 2006). The GMVP is structured to include a covariance matrix, which captures the relationships between the returns of different assets and a shrinkage estimator, which reduces estimation errors (Kempf and Memmel, 2006). This approach is especially valuable for low-volatility ETFs, as they attract risk-averse investors (Kempf and Memmel, 2006).

Other ETF optimization strategies include smart beta, equal-weighted, risk-parity and multi-factor strategies. Smart beta ETFs seek to capture specific factors that have been observed to generate excess returns over periods of time (Bowes and Ausloos, 2021). Examples of smart beta strategies include value, momentum, low volatility, quality and size. These types of ETFs will typically weight their holdings based on the above-mentioned factors rather than market capitalization. ETFs that follow smart-beta strategies use Fama and French's model (1993) as a foundation. These ETFs are constructed to provide exposure to specific risk factors, as mentioned prior, in addition to market-beta (Bowes and Ausloos, 2021). As opposed to weighting the holdings of an ETF by market capitalization, equal-weighted ETFs seek to assign equal importance to each constituent stock (DeMiguel, Garlappi and Uppal, 2007; Blitz and De Groot, 2013). This strategy results in gaining more balanced exposure across all holdings of the fund, while potentially reducing concentration risk and capturing the performance of smaller companies (Blitz and De Groot, 2013).

ETFs that employ risk-parity strategies will aim to allocate capital across different asset classes based on their risk contributions as opposed to their market values. This approach to index replication seeks to achieve more balanced risk exposure across asset classes, potentially enhancing diversification benefits and reducing portfolio volatility (Steiner, 2012; Rubesam and Huang, 2018). Multifactor strategy ETFs have gained traction in recent years as a way to provide investors with exposure to multiple factors that drive stock returns (Braun, 2018). ETFs that follow multi-factor strategies use a combination of factors such as value, momentum, quality and market capitalization to construct diversified portfolios (Braun, 2018). Through diversification across factors, these ETFs aim to capture different sources of return and reduce the impact of individual factor fluctuations on the portfolio (Braun, 2018). While multifactor funds offer a convenient package for factor diversification, their performance has been disappointing, often underperforming broad market funds and homemade factor diversification strategies (Estrada, 2024). Factor-based ETFs aim to achieve superior risk-adjusted returns by overweighting favourable characteristics and underweighting those that are unfavourable (Estrada, 2024).

Research suggests that simple equal-weighting of multiple-factor indices has historically been more effective than complex approaches, although dynamic factor-weighting strategies based on fundamental signals may be beneficial for skilled investors (Alighanbari and Chia, 2016). In a multi-factor world, diversification benefits depend more on idiosyncratic volatility after restructuring portfolios to align factor sensitivities rather than on correlation (Roll, 2013). Therefore, accurately measuring underlying factors and estimating factor sensitivities for assets is integral for effective multifactor investing (Roll, 2013).

ETFs that follow optimization techniques are transparent in their release of information regarding how the ETF portfolio is constructed and how the investment strategy is implemented (Estrada, 2024). This helps investors assess whether the ETF aligns with their investment objectives and risk appetite. Optimized ETFs are observed to be predisposed to slightly higher expense ratios in comparison to traditional equity ETFs (Vanguard Asset Management, 2023). However, they often remain cost-effective in comparison to actively managed mutual funds (Vanguard Asset Management, 2023). Investors can benefit from the optimized ETF structure's lower operating costs and potential tax efficiency.

Overall optimized ETFs carry many of the favourable characteristics of stratified sampling and full physical replication. However, it is essential to note that while an ETF's prospectus may indicate that it employs optimization or sampling techniques, a manager may choose to fully replicate the underlying index. However, the reverse of that strategy is not permitted (Vanguard Asset Management, 2023). The subsequent figure 2-4 depicts the similarities and differences in ETF construction under the three forms of physical replication that have been discussed.

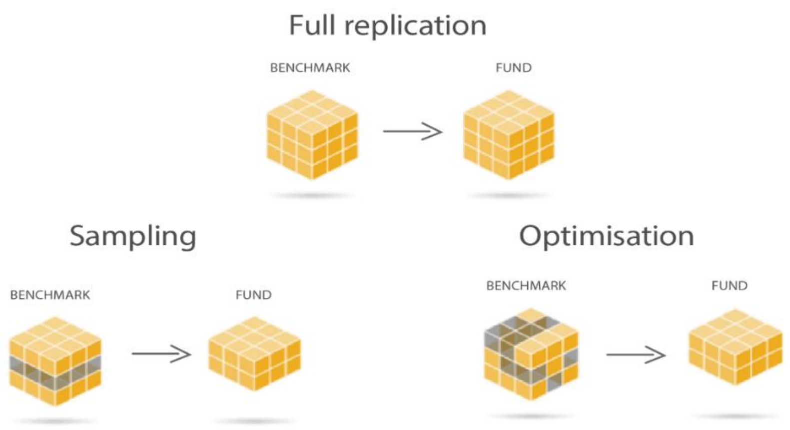

Figure 2-4: Physical Replication Approaches

(Vanguard Asset Management, 2023, para. 3)

2.2.4. Synthetic Replication

Synthetic ETFs achieve index replication using derivatives such as swaps (Kim, Cho and Seok, 2023). Synthetic replication involves ETF managers entering derivative contracts (for example, Total Return Swaps) with counterparties, who are generally investment banks. The ETF manager will enter into agreements with counterparties (financial institutions) to receive the return of the index in exchange for the payment of a fee (Vanguard Asset Management, 2023). These derivative contracts provide the ETF with exposure to the index's returns without direct ownership of the underlying securities (Meinhardt, Mueller and Schoene, 2015).

The construction and creation processes of synthetically replicated ETFs are very similar to those of physically replicated ETFs. The difference is that after selecting a benchmark, the issuer considers possible counterparties and derivatives that will meet their requirements (Meinhardt, Mueller and Schoene, 2015). The ETF issuer will negotiate the terms of the derivative contracts with the chosen counterparties. This includes the specification of the notational amount of the swap, the duration of the contract, the payment terms and any other relevant terms and conditions (Meinhardt, Mueller and Schoene, 2015). The same process of obtaining regulatory approval and listing on the exchange then follows.

Synthetic replication is commonly used in emerging market ETFs. This is because emerging market stocks tend to be less liquid and harder to access than those domiciled in developed markets (Vanguard Asset Management, 2023). Synthetic replication is also widely used for UCITS ETFs tracking the S&P500 Index, as in the US, synthetic ETFs offer a tax advantage over their physical counterparts (Vanguard Asset Management, 2023). Some equity-linked instruments, including synthetic S&P500 ETFs, are exempt from withholding taxes and, as a result, receive 100% of the dividends paid by the stocks in the S&P500 (Vanguard Asset Management, 2023).

The two main structures used in synthetic replication are the unfunded and funded swap models. Regarding the unfunded swap model, the ETF issuer creates new shares in exchange for cash from the AP and enters a total return swap contract with a counterparty (Aramonte, Caglio and Tuzun, 2017). This differs from the typical in-kind process for physical ETFs. The ETF issuer will use the investor's cash to purchase a basket of securities (substitute basket or collateral basket) from the swap counterparty (Aramonte, Caglio and Tuzan, 2017). The swap counterparty is committed to delivering the return of the benchmark index, less a swap fee, if applicable. In exchange, the swap counterparty receives the return generated by the substitute basket. Under the unfunded model, the ETF issuer owns and has direct access to the assets in the substitute basket and can immediately liquidate them if the swap counterparty defaults (Aramonte, Caglio and Turzan, 2017).

The funded swap model follows the same creation process for the ETF shares, with the ETF issuer transferring the cash received from the investors to the swap counterparty. However, under the funded swap model, the collateral basket is placed into a separate account with an independent custodian, as opposed to being owned by the ETF issuer (Aramonte, Caglio and Turzan, 2017). The subsequent figure shows the differences between the unfunded and funded swap models for synthetic ETFs. Additionally, the collateral basket will generally make up around 110-120% of the underlying NAV which results in the ETF being overcollateralized (Jeambart and Nakano, 2017). As a result, if the counterparty defaults, the issuer can gain access to the collaterals and liquidate them (Jeambart and Nakano, 2017).

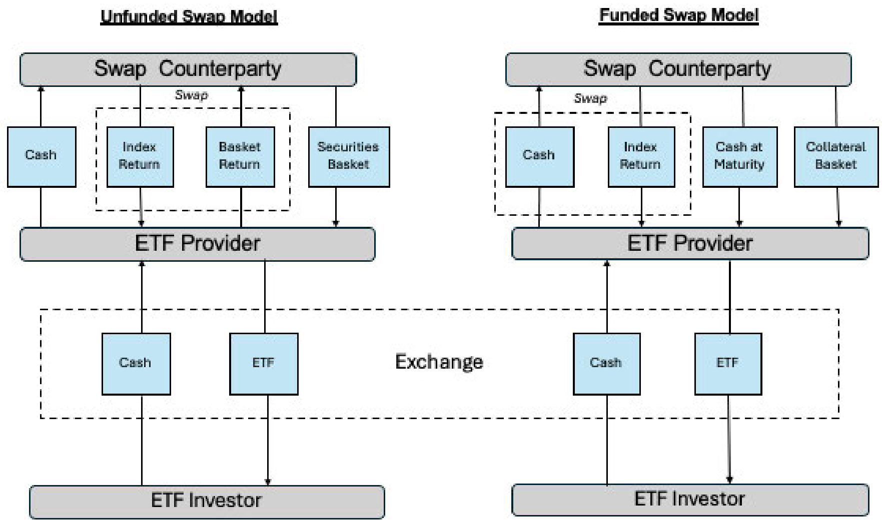

Figure 2-5: Structure of the Unfunded and Funded Swap Models

(Author's own construction (2024); Adapted from Jeambart and Nakano (2017))

The funded swap model for synthetic ETFs was developed in 2009 in response to the issues that arose with unfunded swap models during the Global Financial Crisis (GFC) (Jeambart and Nakano, 2017). Since then, it has been the more commonly used model for synthetic replication. The concern surrounding the unfunded swap model during the GFC was that in the event of counterparty default, the ETF issuer would be left with possibly non-correlated assets to the index, that they would have to sell on a stressed market with a high potential to suffer significant losses (Jeambart and Nakano, 2017). While the inner workings of the funded swap model address this concern, other issues, such as the timing of the liquidation, should still be considered. However, due to the time it takes to get the stocks, the high correlation with the index may make the loss less significant than in the case of the unfunded swap model (Jeambart and Nakano, 2017).

As with physical ETFs, synthetic ETFs are also exposed to counterparty risk. However, the source of the counterparty risk in synthetic ETFs differs from that of physical ETFs. Counterparty risk in synthetic ETFs arises from their reliance on over-the-counter derivatives (Ducoulombier and Goltz, 2012). The counterparty risk inherent to synthetic ETFs arises from the possibility that the total return swap counterparty may fail to deliver the index return (Hurlin *et al.*, 2019). In 2011, the Financial Stability Board (FSB) and the International Monetary Fund (IMF) put out warnings that highlighted the potential financial stability issues that may arise because of synthetic ETFs being poorly collateralized and allowing banks to engage in regulatory arbitrage by using risky assets as collateral (Hurlin *et al*., 2019).

Synthetic ETFs that follow the unfunded model are exposed to a high level of counterparty risk (Vanguard Asset Management, 2023). This risk is measured as the differential (valuation gap) between the ETF's NAV and the value of the reference basket (Vanguard Asset Management, 2023). As per a directive by the UCITS, the valuation gap cannot exceed 10% of the ETF's NAV. If this does occur, swap reset mechanisms are triggered (Vanguard Asset Management, 2023). These reset mechanisms include the counterparty transferring additional securities to the reference basket (Vanguard Asset Management, 2023). However, the swap reset mechanisms vary between products (Vanguard Asset Management, 2023). While synthetic ETFs exhibit higher counterparty and liquidity risks than physical ETFs, they counteract these risks by offering additional returns and lower tracking errors (Kim, Cho and Seok, 2023).

To achieve effective mitigation of counterparty risk in synthetic ETFs, factors such as the level of collateralization, the quality of the assets taking on the economic role of collateral and the ability of the fund to enforce its rights against collateral in the event of default by the swap counterparty need to be closely monitored (Ducoulombier and Goltz, 2012). Further issues inherent to the synthetic replication of ETFs are complexity and a lack of transparency. Since synthetic ETFs do not hold the underlying securities directly, investors may have limited visibility into the composition of the ETF's portfolio and the counterparties involved in the derivative contracts (Kosev and Williams, 2011). A significant portion of synthetic ETFs contain complicated structures using derivatives to create leverage, as well as funds based on "opaque" performance benchmarks (Kosev and Williams, 2011, p.56). In such cases, the exact structure and types of derivatives being used by the ETFs are unclear to investors (Kosev and Williams, 2011).

Synthetic ETFs are more complex than physically replicated ETFs due to their use of derivatives and associated counterparty relationships. These more complex funds can vary significantly in both their structures and the risks they present (Kosev and Williams, 2011). It is advised that investors have a better understanding of derivatives and their associated risks, to make an informed decision on whether to invest in a synthetic ETF. Another important factor for investors to consider when investing in synthetic ETFs is their tracking error predisposition. Synthetic replication can also introduce tracking errors due to factors such as counterparty risk, collateral management and the complexity of derivate contracts (Naumenko and Chystiakova, 2015). Existing research on the tracking error of synthetic and physical ETFs has yielded mixed results. While some studies found that synthetic ETFs have lower tracking errors (Elia, 2012; Fassas, 2012), others reported higher tracking errors (Naumenko and Chystiakova, 2015). Meinhardt, Mueller and Schoene (2015) found no significant difference in the tracking errors between physical and synthetic equity ETFs.

The use of derivatives leads to a more precise replication of the index’s performance (Elia, 2012). However, the effectiveness of the tracking ability of synthetic ETFs is dependent on the effectiveness of the derivative contracts and the management of counterparty risk (Elia, 2012). Synthetic ETFs are predisposed to lower operating costs when compared to physically backed ETFs. However, they may incur additional costs associated with derivative contracts and counterparty relationships. These additional transaction costs include fees paid to counterparties and expenses related to the management of derivatives (Elia, 2012). Synthetic ETFs have grown significantly in popularity and complexity, giving rise to regulatory concerns (Aggarwal and Schofield, 2014; Johnson, Bioy and Rose, 2012).

Synthetic ETFs may be predisposed to additional regulatory scrutiny due to their use of derivatives and exposure to counterparty risk. We have previously explored the regulations that govern ETFs and inhibit the creation of synthetic funds that take on more active investment traits in the US in section *2.2.2. Active versus Passive ETFs*. In Europe, almost all ETFs are governed by the provisions of the Undertakings for Collective Investment in Transferable Securities (UCITS) Directives (Amenc, Ducoulombier, Goltz and Tang, 2012). Under the UCITS, in the context of synthetic ETFs, ESMA (the body that governs the UCITS) states that the ETF’s prospectus should clearly outline information about the underlying investment portfolio or benchmark index, the counterparties, collateral and the risk of counterparty default and its impact on the returns of the fund (Amenc *et al.*, 2012). Additionally, ESMA requires that synthetic ETFs must include information in their annual report about the exposure obtained through financial derivative instruments, counterparties and collateral held to reduce counterparty risk (Amenc *et al*., 2012). Regulatory changes can impact the feasibility of synthetic replication, as seen with the European regulations restricting the use of certain derivatives for ETFs. Regulatory requirements are dependent on and vary according to the jurisdiction within which the ETF is created.

Synthetic ETFs were found to be more efficient, particularly in tracking emerging market benchmarks (Elia, 2012). Synthetic ETFs tend to outperform their physical counterparts in less-liquid areas of the market, such as emerging market equities, where physically replicated ETFs are more likely to employ sampling or optimization techniques (Vanguard Asset Management, 2023). There are tax advantages offered by synthetic ETFs in certain jurisdictions, as they may have lower portfolio turnover compared to physically replicated ETFs. However, tax treatment may vary depending on factors such as the structure of the ETF and local tax regulations.

The first synthetic ETF was created in 2001, and European interest in them grew substantially from that point, becoming excessively popular; they accounted for more than one-third of all ETFs in European equity markets. However, after the Financial Crisis of 2008/2009 and the Euro Crisis, there was a significant decline in these products, as regulators such as the Financial Stability Board (FSB) and International Monetary Fund (IMF) issued warning reports that highlighted concerns over counterparty and liquidity risk in 2011 (Bajpai, 2021). As a result, there was a gradual decline in the assets under management (AUM) of synthetic ETFs. In 2010, 46% of assets in equity ETFs were held in synthetic funds in Europe; however, by the end of 2020, it had shrunk to 17% (Bajpai, 2021). The size of the synthetic ETF market varies across different countries and depending on regional regulations. In comparison to Europe, the US synthetic ETF market is significantly smaller. This is due to the restriction on the launch of new synthetic ETFs by the US Securities and Exchange Commission (SEC), stating that the launch of a new synthetic ETF "can only be done by an asset manager who was already sponsoring synthetic ETFs prior to 2010" (Bajpai, 2021, para.7). As per Bloomberg report (2021, para.4), "In the entire ETF universe, only 1020 ETFs are synthetic, accounting for approximately 11% of the universe; of that, 67% are domiciled in the EMEA, 23% in the Americas and 10% in the Asia-Pacific."

In more recent years, there has been a renewed interest in the synthetic ETF market, specifically for European-domiciled US equity synthetic ETFs, due to a favourable regulatory taxation regime (Bajpai, 2021). Under Section 871(m) of the Internal Revenue Code of the Internal Revenue Services (IRS) of the United States of America, the use of total return swaps allows investors to increase their total return derived from the underlying index without taking any additional market risks (Deloitte, 2017; Bajpai, 2021). This suggests that the returns received by synthetic ETF investors are "free of withholding tax on dividends" as opposed to a withholding tax of 15% to 30% charged on the returns of regular ETFs (Bajpai, 2021, para.8).

Some of the most popular indices that are tracked through synthetic replication are the NASDAQ-100, S&P500 and the MSCI World Indices. In September of 2020, BlackRock launched the iShares S&P500 Swap UCITS ETF (I500), this ETF has $919.83 million in AUM. Additionally, BlackRock had also incepted a synthetic ETF that tracks the NASDAQ-100, known as the iShares NASDAQ-100 UCITS ETF (EXXT). Other popular synthetic ETFs that track major indices have been incepted by Invesco, Amundi, Lyxor and DWS (Xtrackers), such as the Amundi MSCI Europe Banks UCITS ETF (CB5), which tracks the MSCI Europe Banks Index, the ProShares Short DOW30 (DOG), which tracks the inverse of the Dow Jones Industrial Average (DJIA), the ProShares Short QQQ (PSQ), which tracks the inverse of the NASDAQ-100 and the ProShares Short S&P500 (SH), which tracks the inverse of the S&P500 (Bajpai, 2021), two of which make up part of the synthetic and leveraged ETF data sample of this study.

2.2.5. Leveraged Replication

Leveraged ETFs are financial products designed to deliver multiples of daily index returns, either positive or negative (Wagalath, 2014; Charupat and Miu, 2016). They use derivatives to achieve this objective. In 2006, ProShares introduced two unique types of ETFs: leveraged bull (ultra-long) and leveraged bear (ultra-short) ETFs (Holzhauer, Lu, McLeod and Mehran, 2013). These ETFs provide investors with exposure to various markets with either small, mid- or large capitalization values, that are either domestic or foreign, and broad or sector (Rompotis, 2016). Leveraged ETFs aim to beat the benchmark indices and are designed to deliver multiples of the benchmark's performance (before fees and expenses), over a specified period, which is generally limited to one day

(Rompotis, 2016). Inverse leveraged ETFs aim to short the market and provide performance that is the opposite of that of their underlying benchmarks on a daily basis (Rompotis, 2016). Leveraged (inverse leveraged) ETFs are designed to include the securities in the index, derivatives of the index's securities and the index itself (Rompotis, 2016). This enables them to achieve their daily targets of outperforming (shorting) their benchmark index (Rompotis, 2016).

These funds exhibit unique characteristics, including daily re-leveraging, which can exacerbate market volatility and create microstructure effects (Cheng and Madhavan, 2009). In comparison to regular ETFs, leveraged ETFs generally have lower liquidity and higher expense ratios (Rompotis, 2016). While inverse leveraged ETFs (bear) tend to underperform their benchmark, leveraged ETFs (bull) may slightly outperform their respective benchmark but with increased risk (Rompotis, 2012b). The structure of leveraged ETFs contains an embedded path-dependant option that can lead to value destruction for long-term investors (Cheng and Madhavan, 2009). Hougan (2009) found that the daily returns of leveraged ETFs remain within their targets, and the daily tracking errors are insignificant. However, when the investment horizon is extended, tracking error increases (Hougan, 2009). Due to their high transaction costs, tax inefficiency and potential value erosion over time, these funds are generally considered unsuitable for buy-hold investors (Cheng and Madhavan, 2009).

Leveraged ETFs need to be rebalanced more frequently to ensure that their holdings reflect the benchmark index (Holzhauer *et al.*, 2013). The frequency of the rebalancing of leveraged and inverse ETFs ranges from 3-4 times a year for long-levered positions on low-volatility indices to weekly for inverse positions on high volatility indices, with some leveraged ETFs being rebalanced daily to maintain their stated leverage ratio (Hill and Teller, 2009; Avellaneda and Dobi, 2012). The daily/weekly/quarterly rebalancing of leveraged ETFs requires the ETF manager to systematically alter the amount of index exposure daily/weekly/quarterly to achieve the investment objective of the fund, which is to provide multiples of the daily returns on the underlying benchmark index (Avellaneda and Dobi, 2012). The daily or weekly rebalancing requirement of some leveraged ETFs presents a unique characteristic of these funds, which differs from the traditional quarterly or annual rebalancing approaches undertaken by physical and swap-based synthetic ETFs (Hill and Teller, 2009). The dynamic rebalancing requirement of these ETFs results in a phenomenon known as the "constant leverage trap", which refers to leveraged ETF holders always chasing their own positions because they are required to constantly buy low and sell high (Holzhauer *et al.*, 2013, p.1170). Additionally, frequent rebalancing increases volatility towards the market close, which amplifies the effects of the constant leverage trap and increases transaction costs (Holzhauer *et al.*, 2013).

The daily rebalancing of some leveraged and inverse ETFs provides justification as to why it is widely stated that they are only suitable for short-term investors (Holzhauer *et al.*, 2013). A 2009 regulatory notice by the Financial Industry Regulatory Authority (FINRA) further highlighted the short-term nature of leveraged ETFs. This notice informed investors that these ETFs are designed to achieve their stated objectives on a daily basis and, because of compounding their performance over extended periods of time, may differ significantly from their objectives, especially in more volatile markets (Holzhauer *et al.*, 2013).

The growing interest in applying active investment techniques to ETFs gave rise to leveraged and inverse leveraged ETFs (Rompotis, 2016). Swap-based ETFs, such as the Xtrackers ShortDAX x2 Daily Swap UCITS ETF 1C, which aims to generate 2x the returns of the ShortDax Daily Index, is an example of a leveraged ETF. While leveraged ETFs pose an interesting investment opportunity, they also carry with them a significantly higher level of risk. This could lead to amplified losses in volatile markets, specifically those marked by financial crises. By theoretical definition, this characteristic is what demonstrates the activeness of some synthetic or derivative-based ETFs. Despite their growing popularity, evidence shows that these funds often fail to meet their daily targets of generating returns that are a multiple of their benchmark index's returns (Rompotis, 2016).

As both synthetic and physical ETFs continue to grow in popularity, the preferred choice from an investor's point of view between the two methods would be highly dependent on the underlying asset, region, taxation laws, investor sentiment and risk tolerance. Findings have concluded that synthetic ETFs may be more suitable for risk-tolerant investors, while physical ETFs are better suited to risk-averse investors (Broby and Spence, 2020).

2.3. Tracking Performance and Tracking Error

There exists tracking inefficiency in the form of tracking errors in ETFs (Rompotis, 2005). Tracking error is the resultant measurement of the difference between the return on the ETF and the return on its underlying benchmark index (Rompotis, 2005). This measure signals that the ETF is not perfectly tracking its underlying index. As ETFs grew in popularity in recent years, their tracking ability became a topic of scrutiny. Factors that significantly influence tracking performance include fund size, expense ratios, assets under management, replication strategies, trading volume and volatility (Singh and Kaur, 2016; Chen, Chen and Frijns, 2017; Tsalikis and Papadopoulos, 2019). Rompotis (2012a, b) stated that the presence of risk factors, fund expenses and fund age also contribute to the level of tracking error in equity ETFs.

Singh and Kaur (2016) found that in their sample of 12 ETFs, all were predisposed to a significant level of tracking error. Therefore, they measured the ETF's performance based on the magnitude of the tracking error. The findings from their study informed their suggestion that an ETF's tracking performance should be assessed on its ability to minimize tracking error rather than the absence of it (Singh and Kaur, 2016). As such, this study considers the persistence of tracking errors and, therefore, will rank the performance of each ETF in the sample based on the magnitude of its tracking error. Singh and Kaur (2016) further deduced that despite controlling various factors surrounding ETFs such as the fund size and expense ratios, they are still bound to suffer from deviations to perfect replication of their benchmark index. This is due to the presence of frictions in the market such as transaction costs, changes in benchmark index composition and volatility, which they had identified as key contributors to tracking errors (Singh and Kaur, 2016).

In further support of measuring tracking performance as the minimization of tracking error rather than its absence, Strydom, Charteris and McCullough (2015) state that a passive investment strategy, which is what is most predominantly applied to ETF investing, should have its success assessed by its ability to limit tracking error. While tracking error is considered to be a constant and negative component of ETFs due to market frictions, studies such as Rompotis (2012a) contradict the negativity of this phenomenon. Rompotis (2012a) conducted a study on the performance dynamics of 50 iShares ETFs and found that the ETFs included in this sample significantly outperformed their benchmark index, the S&P500. This finding signalled that tracking error may not necessarily always be a negative concept; in some instances, it may enable the ETF to outperform its index and, therefore, produce positive returns (Rompotis, 2012a).

Rompotis (2012a) further deduced through regression analysis that the tracking error of ETFs are strongly persistent. This suggests that ETF participants should always be aware that the performance of passively managed funds may deviate from the performance of their underlying index persistently (Rompotis, 2012a). As a result, they should always be willing to receive less than the market return. A further finding derived from Rompotis (2012a) is the predictability of the tracking performance of ETFs. Results obtained from a raw data regression were all positive and significant at a level of 1%, implying that tracking performance is predictable. This indicates that when an ETF is deemed a top performer in a particular year, it is highly likely that it will perform well in subsequent years (Rompotis, 2012a). Results from the Sharpe and Sortino measures further justify this observation as they were positive and statistically significant. The combined results showed that the lagged performance of ETFs is indicative of future returns (Rompotis, 2012a).

The predisposition of tracking errors to secondary-market liquidity is a further factor that influences the size of tracking errors and the overall tracking performance of ETFs. To recapitulate, an integral part of an ETF’s construction and structure is the adoption of the creation and redemption processes of open-end funds with the continuous trading mechanism of closed-end funds (Bae and Kim, 2020). These creation and redemption strategies are undertaken through arbitrage processes by the authorized participants to eliminate any ETF return deviations from the fund’s NAV returns. This arbitrage mechanism can be significantly impacted if either the ETFs or the underlying assets are predisposed to lower liquidity (Bae and Kim, 2020). A lack of liquidity in the underlying assets can generate higher levels of tracking error as it may deter the authorized participants from replicating the index at the time of trading the basket of securities (Bae and Kim, 2020). Furthermore, low liquidity results in a mispricing problem in the NAV and index returns, as arbitrage activities need to take place simultaneously on both the ETF and the underlying asset markets, this further induces tracking errors (Bae and Kim, 2020).

The “liquidity provision and tracking error problem” is amplified as a significant issue in the ETF market, as it could further lead to delayed elimination of tracking errors (Bae and Kim, 2020, p.224). Delayed minimization of tracking error occurs when the authorized participants may be discouraged from actively participating in arbitrage trading. A further contributing factor to delayed tracking error limitation is if the authorized participant requires additional returns to engage in arbitrage processes. This then results in a strategic waiting game for the tracking error to get larger (Bae and Kim, 2020). This occurs as it creates a bigger arbitrage opportunity, or the APs may alternatively increase the bid-ask spread to make the additional required return on risk. These practices result in investors being required to pay higher transaction fees, which ultimately leads to a situation in which the elimination of tracking errors will be delayed (Bae and Kim, 2020).

Bae and Kim (2020) found that liquidity poises a significant determinant of tracking error. They suggest that illiquid ETFs tend to demonstrate higher levels of tracking errors. Further to that, they found through using a threshold list of ETFs as an instrumental variable that there exists a causal link between liquidity and tracking error. It was also determined that both the liquidity or illiquidity of the underlying assets and that of the ETF affect tracking errors (Bae and Kim, 2020). Specifically, it was determined that ETFs that hold illiquid underlying assets demonstrate tracking errors that are more sensitive to ETF illiquidity (Bae and Kim, 2020).

Ultimately, the theoretical framework section of this study has provided a conceptualized basis for the study. It has included an in-depth analysis of each component, ranging from the various theoretical facets of ETFs to the dichotomization of tracking error as a metric of tracking performance. Additionally, it provides a guideline of which the data, methodology and findings sections can emulate. The purpose of this study is dichotomized into three parts. Firstly, with all contributing factors considered, to encapsulate the effects that five types of fund replication have on tracking error. The structure and characteristics of the replication strategies of interest have all been explored in this section. Secondly, the linkage between tracking error and emerging and developed markets will be determined. Lastly, we seek to explore how crisis periods such as the Global Financial Crisis (GFC) and the COVID-19 Pandemic have impacted the tracking errors of ETFs.

3. Literature Review

This section focuses on summarizing the existing findings of academic papers analysing tracking error, the effect of replication strategy on tracking error, the effect a fund's domicile and its level of development has on tracking error, and a special consideration of how ETFs perform during shock events.

3.1. Tracking Performance

The main objective of a passive investor who seeks to invest in index-tracking funds is to invest in a fund that can minimize total fees and tracking errors (Agapova, 2011). While the fund manager aims to replicate both the risk and return profiles of the index identically, some tracking error is unavoidable, as, in theory, the fund manager attempts to measure the underlying index as a "paper portfolio"[1] (Aber, Li and Can, 2009, p.218). However, in reality this is not the case, as it is subject to market friction (Aber, Li and Can, 2009). Chu (2011) found in their study on the determinants of tracking error, that due to the persistence of market frictions, it is nearly impossible for an ETF to deliver identical risk and return to that of its underlying benchmark index. Shin and Soydemir (2010) found through studying the tracking errors of a sample of Asian ETFs that due to the inefficiency of Asian markets in disseminating information, higher levels of tracking error were observed.

Charupat and Miu (2013) studied the pricing efficiency and tracking error predisposition of ETFs and how these factors impact the underlying stocks of the ETFs. They found that further factors that affect tracking error are management fees, transaction costs, dividends and replication strategies. Aber, Li and Can (2009) investigated the tracking ability of four iShares ETFs. The sample consisted of three US domiciled ETFs that track the S&P500 index, namely the IVV, IWF and IWM, and one international ETF, the EFA, which tracks the MSCI EAFE index. The results obtained from the standard deviation of the active returns suggested that tracking error was persistent across all ETFs in the sample irrespective of whether they were domiciled domestically or internationally. However, EFA showed a higher magnitude of tracking error than IVV, suggesting that a

[1] A list of investments and transactions for an investment strategy that are not actually held by the portfolio but can be back tested over historical periods and/or run contemporaneously (Boersma and Juillerat, 2020).

fund's domicile and its exposure to different market conditions affects its level of tracking error.

Baş and Sarioğlu (2015) evaluated the tracking errors and pricing efficiencies of 16 ETFs listed on Turkish Capital Markets during the period 2005-2013. Their paper was one of the first on ETFs listed on Turkish Capital Markets. Three methods of tracking error were used, the arithmetic mean (TE1), absolute mean (TE2) and quadratic tracking error (TE3). The ETF sample was divided into two sub-samples, A and B. Baş and Sarioğlu (2015), found that tracking error was persistent across both samples. TE1 varied between an average of 0.01202% for sample A and 0.05303% for sample B, TE2 showed an average measure of 1.63103% for sample A and 1.32246% for sample B, and TE3 resulted in an average measure of 2.12523% and 1.53956% for samples A and B, respectively. These results suggested that the ETFs, on average, failed to accurately track the performance of their underlying benchmark index during the analysis period (Baş and Sarioğlu, 2015).

Singh and Kaur (2016) conducted a study on the tracking efficiency of Indian equity ETFs using a sample of 12 ETFs for the period 2011 to 2015. The study computed tracking error using the mean absolute difference and standard deviation in the returns between the ETF and its underlying index, and the standard error of the regression of the return of the ETF against that of its underlying index. The tracking error measures ranged from 0.22% to 1.95% for tracking error measure one, from 0.31% to 2.92% for measure two, and from 0.30% to 2.74% for measure three (Singh and Kaur, 2016). These results suggested that tracking error was significant across all ETFs in the sample, implying that ETFs in India fail to replicate their benchmark index perfectly.

To analyse the factors with a significant impact on the magnitude of the tracking errors, Singh and Kaur (2016) included the following into a Random Effects Model: Assets Under Management (AUM), Total Expense Ratio (TER), volume, volatility and the fund's maturity. These results showed AUM as significantly negative, implying that the asset size of an ETF has a significant effect on its performance. An ETF with a larger fund size will demonstrate lower levels of tracking error and vice versa. The TER variable was insignificant (no significant impact on fund performance and tracking error), in contrast to existing studies on the same topic. The insignificance of the TER variable was attributed to its firm-specific nature (Singh and Kaur, 2016). Volume was used as a proxy for liquidity and was shown to have a significant negative effect on tracking errors (Singh and Kaur, 2016).

Chen, Chen and Frijns (2017) investigated the tracking performance and tracking error determinants of New Zealand-domiciled ETFs using the NZ Top 50 (FNZ), the NZ Top 10 (TNZ) and the NZ Mid Cap (MDZ). This was the first study to place emphasis on the dynamics of New Zealand-based ETFs. They used regression (CAPM[2]), cointegration analysis (Engle and Granger (1987) and Johansen (1988) processes) and the Error Correction (ECM) model. They computed tracking errors by using the Mean Absolute Deviation in Returns (MAD), the standard deviation of the return differences and the standard error of the residuals derived from the linear regression of the ETF returns on their benchmark index returns. They also used multivariate regressions to examine the determinants of tracking error.

Chen, Chen and Frijns (2017) found from the CAPM and cointegration analysis that at daily frequency, the ETFs in the sample demonstrate significantly different exposures to their benchmark indices from what is expected. However, at monthly frequency tracking performance improves but still shows significant differences between the ETF and its benchmark index (Chen, Chen and Frijns, 2017). The conclusion on the tracking performance of the sample of ETFs was that price deviations are quite large and persistent over time, particularly just after the inception of the ETFs. However, their magnitude did decrease over time suggesting that tracking performance improves over time. When examining tracking error exposure, the authors found that tracking error is present across all three ETFs in their sample. However, a downward trend in the variation of tracking error is observed over time, suggesting that tracking error decreases over lagged periods of time.

The study further examined the driving factors of tracking error by considering the characteristics of the ETF (and the underlying index), such as the average percentage spread of the ETF (stocks in the underlying index), the log of the volume traded of the ETF (constituents of the index) and the volatility of the index that the ETF tracks (Chen, Chen and Frijns, 2017). The authors found that the regression results showed that overall,

[2] Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965).

the characteristics of the ETF are related to tracking error, where the ETF percentage spread has a positive impact on tracking error and the ETF traded volume has a negative impact. These results were consistent across all three measures of tracking error and suggest that the illiquidity of the ETF contributes to tracking error (because of large price movements due to large spreads) (Chen, Chen and Frijns, 2017). Like the ETF characteristics, the percentage spread and trading volume of the index constituents have a positive and negative effect on tracking error, respectively. This suggests that illiquidity in the stock composition of the underlying index of the ETF is also a factor that affects the ETF's tracking error (Chen, Chen and Frijns, 2017). It is observed that the effect of index volatility on tracking error is both positive and significant, implying that the tracking error of an ETF is observably higher during high volatility periods. This could be a result of either increased difficulty or the increased costs of matching the ETF with the underlying index during volatile periods (Chen, Chen and Frijns, 2017).

Warne and Monika (2023) looked at the tracking errors of ETFs listed on the NSE of India. They computed the mean absolute deviation and standard deviation of the difference in returns between a sample of five ETFs and their respective benchmark indices to determine tracking error. They had also computed the standard error of the regression as a further measure of tracking error. The results from Warne and Monika (2023) were in line with that of Chu (2011). It showed that there is a significant level of tracking error persistence across all ETFs in the sample, and that ETFs fail to perfectly replicate their benchmark index due to factors such as costs, fees, changes in index composition and volatility (Warne and Monika, 2023).

3.2. Replication Strategies

This subsection of the literature review focuses on how the replication strategies of ETFs and their tracking performance are interconnected, through the analysis of pre-existing literature.

In 2011, three prominent international organizations, the International Monetary Fund (IMF), the Bank for International Settlements and the Financial Stability Board (FSB), published articles on the risks associated with investing in synthetic ETFs and the negative implications they have on the financial system. Contrary to their argument, the

Investment Company Institute and various major ETF sponsor firms spoke out in defence of their products. However, despite the controversy surrounding synthetic ETFs, vary few academic researchers have provided empirical studies to estimate the risk in terms of tracking error and the implications synthetic ETFs have on the financial stability of the investment market. Hence, this has created a gap in research which this study aims to address by quantifying the predisposition of the different replication strategies to tracking error.

Rompotis (2012b) performed an analysis on 43 German ETFs that were traded on the XTRA market from 2003 to 2005 to investigate their tracking performance and trading characteristics. During the period of study used in Rompotis (2012b), German ETFs did not adopt full replication strategies, which made them predisposed to substantial levels of tracking error (Rompotis, 2012b). However, current research shows that at present there are many German ETFs that now adopt full replication strategies. Rompotis (2012b) applied three methods of tracking error estimation to this study, the standard error of the regression of ETF returns against the returns of its underlying benchmark index, the mean absolute deviation (MAD) in the returns between the ETFs and their underlying benchmark index and the standard deviation of the return difference between the ETF and its underlying benchmark index. The results obtained from this study showed that across all three measures, tracking error was significant and persistent (Rompotis, 2012b). Findings from Rompotis (2012b) suggest that the partial replication of the benchmark index by German ETFs results in tracking errors of significant magnitudes and reflects deviations in the ability of synthetic ETFs to track their underlying benchmark index accurately.

Further to that, Rompotis (2012b) found that ETFs that show greater levels of departure from a full replication strategy suffer from higher tracking errors. This observation was justified by the ETFs in the sample such as, the UBS-ETF, UBS DJ US Technology ETF, Lyxor MSCI US Technology ETF and the NASDAQ-100 Europe Track ETF showing considerable deviations from a full replication strategy and producing tracking errors that were significant at a 1% level across all three measures of tracking error. This indicates that ETFs that do not follow full replication strategies are predisposed to higher magnitudes of tracking errors.

Elia (2012) investigated the tracking ability of physical and synthetic ETFs domiciled in Europe. The data sample consisted of 21 physical ETFs and 27 synthetic ETFs, to which four methods of tracking error estimation were applied. Elia (2012) found that the results of three out of four metrics were conclusive that synthetic ETFs show lower levels of tracking error on average than physical ETFs over the sample period of interest.

Meinhardt, Mueller and Schoene (2015) evaluated the tracking ability of traditional and synthetic European ETFs. The authors applied four commonly used methods of tracking error estimation derived from Frino and Gallagher (2002), Roll (1992), Pope and Yadav (1994) and Larsen and Resnick (1998) to 21 traditionally replicated ETFs and 27 synthetic ETFs. Meinhardt, Mueller and Schoene (2015) found that both traditional and synthetic ETFs that are traded in Europe are susceptible to tracking errors. However, statistical evidence showed that the synthetic replication of ETFs can reduce tracking errors over lagged periods of time. Additionally, synthetic ETFs were found to be more efficient when tracking emerging-market benchmark indices. While both forms of replication underperform their benchmarks, synthetic ETFs were shown to better recover from tracking error predisposition and adjust their returns to be in line with their underlying benchmark index (Meinhardt, Mueller and Schoene, 2015).

Mateus and Rahmani (2017) analysed the tracking performance of physical and synthetic ETFs listed on the London Stock Exchange (LSE), from 2008 to 2013. They applied two metrics for tracking error estimation namely the standard deviation and the mean absolute deviation (MAD) of the difference in daily returns between the ETF and its underlying benchmark index. Mateus and Rahmani (2017) found that across the entire ETF sample, ETFs using synthetic replication did not exhibit significantly lower levels of tracking error than physical ETFs. The daily tracking errors varied over time, across different categories and fund domiciles (Mateus and Rahmani, 2017). UK domiciled synthetic ETFs showed better tracking performance (i.e. lower tracking errors) during 2013, in comparison to UK-based physical ETFs (Mateus and Rahmani, 2017). They also found that synthetic ETFs that track emerging market indices demonstrate higher levels of tracking error because of the indices being very small.

The findings from Mateus and Rahmani (2017) are inconsistent with Johnson, Bioy, Kellet and Davidson (2013) whose findings stated that synthetic ETFs produce tracking errors that are, on average, 0.30% lower than that of physical ETFs. Johnson *et al*. (2013) attributed this finding to the observation that synthetic ETFs have lower transaction costs and do not declare dividends.

Fassas (2012) examined the tracking ability of physical and synthetic ETFs by applying three commonly used tracking error estimators to three physical ETFs and seven synthetic ETFs. Fassas (2012) found that across all three methods of tracking error estimation, the sample of physical ETFs exhibited lower levels of tracking error in comparison to the synthetic ETFs. This suggested that physically replicated ETFs can better mimic their underlying benchmark index than synthetically replicated ETFs (Fassas, 2014).

Maurer and Williams (2015) performed a risk analysis between physically and synthetically replicated trackers. Maurer and Williams (2015) detailed the sources of tracking error and risks inherent to each method of fund replication to determine whether investors should prefer one structure over the other. The authors used a data sample consisting of 49 funds derived from three fund families, namely iShares (Blackrock), Lyxor (Société Générale) and db. X-trackers (Deutsche Bank), to control for management styles. They applied tracking error metrics derived from Milonas and Rompotis (2010) and Shin and Soydemir (2010).

The results obtained from Maurer and Williams (2015) showed that synthetically replicated funds do not show superior replication of their underlying benchmark index in comparison to physically replicated funds, on a global basis. Additionally, they found that at the country level, a currency zone effect is shown to impact fund performance. The findings show that ETFs domiciled in Europe (Lyxor and Deutsche Bank), which track eurozone benchmarks, present significantly smaller average tracking errors than the US-domiciled iShares funds on the European indices (Maurer and Williams, 2015). The study was not able to determine conclusively whether investors in synthetic ETFs are compensated for the extra level of risk they take on (Maurer and Williams, 2015).

Kumar (2018) examined the linkage between the pricing efficiency and replication strategy of equity and gold ETFs, from 2012 to 2017. Kumar (2018) used a data sample comprised of six ETFs, three of which were equity-based and tracked the Nifty 50 Index. The replication type of the ETFs was determined by analysing their beta values. From the beta analysis, it was concluded that all ETFs in the sample followed a selective replication process (not full physical replication) (Kumar, 2018). The author used two methods of tracking error quantification: the mean absolute deviation (MAD) in returns between the ETF and its underlying index and the standard error of the ETF returns from the OLS regression. Kumar (2018) found that when selective replication techniques are adopted, tracking errors are significant and persistent.

Broby and Spence (2020) studied the tracking efficiency of physical and synthetic ETFs. Their data sample consisted of 58 European-domiciled ETFs that track European, US and emerging market indices. Broby and Spence (2020) calculated the tracking error of the ETFs using the mean absolute deviation (MAD) and standard deviation of the return differences between the ETF and its benchmark index. They further conducted a univariate analysis to identify the variables that influence ETF tracking efficiency, focusing on the effect of replication strategy and regional diversity. Broby and Spence (2020) found significant persistence of tracking error for all ETFs in the sample across the period of study, concluding that ETFs continuously fail to accurately replicate their benchmark index. They deduced from the results of the univariate analysis that synthetic ETFs do not produce significantly lower tracking errors than physical ETFs. Additionally, they found that the group of ETFs that demonstrated the highest levels of tracking error were emerging market synthetic ETFs (Broby and Spence, 2020).

Charupat and Miu (2011) studied the pricing efficiency and tracking error implications of leveraged ETFs, using a sample of eight leveraged and four traditional ETFs. Charupat and Miu (2011) measured the fund's returns based on the changes in the fund's NAV. The authors then applied a tracking error estimator in the form of a regression of the ETF's returns against its benchmark index's returns. Findings from Charupat and Miu (2011) suggested that the longer the holding periods, the larger the magnitude of the tracking error. The results showed that for daily returns (which suggests a holding period of 1 day), the slope coefficients are not significantly different from the expected ratios at a 5% level of significance, suggesting that the leveraged ETFs used in the sample are successful in delivering expected daily performance. This was expected as the funds make use of forward contracts to achieve their returns (Charupat and Miu, 2011). The same result was obtained for weekly return data (i.e. a holding period of 1 week). However, Charupat and Miu (2011) found that when the holding period was increased to one month (i.e. using monthly returns), the tracking errors became significantly larger in magnitude and the slope coefficients moved away from their leverage ratios.

Bansal and Marshall (2015) evaluated the tracking error predispositions of leveraged ETFs. The authors applied a simulation analysis to historical return data to determine how leveraged ETFs of the 2x, 3x, -2x and -3x varieties behave under scenarios of various return and volatility magnitudes. Bansal and Marshall (2015) concluded from their findings that while leveraged ETFs are predisposed to significant and sizable tracking errors and underperform the expectations of short-term investors, they may be favourable to long-horizon investors. Additionally, Bansal and Marshall (2015) noted that the tracking errors of all four leverage multiples were positive, suggesting that leveraged ETFs are beneficial to the bullish investor. Further to that, it was observed that the greater the leverage multiple, the more favourable the magnitude of the tracking error (Bansal and Marshall, 2015).

Charupat and Miu (2016) analysed the tracking performance and tracking errors of six leveraged ETFs that are all managed by ProShares and that track the NASDAQ-100 index. As per Rompotis (2013b), Charupat and Miu (2016) applied the regression approach to tracking error estimation. Findings from Charupat and Miu (2016) suggested that leveraged ETFs are predisposed to significant and persistent tracking errors that increase in magnitude relative to an increase in the holding period.

Rompotis (2016) examined the performance and volatility characteristics of leveraged ETFs that track emerging market stock indices. Rompotis (2016) used a sample of 12 leveraged and 11 inverse leveraged ETFs that cover regional emerging market indices. Rompotis (2016) employed a time series regression analysis to the daily return data of the ETFs and their target indices. The findings from Rompotis (2016) suggested that in the short run, leveraged ETFs minimize tracking errors. However, in the long run, the magnitude of their tracking errors increases significantly, specifically as the holding period increases. The results further showed that ETFs adopting a more bullish investment strategy were able to achieve returns that closely replicated their underlying benchmark, over a weekly period at maximum (Rompotis, 2016). Whereas bearish ETFs were able to achieve closely replicated returns over a 2-day period at maximum (Rompotis, 2016). These findings suggested that leveraged ETFs are most suitable for investors with very short-term trading horizons, while buy-and-hold investors may not be able to achieve their investment return goals using these types of funds (Rompotis, 2016).

Avdiu and Unger (2023) analysed the tracking errors of different optimization techniques applied to equity and fixed-income ETFs. The authors studied the correlation between the index and the ETF in the target function. Avdiu and Unger (2023) aimed to compare the tracking errors of the following optimization techniques: genetic algorithm, particle swarm optimization, Levenberg-Marquardt and Nelder-Mead Simplex algorithm. Avdiu and Unger (2023), found that when applying the correlation coefficient as the target function, the tracking error of funds that exhibit active management characteristics can be significantly minimized. Further to that, Avdiu and Unger (2023) concluded from the results of their study that when applying the genetic algorithms and Nelder-Mead Simplex algorithms, the tracking errors of the ETFs in the sample were significantly reduced.

3.3. Fund Domicile

This subsection of the literature review explores the linkages between fund domicile and tracking performance. This study considers a fund's domicile as either an emerging or developed market to determine the effect of market development on fund tracking performance. Through the analysis of pre-existing literature that focuses on ETF tracking performance and its dependency on fund domicile, we seek to determine how the level of market development of a fund's domicile country impacts the magnitude of its tracking error predisposition.

Strydom, Charteris and McCullough (2015) suggested that various empirical studies found evidence that tracking error differs between markets. These include Chu (2011), who examined the tracking errors of various Hong Kong-based ETFs. Chu (2011) found that Hong Kong ETFs showed higher levels of tracking errors than those in the United States or Australia, implying that a country's level of development may influence the tracking performance of its ETFs. While the issue of tracking errors within equity ETFs has been explored in developed market contexts, it still seems to be a scarce area of research within emerging economies. Various studies that focus on the tracking performance of ETFs in foreign markets have found that while the differences are similar, tracking errors do tend to vary between different markets (Chu, 2011). Shin and Soydemir (2010) discovered through regressive analysis and tracking error quantification techniques that the tracking error of US-based ETFs was higher than that of South American, Asian and European ETFs.

Blitz and Huij (2012) contradict the findings of Shin and Soydemir (2010). Blitz and Huij (2012) examined the tracking performance of emerging market ETFs against that of developed markets. They found that the tracking error of ETFs that tracked the MSCI Emerging Market Index was significantly higher than the passive funds tracking broad equity indices for developed markets.

Zawadzki (2020) analysed 18 different iShares ETFs across three regions, namely the Americas, Asia and Europe. Zawadzki (2020) applied three different tracking error metrics, namely, the difference in returns between the ETF and its benchmark index, the arithmetic average of the absolute values of the daily tracking error levels and the standard deviation of the return differences between the ETF and its benchmark index. Findings from Zawadzki (2020) suggested that higher tracking errors had been observed amongst the emerging nation's ETFs, whereas the USA and Canada (classified as developed) had the lowest values.

Shin and Soydemir (2010), Qadan and Yagil (2012) and Bas and Sarioglu (2015) used regression analysis to consider possible determinants of higher tracking errors in emerging market ETFs. Contributing factors to tracking error deviations in the context of market development and geographical position included higher price volatility in emerging markets, the non-synchronous trading hours of stock exchanges across different time zones, exchange rate fluctuations and differing transaction costs (Shin and Soydemir, 2010; Qadan and Yagil, 2012; Bas and Sarioglu, 2015).

Johnson (2009) considered daily and monthly data of 20 different foreign country ETFs over the period of 1997 to 2006. All ETFs were managed by Barclays to ensure that there is no bias between fund management style and rules. Johnson (2009) calculated correlation coefficients between the ETF and index returns and used regression models to determine the factors that influenced them. The key explanatory variables used were the measure of investment ease/difficulty, G7 membership (as a proxy for economic integration), the convergence in US trading hours and foreign exchange trading hours and the yearly difference in returns between foreign indices and the US indices. The correlation coefficients of these regressions represented the existence and magnitude of tracking error (Johnson, 2009).

These results showed that the market segmentation/integration hypothesis was not supported, as measures of market integration were not significant in explaining differences in correlation coefficients between foreign ETFs and their underlying indices (Johnson, 2009). The hours of overlap between foreign exchanges and the US exchange were a significant and positive factor in explaining the tracking error persistence (Johnson, 2009). The difference in yearly returns between the foreign index and the US index was a significant and positive factor in explaining the correlation coefficients (tracking error existence) using daily data, but not monthly data (Johnson, 2009).

Khan, Bacha and Masih (2015) analysed the performance and trading characteristics of 43 passively managed equity-backed ETFs domiciled across developed and emerging markets. They compared the developed and emerging ETFs' risk-adjusted performance, tracking error and trading characteristics. They further examined how fund characteristics such as asset size and expense ratio impacted ETF performance. Findings from Khan, Bacha and Masih (2015) suggested that emerging market ETFs have higher tracking errors and are less efficient in replicating their benchmark index compared to developed market ETFs. However, they also found that emerging market ETFs provide better risk-adjusted performance compared to developed market ETFs (Khan, Bacha and Masih, 2015). The results further showed that larger asset size has a positive impact on ETF performance, while higher expense ratios have a negative impact (Khan, Bacha and Masih, 2015).

Yavas and Rezayat (2016) investigated the linkages between equity ETF returns and volatility transmissions from the USA, Europe and key emerging countries' exchanges. The authors applied a MARMA model to analyse the co-movements of daily ETF returns and a GARCH (1,1) model to analyse the persistence and transmission of volatility. Findings from Yavas and Rezayat (2016) suggested that there exists significant co-movement of returns among all the country ETFs that were studied, but there still exist opportunities for diversification, such as US and European investors investing in Chinese, South African and Turkish ETFs. They found that volatility is not transmitted from the sample countries to the US, Brazil, China and South Africa, but US market volatility is transmitted to India, Russia, Mexico and Turkey, and European volatility spills over to Mexico and South Korea. Yavas and Rezayat (2016) found evidence of both return and volatility spillovers among the equity markets studied.

Saunders (2018) examined the fund and country-specific factors that predict the accurate tracking performance of country-specific ETFs. Saunders (2018) analysed a sample of 93 country-specific ETFs from 47 different countries. The methodology employed by Saunders (2018) included the mean absolute deviation in returns between the ETF and its underlying benchmark index to measure tracking error and an OLS regression with tracking error as the dependent variable and the factors of study as the independent variables. The independent variables considered were market overlap, economic freedom, relative return to the US, fund characteristics (holdings and size) and expense ratio. The results from Saunders (2018) showed that The Heritage Economic Freedom Index and the ETF return relative to the US equity market return are significant explanatory variables for tracking error, where higher economic freedom and integration, and higher relative returns lead to lower tracking errors. The ETF expense ratio was also found to be a significant variable for tracking error, where higher expense ratios lead to higher tracking error. The other independent variables did not have a statistically significant effect on tracking error (Saunders, 2018).

Neto, Klotzle and Pinto (2021) analysed how market conditions affect ETF tracking efficiency. Neto, Klotzle and Pinto (2021) examined the tracking efficiency of a sample of ETFs derived from 7 different emerging and developed markets. The findings suggested that ETFs in emerging markets demonstrate higher tracking errors (lower tracking efficiency) compared to ETFs in developed markets. Kenneth, Lai and He (2013) evaluated the performance characteristics of emerging market ETFs. Kenneth, Lai and He (2013) found that the performance of emerging market ETFs is inferior to the benchmark indices they track. The findings further suggested that emerging ETF performance is sensitive to their geographical location and economic development (Kenneth, Lai and He, 2013).

Dobson (2020) analysed the tracking errors of global market ETFs with the consideration of regional diversity. Dobson (2020) calculated the tracking errors for a sample of 18 iShares ETFs, with 6 domiciled in each of 3 regions: the Americas, Asia and Europe. Dobson (2020) further examined how the tracking error values are related to the geographical region and degree of market development. The results suggested that the ETFs did not track their benchmark indices accurately and produced significant negative tracking errors. The results further concluded that the value of the tracking errors was dependent on the geographic region and the level of market development (Dobson, 2020).

Tripathi and Sethi (2022) performed a tracking error analysis to evaluate the price deviations of Indian ETFs from their underlying benchmark indices. Tripathi and Sethi (2022) also compared the tracking abilities of Indian ETFs to those in developed markets such as the USA and Europe. The findings from their study concluded that ETFs in developed markets exhibit superior tracking performance compared to Indian ETFs (Tripathi and Sethi, 2022).

3.4. ETFs in Crisis Periods

This subsection of the literature review focuses on how ETF tracking performance deviates during periods of market crisis. In this study, two distinct periods of market crisis are considered, namely the Global Financial Crisis (GFC) of 2008/2009 and the COVID-19 pandemic. An analysis of pre-existing literature will be undertaken to deduce the impact of the GFC and the COVID-19 pandemic on tracking performance and tracking errors. Research on the effect of crisis periods on ETF tracking performance has yielded mixed results, with some studies finding significant impacts on the performance dynamics of ETFs and others finding no conclusive result.

Arestad and Broström (2011) looked at 17 ETFs listed on the New York Stock Exchange (NYSE) that tracked European and Asian indices from 2006 to 2011; this period included the GFC, with its effects being felt from 2007 to 2009. Their objective was to evaluate the performance and tracking ability of ETFs during extreme volatile periods such as the GFC. The authors applied Jensen's model and commonly used tracking error metrics to assess the ETF's tracking ability. The study yielded ambiguous results regarding how well the ETFs in the sample were able to track their benchmark indices. Results obtained from the Jensen's model showed insignificant alphas across the period of study, which are indicative of the ETF's having effectively tracked their benchmark indices during the volatile periods, suggesting that tracking performance was not impacted during the GFC.

Goltz and Schröder (2011) conducted two surveys in 2008 and 2009, respectively, whereby they interviewed ETF users to deduce investor's perceptions of ETFs and other indexing products before and after the GFC. Results obtained from their study found that ETFs in standard asset classes (i.e. equities and government bonds) remained unaffected by the GFC, while ETFs in alternative classes suffered a decrease in usage. Further to that, they found that ETFs generally ranked highly compared to other indexing products, likely due to an increased focus on liquidity and transparency. By qualitatively analysing the impact of the GFC on investor's perceptions of ETFs, Goltz and Schröder (2011) found that the overall investment in ETF products remained stable during the GFC. During this period of financial distress, both the usage and average amount of money invested in ETFs remained largely constant (Goltz and Schröder, 2011). These findings suggest that during times of financial crisis, ETFs remain relatively unaffected due to their higher liquidity. The flight to liquidity during periods of financial distress led to ETFs on standard asset classes enjoying increased investment (Goltz and Schröder, 2011). Theoretically, the findings from Goltz and Schröder (2011) should mean that the tracking performance of ETFs remained relatively stable during the GFC as their trading volume was not negatively impacted.

Suk Kim (2011) deduced from their study on Asia-Pacific and US ETFs that during high volatility periods marked by financial distress, such as the GFC, the interrelationship between emerging and developed ETF markets becomes more cointegrated. Therefore, suggesting crises that occur in developed markets can have spillover effects on emerging markets and impact the returns of emerging market ETFs, however at a differing degree, due to fundamental and economic factors. Khan, Bacha and Masih (2015) found from their study on the tracking performance of emerging and developed ETFs during the GFC that, the average tracking error of all ETFs is higher during crisis periods, which indicates that ETF pricing is more volatile during market downturns.

Liu and Lee (2022) examined the impact of the COVID-19 pandemic on the performance and systematic risk of ETFs. Liu and Lee (2022) used Jensen’s alpha to measure ETF tracking performance. This study focused on using a sample of two ETFs listed on the Taiwan Stock Exchange (ETF50 and SSE50) to measure the impact of the pandemic on the performance of Taiwanese and Chinese-domiciled ETFs. Liu and Lee (2022) found that Jensen’s alpha model overestimated the performance of the ETF50 (domiciled in Taiwan) and after considering the residual heterogeneity, there was no evidence of significant positive abnormal returns. The COVID-19 pandemic significantly increased the systematic risk of the SSE50 (domiciled in China) and decreased its fund size, thereby impacting its tracking performance. The performance of the SSE50 ETF was more affected by the COVID-19 pandemic, reflecting the more severe impact of the pandemic in China compared to Taiwan (Liu and Lee, 2022).

Saha, Madhavan and Chandrashekhar (2022) applied an entropy-based analysis[3] to examine the informational efficiency of domestic equity ETFs compared to their underlying market indices during the COVID-19 pandemic. Findings from this study suggested that the informational efficiency of ETFs and their underlying indices declined sharply during the COVID-19 pandemic. The decline in efficiency was more significant for ETFs and indices domiciled in the USA and Canada in comparison to China, Hong-Kong and Taiwan (Saha, Madhavan and Chandrashekhar, 2022). However, it was noted that even prior to COVID-19, ETFs and indices domiciled in certain developed markets were less efficient than their emerging market counterparts. The concluding result was that ETFs do not perfectly mimic the performance of their underlying indices during periods of market distress (Saha, Madhavan and Chandrashekhar, 2022). Additionally, Saha, Madhavan and Chandrashekhar (2022) found that all ETFs in the sample suffered from decreased tracking performance during the COVID-19 pandemic period.

[3] Entropy measures the extent of disorder in a system. In information theory, higher values of entropy for a time series analysis corresponds to higher levels of efficiency (Gulko, 1999).

Saffi and Zheng (2023) analysed 2290 European equity and fixed-income ETFs from 2001 to 2020 which included synthetic and physical ETFs. The objective of their study was to determine how the replication method of an ETF affects its tracking performance, specifically during periods of market crisis. To ensure a like-for-like comparison, the authors isolated synthetic and physical ETFs that track the same index. Saffi and Zheng (2023) found that while there was no persistent evidence that synthetic ETFs outperform physically replicated ETFs in respect to tracking efficiency, synthetic ETFs were found to be more vulnerable to declines in tracking efficiency during periods of increased counterparty risk. However, they are less affected by liquidity shocks than physical ETFs. In comparing the results from the GFC subperiod to the COVID-19 subperiod, they found that the tracking performance of both synthetic and physical ETFs became less sensitive to market distress after the GFC. This, therefore, suggests that improvements in risk management since the GFC, had enabled both synthetic and physical ETFs to better maintain their pre-crisis tracking performance levels during the COVID-19 pandemic.

Malhotra and Sinha (2023) examined 35 ETFs that track broad market indices in India to deduce the impact of the COVID-19 pandemic on tracking performance. The period of study was from 2015 to 2021, divided into subperiods of January 2015 to 6 March 2020 (Pre-COVID-19) and 7 March 2020 to July 2021 (During COVID-19). The authors employed the three most commonly used methods of tracking error estimation (the mean absolute deviation and standard deviation of the return difference between the ETF and its underlying benchmark index and the standard error of the regression analysis). Additionally, Malhotra and Sinha (2023) utilized the Sharpe-Litner (1965) adaption of the CAPM to measure the tracking efficiency of the ETFs in the sample and the Error Correction Model (ECM) to determine the cointegration between the returns of the ETF and its underlying benchmark.

Findings from Malhotra and Sinha (2023) suggested that ETFs in India experienced increased tracking errors, pricing inefficiencies and faster adjustments during the COVID-19 pandemic compared to the pre-pandemic period. The results from all three measures of tracking error suggests that there was considerable variation in tracking errors between the two periods and that tracking errors increased significantly during the COVID-19 period. Results from the regression analysis showed that the ETFs transitioned from trading at a discount to a premium to the benchmark during the COVID-19 period, however the market was able to correct these pricing inefficiencies more quickly (Malhotra and Sinha, 2023). The results further showed that the market was able to correct pricing inefficiencies between the ETFs' NAV and market price more expeditiously and as a result ETF returns became more closely aligned with their benchmark indices during the COVID-19 period in comparison to before the pandemic, demonstrating ETF resilience in the face of market uncertainty (Malhotra and Sinha, 2023).

The findings from pre-existing literature in this section highlight the complex dynamics of ETF performance during crises and suggest caution for investors. This study will further assess the impact of market crises on the tracking performance of ETFs with the inclusion of the Global Financial Crisis (GFC) and the COVID-19 pandemic in the period of study.

3.5. Literature Review Summary and Conclusion

From the literature review section, it is clear that, while there exists a considerable amount of literature on physical and synthetic ETFs, existing research on other types of fund replication strategies remains limited. Hence, the purpose of this study is to fill this gap in research by including a more extensive range of replication strategies than what is currently available in the literature. As per extensive research on the topic of ETF replication strategies, it can be said that this study is the first of its nature to perform a comparative analysis of tracking performance across all five Bloomberg Professional categorizations of replication strategy, while also collectively using fund domicile and crisis periods as further factors of study.

The pre-existing studies reviewed have provided a benchmark against which the research questions will be answered. In the following sections we seek to determine which fund replication strategy is predisposed to the lowest level of tracking error, whether emerging or developed market ETFs show superior tracking performance, and the effect the GFC and COVID-19 pandemic have had on the tracking performance of all ETFs (with a suitable inception date, *i.e. before 2006*) considered in the sample.

4. Data and Methodology

4.1. Data

The data sample used in this study consists of the adjusted daily closing prices and daily NAV values of 52 equity-backed ETFs and the adjusted daily closing prices of their respective underlying benchmark indices (a total of 46 different indices are used). All closing price and NAV (assuming reinvested dividends) data used in this study were collected from the Bloomberg Professional Terminal (2024) and the US$ was set as the default currency measure.

In this study, we use daily data as done in previous studies such as Pinheiro and Varela (2018) and Peltomäki (2017). Daily data is the preferred frequency for ETFs as the creation and redemption processes of ETFs generally take place at the end of the trading day (Peltomäki, 2017; Pinheiro and Varela, 2018). Daily data is also used to enhance the accuracy of results, clearly show trends and minimize timing imperfections.

Johnson (2009) observed that, when using daily closing price and return data to compute tracking error, the estimates show greater levels of explanatory power. Grinold and Kahn (1999) found that using higher frequency data enables the accurate measurement of portfolio performance and risk, which is directly related to tracking error. Grinold and Kahn (1999) and Sinclair (2013) found that daily data reduces estimation errors, which is crucial to effectively measuring and managing tracking errors. Therefore, by using daily return data one can better capture the day-to-day fluctuations and correlations, since lower frequency data may mask the true volatility and autocorrelation within the data set resulting in an underestimation of tracking error (Grinold and Kahn, 1999; Sinclair, 2013). Higher frequency data also enhances the statistical robustness of tracking error calculations and improves the reliability of the results (Sinclair, 2013).

The total ETF universe, as listed on Bloomberg (2024), consists of 10800 ETFs. We then applied various refinements to arrive at a final sample of 52 ETFs. An important consideration was the elimination of ETFs backed by bonds, currencies, and commodities. This is described by refinement one in the subsequent table 4-1, where only equity-backed ETFs were considered, resulting in 7600 ETFs being available.

Next, the fund universe of 7600 equity-backed ETFs was filtered to consider each of the five possible replication styles, namely: full physical, stratified sampling, optimization, synthetic and leveraged replication. Any funds that were not formally classified into one of these types were excluded, resulting in 5200 available ETFs. This exclusion was based on the replication strategy not being clearly provided by the Bloomberg replication filter. The ETFs in the data sample consist of funds that employ passive, active and hybrid (combination of passive and active) investment strategies. Synthetic replication can either demonstrate active or passive characteristics or a combination of the two (Vanguard, 2023). Additionally, 6 leveraged ETFs have been included in the sample and these funds are particularly active in nature.

The third refinement applied to the data sample was the Bloomberg filter, geographical focus. The 5200 available ETFs were screened to include only equity-based (index-tracking) ETFs with a geographical focus on developed and emerging markets. This resulted in an ETF population of 418 ETFs.

As one of the primary objectives of this study is to investigate how tracking performance differs during periods of financial crisis, we consider a timeline that includes the Global Financial Crisis and the COVID-19 pandemic. We also require at least two years of data before and after the respective crises for comparative purposes. For this reason, the period of study was determined to be 2006 to 2024. Therefore, we required the ETFs in the sample to have an inception date prior to 2006. However, due to the inclusion of varying replication strategies, a limitation arose as most synthetic (swap-based) and leveraged index-tracking ETFs were only introduced after 2006. To address this limitation, we subdivided the data sample into ETFs introduced before 2006 and ETFs that were created after 2006. Further to that, to be included in the data sample, an ETF's inception date is required to be no later than the 31st of December 2011 and continuously listed through to the 4th of January 2024. The result being that we have two ETF samples, one to be analysed from 2006-2024, and the other to be analysed from 2012-2024. ETFs launched after the 31st of January 2011 were excluded to maintain a consistent sample for the crisis period analysis and to ensure sufficient historical data to clearly show the tracking performance trends for each replication/domicile category.

The available funds that met the inception restriction were sorted by market capitalization and Total Expense Ratio (TER). The use of ETF market capitalization value as a guideline for sample selection is informed by Elton and Gruber (2020). Elton and Gruber (2020) stated that for actively traded ETFs, the difference between the NAV and the market price is generally small; however, for thinly traded ETFs and international ETFs, it can be large. Therefore, to mitigate the size difference between the NAV and price, we selected the ETFs with the largest market capitalization values from the available set. The TER was used as a further selection criterion for the ETF sample as done by previous studies such as Elton, Gruber and De Souza (2019) and Charteris and McCullough (2020). Elton, Gruber and De Souza (2019) showed that selecting the lowest expense ratio ETF from a sample of ETFs following the same index is optimum or very close to optimum in all cases (Elton, Gruber and De Souza, 2019). By selecting the available ETFs under each replication strategy (considering fund domicile and inception) with the lowest TER, a sample of 52 ETFs tracking a total of 46 different indices was obtained. The market capitalization values, and total expense ratios of each ETF were collected from the Fund Factsheets, which were sourced from Bloomberg Professional Terminal (2024).

The sample of 52 ETFs contains 12 full physical, 12 that follow stratified sampling, 12 optimized, 12 synthetic and 6 leveraged ETFs. In accounting for the analysis of the tracking performance differences between emerging and developed markets, 17 ETFs are domiciled in emerging nations, and 35 are domiciled in developed nations. The unequal number of ETFs following each fund domicile was the result of a lack of ETFs with an emerging market geographical focus created prior to 31st December 2011. The complete ETF selection process that was carried out to obtain the sample is summarized in the subsequent figure 4-1.

While we were able to source an equal number of ETFs under full physical, stratified, optimized and synthetic replication, the choice of 6 leveraged ETFs was informed by the decision to use leveraged ETFs only managed by ProShares, for fund management consistency, following Rompotis (2016). Additionally, all developed market leveraged ETFs were required to track the S&P500 for more accurate comparison between the tracking errors of the leveraged (positive multiple) and inverse-leveraged (negative multiple) ETFs.

Only ETFs with an inception date before the 31st of December 2005 are used for the analysis of tracking performance during the Global Financial Crisis and the COVID-19 pandemic, to allow for an accurate analysis between the two crises. A sub-sample of 23 ETFs with the suitable inception date was selected from the full sample. Only 2 of these follows synthetic replication, however, this is expected as many of the synthetic and leveraged ETFs are new, as these replication types have mostly gained traction post-GFC (Marszk, 2016; Zheng, 2021).

The sample ETFs cover a variety of fund issuers. The full physical ETFs used belong to iShares (Blackrock), Ameriprise Financial (ETF: ECON US), Colombia Threadneedle (ETF: INCO US), First Trust, SPDR (State Street Global Advisors), Invesco and Vanguard. The stratified ETFs are all managed by iShares (Blackrock). We restricted the fund issuer of the stratified sample to iShares for consistency of the representative sampling technique used. The representative sampling technique used by iShares is based on investing in at least 90% of the underlying assets. This was necessary as the sampling process may also enhance tracking errors (Vanguard Asset Management, 2023). Therefore, by limiting the fund issuer of the stratified sample, we can control tracking errors induced by sampling processes so that the tracking error results are free from that bias. The optimized ETFs are issued by iShares (Blackrock), Vanguard, SPDR and Schwab Asset Management. The synthetic ETF fund issuers are Amundi and Xtrackers (DWS). All leveraged ETFs are managed by ProShares (ProFunds).

The entire sample of ETFs used was not restricted to a particular fund family (except the stratified and leveraged ETFs) due to the inclusion of various replication strategies. As a result, a wider net needed to be cast to consider ETFs that demonstrate characteristics of different replication strategies. With respect to index selection, the ETFs included in the sample track both broad market indices (such as the S&P500 and the NASDAQ-100), as well as country-specific indices (e.g. MSCI South Africa 25/50 Net Total Return Index). A total of 46 different indices are considered in this study.

A further barrier that arose in the collection of data is that the underlying benchmark indices of some ETFs changed over the full period of study. This was addressed by collecting the adjusted closing prices of the previous indices, the MSCI Prime Market Growth Index (VUG), the MSCI Broad market Index (VTI) and the NASDAQ Emerging Markets Index (FEM) to ensure that the tracking index was accurately represented. An important note to consider in respect to the data collection conducted for this study is that due to the use of a significantly large and representative sample, no conflicts of interest or bias are reported. Additionally, the subdivision of the data sample was done to ensure that each section of the analysis would be comprehensive and representative of the observations in previous studies.

The subsequent tables 4-2, 4-3, 4-4, 4-5 and 4-6, provide a summary of the details of each ETF, divided as per the replication strategy followed.

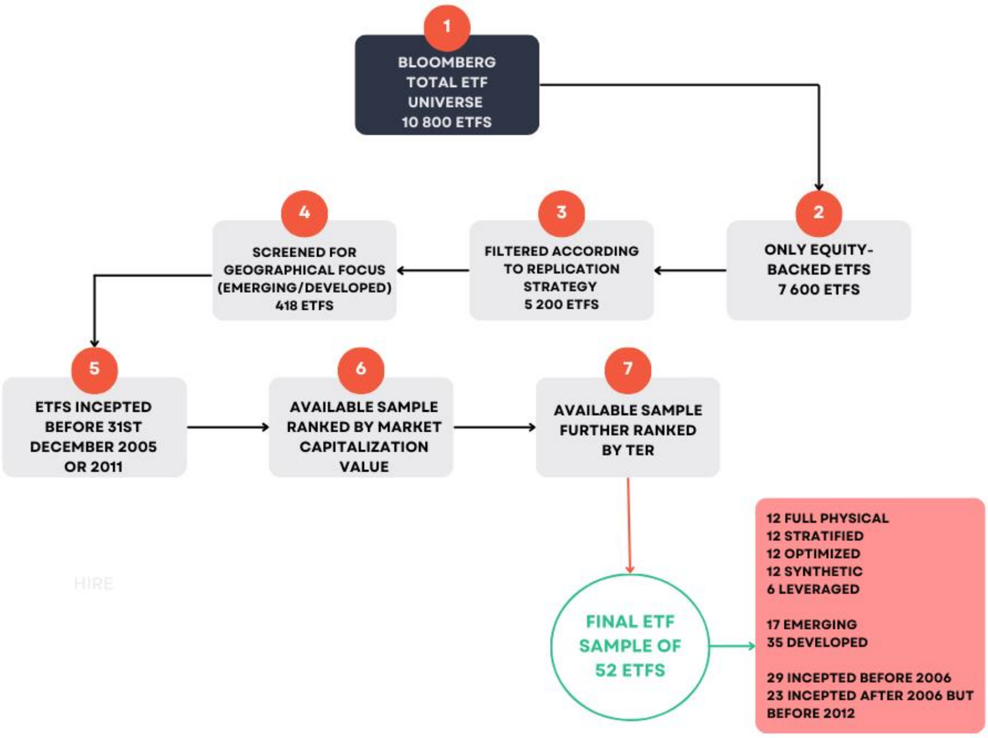

Figure 4-1: ETF Selection Criteria

(Author's own construction, 2024)

Table 4-1: Selection Process of the ETF Sample

Number of Refinements	Description of Refinements	Total ETFs Available
0 Refinements	All asset classes and exchanges	10800 ETFs
1 Refinement	Equity-backed ETFs only	7600 ETFs
2 Refinements	Equity-backed ETFs Replication Strategy (*excl. 'unknown' and 'not applicable').*	5200 ETFs
3 Refinements	Equity-backed ETFs Replication Strategy Geographical Focus: Developed and Emerging	418 ETFs
4 Refinements + Rankings	Equity-backed ETFs Replication Strategy Geographical Focus: Developed and Emerging Inception before 31st December 2011 Ranking: Market Capitalization Value and Total Expense Ratio (TER)	52 ETFs

(Author's own construction; Bloomberg (2024))

Table 4-2: ETFs following Full Physical Replication

ETF Name and Ticker	Domicile	Year of Inception	Benchmark Index and Ticker	Market Capitalization Value (2024) (USD)	Total Expense Ratio (TER) (%)
iShares MSCI Mexico (EWW)	Emerging	1996	MSCI Mexico IMI 25/50 (M1MX51M)	1.37 billion	0.500
iShares MSCI South Africa (EZA)	Emerging	2003	MSCI South Africa 25/50 Net Return (M1CXBAC)	287.53 million	0.590
iShares MSCI BIC (BFK)	Emerging	2007	MSCI EM BIC Net Total Return USD (NDUEBRIC)	70.49 million	0.700
Colombia Research Enhanced Emerging Economies (ECON US)	Emerging	2010	Dow Jones Emerging Markets Consumer Titans Index (till 06/28/2024). (DJECONT) *	50.28 million	0.490
Colombia India Consumer ETF (INCO US)	Emerging	2011	Indxx India Consumer (IINC0T)	437.84 million	0.750
First Trust Emerging Markets Alpha Dex Fund (FEM)	Emerging	2011	NASDAQ Emerging Markets (Base Index) NASDAQ Alpha Dex Emerging Markets (from 2015)	422.80 million	0.800
SPDR S&P500 ETF Trust (SPY)	Developed	1993	S&P500 (SPXT)	552.51 billion	0.095
Invesco S&P500 Equal Weight (RSP)	Developed	2003	S&P500 Equal Weight (SPXEWTR)	61.50 billion	0.200
Vanguard Growth ETF (VUG)	Developed	2004	MSCI Prime Market Growth (till April 2013) (MZUSPG) CRSP US Large Cap Growth (from May 2013) (CRSPLCGT)	131.94 billion	0.040
SPDR Portfolio S&P500 (SPLG)	Developed	2005	S&P500 Total Return (SPXT)	43.65 billion	0.020
Vanguard FTSE Developed Markets ETF (VEA)	Developed	2007	FTSE Developed All Cap ex US (ACDXUSR)	138.74 billion	0.060
Vanguard S&P500 (VOO)	Developed	2010	S&P 500 Total Return 4 Jan 1988 (SPTR)	498.31 billion	0.030

Note: As of 06/28/2024, the ECON US fund tracks the Beta Advantage Research Enhanced Solactive Emerging Economies Index (BAREEM). This date falls outside the research period, therefore it does not affect our data sample. (Author's own construction; Bloomberg (2024))

Table 4-3: ETFs following Stratified Sampling

ETF Name and Ticker	Domicile	Year of Inception	Benchmark Index and Ticker	Market Capitalization Value (2024) (USD)	Total Expense Ratio (TER) (%)
iShares Latin America 40 (ILF)	Emerging	2001	S&P Latin America 40 Index (SPLAC)	1.37 billion	0.480
iShares China Large Cap (FXI)	Emerging	2004	FTSE China 50 Index (XIN0U)	3.82 billion	0.740
iShares Core S&P Mid-Cap (IJH)	Developed	2000	S&P MidCap400 (SPTRMDCP)	87.21 billion	0.050
iShares Core S&P Small-Cap (IJR)	Developed	2000	S&P Small Cap 600 Index (SPTRSMCP)	83.75 billion	0.060
iShares Russell 3000 (IWV)	Developed	2000	Russell 3000 (RU30INTR)	14.33 billion	0.200
iShares S&P 100 (OEF)	Developed	2000	S&P 100 (OEX)	13.11 billion	0.200
iShares Russell 2000 Value (IWN)	Developed	2000	Russell 2000 Value (RU20VATR)	12.14 billion	0.240
iShares Russell 2000 Growth (IWO)	Developed	2000	Russell 2000 Growth (RU20GRTR)	11.35 billion	0.240
iShares S&P Mid-Cap 400 Growth (IJK)	Developed	2000	S&P Mid Cap 400 Growth (SPTRMG)	9.55 billion	0.170
iShares MSCI Eurozone (EZU)	Developed	2000	MSCI EMU Index (NDDUEMU)	7.73 billion	0.510
iShares S&P Mid-Cap Value (IJJ)	Developed	2000	S&P Mid Cap 400 Value (SPTRMV)	7.56 billion	0.180
iShares S&P Small-Cap 600 Value (IJS)	Developed	2000	S&P Small-Cap 600 Value (SPTRSV)	7.03 billion	0.180

(Author's own construction; Bloomberg (2024))

Table 4-4: ETFs following Optimized Replication

ETF Name and Ticker	Domicile	Year of Inception	Benchmark Index and Ticker	Market Capitalization Value (2024) (USD)	Total Expense Ratio (TER)% (%)
iShares MSCI Emerging Markets (EEM)	Emerging	2003	MSCI Emerging Markets (NDUEEGF)	17.31 billion	0.700
Vanguard FTSE Emerging Markets (VWO)	Emerging	2005	FTSE Emerging Markets All Cap China A Inclusion (FQEACR)	77.43 billion	0.080
iShares Core S&P500 (IVV)	Developed	2000	S&P500 (SPTR)	511.38 billion	0.030
iShares Russell1000 Growth (IWF)	Developed	2000	Russell1000 Growth (RU10GRTR)	93.01 billion	0.190
iShares S&P500 Growth (IVW)	Developed	2000	S&P500 Growth (SPTRSGX)	51.11 billion	0.180
SPDR Portfolio S&P500 Growth (SPYG)	Developed	2000	S&P500 Growth (SPTRSGX)	27.71 billion	0.040
SPDR Portfolio S&P500 Value (SPYV)	Developed	2000	S&P500 Value (SPTRSVX)	23.44 billion	0.040
Vanguard Total Stock Market (VTI)	Developed	2001	MSCI US Broad Market (from 2005-June 2nd, 2013) (MSCIBM) CRSP US Total Market (from June 3rd, 2013) (CRSPTMT)	420.95 billion	0.030
iShares MSCI World UCITS (IWRD)	Developed	2005	MSCI World (NDDUWI)	7.23 billion	0.500
iShares Core MSCI World UCITS (SWDA)	Developed	2009	MSCI World (NDDUWI)	80.64 billion	0.200
Schwab International Equity (SCHF)	Developed	2009	FTSE Developed ex-US (AWDXUSR)	40.73 billion	0.060
Schwab US Broad Market (SCHB)	Developed	2009	Dow Jones US Broad Stock Market (DW25T)	29.96 billion	0.030

(Author's own construction, Bloomberg (2024))

Table 4-5: ETFs following Synthetic Replication

ETF Name and Ticker	Domicile	Year of Inception	Benchmark Index and Ticker	Market Capitalization Value (2024) (USD)	Total Expense Ratio (TER) (%)
Amundi MSCI India II UCITS (INR)	Emerging	2006	MSCI India Index (NDEUSIA)	1.29 billion	0.850
Amundi MSCI Emerging Markets III UCITS (LEM)	Emerging	2007	MSCI Emerging Markets Index (NDUEEGF)	923.04 million	0.550
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	Emerging	2007	MSCI Emerging Markets Index (NDUEEGF)	682.68 million	0.490
Amundi ETF MSCI Brazil UCITS (BRZ)	Emerging	2010	MSCI Brazil Net Total Return USD (NDUEBRAF)	6.57 million	0.550
Amundi MSCI Emerging Markets Asia (AASU)	Emerging	2011	MSCI Emerging Markets Asia (NDUEEGFA)	589.31 million	0.200
Xtrackers MSCI Africa Top 50 Swap UCITS ETF (XMKA)	Emerging	2011	MSCI EFM Africa Top 50 Capped 10/40 Daily Net Total Return (MSEUFM$N)	32.25 million	0.650
Amundi NASDAQ-100 II (ANXU)	Developed	2001	NASDAQ-100 Total Return (XNDXNNR)	3.15 billion	0.220
Amundi Dow Jones Industrial Average UCITS (DJE)	Developed	2002	Dow Jones Industrial Average (DJINR)	344.88 million	0.500
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	Developed	2006	STOXX Europe Select Dividend 30 (SD3R)	178.02 million	0.300
Amundi FTSE 100 (L100)	Developed	2007	FTSE 100 Total Return (TUKXG)	1.12 billion	0.140
Amundi MSCI Europe Banks UCITS ETF (CB5)	Developed	2008	MSCI Europe Banks (M7EU0BK)	834.98 million	0.250
Amundi NASDAQ-100 UCITS (ANX)	Developed	2008	NASDAQ-100 (XNDXNNR)	303.26 million	0.230

(Author's own construction, Bloomberg (2024))

Table 4-6: ETFs following Leveraged Replication

ETF Name and Ticker	Domicile	Year of Inception	Benchmark Index and Ticker	Market Capitalization Value (2024) (USD)	Total Expense Ratio (TER) (%)
ProShares Ultra MSCI Emerging Markets (EET)	Emerging	2009	MSCI Emerging Markets (2x) daily performance (MXEF)	18.57 million	0.960
ProShares Ultra S&P500 (SSO)	Developed	2006	S&P500 (2x) daily performance (SPX)	4.83 billion	0.910
ProShares Ultra Pro S&P500 (UPRO)	Developed	2006	S&P500 (3x) daily performance (SPX)	3.50 billion	0.920
ProShares Short S&P500 (SH)	Developed	2006	S&P500 (-1x) inverse (SPX)	978.19 million	0.880
ProShares Ultra Short S&P500 (SDS)	Developed	2006	S&P500 (-2x) inverse (SPX)	459.49 million	0.900
ProShares Ultra Pro Short S&P500 (SPXU)	Developed	2009	S&P500 (-3x) inverse (SPX)	544.32 million	0.900

(Author's own construction, Bloomberg (2024))

4.2. Methodology

A variety of measures have been used to estimate tracking errors in pre-existing literature. Roll (1992), Pope and Yadav (1994) and Frino and Gallagher (2002) suggest three common methods of tracking error estimation, namely, the mean absolute deviation in returns between the ETFs and their benchmark index, the standard deviation of the return differences between ETFs and their benchmark index and the standard error of a regression of the ETF returns and the benchmark index returns. Each method has its own advantages and disadvantages, which is why studies such as Aroskar and Ogden (2012) and Strydom, Charteris and McCullough (2015), applied four different forms of tracking error estimation. Following their approach, this study uses four methods, namely, the standard deviation of the active return between the ETF and its benchmark index, the mean absolute deviation of the active return between the ETF and its benchmark index, the standard error of the active return and the R^2 variable as derived from the Single-Index Market Model of the returns of the fund against the underlying benchmark index. We also analyse the alpha and beta estimates derived from the regression as a complementary analysis to tracking error.

4.2.1. Return

As informed by existing literature such as Strydom, Charteris and McCullough (2015) and Charteris and McCullough (2020), the daily NAV of the ETF is used to compute the daily return on the ETF and the adjusted daily closing price of the underlying benchmark index is used to compute the daily return of the index.

Charteris and McCullough (2020) suggested that the daily NAV was favoured to measure tracking performance for ETFs instead of the closing market price, as it more accurately reflects the fund return since it is not affected by market dynamics. Further justification for using the NAV is provided by Brown (2010) and Strydom, Charteris and McCullough (2015). Fund managers are required to accrue all expenses daily; however, they are offset by the income received by the fund in the form of dividends and consequent interests on a quarterly basis (Strydom, Charteris and McCullough, 2015). Therefore, as directed by Brown (2010), we use the NAV values to calculate the total return since the net impact of such expenditures is reflected in the NAV figures. When using the daily NAV data in this study, we assume that gross dividends have been reinvested.

We use log returns due to the benefits of normalisation and consistency over long time series (Pinheiro and Varela, 2018). These continuous returns are calculated as the natural logarithm of the most recent NAV/closing price divided by the last NAV/closing price, expressed in percentage terms by equation (1).

$$\boldsymbol{Return_t = ln[(NAV_t + D_t)/NAV_{t-1}] * 100 \quad (1)}$$

4.2.2. Stationarity (Unit Root Tests)

Given that the data being used in this study is time-series in nature, it is vital that the stationarity of the data is determined. We need to ensure the stationarity of the variables, as non-stationary variables will potentially give spurious results (Gaba and Kumar, 2021). For each ETF/index fund, the closing NAV/closing price and returns are tested to determine whether they are stationary or not. This test for stationarity was done using the Augmented Dickey-Fuller (ADF) test.

Dickey and Fuller (1979) developed the Augmented Dickey-Fuller Test (ADF), which states that the error terms of a series e_t are correlated. The test augments a random walk, with a drift around a stochastic trend, by adding the lagged values of a dependent variable (Munusamy, Narayanamurthy and Sivanmalaiappan, 2016). The use of the ADF test for stationarity was informed by Patra (2024); Munusamy, Narayanamurthy and Sivanmalaiappan (2016); Gaba and Kumar (2021); Shin and Soydemir (2010); Malhotra and Sinha (2023); Verma and Dhiman (2020); and Warne and Monika (2023), all of which used ADF tests to determine the stationarity of NAV and closing price data. The ADF tests employed for the NAV data follow equations (2.1) – (2.3) below:

$$\boldsymbol{\Delta NAV_t = \delta NAV_{t-1} + \sum_{i=1}^{k} \lambda_j \Delta NAV_{t-i} + e_t \quad (2.1)}$$

$$\boldsymbol{\Delta NAV_t = \alpha + \delta NAV_{t-1} + \sum_{i=1}^{k} \lambda_j \Delta NAV_{t-i} + e_t \quad (2.2)}$$

$$\boldsymbol{\Delta NAV_t = \alpha + \beta T \, \delta NAV_{t-1} + \sum_{i=1}^{k} \lambda_j \Delta NAV_{t-i} + e_t \quad (2.3)}$$

Where e_t is the pure white noise error term, α, β and λ are parameters, t is the time or trend variables, δ represents the drift and "NAV_{t-1} = (NAV_{t-1} – NAV_{t-2})", "NAV_{t-2} = (NAV_{t-2} – NAV_{t-3})", etc.

The null hypothesis, H_0 of the ADF test, is that δ = 0, or that there is a unit root (Dickey and Fuller, 1979), which would mean that the NAV of the ETFs are non-stationary. The alternate hypothesis, H_1, is that $\delta < 0$ and the NAV of the ETFs are stationary. The same methodology is applied to the closing prices of the benchmark indices and the return data. The ADF tests for a unit root are first performed at the level and, if not stationary at the level it is performed again at the first difference. The lag length for the tests is selected using the Schwarz Information Criterion (SIC) as the sample size is significantly large, and the SIC is the most consistent for large samples (Ludden, Beal and Sheiner, 1994). ADF tests were used in this study due to their simplicity and computational efficiency. However, KPSS tests were also conducted to validate stationarity findings, addressing the limitations of ADF tests in detecting structural breaks. The results from the KPSS tests were consistent with that of the ADF tests. An extraction of the KPSS results can be found in Appendix 8.A.1 (Table 8-A.1).

4.2.3. Tracking Error

4.2.3.1. Standard Deviation of the Fund's Active Return

The most popular method for calculating tracking error is the standard deviation of the fund's active return (TE_1), which is the difference in return between the ETF and its underlying benchmark index, as shown in the subsequent equation (4). The difference between the daily return on the ETF and the benchmark index provides the daily active return, as shown in equation (3) below. The TE_1 measure captures the day-to-day variability in the observed difference between the ETF and the underlying benchmark's actual returns (Frino and Gallagher, 2001; Strydom, Charteris and McCullough, 2015). Gastineau (2004) highlighted that the standard deviation of the active return is the primary measure for tracking error estimation. This statement is backed by a plethora of existing research including Frino and Gallagher (2001), Gastineau (2004), Gallagher and Segara (2005), Chu (2011), Rompotis (2011), Strydom, Charteris and McCullough (2015); and Warne and Monika (2023).

The daily active return between the ETF and its benchmark index is expressed as follows:

$$\boldsymbol{Active\ Return = R_{it} - R_{bt} \quad (3)}$$

Where R_{it} is the daily return on the ETF as calculated in equation (1), and R_{bt} is the daily return on the benchmark index, calculated as $R_{bt} = \ln\left[\frac{CP_t}{CP_{t-1}}\right] * 100$, where CP_t is the closing price of the benchmark index at time *t*.

Tracking error as the standard deviation of the fund's active return is expressed as follows:

$$\boldsymbol{Standard\ Deviation\ (TE1)} = \sqrt{\frac{\sum_{t=1}^{n}(e_{it} - \bar{e}_i)^2}{(n-1)}} \quad \mathbf{(4)}$$

Where $e_{it} = R_{it} - R_{bt,}$ where R_{it} is the daily return on the ETF, and R_{bt} is the daily return on the benchmark index *b*; and *n* is the number of days over which the standard deviation will be computed (Frino and Gallagher, 2001; Strydom, Charteris and McCullough, 2015). Equation (4) shows that the lower the tracking error, the more closely the fund's returns match the benchmark returns (Pope and Yadav, 1994; Shin and Soydemir, 2010). The daily return difference is expected to equal zero (Charteris and McCullough, 2020).

A shortcoming of this method is that if a fund consistently underperforms or outperforms the target index by the same magnitude, the tracking error measured by the standard deviation may result in zero (Gallagher and Segara, 2005; Chu, 2011). This may result in an unreliable impression of the risk of the ETF (Steyn, 2019), as it understates the actual tracking difference between the ETF and its underlying benchmark (Steyn, 2019). Drenovak, Urošević and Jelic (2014), stated that the standard deviation measure is more appropriate for passive funds than active funds as it ranks the positive and negative returns of the same size equally, as this study includes ETFs of different replication strategies; there is a possible level of activeness to some of the ETFs included in the sample. However, this possible shortcoming is addressed by employing three other methods of tracking error estimation to ensure unbiased results.

The tracking error estimates derived from the standard deviation measure are ranked according to their statistical significance and magnitude. If the ETFs replicate their benchmark indices effectively, then the mean tracking errors should be equal to zero (Shin and Soydemir, 2010). To test this assumption, we perform t-tests at 1%, 5% and 10% levels of significance to determine if there is a statistically significant difference between the performance of ETFs and their benchmark indices. If the results yielded from the t-tests are not statistically different from zero, we conclude that the ETFs track their benchmark satisfactorily (Shin and Soydemir, 2010).

The estimates will first be ranked according to their statistical significance, with ETFs that are not statistically significant at all three levels (1%, 5% and 10%) being ranked as the most satisfactory with respect to tracking performance. This will be followed by ETFs not statistically significant at individual levels. Once statistical insignificance is proven, the estimates will be ranked ascendingly according to magnitude. All estimates that are found to be statistically significant (i.e. tracking error exists) will be ranked according to tracking error magnitude, from lowest to highest, with the lowest estimates considered the most satisfactory (i.e. they show the lowest predisposition to tracking error). The decision to rank the standard deviation tracking error estimates according to statistical significance and magnitude is informed by previous studies that have employed the same process when using standard deviation as a tracking error metric. These studies include Shin and Soydemir (2010), Steyn (2019) and Strydom, Charteris and McCullough (2015).

4.2.3.2. Mean Absolute Deviation in Returns (MAD)

The second method of tracking error (TE_2) used in this study is the daily mean absolute deviation in returns between the ETF and its underlying benchmark index. This method has been extensively employed in pre-existing literature (Frino and Gallagher, 2001; Shin and Soydemir, 2010; Chu, 2011; Aroskar and Ogden, 2012; Strydom, Charteris and McCullough, 2015). It provides a measure of the extent to which the returns on an ETF differ from the returns on the benchmark index over the sample period and treats any absolute deviation in returns as a tracking error (Chu, 2011).

The daily definition of the Mean Absolute Deviation in Returns (MAD) as a measure of tracking error is as follows:

$$\boldsymbol{MAD\ (TE2) = \frac{\sum_{t=1}^{n} |e_{it}|}{n} \quad (5)}$$

Where $e_{it} = R_{it} - R_{bt}$ is the return of the ETF i in period t, $R_{b.t}$ is the return of the benchmark index b in period t, and n is the number of periods.

Grinold and Kahn (1999) argued that the MAD estimate provides a more concise picture of tracking error than standard deviation as it is less sensitive to extreme values. Gallagher, David and Martin (2003) found that the MAD is a useful complementary measure to standard deviation, specifically when assessing the consistency of tracking performance. It provides a reliable measure of tracking errors in passive and active investment funds (Gallagher, 2003). Fabozzi, Gupta and Markowitz (2002) and Baptista and Alexander (2008) observed that the MAD estimate is preferred when tracking error distributions are non-normal and suggest that it provides a more intuitive approach to tracking error analysis.

Strydom, Charteris and McCullough (2015) applied a standard t-test to their MAD tracking error estimates to determine whether they were statistically different from zero (i.e. does tracking error exist). In accordance with that, we rank the MAD estimates by their statistical significance (not statistically significant to statistically significant) as determined from the application of t-tests and magnitude (lowest to highest) to deduce whether the estimates are statistically significant from 0 (i.e. tracking error is significant) or statistically insignificant (i.e. the ETF replicates its benchmark index well).

4.2.3.3. Single Index Market Model (Alpha, Beta, R^2 and Residuals)

The Single Index Market Model suggests that the return of a security or portfolio can be explained by the return of the market index and an idiosyncratic component (or residual) (Sharpe, 1963).

The Single Index Market Model (Sharpe, 1963) is shown as follows:

$$\boldsymbol{R_{ETF} = \alpha + \beta R_{EQUITY\ INDEX} + e_t \quad (6)}$$

Where R_{ETF} is the return of the ETF, αi is the intercept, which represents the component of return not explained by the market (alpha), βi is the sensitivity of the ETF's return to the market return (a measure of systematic risk), Rm is the return of the market index and ϵi is the error term (residual) representing the idiosyncratic risk.

This model provides a framework to understand how much of the fund's return can be attributed to market movements and how much is due to specific factors unique to the fund (Sharpe, 1963). The remaining two measures of tracking error used in this study are derived from the Single Index Model; these are the Standard Error[4] of the Regression (TE_3) and the R^2 measure (TE_4). The Single Index Market Model (Sharpe, 1963) regresses the return of an ETF against the return of its benchmark index and uses the standard error of the regression to denote the tracking error of the ETF (Singh and Kaur, 2016). Studies that have applied this approach to tracking error estimation include Chu (2011), Rompotis (2012a), Strydom, Charteris and McCullough (2015), Tsalikis and Papadopoulos (2019) and Warne and Monika (2023).

The standard error of the regression (TE_3) provides a description of the day-to-day variability within the sample (Strydom, Charteris and McCullough, 2015). In the context of (passively managed) ETFs, the variation between the dependent variable (the returns on the ETF) and the explanatory variable (the underlying benchmark index) is expected to be small (Strydom, Charteris and McCullough, 2015). Shin and Soydemir (2010) and Rompotis (2009) found that, the standard error of the regression (TE_3) should closely approximate the standard deviation estimates (TE_1). Lower (higher) standard error estimates indicate lower (higher) tracking errors and satisfactory (unsatisfactory) replication of the benchmark index. Drenovak, Urošević and Jelic (2014) and Strydom, Charteris and McCullough (2015) stated that higher standard errors are also indicative of ETFS not adopting a full replication strategy.

Blake, Elton and Gruber (1993); Grinold and Kahn (1999); Fabozzi and Gupta (2002); and Chai, Faff and Ghargori (2013) stated that the standard error provides a direct and intuitive measure of tracking error as it isolates the component of returns that is not explained by the benchmark index. The standard error is an ideal measure of tracking error estimation for this study as it effectively captures the deviations attributable to fund-specific factors (Blake, Elton and Gruber, 1993; Fabozzi and Gupta, 2002).

The standard error estimates are ranked according to their magnitude and statistical significance. We apply t-tests to the estimates at significance levels of 1%, 5% and 10%. The ranking process applied to the standard error estimates (TE_3) mirrors that applied to

[4] The Standard Deviation of the Residuals from the Regression.

the standard deviation (TE_1) and MAD (TE_2) estimates. Previous studies that have applied t-tests for statistical significance on standard error estimates include Shin and Soydemir (2010) and Rompotis (2012b). To ensure the reliability of the standard error results obtained in this study, Variance Inflation Factor (VIF) tests for multicollinearity were carried out on each regression. The results across all regressions were 1, indicating that there is no correlation among the predictor variables, and hence the variance is not inflated as by general rule a VIF exceeding 10 indicates multicollinearity. An extract of the VIF test results can be found in Appendix 8.A.2. (Table 8-A.2).

The fourth and final measure of tracking error applied in this study is the R^2 (TE_4) value of the regression shown in equation (6). Cresson, Cudd and Lipscomb (2002); Chu (2011) and Strydom, Charteris and McCullough (2015) used the R^2 measure to provide an extension to the first three methods of tracking error estimation used. The authors stated that using the R^2 as a further measure of tracking error provides an indication of the closeness to which the ETF replicates its respective underlying benchmark index. The interpretation of the R^2 value, as the ability of the ETFs to track their benchmark, is reflected by the measurement of R^2; the closer to 1, the more closely the ETF replicates its target index (Chu, 2011). As per Strydom, Charteris and McCullough (2015), it is expected that the R^2 estimates for the passively managed ETFs should be close to 1.

In the context of this study, as we consider different replication strategies that take on different investment management characteristics, we expect R^2 values that are smaller in magnitude. An R^2 value that is observably smaller in magnitude is synonymous with the ETF deviating from the weightings of its target index and, therefore, not adopting a full replication strategy (Drenovak, Urošević and Jelic, 2014); Strydom, Charteris and McCullough, 2015). Since we consider a sample of leveraged ETFs in this study, we expect that their R^2 (TE_4) estimates will deviate from 1. We will assess the extent of the deviation based on their statistical significance (Charupat and Miu, 2011; Rompotis, 2016). As per Cresson, Cudd and Lipscomb (2002) and Rompotis (2016), we apply a t-test of unity (to determine if the results are statistically different from 1) on the R^2 (TE_4) estimates obtained in this study. We will further rank the R^2 estimates based on the results of the t-test of unity and their magnitude (i.e. how closely they lie to 1).

Further considerations that are made in conjunction with analysing the standard error (TE_3) and R^2 (TE_4) estimates, is the analysis of the alpha and beta coefficients from the regression shown in equation (6). The alpha coefficient captures the returns achieved above (positive) / below (negative) that of the benchmark index (Strydom, Charteris and McCullough, 2015). The alphas of passively managed funds should not be statistically significant (i.e. they should not be statistically different from zero) (Strydom, Charteris and McCullough, 2015). Studies, such as Rompotis (2012b) and Strydom, Charteris and McCullough (2015) that have used regression analysis to estimate tracking error have all included an analysis of the alpha coefficients. When the alpha estimate is negative, we conclude that the ETF is not perfectly replicating its benchmark index (Strydom, Charteris and McCullough, 2015) and this is at the expense of the investor's return as the ETF is earning less than the benchmark index.

As done in Rompotis (2012a), Strydom, Charteris and McCullough (2015) and Rompotis (2016), in this study, we will employ a t-test on the alpha estimates to determine the statistical significance of the observed systemic over/underperformance of the ETFs against its benchmark index. This will provide us with plausibility in concluding whether an ETF perfectly replicates its benchmark index or not. With respect to the analysis of the alpha estimates obtained in this study, we will assess them based on their statistical significance and magnitude as done in Rompotis (2012a).

The beta coefficient of the regression indicates the linearity of the relationship between the ETF and its underlying benchmark index (Strydom, Charteris and McCullough, 2015, p.123). To determine whether a passive ETF is tracking its benchmark index effectively, we need to conclude whether the beta estimates are statistically different from 1 (Pope and Yadav, 1994; Welch, 2007). A beta of 1 is indicative of the observation that the ETF is perfectly tracking its target benchmark index (Pope and Yadav, 1994; Strydom, Charteris and McCullough, 2015). Pope and Yadav (1994) explained that if the beta of the regression is not perfectly equal to 1, the standard errors (TE_3) will be biased and, therefore, differ from the standard deviation (TE_1). Welch (2007) found that when using the standard errors as a tracking error estimate if the beta coefficient differs from 1, the estimates will be overstated due to negative serial correlation.

Additionally, Rompotis (2009) found that since the magnitude of the beta coefficient is a measure of systematic risk, it could also be used as an indicator for the aggressiveness of the ETF management strategy. A beta coefficient that exceeds 1 is suggestive of a fund that moves more aggressively than the target index (a more active management strategy), whereas a beta coefficient less than 1 is indicative of a more passive investment strategy (Rompotis, 2009). Rompotis (2009) stated that beta estimations can also be used as an indicator of a fund's replication strategy. A beta of 1 reflects a full physical replication strategy and a beta that significantly differs from 1 suggests that the fund manager applies selection techniques to pick the stocks that will achieve better returns (Rompotis, 2009). Various studies such as Rompotis (2009), Shin and Soydemir (2010), Rompotis (2012a and b), Strydom, Charteris and McCullough (2015) and Charteris and McCullough (2020) have analysed the beta estimates as a complementary factor to TE_3.

Rompotis (2009), Rompotis (2012b) and Strydom, Charteris and McCullough (2015) state that simply analysing the betas by how closely it approximates 1 is not a sufficient requirement and, therefore, this relationship was tested statistically. As per Rompotis (2009), Rompotis (2012b) and Strydom, Charteris and McCullough (2015), we employ a t-test of unity on the beta estimates at 1%, 5% and 10% levels of significance to test the null hypothesis that the beta estimates are statistically different from unity. If results of the t-test of unity suggest that the beta estimates are statistically different from unity (i.e. the null hypothesis is accepted), we can conclude that the ETF does not replicate the patterns of its underlying benchmark index (i.e. there exists tracking error) (Strydom, Charteris and McCullough, 2015). The converse is true if the beta estimates are found to be statistically insignificant (i.e. the ETF tracks its benchmark effectively). In this study, we analyse the beta estimates based on how closely they approximate 1 and on their statistical significance at 1%, 5% and 10% levels, using the t-test of unity.

For the leveraged ETFs (which are considerably more actively managed), we apply further analysis of the regression in equation (6) as per the workings of Charupat and Miu (2011). Where we test whether the intercept (α) of the regression is statistically different from zero and whether the slope coefficients (β) are statistically different from the multipliers of the leveraged ETFs (i.e. 2 for bull ETFs or -1, -2 and -3 for bear/inverse-leveraged ETFs). According to Charupat and Miu (2011) and Rompotis (2016), if the leveraged ETFs deliver their promised ratio returns, then the intercepts (alphas) should be zero and the coefficients (betas) should be equivalent to the respective multipliers.

4.2.4. Summary of Data and Methodology

Consistent with the main objectives of this study, which are to determine the effects of a fund's adopted replication strategy, the fund's domicile and periods of market crisis on the tracking performance of equity tracking ETFs, this chapter has detailed the ETF sample and tracking error estimators used. An extensive and carefully curated sample was chosen by applying various Bloomberg Professional refinements that were informed by research into the fund replication strategies and fund domiciles, found in both academic literature and articles published by various fund managers such as Vanguard and Blackrock. The TE measures will be used to estimate tracking error to consider ETF replication style, ETF fund domicile and the impact of crisis periods on tracking performance. This methodology is supported by several previous studies, including Strydom, Charteris and McCullough (2015), Rompotis (2012a and 2012b), Rompotis (2016), Charteris and McCullough (2020) and Warne and Monika (2023).

The table below summarizes the key steps taken in applying the methodology of this study and provides a guideline that the results section will mirror.

Table 4-7: Summary of Methodology

Step	Methodology	Equation/Test
1	Computation of the individual daily NAV and adjusted closing price series of each ETF and their corresponding benchmark index into the return series.	4-1
2	Application of ADF tests on the individual NAV, adjusted closing price and return series to determine stationarity in the levels and first difference.	4-2.1 – 4-2.3
3	After stationarity of the individual return series is determined, the return series of the ETF and its benchmark index are converted into the active return series which is tested for stationarity using ADF tests before proceeding to TE computation.	4-3
4	Each ETF and their corresponding benchmark index are tested for tracking error, using four methods of tracking error quantification. Method One: The Standard Deviation of the Active Return Method Two: The Mean Absolute Deviation of the Active Return Method Three: The Standard Error of the Residuals derived from Sharpe (1963) Method Four: Analysis of the R^2 estimates derived from Sharpe (1963)	 4-4 4-5 4-6 4-6
5	Analysis of the alpha and beta values derived from Sharpe (1963)	4-6
6	t-tests for statistical significance/ t-tests for unity are applied to each individual estimate and the average estimates for TE_1, TE_2, TE_3, TE_4, α, and β	t-tests
7	Ranking of TE_1, TE_2, TE_3, TE_4 estimates. The ranking process involves attributing a rank to the respective estimates dependent on the results of the t-tests for statistical significance/unity and the magnitude of their values. The estimates are ranked within each period as per the replication strategy tables for tables 5-2 to 5-31. The average tracking error estimates are ranked vertically across time periods. For tables 5-32 to 5-37 the ranking of TE_1, TE_2, TE_3 and TE_4 is performed within each fund domicile with the average tracking error estimates ranked across the periods of study.	-

(Author's own construction, 2024)

5. Results and Analysis

The following section presents an analysis and discussion of the results. Beginning with the results of the preliminary unit root tests, these are followed by tracking error estimations against fund replication strategy, domicile and crisis period. Complementary to the tracking error estimations, the alpha and beta estimates as derived from Sharpe's Single Index Market Model (1963) are presented and discussed. Lastly, we provide an additional analysis on the average total expense ratio (TER) of each fund replication strategy and fund domicile, to understand the implications between TER and tracking error.

5.1. Augmented Dickey-Fuller (ADF) Tests

Due to the size of the sample, the unit root test results of only one ETF under each replication strategy is provided in table 5-1 below. The results show that the daily closing NAV values and daily closing prices for each ETF and their underlying benchmark index respectively, are non-stationary in the levels across most of the sample, with the daily NAV data of XMEM (Index: NDUEEGF) being the only set that is stationary in the levels. Since, a prerequisite of the data used in this study is that it should be stationary in either the level or difference, we accept the NAV data of XMEM being stationary in the levels.

These results are expected, since NAV and closing price data are time series in nature suggesting the presence of a unit root. All t-statistics in the ETF/Index return samples are statistically significant at a 1% significance level and therefore the null hypothesis for the presence of a unit root can be rejected. The results obtained from the unit root tests mimic those of previous studies such as Suk Kim (2011). This result is expected given that non-stationary series can be transformed into stationary series through the processes of differencing and detrending (Ali and Thalheimer, 1983; Rosca, 2010).

The daily NAV return (of the ETF), daily closing price return (of the benchmark index) and the return difference between the ETF and its underlying benchmark index are all stationary at a 1% level of significance for the entire ETF sample used in this study. As we use the difference in the return between the ETF and its underlying benchmark index (the active return) to compute the tracking errors, we proceed to the tracking error estimation, due to the stationarity of the return data as determined by the ADF tests.

Table 5-1: Results of Unit Root Tests

ETF/Index	Level	First Difference
EWW NAV	-2.766735*	-61.95825***
EWW NAV Return	-63.04241***	-26.46989***
M1MX51M Closing Price	-2.236739	-60.11613***
M1MX51M Closing Price Return	-60.39748***	-26.62112***
Daily Active Return between EWW and M1MX51M	-36.47591***	-25.37818***
IJH NAV	-0.427921	-21.62181***
IJH NAV Return	-72.35615***	-23.24320***
SPTRMDCP Closing Price	-0.104258	-21.56448***
SPTRMDCP Closing Price Return	-72.28746***	-23.21532***
Daily Active Return between IJH and SPTRMDCP	-33.48584***	-25.9373***
SPYG NAV	0.275865	-21.88528***
SPYG NAV Return	-75.18928***	-27.18569***
SPTRSGX Closing Price	0.488923	-21.85323***
SPTRSGX Closing Price Return	-76.29453***	-27.17268***
Daily Active Return between SPYG and SPTRSGX	-66.34913***	-25.81593***
XMEM NAV	-43.28219***	-164.8199***
XMEM NAV Return	-55.09507***	-22.44646***
NDUEEGF Closing Price	2.43918	-101.9907***
NDUEEGF Closing Price Return	-55.09429***	-22.31875***
Daily Active Return between XMEM and NDUEEGF	-22.58175***	-23.66938***
SSO NAV	-2.178336	-17.74375***
SSO NAV Return	-18.07853***	-23.74936***
SPX Closing Price	-0.390835	-17.40324***
SPX Closing Price Return	-17.60648***	-21.66978***
Daily Active Return between SSO and SPX	-57.76015***	-23.61081***

*Note: Full physical: EWW (Index:M1MX51M), stratified sampling: IJH (Index: SPTRMDCP), optimized: SPYG (Index: SPTRSGX), synthetic: XMEM (Index: NDUEEGF) and leveraged: SSO (Index: SPX (2x)). Lags = 4. The lag length is based on SIC (Schwarz Information Criterion). ***, **, * indicates significance at 1%, 5% and 10% levels. (Author's own construction, 2024)*

5.2. Tracking Error

The results obtained from generating the tracking error estimates of each ETF and index pair in the sample across the four measures of tracking error are presented in tables 5-2 to 5-21. The alpha and beta estimates from the OLS regression (Sharpe's Single Index Market Model) of the ETF's NAV return on the return of their underlying benchmark index are presented in tables 5-22 to 5-31.

The tracking error, alpha and beta estimates have been computed across six one-year sub periods and the full period of 2012 to 2024 for the tracking error and replication strategy and fund domicile analyses due to the unavailability of sufficient synthetic and emerging ETFs prior to 2006. For the crisis period analysis, the estimates have been computed across 11 one-year sub periods and for the full period of 2006-2024.

Each table presents one of the tracking error estimates (TE_1, TE_2, TE_3, TE_4 (alpha, beta)) for each of the replication strategies (full physical, stratified sampling, optimized, synthetic and leveraged). Fund domicile is indicated in column two with the top panels representing the emerging market ETFs and the bottom panel showing the developed market ETFs. The first, overarching observation derived from these results, is that, in line with previous studies, tracking error is found to be present and persistent across this sample of ETFs. The rest of this chapter discusses these estimates in relation to this study's research objectives around replication, domicile and crises.

5.2.1. Tracking Error and Replication Strategy

This sub section is divided into two. The tracking error results from the leveraged ETFs are analysed separately due to their extreme deviation from the estimates of the other replication types and their difference in characteristics as highlighted in chapter two (*see 2.2.5.*). Leveraged ETFs are also extremely active in nature in comparison to the other replication strategies which take on a more passive approach, therefore their tracking error results are not consistent with the other replication strategies. The leveraged ETFs are analysed by comparing the differences in their tracking error in respect to their leveraged and inverse leveraged multipliers (i.e. 2x, 3x, -1x, -2x, -3x). The highest ranked ETFs under each replication strategy and across each period of study is highlighted in the columns of the relevant TE tables.

5.2.1.1. Tracking Error (Full, Stratified Sampling, Optimized, Synthetic)

5.2.1.1. (a) Standard Deviation of the Difference in Returns (TE_1)

The estimates for the first tracking error measure (TE_1), the standard deviation of the difference between the ETF returns and the index returns, are shown for each replication strategy in the subsequent tables 5-2 to 5-5. The magnitude of the tracking errors measured by method one is quite large, consistent with the findings of Mateus and Rahmani (2017). The stratified ETF sample demonstrated the lowest levels of average tracking error for four out of a total of seven periods of study, and the optimized ETFs showed the lowest average TE_1 estimates for the remaining three periods of study. Therefore, we can conclude that ETFs following partial physical replication (stratified and optimized) demonstrate the highest level of tracking performance when using method one of tracking error estimation.

Between 2012 and 2024, the stratified sampled ETFs (a form of partial physical replication) demonstrated significantly lower levels of tracking error than their counterparts during 2012-2013, 2014-2015, 2016-2017, 2018-2019, with average TE_1 period estimates ranging from 0.082891% (2014-2015) to 0.090419% (2012-2013). However, none of the average estimates for stratified ETFs across these sub periods were statistically significant. This suggests that between 2012-2019 stratified ETFs showed superior levels of tracking performance since there was no significant presence of tracking errors. The stratified sampled ETF with the lowest level of tracking error (TE_1) within the sub periods between 2012 and 2019, is observed to be IWO with a TE_1 estimate of 0.022745% (2018-2019) and the highest is observed to be ILF with a TE_1 estimate of 0.296672% (2016-2017). Between 2020 and 2024, and over the full period (2012-2024), we observe that the stratified ETFs show higher and statistically significant (5%) average TE_1 estimates ranging from 0.165349% (2012-2024) to 0.291402% (2022-2024).

During 2020-2021 and 2022-2024 and the full period of study, under TE_1, the optimized ETF sample (a form of partial physical replication) demonstrated the lowest levels of tracking error. The average TE_1 estimates for the optimized ETFs during 2020-2021 were 0.158076%, 0.190715% during 2022-2024 and 0.145389% over the full period, which were observably lower than those of the other replication strategies. The optimized ETFs with the lowest and highest TE_1 estimates between 2020 and 2024 and the full period, are observed to be IWF with 0.023244% (2020-2021) and EEM with 0.815281% (2022-2024), respectively.

During the sub periods between 2012 to 2024 and the full period of study, full physically replicated ETFs demonstrated the highest level of tracking errors under method one of tracking error estimation. This suggests that ETFs that follow full physical replication demonstrate higher levels of tracking errors than ETFs that follow partial replication (stratified sampling and optimization) and synthetic replication when using TE_1.

The synthetically replicated ETFs are shown to outperform the full physically replicated ETFs. This observation contradicts the findings of Rompotis (2012b) who found that ETFs departing from full replication of the benchmark index suffer from higher tracking errors. However, our results conform to an extent with studies such as Elia (2012) and Johnson *et al*. (2013), as the TE_1 estimates for the synthetic ETFs in this study are observably lower than the full physical ETFs. Many of these studies considered only full physical and synthetic ETFs, whereas this study considers partial physical replication as a separate category, demonstrating that, while the TE_1 estimates for synthetic ETFs are lower than the full physical ETFs, the partial physical ETFs show the lowest TE_1.

An important deduction from the results in this study, is that we find, when using the standard deviation of the return difference (TE_1) as a tracking error measure, partial physically replicated ETFs (stratified sampling and optimization) outperform both synthetic and full physical ETFs, with the average TE_1 estimates for synthetic ETFs ranging from 0.137441% (2016-2017) to 0.198568% (2022-2024), and full physically replicated ETFs ranging from 0.109790% (2014-2015) to 0.747892% (2016-2017), both of which are higher than the partial physical ETF estimates. A further observation from the TE_1 estimations is that most of the stratified sampled, optimized and synthetic ETF estimates do not differ significantly from zero. This suggests that these forms of replication have minimal insignificant tracking errors, and that ETFs that follow partial physical and synthetic replication mimic their underlying benchmark better than those following full physical replication. The TE_1 estimates for the full physically replicated ETFs are mostly statistically significant at a 1% level, suggesting that some tracking error is inherent to this form of replication, and that the ETFs in this sample that follow full physical replication do not accurately replicate their benchmark indices.

Table 5-2: The Standard Deviation of the Active Return (TE_1) for Full Physically Replicated ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares MSCI Mexico (EWW)	Emerging	0.152980 *** (5)	0.209345 *** (5)	0.097184 (5)	0.146889 * (6)	0.073060 (7)	0.087695 (9)	0.120664 (9)	1.107203 *** (12)	0.547664 *** (8)	0.512580 *** (8)	0.428512 *** (4)
iShares MSCI South Africa (EZA)	Emerging	0.986973 *** (6)	1.494348 *** (6)	1.011790 *** (6)	0.904729 *** (11)	0.864784 *** (12)	7.255979 *** (12)	0.455616 *** (10)	0.516893 *** (9)	0.808447 *** (11)	3.035107 *** (12)	2.570977 *** (6)
iShares MSCI BIC (BFK)	Emerging	-	-	-	0.174947 ** (8)	0.136796 (9)	0.084204 (8)	0.101196 (8)	0.460421 ** (8)	1.008222 *** (12)	0.464216 *** (7)	-
Colombia Research Enhanced Emerging Economies (ECON US)	Emerging	-	-	-	0.067957 (3)	0.080837 (8)	0.079456 (7)	0.097366 (7)	0.058967 (5)	0.146572 (6)	0.092736 (5)	-
Colombia India Consumer (INCO US)	Emerging	-	-	-	0.150429 * (7)	0.071760 (6)	0.039897 (1)	0.067641 (5)	0.304898 * (7)	0.476545 *** (7)	0.245803 ** (6)	-
First Trust Emerging Markets Alpha Dex Fund (FEM)	Emerging	-	-	-	0.561686 *** (9)	0.618097 *** (11)	0.640706 *** (11)	0.556867 *** (12)	0.665619 *** (10)	0.580809 *** (9)	0.604984 *** (9)	-
SPDR S&P500 ETF Trust (SPY)	Developed	0.060886 (1)	0.077054 (3)	0.065308 (3)	0.068289 (4)	0.064257 (4)	0.065088 (5)	0.060292 (3)	0.051196 (3)	0.050107 (2)	0.060214 (3)	0.062933 (2)
Invesco S&P500 Equal Weight (RSP)	Developed	0.082470 * (3)	0.060673 (2)	0.047169 (2)	0.049440 (1)	0.049738 (2)	0.047569 (3)	0.057735 (2)	0.062346 (6)	0.057712 (5)	0.054324 (1)	0.058110 (1)
Vanguard Growth (VUG)	Developed	0.082124 * (2)	0.044199 (1)	0.041024 (1)	2.602239 *** (12)	0.040538 (1)	0.042293 (2)	0.035415 (1)	0.022525 (1)	0.020907 (1)	1.061420 *** (11)	0.867197 *** (5)
SPDR Portfolio S&P500 (SPLG)	Developed	0.093830 ** (4)	0.102232 (4)	0.069577 (4)	0.076373 (5)	0.070155 (5)	0.069836 (6)	0.075332 (6)	0.053199 (4)	0.050733 (3)	0.066433 (4)	0.074299 (3)
Vanguard FTSE Developed Markets (VEA)	Developed	-	-	-	0.593993 *** (10)	0.522917 *** (10)	0.498866 *** (10)	0.543864 *** (11)	0.800256 *** (11)	0.712864 *** (10)	0.621361 *** (10)	-
Vanguard S&P500 (VOO)	Developed	-	-	-	0.066933 (2)	0.063422 (3)	0.063112 (4)	0.062132 (4)	0.041731 (2)	0.051112 (4)	0.059856 (2)	-
Average TE1 for full physical ETFs	-	**0.243211 *** (5)**	**0.331309 *** (6)**	**0.222009 *** (4)**	**0.455325 *** (8)**	**0.221363 ** (3)**	**0.747892 *** (11)**	**0.186177 * (1)**	**0.345438 * (2)**	**0.375974 *** (7)**	**0.573253 *** (9)**	**0.677005 *** (10)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_1 significance and magnitude for each column, and across the row for the average TE_1. (Author's own construction, 2024)*

Table 5-3: The Standard Deviation of the Active Return (TE_1) for Stratified Sampled ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares Latin America 40 (ILF)	Emerging	0.233013 *** (11)	0.363501 *** (11)	0.227678 *** (12)	0.245459 *** (12)	0.291600 *** (12)	0.296672 ** (12)	0.269650 *** (12)	0.504093 *** (11)	0.479345 *** (10)	0.362658 *** (10)	0.337811 *** (10)
iShares China Large Cap (FXI)	Emerging	0.108548 ** (6)	0.806863 *** (12)	0.128303 * (10)	0.178959 ** (11)	0.152200 * (11)	0.141610 (11)	0.194647 ** (11)	0.782963 *** (12)	1.727310 *** (12)	0.785661 *** (12)	0.697811 *** (12)
iShares Core S&P Mid Cap (IJH)	Developed	0.181763 *** (9)	0.097524 (7)	0.038926 (4)	0.046552 (3)	0.045984 (4)	0.047530 (5)	0.051182 (4)	0.047752 (5)	0.052756 (7)	0.048649 (4)	0.080359 (7)
iShares Core S&P Small Cap (IJR)	Developed	0.217811 *** (10)	0.121936 (9)	0.036773 (3)	0.048500 (4)	0.043442 (3)	0.042071 (3)	0.047097 (3)	0.052011 (6)	0.046994 (5)	0.046764 (3)	0.092244 (9)
iShares Russell 3000 (IWV)	Developed	0.086603 * (5)	0.073649 (5)	0.056380 (7)	0.060238 (7)	0.055971 (7)	0.056347 (7)	0.057793 (7)	0.044117 (3)	0.046814 (4)	0.053827 (6)	0.060967 (3)
iShares S&P 100 (OEF)	Developed	0.056716 (2)	0.083450 (6)	0.066034 (9)	0.068245 (8)	0.063493 (8)	0.064517 (9)	0.063172 (9)	0.046298 (4)	0.044043 (3)	0.059009 (7)	0.062738 94)
iShares Russell 2000 Value (IWN)	Developed	0.075375 * (4)	0.071401 (4)	0.062317 (8)	0.076480 (9)	0.063515 (9)	0.062679 (8)	0.060117 (8)	0.059960 (8)	0.069696 (9)	0.065615 (9)	0.067053 (6)
iShares Russell 2000 Growth (IWO)	Developed	0.066495 (3)	0.030150 (2)	0.023568 (2)	0.044244 (2)	0.026028 (1)	0.030142 (1)	0.022745 (1)	0.016324 (1)	0.025616 (1)	0.028788 (1)	0.034701 (1)
iShares S&P Mid Cap 400 Growth (IJK)	Developed	0.180505 *** (8)	0.024217 (1)	0.020848 (1)	0.033133 (1)	0.032504 (2)	0.035508 (2)	0.034118 (2)	0.024241 (2)	0.037073 (2)	0.032990 (2)	0.066655 (5)
iShares MSCI Eurozone (EZU)	Developed	0.490206 *** (12)	0.231523 *** (10)	0.148347 ** (11)	0.169891 * (10)	0.117533 (10)	0.134648 (10)	0.163253 * (10)	0.312993 * (10)	0.854306 *** (11)	0.390195 *** (11)	0.369401 *** (11)
iShares S&P Mid Cap Value (IJJ)	Developed	0.178085 *** (7)	0.119144 (8)	0.055383 (6)	0.058061 (6)	0.055058 (6)	0.054396 (6)	0.056765 (6)	0.067525 (9)	0.062096 (8)	0.059117 (8)	0.088074 (8)
iShares S&P Small Cap 600 Value (IJS)	Developed	0.047065 (1)	0.062566 (3)	0.043128 (5)	0.055262 (5)	0.047362 (5)	0.046050 (4)	0.052477 (5)	0.053222 (7)	0.050771 (6)	0.050918 (5)	0.051137 (2)
Average TE1 for stratified sampled ETFs	-	**0.160182 *** (11)**	**0.173827 ** (9)**	**0.075641 (1)**	**0.090419 (5)**	**0.082891 (2)**	**0.084347 (3)**	**0.089418 (4)**	**0.167625 * (8)**	**0.291402 ** (10)**	**0.165349* * (6)**	**0.167413 * (7)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_1 significance and magnitude for each column and, across the row for the average TE_1. (Author's own construction, 2024)*

Table 5-4: The Standard Deviation of the Active Return (TE_1) for Optimized ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares MSCI Emerging Markets (EEM)	Emerging	0.644314 *** (7)	1.081183 *** (7)	0.283841 *** (6)	0.099824 (8)	0.105757 (10)	0.094875 (9)	0.124372 (10)	0.393435 ** (11)	0.815281 *** (12)	0.379409 *** (11)	0.529963 *** (6)
Vanguard FTSE Emerging Markets (VWO)	Emerging	0.861743 *** (8)	1.777977 *** (8)	0.866734 *** (7)	0.508800 *** (12)	0.508807 *** (12)	0.472651 *** (12)	0.572302 *** (12)	0.732152 *** (12)	0.741571 *** (11)	0.598873 *** (12)	0.869644 *** (8)
iShares Core S&P500 (IVV)	Developed	0.064215 (2)	0.233566 *** (4)	0.064546 (3)	0.065588 (4)	0.065090 (7)	0.063742 (6)	0.065978 (6)	0.052824 (5)	0.051321 (6)	0.061017 (5)	0.097311 (3)
iShares Russell 1000 Growth (IWF)	Developed	0.078850 * (3)	0.209986 *** (3)	0.044403 (1)	0.050196 (1)	0.043519 (1)	0.042733 (1)	0.035271 (1)	0.023244 (1)	0.025736 (1)	0.038027 (1)	0.082319 (2)
iShares S&P500 Growth (IVW)	Developed	0.050671 (1)	0.176832 ** (2)	0.049322 (2)	0.054436 (3)	0.046577 (2)	0.046756 (2)	0.047841 (3)	0.025978 (2)	0.031296 (2)	0.043296 (2)	0.072681 (1)
SPDR Portfolio S&P500 Growth (SPYG)	Developed	0.162352 *** (6)	0.250291 *** (5)	0.099876 (5)	0.054113 (2)	0.047618 (3)	0.048986 (3)	0.045567 (2)	0.045693 (3)	0.035286 (3)	0.046534 (3)	0.111521 (4)
SPDR Portfolio S&P500 Value (SPYV)	Developed	0.133142 *** (5)	0.285984 *** (6)	0.096842 (4)	0.074483 (6)	0.074628 (8)	0.088906 (8)	0.081491 (7)	0.092693 (7)	0.066172 (7)	0.080195 (7)	0.128040 (5)
Vanguard Total Stock Market (VTI)	Developed	0.088205 ** (4)	0.073072 (1)	1.830149 *** (8)	0.066827 (5)	0.059767 (5)	0.060462 (5)	0.060212 (5)	0.048850 (4)	0.050274 (4)	0.058019 (4)	0.613450 *** (7)
iShares MSCI World UCITS (IWRD)	Developed	-	-	-	0.105086 (10)	0.084867 (9)	0.104850 (10)	0.103500 (9)	0.151835 (10)	0.146073 (10)	0.118597 (9)	-
iShares Core MSCI World UCITS (SWDA)	Developed	-	-	-	0.085242 (7)	0.060322 (6)	0.086509 (7)	0.085451 (8)	0.148209 (9)	0.136931 (8)	0.105640 (8)	-
Schwab International Equity (SCHF)	Developed	-	-	-	0.159203 * (11)	0.161673 * (11)	0.155240 (11)	0.168430 * (11)	0.127983 (8)	0.137585 (9)	0.152210 (10)	-
Schwab US Broad Market (SCHB)	Developed	-	-	-	0.087899 (9)	0.058858 (4)	0.059338 (4)	0.059312 (4)	0.054010 (6)	0.051056 (5)	0.062854 (6)	-
Average TE1 for optimized ETFs	-	**0.260436 *** (8)**	**0.511111 *** (11)**	**0.416964 *** (10)**	**0.117641 (3)**	**0.109790 (1)**	**0.110421 (2)**	**0.120810 (4)**	**0.158076 (6)**	**0.190715 (7)**	**0.145389 (5)**	**0.313116 *** (9)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_1 significance and magnitude for each column, and across the row for the average TE_1. (Author's own construction, 2024)*

Table 5-5: The Standard Deviation of the Active Return (TE_1) for Synthetic ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Amundi MSCI India II UCITS (INR)	Emerging	-	-	-	0.201743 ** (6)	0.207991 ** (6)	0.214125 (8)	0.168860 * (6)	0.182915 (4)	0.257027 ** (6)	0.207178 * (7)	-
Amundi MSCI Emerging Markets III UCITS (LEM)	Emerging	-	-	-	0.201974 ** (7)	0.208038 ** (7)	0.214056 (7)	0.175075 * (7)	0.186118 (6)	0.260962 ** (8)	0.209357 ** (9)	-
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	Emerging	-	-	-	0.217732 ** (10)	0.213175 ** (9)	0.239520 * (10)	0.352757 *** (11)	0.299472 * (10)	0.335516 *** (10)	0.281758 (6)	-
Amundi MSCI Brazil UCITS (BRZ)	Emerging	-	-	-	0.060561 (2)	0.006908 (4)	0.032112 (5)	0.004806 (2)	0.002452 (2)	0.149320 (5)	0.067328 (3)	-
Amundi MSCI Emerging Markets Asia (AASU)	Emerging	-	-	-	0.035490 (1)	0.001666 (2)	0.001244 (1)	0.001195 (1)	0.002124 (1)	0.000688 (1)	0.014529 (1)	-
Xtrackers MSCI Africa Top 50 Swap UCITS (XMKA)	Emerging	-	-	-	0.248926 *** (11)	0.217151 ** (10)	0.276389 ** (11)	0.448031 *** (12)	0.302923 * (11)	0.409797 *** (11)	0.327870 *** (12)	-
Amundi NASDAQ-100 II (ANXU)	Developed	-	-	-	0.088964 (4)	0.001161 (1)	0.005366 (2)	0.076351 (5)	0.199959 (8)	0.001950 (3)	0.094745 (5)	-
Amundi FTSE 100 (L100)	Developed	-	-	-	0.083916 (3)	0.074761 (5)	0.019660 (4)	0.054953 (4)	0.184626 (5)	0.000960 (2)	0.091416 (4)	-
Amundi MSCI Europe Banks UCITS (CB5)	Developed	-	-	-	0.110393 (5)	0.005428 (3)	0.008015 (3)	0.010204 (3)	0.022985 (3)	0.010652 (4)	0.046418 (2)	
Amundi Dow Jones Industrial Average UCITS (DJE)	Developed	0.486795 ***	0.475812 ***	0.325067 ***	0.210348 ** (9)	0.221125 ** (11)	0.221807 (9)	0.216597 ** (9)	0.455071 * (12)	0.284782 ** (9)	0.282223 ** (10)	0.340770 ***
Amundi NASDAQ-100 UCITS (ANX)	Developed	-	-	-	0.208528 ** (8)	0.209942 ** (8)	0.213870 (6)	0.175080 * (8)	0.186336 (7)	0.260949 ** (7)	0.210724 * (8)	-
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	Developed	-	-	-	0.283151 *** (12)	0.281941 *** (12)	0.279286 ** (12)	0.297751 *** (10)	0.246068 (9)	0.410213 *** (12)	0.304211 ** (11)	-
Average TE1 for synthetic ETFs	-	**0.486795 *** (11)**	**0.475812 *** (10)**	**0.325067 *** (8)**	**0.162644 * (6)**	**0.137441 (1)**	**0.143788 (2)**	**0.165138 * (7)**	**0.189254 (4)**	**0.198568 (5)**	**0.178146 (3)**	**0.340770 *** (9)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_1 significance and magnitude for each column, and across the row for the average TE_1. (Author's own construction, 2024)*

In summary, when using TE_1, we can conclude that the stratified sampled and optimized ETFs (partial physical replication) show the highest level of tracking performance (lowest tracking errors) and the full physically replicated ETFs show the lowest level of tracking performance (highest tracking errors), with the tracking performance of synthetic ETFs being less satisfactory than the partial physical ETFs, but better than the full physical ETFs, across the sub periods and full period of study.

5.2.1.1. (b) Mean Absolute Deviation (MAD) (TE_2)

The Mean Absolute Deviation (MAD) of the return difference between the ETF and its underlying benchmark (TE_2) estimates for the ETFs under each replication strategy, and across each sub period and the full period of study are shown in the subsequent tables 5-6 to 5-9. The magnitude of the TE_2 estimates across all four replication strategies, the sub periods and the full period (2012-2024), are significantly lower in comparison to the TE_1 estimates, this is consistent with the findings of Mateus and Rahmani (2017), who suggested that different ETF tracking error methods can result in differing tracking error magnitudes.

The TE_2 estimates in this study, demonstrate that stratified sampled ETFs which are partially physically replicated show superior levels of tracking performance due to minimal and insignificant average tracking error estimates, while full physically replicated ETFs show the least satisfactory levels of tracking performance because of large and statistically significant average tracking errors. Synthetic ETFs are shown to outperform full physical ETFs in respect to lower tracking error estimates derived from the MAD (TE_2) measure, for five out of the six sub periods and for the full period.

These results are consistent with those obtained under TE_1 as we observe that the stratified sampled ETFs demonstrate the lowest levels of average tracking error across all periods except 2022-2024. During 2022-2024, synthetic ETFs demonstrated the lowest average tracking error (0.109295%), followed by optimized ETFs (0.110763%) and then stratified ETFs (0.174567%). Optimized ETFs show lower TE_2 estimates than the synthetic ETFs for the full period and all sub periods except 2022-2024. The stratified ETFs also demonstrate the lowest level of average tracking error for the full period of study (0.051724%). Between 2012-2021 the individual TE_2 estimates for the stratified sample range from 0.003843% (2020-2021) for IWO to 0.351406% (2020-2021) for FXI.

Therefore, under TE_2 the stratified ETFs show the best level of tracking performance. The full physically replicated ETFs show the highest level of average tracking error across all sub periods except the 2018-2019 period, where synthetic ETFs show the highest average tracking error (0.079004%) in comparison to full physical ETFs (0.076791%). The full physical ETFs also demonstrate the highest level of average tracking error for the full period of study (0.139978%). The individual TE_2 estimates for the full physical sample range from 0.004062% (2022-2024) for VUG, to 0.688315% (2012-2013) for EZA. The full physical sample's average TE_2 estimates across four out of the six sub periods and the full period are statistically significant at 5% and 1% significance levels, indicating that the tracking error for full physical ETFs differ significantly from zero which is suggestive of poor replication of the benchmark index, and that the full physical ETFs show the least satisfactory level of tracking performance.

The results obtained from the TE_2 estimation in this study differ from that of Naumenko and Chystiakova (2015), whose average tracking error estimates under the MAD method reflected a higher value of 0.763% for synthetic ETFs in comparison to a lower value of 0.627% for physical ETFs. This observational difference could possibly be a result of the consideration of only developed market ETFs that are listed and traded on the Swiss Exchange being used by Naumenko and Chystiakova (2015), whereas this study considers ETFs of different replication strategies domiciled in both emerging and developed economies. The results under the MAD (TE_2) method of tracking error in this study closely mimic those of Elia (2012) whose MAD estimates ranged from 0.004% to 0.617% for synthetic and physical ETFs. Consistent with the results in this study, Elia (2012) concluded from the MAD estimates that synthetic ETFs show lower levels of tracking error than full physically replicated ETFs.

Table 5-6: The Mean Absolute Deviation (MAD) of the Active Return (TE_2) for Full Physically Replicated ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares MSCI Mexico (EWW)	Emerging	0.099139 *** (5)	0.136401 ** (5)	0.062677 ** (5)	0.046723 (6)	0.018843 (5)	0.015575 (5)	0.018255 (5)	0.218672 ** (10)	0.391652 *** (8)	0.118344 (8)	0.112037 *** (5)
iShares MSCI South Africa (EZA)	Emerging	0.736280 *** (6)	1.117052 *** (6)	0.746311 *** (6)	0.688315 *** (12)	0.647209 *** (12)	1.023516 *** (12)	0.038063 (9)	0.206083 ** (8)	0.595532 *** (11)	0.532890 *** (12)	0.644271 *** (6)
iShares MSCI BIC (BFK)	Emerging	-	-	-	0.072961 (8)	0.030194 (7)	0.020770 (7)	0.024675 (7)	0.217516 ** (9)	0.761248 *** (12)	0.187899 ** (9)	-
Colombia Research Enhanced Emerging Economies (ECON US)	Emerging	-	-	-	0.037075 (5)	0.027057 (6)	0.047905 (9)	0.031076 (8)	0.015807 (6)	0.032285 (5)	0.031853 (6)	-
Colombia India Consumer (INCO US)	Emerging	-	-	-	0.066384 (7)	0.052833 (9)	0.011725 (4)	0.021270 (6)	0.081859 (7)	0.120816 (6)	0.058957 (7)	-
First Trust Emerging Markets Alpha Dex Fund (FEM)	Emerging	-	-	-	0.411115 *** (10)	0.452964 *** (11)	0.296565 *** (10)	0.346820 *** (11)	0.431830 *** (11)	0.405155 *** (9)	0.390783 *** (10)	-
SPDR S&P500 ETF Trust (SPY)	Developed	0.016690 (1)	0.021194 (3)	0.016688 (3)	0.017097 (3)	0.016328 (4)	0.016188 (6)	0.015102 (4)	0.012962 (5)	0.012782 (7)	0.015075 (3)	0.016115 (2)
Invesco S&P500 Equal Weight (RSP)	Developed	0.017384 (2)	0.019841 (2)	0.009712 (1)	0.008884 (1)	0.008138 (1)	0.007356 (1)	0.008503 (2)	0.008885 (4)	0.009042 (4)	0.008468 (1)	0.010862 (1)
Vanguard Growth (VUG)	Developed	0.018828 (3)	0.015260 (1)	0.012937 (2)	0.140109 ** (9)	0.008464 (2)	0.008079 (2)	0.006681 (1)	0.004514 (1)	0.004062 (1)	0.028592 (5)	0.024283 (3)
SPDR Portfolio S&P500 (SPLG)	Developed	0.045684 (4)	0.059361 (4)	0.032195 (4)	0.034047 (4)	0.036099 (8)	0.033257 (8)	0.039091 (10)	0.008439 (3)	0.007354 (2)	0.026176 (4)	0.032300 (4)
Vanguard FTSE Developed Markets (VEA)	Developed	-	-	-	0.437372 *** (11)	0.381377 *** (10)	0.348536 *** (11)	0.362528 *** (12)	0.517637 *** (12)	0.544813 *** (10)	0.432082 *** (11)	-
Vanguard S&P500 (VOO)	Developed	-	-	-	0.013240 (2)	0.010015 (3)	0.009582 (3)	0.009424 (3)	0.007708 (2)	0.007496 (3)	0.009575 (2)	-
Average TE2 for full physical ETFs	-	**0.155667 *** (9)**	**0.228185 *** (11)**	**0.146753 *** (7)**	**0.164443 *** (10)**	**0.140793 ** (3)**	**0.153255 *** (8)**	**0.076791 (1)**	**0.144326 (2)**	**0.241020 ** (5)**	**0.153391 ** (4)**	**0.139978 *** (6)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_2 significance and magnitude for each column, and across the row for the average TE_2. (Author's own construction, 2024)*

Table 5-7: The Mean Absolute Deviation (MAD) of the Active Return (TE_2) for Stratified Sampled ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares Latin America 40 (ILF)	Emerging	0.163230 *** (12)	0.234464 *** (12)	0.153340 *** (12)	0.164258 ** (12)	0.197406 *** (12)	0.221861 *** (12)	0.184543 *** (12)	0.235165 ** (11)	0.102306 (10)	0.184301 ** (11)	0.184114 *** (11)
iShares China Large Cap (FXI)	Emerging	0.049372 (10)	0.108993 * (11)	0.043214 (11)	0.039449 (11)	0.036225 (11)	0.030073 (11)	0.043307 (11)	0.351406 *** (12)	1.293446 *** (12)	0.299018 *** (12)	0.221726 *** (12)
iShares Core S&P Mid Cap (IJH)	Developed	0.027836 (7)	0.015289 (6)	0.006611 (4)	0.007955 (3)	0.008573 (3)	0.008199 (3)	0.008386 (3)	0.007365 (4)	0.006976 (5)	0.007909 (3)	0.010795 (6)
iShares Core S&P Small Cap (IJR)	Developed	0.031049 (9)	0.016346 (7)	0.006267 (3)	0.008905 (4)	0.008936 (4)	0.009715 (5)	0.010684 (8)	0.010291 (6)	0.006878 (4)	0.009236 (5)	0.012115 (7)
iShares Russell 3000 (IWV)	Developed	0.016910 (5)	0.015072 (5)	0.009475 (6)	0.010837 (8)	0.010284 (8)	0.009762 (6)	0.009557 (5)	0.007307 (3)	0.006993 (6)	0.009122 (4)	0.010687 (5)
iShares S&P 100 (OEF)	Developed	0.012593 (2)	0.014800 (3)	0.010585 (7)	0.010297 (6)	0.009845 (6)	0.011501 (8)	0.010680 (7)	0.007935 (5)	0.006476 (3)	0.009455 (6)	0.010524 (3)
iShares Russell 2000 Value (IWN)	Developed	0.014961 (4)	0.017719 (8)	0.011712 (9)	0.012984 (9)	0.011792 (9)	0.011609 (9)	0.010809 (9)	0.011963 (9)	0.011717 (9)	0.011812 (9)	0.012808 (8)
iShares Russell 2000 Growth (IWO)	Developed	0.010448 (1)	0.009450 (2)	0.005979 (2)	0.007429 (2)	0.006399 (2)	0.006285 (1)	0.005157 (1)	0.003843 (1)	0.005193 (1)	0.005716 (1)	0.006686 (1)
iShares S&P Mid Cap 400 Growth (IJK)	Developed	0.022757 (6)	0.006062 (1)	0.004023 (1)	0.006528 (1)	0.006391 (1)	0.006499 (2)	0.006524 (2)	0.005737 (2)	0.005463 (2)	0.006190 (2)	0.007770 (2)
iShares MSCI Eurozone (EZU)	Developed	0.154886 *** (11)	0.053922 (10)	0.023098 (10)	0.021223 (10)	0.018445 (10)	0.020449 (10)	0.020620 (10)	0.133346 (10)	0.632801 *** (11)	0.141141 * (10)	0.119813 *** (10)
iShares S&P Mid Cap Value (IJJ)	Developed	0.028852 (8)	0.019864 (9)	0.009319 (5)	0.010243 (5)	0.009873 (7)	0.009947 (7)	0.009554 (4)	0.010837 (7)	0.008561 (8)	0.009837 (8)	0.013003 (9)
iShares S&P Small Cap 600 Value (IJS)	Developed	0.011454 (3)	0.014840 (4)	0.010814 (8)	0.010828 (7)	0.009655 (5)	0.009710 (4)	0.009596 (6)	0.010923 (8)	0.007998 (7)	0.009785 (7)	0.010648 (4)
Average TE2 for stratified sampled ETFs	-	**0.045362 (7)**	**0.043902 (6)**	**0.024536 (1)**	**0.025911 (2)**	**0.027819 (4)**	**0.029634 (5)**	**0.027451 (3)**	**0.066343 (9)**	**0.174567 * (11)**	**0.058627 (8)**	**0.051724 * (10)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_2 significance and magnitude for each column, and across the row for the average TE_2. (Author's own construction, 2024)*

Table 5-8: The Mean Absolute Deviation (MAD) of the Active Return (TE_2) for Optimized ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares MSCI Emerging Markets (EEM)	Emerging	0.477970 *** (7)	0.698541 *** (7)	0.197261 *** (7)	0.028789 (10)	0.022294 (10)	0.018600 (10)	0.020416 (9)	0.189303 * (11)	0.623069 *** (12)	0.150436 ** (11)	0.253021 *** (7)
Vanguard FTSE Emerging Markets (VWO)	Emerging	0.613191 *** (8)	1.187554 *** (8)	0.587600 *** (8)	0.381984 *** (12)	0.375304 *** (12)	0.328256 *** (12)	0.397445 *** (12)	0.525894 *** (12)	0.571186 *** (11)	0.430073 *** (12)	0.552308 *** (8)
iShares Core S&P500 (IVV)	Developed	0.017643 (3)	0.042901 (4)	0.016581 (3)	0.016973 (7)	0.016503 (7)	0.016305 (8)	0.016183 (7)	0.012820 (6)	0.012720 (7)	0.015249 (7)	0.018744 (3)
iShares Russell 1000 Growth (IWF)	Developed	0.015133 (2)	0.031751 (3)	0.007342 (1)	0.009730 (2)	0.009185 (3)	0.008408 (2)	0.007244 (2)	0.004480 (1)	0.004138 (1)	0.007196 (1)	0.010828 (2)
iShares S&P500 Growth (IVW)	Developed	0.013044 (1)	0.027296 (2)	0.008028 (2)	0.010072 (3)	0.008901 (2)	0.008664 (3)	0.008756 (4)	0.005802 (2)	0.004786 (2)	0.007828 (3)	0.010598 (1)
SPDR Portfolio S&P500 Growth (SPYG)	Developed	0.121013 *** (6)	0.181048 *** (5)	0.054884 *** (5)	0.008668 (1)	0.007964 (1)	0.007613 (1)	0.007016 (1)	0.007355 (4)	0.005752 (3)	0.007394 (2)	0.044619 (5)
SPDR Portfolio S&P500 Value (SPYV)	Developed	0.090751 *** (5)	0.208686 *** (6)	0.045373 (4)	0.011872 (4)	0.011957 (6)	0.012765 (7)	0.012063 (6)	0.015956 (7)	0.010377 (6)	0.012501 (6)	0.046716 * (6)
Vanguard Total Stock Market (VTI)	Developed	0.019602 (4)	0.020529 (1)	0.098711 *** (6)	0.015483 (5)	0.010863 (5)	0.010710 (5)	0.010391 (5)	0.008342 (5)	0.008418 (5)	0.010698 (5)	0.022570 (4)
iShares MSCI World UCITS (IWRD)	Developed	-	-	-	0.033218 (11)	0.024244 (11)	0.023738 (11)	0.025378 (11)	0.031671 (10)	0.035854 (10)	0.029028 (10)	-
iShares Core MSCI World UCITS (SWDA)	Developed	-	-	-	0.025402 (8)	0.017275 (8)	0.016582 (9)	0.018178 (8)	0.028172 (9)	0.029363 (9)	0.022425 (9)	-
Schwab International Equity (SCHF)	Developed	-	-	-	0.027317 (9)	0.021636 (9)	0.012742 (6)	0.023796 (10)	0.016132 (8)	0.015867 (8)	0.021256 (8)	-
Schwab US Broad Market (SCHB)	Developed	-	-	-	0.016226 (6)	0.010730 (4)	0.009287 (4)	0.008543 (3)	0.007190 (3)	0.007630 (4)	0.009930 (4)	-
Average TE2 for optimized ETFs	-	**0.171043 *** (10)**	**0.299788 *** (11)**	**0.126972 *** (9)**	**0.048811 (4)**	**0.044738 (2)**	**0.039472 (1)**	**0.046284 (3)**	**0.071093 (6)**	**0.110763 (7)**	**0.060335 (5)**	**0.119926 *** (8)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_2 significance and magnitude for each column, and across the row for the average TE_2. (Author's own construction, 2024)*

Table 5-9: The Mean Absolute Deviation (MAD) of the Active Return (TE_2) for Synthetic ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Amundi MSCI India II UCITS (INR)	Emerging	-	-	-	0.153309 ** (7)	0.153977 ** (7)	0.156739 *** (9)	0.122646 * (7)	0.130872 (7)	0.188990 * (7)	0.151103 ** (7)	-
Amundi MSCI Emerging Markets III UCITS (LEM)	Emerging	-	-	-	0.153483 ** (8)	0.154121 ** (8)	0.156619 *** (8)	0.129475 * (9)	0.135194 (8)	0.196089 ** (9)	0.154189 ** (8)	-
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	Emerging	-	-	-	0.162646 ** (11)	0.157980 ** (11)	0.172854 *** (11)	0.183392 *** (11)	0.174163 * (12)	0.224957 ** (11)	0.179441 ** (11)	-
Amundi MSCI Brazil UCITS (BRZ)	Emerging	-	-	-	0.006706 (2)	0.004583 (4)	0.006274 (5)	0.004015 (2)	0.003321 (2)	0.014706 (5)	0.006613 (5)	-
Amundi MSCI Emerging Markets Asia (AASU)	Emerging	-	-	-	0.006699 (1)	0.002251 (2)	0.002033 (2)	0.001941 (1)	0.001572 (1)	0.000743 (1)	0.002535 (1)	-
Xtrackers MSCI Africa Top 50 Swap UCITS (XMKA)	Emerging	-	-	-	0.172388 *** (12)	0.159551 ** (12)	0.183609 *** (12)	0.197163 *** (12)	0.169224 (11)	0.249349 ** (12)	0.188679 ** (12)	-
Amundi NASDAQ-100 II (ANXU)	Developed	-	-	-	0.013203 (5)	0.001069 (1)	0.000993 (1)	0.006658 (5)	0.012808 (4)	0.001130 (3)	0.005981 (2)	-
Amundi FTSE 100 (L100)	Developed	-	-	-	0.008591 (3)	0.007385 (5)	0.002134 (3)	0.004861 (3)	0.013436 (5)	0.001088 (2)	0.006256 (3)	-
Amundi MSCI Europe Banks UCITS (CB5)	Developed	-	-	-	0.011827 (4)	0.003750 (3)	0.004941 (4)	0.005373 (4)	0.007393 (3)	0.005214 (4)	0.006414 (4)	-
Amundi Dow Jones Industrial Average UCITS (DJE)	Developed	0.298021 ***	0.311252 ***	0.245413 ***	0.153545 ** (9)	0.155710 ** (9)	0.158235 *** (10)	0.137938 * (10)	0.164570 (10)	0.202506 ** (10)	0.162181 ** (10)	0.203058 ***
Amundi NASDAQ-100 UCITS (ANX)	Developed	-	-	-	0.156233 ** (10)	0.155719 ** (10)	0.156441 *** (7)	0.129350 * (8)	0.135213 (9)	0.195990 ** (8)	0.154848 ** (9)	-
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	Developed	-	-	-	0.026219 (6)	0.024259 (6)	0.023312 (6)	0.025238 (6)	0.022879 (6)	0.030783 (6)	0.025460 (6)	-
Average TE2 for synthetic ETFs	-	**0.298021 *** (10)**	**0.311252 *** (11)**	**0.245413 *** (9)**	**0.085404 (4)**	**0.081696 (3)**	**0.085349 * (7)**	**0.079004 (1)**	**0.080887 (2)**	**0.109295 (6)**	**0.086975 (5)**	**0.203058 *** (8)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_2 significance and magnitude for each column, and across the row for the average TE_2. (Author's own construction, 2024)*

In summary, we can conclude from the results of the TE_2 estimates that partial physical replication (stratified sampling and optimization) shows superior tracking of the benchmark index, while full physical ETFs fail to track their benchmark index accurately. Synthetic ETFs show superior tracking performance to full physical ETFs, despite being less accurate in tracking the benchmark index than the partially replicated ETFs

5.2.1.1. (c) Standard Error (TE_3)

The standard error of the regression (TE_3), the third measure of tracking error estimation applied in this study, should, theoretically, produce estimates of tracking error that closely approximate the standard deviation of the active return, as pre-existing literature such as Rompotis (2009), Shin and Soydemir (2010) and Strydom, Charteris and McCullough (2015) have reported. The results from this measure are displayed in tables 5-10 to 5-13.

As with the results reported for TE_1 and TE_2, we find that when using TE_3 as a measure of tracking error, the ETF samples that follow partial physical replication show superior tracking of their benchmark, while full physically backed ETFs show the highest levels of tracking error and have the lowest level of tracking performance. Additionally, despite synthetic ETFs showing higher levels of tracking error than partially physically replicated ETFs, they show superior tracking performance to full physically replicated ETFs.

For all four replication strategies, the results conform to the expectation that estimates based on TE_1 and TE_3 will be similar. As with the results obtained from TE_1, the stratified sample of ETFs shows the lowest levels of average tracking error during all sub periods between 2012 and 2019 (0.082385% to 0.088542%), with the optimized ETFs demonstrating the lowest levels of average tracking error during 2020-2021 and 2022-2024 (0.158117% and 0.184356%) and for the full period, 2012-2024 (0.144741%), suggesting that partial physical replication of the benchmark index by the ETF results in superior tracking performance.

The full physically replicated ETFs demonstrate the highest level of average tracking errors across all subperiods (0.184649% to 0.367723%) and the full period of study (0.434221%). The average tracking error estimates for full physical ETFs are statistically significant at a 1% level across all periods, suggesting that tracking error is persistent and significant. In consensus with the first two methods, the standard error of the regression

(TE_3) results suggest that partial replication better mimics the underlying benchmark index than synthetic replication (average tracking errors: 0.137502% to 0.197940%), while synthetic ETFs minimizes tracking error to a greater extent than full physically replicated ETFs. The standard error results are consistent with Johnson *et al*. (2013) which found that in considering the standard errors of the regression, synthetic ETFs show superior tracking performance to full physically replicated ETFs.

Table 5-10: The Standard Error of the Regression (TE_3) for Full Physically Replicated ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024	2006-2024
iShares MSCI Mexico (EWW)	Emerging	0.148225 *** (5)	0.208119 *** (5)	0.096756 ** (5)	0.146801 *** (6)	0.072683 ** (7)	0.087771 ** (9)	0.121586 *** (9)	1.105504 *** (12)	0.543203 *** (8)	0.511688 *** (8)	0.427651 *** (4)
iShares MSCI South Africa (EZA)	Emerging	0.926827 *** (6)	1.304206 *** (6)	0.868930 *** (6)	0.866371 *** (12)	0.836002 *** (120	1.834223 *** (12)	0.456019 *** (10)	0.517147 *** (9)	0.779773 *** (11)	1.641050 *** (12)	1.734271 *** (6)
iShares MSCI BIC (BFK)	Emerging	-	-	-	0.174058 *** (8)	0.136806 *** (9)	0.084245 ** (8)	0.101233 **** (8)	0.460045 *** (8)	0.969934 *** (12)	0.459758 *** (7)	-
Colombia Research Enhanced Emerging Economies (ECON US)	Emerging	-	-	-	0.067847 * (2)	0.080917 ** (8)	0.077922 * (7)	0.097456 *** (7)	0.059008 (5)	0.146592 *** (6)	0.092742 * (5)	-
Colombia India Consumer (INCO US)	Emerging	-	-	-	0.150604 *** (7)	0.071734 ** (6)	0.039834 (1)	0.067708 ** (5)	0.304818 *** (7)	0.476914 *** (7)	0.245842 *** (6)	-
First Trust Emerging Markets Alpha Dex Fund (FEM)	Emerging	-	-	-	0.556073 *** (9)	0.618029 *** (11)	0.568650 *** (11)	0.550143 *** (12)	0.666147 *** (10)	0.569594 *** (9)	0.598089 *** (9)	-
SPDR S&P500 ETF Trust (SPY)	Developed	0.060767 (1)	0.076552 (3)	0.065251 (3)	0.068343 * (3)	0.064301 * (4)	0.065129 (5)	0.060343 * (3)	0.051227 (3)	0.050156 (2)	0.060222 (3)	0.062894 (2)
Invesco S&P500 Equal Weight (RSP)	Developed	0.082121 * (3)	0.060717 (2)	0.046946 (2)	0.049452 (1)	0.049771 (2)	0.047573 (3)	0.057717 * (2)	0.062235 (6)	0.057748 (5)	0.054323 (1)	0.058110 (1)
Vanguard Growth (VUG)	Developed	0.081973 * (2)	0.044238 (1)	0.041064 (1)	0.764502 *** (11)	0.040561 (1)	0.042311 (2)	0.035374 (1)	0.022408 (1)	0.020927 (1)	0.803924 *** (11)	0.726263 *** (5)
SPDR Portfolio S&P500 (SPLG)	Developed	0.092484 ** (4)	0.098524 (4)	0.069594 (4)	0.076385 ** (5)	0.070223 ** (5)	0.069431 * (6)	0.075343 ** (6)	0.053205 (4)	0.050707 (3)	0.066424 (4)	0.074126 (3)
Vanguard FTSE Developed Markets (VEA)	Developed	-	-	-	0.586762 *** (10)	0.521302 *** (10)	0.487502 *** (10)	0.530698 *** (11)	0.800635 *** (11)	0.696003 *** (10)	0.616753 *** (10)	-
Vanguard S&P500 (VOO)	Developed	-	-	-	0.066931 * (4)	0.063372 * (3)	0.063152 (4)	0.062170 * (4)	0.050559 (2)	0.051119 (4)	0.059836 (2)	-
Average TE3 for full physical ETFs	-	**0.232066 *** (4)**	**0.298726 *** (7)**	**0.198090 *** (2)**	**0.297844 *** (6)**	**0.218808 *** (3)**	**0.288979 *** (5)**	**0.184649 *** (1)**	**0.346078 *** (8)**	**0.367723 *** (9)**	**0.434221 *** (10)**	**0.513886 *** (11)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_3 significance and magnitude for each column, and across the row for the average TE_3. (Author's own construction, 2024)*

Table 5-11: The Standard Error of the Regression (TE_3) for Stratified Sampled ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares Latin America 40 (ILF)	Emerging	0.223995 *** (11)	0.362536 *** (11)	0.219429 *** (12)	0.238047 *** (12)	0.285044 *** (12)	0.287831 *** (12)	0.260433 *** (12)	0.504057 *** (11)	0.479525 *** (10)	0.361461 *** (10)	0.335936 *** (10)
iShares China Large Cap (FXI)	Emerging	0.108559 ** (6)	0.804171 *** (12)	0.127817 *** (10)	0.178803 *** (11)	0.152293 *** (11)	0.141738 *** (11)	0.194838 *** (11)	0.763283 *** (12)	1.568510 *** (12)	0.758272 *** (12)	0.685634 *** (12)
iShares Core S&P Mid Cap (IJH)	Developed	0.179211 *** (9)	0.097301 (7)	0.038755 ** (9)	0.046590 (3)	0.046000 (4)	0.047414 *** (9)	0.050977 (4)	0.047786 (5)	0.052733 (7)	0.048636 (4)	0.080293 (7)
iShares Core S&P Small Cap (IJR)	Developed	0.214430 *** (10)	0.121811 * (9)	0.036665 (3)	0.048400 (4)	0.043474 (3)	0.041925 (3)	0.046957 (3)	0.052062 (6)	0.046985 (5)	0.046761 (3)	0.092152 (9)
iShares Russell 3000 (IWV)	Developed	0.086509 ** (5)	0.073517 (5)	0.056330 (6)	0.060291 * (7)	0.056026 * (7)	0.056324 (6)	0.057560 * (7)	0.044160 (3)	0.046818 (4)	0.053819 (6)	0.060964 (3)
iShares S&P 100 (OEF)	Developed	0.056772 (2)	0.082995 (6)	0.065761 (8)	0.068281 * (8)	0.063529 * (8)	0.064385 (8)	0.063017 * (9)	0.046319 (4)	0.044046 (3)	0.058983 (7)	0.062730 (4)
iShares Russell 2000 Value (IWN)	Developed	0.075436 * (4)	0.071357 (4)	0.062308 (7)	0.076429 ** (9)	0.063566 * (9)	0.062654 (7)	0.059947 * (8)	0.059954 (8)	0.069693 (9)	0.065625 (9)	0.067052 (6)
iShares Russell 2000 Growth (IWO)	Developed	0.066533 (3)	0.030015 (2)	0.023506 (2)	0.044257 (2)	0.026047 (1)	0.030134 (1)	0.022719 (1)	0.016333 (1)	0.025641 (1)	0.028792 (1)	0.034694 (1)
iShares S&P Mid Cap 400 Growth (IJK)	Developed	0.177563 *** (8)	0.024102 (1)	0.020748 (1)	0.033120 (1)	0.032526 (2)	0.035441 (2)	0.034036 (2)	0.024261 (2)	0.037084 (2)	0.032988 (2)	0.066600 (5)
iShares MSCI Eurozone (EZU)	Developed	0.479734 *** (12)	0.231318 *** (10)	0.148233 *** (11)	0.170059 *** (10)	0.117632 *** (10)	0.134781 *** (10)	0.163315 *** (10)	0.310524 *** (10)	0.817583 *** (11)	0.386174 *** (11)	0.366933 *** (11)
iShares S&P Mid Cap Value (IJJ)	Developed	0.176047 *** (7)	0.118862 * (8)	0.055173 (5)	0.058066 (6)	0.055095 (6)	0.054260 (5)	0.056377 * (6)	0.067546 (9)	0.062025 (8)	0.059113 (8)	0.088005 (8)
iShares S&P Small Cap 600 Value (IJS)	Developed	0.047111 (1)	0.062305 (3)	0.043009 (4)	0.055190 (5)	0.047390 (5)	0.045840 (4)	0.052330 (5)	0.053273 (7)	0.050752 (6)	0.050913 (5)	0.051134 (2)
Average TE3 for stratified sampled ETFs	-	**0.157658 *** (9)**	**0.173358 ** (7)**	**0.074811 (1)**	**0.089794 ** (4)**	**0.082385 ** (2)**	**0.083561 ** (3)**	**0.088542 *** (8)**	**0.165797 ** (6)**	**0.275116 *** (11)**	**0.162628 *** (10)**	**0.166011 ** (5)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_3 significance and magnitude for each column, and across the row for the average TE_3. (Author's own construction, 2024)*

Table 5-12: The Standard Error of the Regression (TE_3) for Optimized ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares MSCI Emerging Markets (EEM)	Emerging	0.643700 *** (7)	1.081063 *** (7)	0.284032 *** (6)	0.099920 *** (9)	0.105862 *** (10)	0.094966 ** (9)	0.124371 *** (10)	0.393359 *** (11)	0.774008 *** (12)	0.376054 *** (11)	0.529624 *** (6)
Vanguard FTSE Emerging Markets (VWO)	Emerging	0.854561 *** (8)	1.774737 *** (8)	0.867539 *** (7)	0.508498 *** (12)	0.507494 *** (12)	0.465998 *** (12)	0.566351 *** (12)	0.732796 *** (12)	0.706883 *** (11)	0.594518 *** (12)	0.866333 *** (8)
iShares Core S&P500 (IVV)	Developed	0.064274 (2)	0.232762 *** (4)	0.064280 (3)	0.065643 * (4)	0.065119 * (7)	0.063647 (6)	0.065778 ** (6)	0.052876 (6)	0.051276 (6)	0.060992 (5)	0.097245 (3)
iShares Russell 1000 Growth (IWF)	Developed	0.078677 * (3)	0.209792 *** (3)	0.044380 (1)	0.050246 (1)	0.043559 (1)	0.042714 (1)	0.035210 (1)	0.023265 (2)	0.025750 (1)	0.038027 (1)	0.082288 (2)
iShares S&P500 Growth (IVW)	Developed	0.050717 (1)	0.176532 ** (2)	0.049149 (2)	0.054461 (3)	0.046599 (2)	0.046705 (2)	0.047853 (3)	0.026004 (1)	0.031324 (2)	0.043298 (2)	0.072647 (1)
SPDR Portfolio S&P500 Growth (SPYG)	Developed	0.162439 *** (6)	0.249150 *** (5)	0.097488 * (4)	0.054149 (2)	0.047659 (3)	0.049019 (3)	0.045569 (2)	0.045600 (3)	0.035177 (3)	0.046519 (3)	0.111335 * (4)
SPDR Portfolio S&P500 Value (SPYV)	Developed	0.128163 *** (5)	0.254474 *** (6)	0.092601 * (5)	0.074553 ** (6)	0.074691 ** (8)	0.088889 ** (8)	0.081373 ** (7)	0.092758 (7)	0.066091 (7)	0.080208 * (7)	0.123684 * (5)
Vanguard Total Stock Market (VTI)	Developed	0.088191 ** (4)	0.073134 (1)	1.098052 *** (8)	0.066847 * (5)	0.059824 * (5)	0.060471 (5)	0.060014 * (5)	0.048509 (4)	0.050249 (4)	0.058027 (4)	0.554023 *** (7)
iShares MSCI World UCITS (IWRD)	Developed	-	-	-	0.104862 *** (10)	0.084896 ** (9)	0.104954 ** (10)	0.103559 *** (9)	0.151986 ** (10)	0.146069 *** (10)	0.118612 ** (9)	-
iShares Core MSCI World UCITS (SWDA)	Developed	-	-	-	0.085245 ** (7)	0.060374 * (6)	0.086544 ** (7)	0.085526 ** (8)	0.148128 ** (9)	0.136777 *** (8)	0.105582 ** (8)	-
Schwab International Equity (SCHF)	Developed	-	-	-	0.159341 *** (11)	0.161824 *** (11)	0.155053 *** (11)	0.167415 *** (11)	0.128081 * (8)	0.137718 *** (9)	0.152188 *** (10)	-
Schwab US Broad Market (SCHB)	Developed	-	-	-	0.087920 ** (8)	0.058884 * (4)	0.059293 (4)	0.059329 * (4)	0.054036 (5)	0.050951 (5)	0.062864 (6)	-
Average TE3 for optimized ETFs	-	**0.258840 *** (8)**	**0.506456 *** (11)**	**0.324690 *** (10)**	**0.117640 *** (4)**	**0.109732 *** (2)**	**0.109854 *** (3)**	**0.120196 *** (5)**	**0.158117 ** (1)**	**0.184356 *** (7)**	**0.144741 *** (6)**	**0.304647 *** (9)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_3 significance and magnitude for each column, and across the row for the average TE_3. (Author's own construction, 2024)*

Table 5-13: The Standard Error of the Regression (TE_3) for Synthetic ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024	2012-2024	2006-2024
Amundi MSCI India II UCITS (INR)	Emerging	-	-	-	0.201723 *** (8)	0.207828 *** (6)	0.214186 *** (8)	0.168324 *** (6)	0.182625 *** (4)	0.256625 *** (6)	0.207028 *** (6)	-
Amundi MSCI Emerging Markets III UCITS (LEM)	Emerging	-	-	-	0.199488 *** (6)	0.208153 *** (7)	0.212538 *** (6)	0.175212 *** (8)	0.185588 *** (7)	0.260697 *** (8)	0.208854 *** (7)	-
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	Emerging	-	-	-	0.215294 *** (10)	0.213303 *** (10)	0.236628 *** (10)	0.351085 *** (11)	0.297059 *** (10)	0.334166 *** (10)	0.280194 *** (9)	-
Amundi MSCI Brazil UCITS (BRZ)	Emerging	-	-	-	0.060544 * (2)	0.006915 (4)	0.032137 (5)	0.004804 (2)	0.002454 (2)	0.148815 *** (5)	0.067312 (3)	-
Amundi MSCI Emerging Markets Asia (AASU)	Emerging	-	-	-	0.035524 (1)	0.001660 (1)	0.001244 (1)	0.001196 (1)	0.002126 (1)	0.000688 (1)	0.014532 (1)	-
Xtrackers MSCI Africa Top 50 Swap UCITS (XMKA)	Emerging	-	-	-	0.243358 *** (11)	0.217335 *** (11)	0.268779 *** (11)	0.442662 *** (12)	0.299129 *** (11)	0.407811 *** (11)	0.324531 *** (12)	-
Amundi NASDAQ-100 II (ANXU)	Developed	-	-	-	0.088656 ** (4)	0.001159 (2)	0.005366 (2)	0.076358 ** (5)	0.199557 *** (8)	0.001952 (3)	0.094625 * (5)	-
Amundi FTSE 100 (L100)	Developed	-	-	-	0.083840 ** (3)	0.074819 ** (5)	0.019673 (4)	0.054990 * (4)	0.184677 *** (6)	0.000957 (2)	0.091392 * (4)	-
Amundi MSCI Europe Banks UCITS (CB5)	Developed	-	-	-	0.110414 *** (5)	0.005432 (3)	0.008017 (3)	0.010209 (3)	0.023006 (3)	0.010661 (4)	0.046418 (2)	-
Amundi Dow Jones Industrial Average UCITS (DJE)	Developed	0.477719 ***	0.475616 ***	0.325285 ***	0.210451 *** (9)	0.221338 *** (9)	0.222018 *** (9)	0.216812 *** (9)	0.455000 *** (12)	0.283749 *** (9)	0.282269 *** (10)	0.340620 ***
Amundi NASDAQ-100 UCITS (ANX)	Developed	-	-	-	0.208399 *** (7)	0.209937 *** (8)	0.214034 *** (7)	0.175202 *** (7)	0.184153 *** (5)	0.258563 *** (7)	0.210754 *** (8)	-
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	Developed	-	-	-	0.283195 *** (12)	0.282145 *** (12)	0.279354 *** (12)	0.298003 *** (10)	0.246298 *** (9)	0.410591 *** (12)	0.304261 *** (11)	-
Average TE3 for synthetic ETFs	-	**0.477719 *** (11)**	**0.475616 *** (10)**	**0.325285 *** (8)**	**0.161741 *** (3)**	**0.137502 *** (1)**	**0.142831 *** (2)**	**0.164571 *** (4)**	**0.188473 *** (6)**	**0.197940 *** (7)**	**0.177681 *** (5)**	**0.340620 *** (9)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_3 significance and magnitude for each column, and across the row for the average TE_3. (Author's own construction, 2024)*

In summary, we find that the results from the TE_3 measure further conform with the results of the previous estimations (TE_1 and TE_2), suggesting that partially physically replicated ETFs show the most superior tracking performance in comparison to the other replication strategies. Additionally, we find that synthetic ETFs minimize tracking error and, therefore, demonstrate better levels of tracking performance than full physical ETFs, which are observed to show the highest levels of tracking error in the sample.

5.2.1.1. (d) R^2 (TE_4)

The results for the R^2 measure (TE_4) as derived from the regression in equation (6) are provided in tables 5-14 to 5-17. In this study we have also performed a t-test of unity on the R^2 (TE_4) measures, this was done in order to rank the R^2 estimates according to how closely they estimate 1. The ranking of the R^2 (TE_4) measures are shown in (#) for each ETF, where ranking is applied for each column, and across the row for the average TE_4. The purpose behind ranking the R^2 estimates in this study is to show us which replication strategies demonstrate TE_4 estimates that approximate 1 the closest. The expectation is that the R^2 measure for the full physical, stratified sampled, optimized and synthetic ETFs should lie very close to 1 due to the passive nature of the funds adopting those replication strategies (Strydom, Charteris and McCullough, 2015). The R^2 (TE_4) estimates show that, in line with the previous three tracking error measures, that the partially replicated ETFs show the lowest tracking errors and the highest levels of tracking performance in comparison to the other replication strategies. Additionally, we observe that the synthetic ETFs minimize tracking error to a greater extent than the full physical ETFs, which show the highest level of tracking error across the samples.

We observe from the R^2 (TE_4) estimates, that the stratified sampled ETFs demonstrate average R^2 values across the sub periods and the full period that approximate 1 the closest (0.922218 to 0.992784), and do not significantly differ from 1 (5% or 1% level) in respect to the results of the t-test of unity. This observation conforms with the results of the previous measures of tracking error which found that the stratified sample demonstrates the lowest level of tracking error in comparison to the other replication strategies. Since, the R^2 (TE_4) estimates closely approximate 1 for the stratified ETFs, we deduce that most of the variation in the returns of the stratified ETFs can be explained by the returns on the benchmark index (Strydom, Charteris and McCullough, 2015). Further to that, in reference to tables 5-16 and 5-17 and the ranking of the TE_4 estimates, we observe that the average R^2 (TE_4) estimates for the optimized ETF sample approximate 1 closer than the synthetic ETF sample for all sub periods and the full period, except 2020-2021 and 2022-2024. Therefore, from this observation we can conclude that partial physical replication (stratified and optimized) minimizes tracking error to a greater extent than synthetic replication.

In table 5-14, we observe that the average R^2 (TE_4) estimates for the full physically replicated ETFs are statistically different from 1 at a 1% level of significance across all sub periods and the full period with significantly lower estimates ranging from 0.782979 to 0.923852, suggesting that the R^2 estimates for the full physical sample demonstrates the furthest deviation from 1 and as a result are ranked the lowest, therefore we conclude that the full physical ETFs show the highest level of tracking errors in the full sample. In comparing the average R^2 (TE_4) estimates of the full physical ETFs to the synthetic ETFs, we find that the synthetic ETFs show closer approximation to 1 across all sub periods and the full period, therefore suggesting that synthetic ETFs show lower tracking errors in comparison to full physical ETFs.

An important consideration that has come up in previous studies such as Chu (2011) is that the frequency of the data affects the magnitude of the R^2 values with daily data resulting in smaller R^2 estimates, from this we find that our estimates closely mirror those of Cresson, Cudd and Lipscomb (2002) and Chu (2011) (ranging between 0.905 and 0.961 and between 0 and 0.942 respectively) who also employed daily data. Our results contrast with the estimates obtained by studies such as Frino and Gallagher (2001, 2002) and Strydom, Charteris and McCullough (2015) who employed monthly data and therefore obtained higher R^2 values (ranging between 0.997 and 1, between 0.993 and 1 and between 0.9638 and 0.9954 respectively).

Table 5-14: R^2 of the Regression (TE_4) for Full Physically Replicated ETFs

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
iShares MSCI Mexico (EWW)	Emerging	0.991583 (2)	0.993896 (5)	0.995866 (5)	0.986018 (7)	0.995696 (4)	0.995995 (3)	0.991592 (7)	0.734903 *** (11)	0.833620 *** (6)	0.877363 *** (7)	0.933516 ** (4)
iShares MSCI South Africa (EZA)	Emerging	0.770584 *** (6)	0.793349 *** (6)	0.774115 *** (6)	0.640008 *** (10)	0.727475 *** (10)	0.013118 *** (12)	0.936736 *** (10)	0.945364 *** (8)	0.820613 *** (7)	0.175073 *** (12)	0.223632 *** (6)
iShares MSCI BIC (BFK)	Emerging	-	-	-	0.970341 (8)	0.985305 (9)	0.992478 (6)	0.989198 (9)	0.903854 *** (9)	0.571801 *** (11)	0.852062 *** (8)	
Colombia Research Enhanced Emerging Economies (ECON US)	Emerging	-	-	-	0.994280 (2)	0.993297 (7)	0.994643 (5)	0.989568 (8)	0.998066 (6)	0.001466 *** (12)	0.992652 (5)	
Colombia India Consumer (INCO US)	Emerging	-	-	-	0.989578 (6)	0.996122 (3)	0.998285 (1)	0.996208 (2)	0.963365 *** (7)	0.818244 *** (8)	0.960999 * (6)	
First Trust Emerging Markets Alpha Dex Fund (FEM)	Emerging	-	-	-	0.677584 *** (9)	0.683350 *** (11)	0.660276 *** (11)	0.694678 *** (11)	0.839207 *** (10)	0.743899 *** (9)	0.735908 *** (9)	
SPDR S&P500 ETF Trust (SPY)	Developed	0.994762 (1)	0.998779 (3)	0.997530 (3)	0.991792 (4)	0.994426 (6)	0.990195 (7)	0.995946 (4)	0.999042 (3)	0.998333 (2)	0.996837 (3)	0.997476 (2)
Invesco S&P500 Equal Weight (RSP)	Developed	0.991195 (3)	0.999396 (2)	0.998972 (2)	0.996431 (1)	0.996685 (2)	0.995790 (4)	0.995948 (3)	0.998821 (5)	0.997693 (5)	0.997644 (1)	0.998160 (1)
Vanguard Growth (VUG)	Developed	0.990519 *** (5)	0.999533 (1)	0.999056 (1)	0.077910 *** (12)	0.998009 (1)	0.996424 (2)	0.998939 (1)	0.999841 (1)	0.999838 (1)	0.568326 *** (11)	0.696956 *** (5)
SPDR Portfolio S&P500 (SPLG)	Developed	0.990717 (4)	0.997942 (4)	0.997394 (4)	0.990876 (5)	0.993283 (8)	0.989193 (9)	0.993727 (6)	0.998968 (4)	0.998288 (3)	0.996236 (4)	0.996625 (3)
Vanguard FTSE Developed Markets (VEA)	Developed	-	-	-	0.629553 *** (11)	0.633153 *** (12)	0.670701 *** (10)	0.507525 *** (12)	0.705736 *** (12)	0.613696 *** (10)	0.642548 *** (10)	
Vanguard S&P500 (VOO)	Developed	-	-	-	0.992207 (3)	0.994519 (5)	0.990868 (8)	0.995677 (5)	0.999060 (2)	0.998262 (4)	0.996864 (2)	
Average TE4 for full physical ETFs	-	**0.954893 *** (3)**	**0.963816 ** (2)**	**0.960489 (1)**	**0.828048 *** (8)**	**0.915943 *** (6)**	**0.857330 *** (7)**	**0.923812 *** (5)**	**0.923852 *** (4)**	**0.782979 *** (11)**	**0.816043 *** (9)**	**0.807727 *** (10)**

*Note: Test of R^2 of R^2 equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_4 significance and magnitude for each column, and across the row for the average TE_4. (Author's own construction, 2024)*

Table 5-15: R^2 of the Regression (TE_4) for Stratified Sampled ETFs

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
iShares Latin America 40 (ILF)	Emerging	0.986733 (7)	0.989252 (11)	0.982802 (12)	0.956127 ** (12)	0.963228 *** (12)	0.967771 (12)	0.966522 ** (12)	0.960320 *** (11)	0.918909 *** (10)	0.954744 ** (10)	0.971872 (10)
iShares China Large Cap (FXI)	Emerging	0.996265 (3)	0.940415 *** (12)	0.994263 (11)	0.981351 (11)	0.987969 (11)	0.985597 (10)	0.976635 (10)	0.794336 *** (12)	0.461591 *** (12)	0.754120 *** (12)	0.863072 *** (12)
iShares Core S&P Mid Cap (IJH)	Developed	0.963359 (10)	0.998364 (7)	0.999399 (5)	0.997310 (4)	0.997306 (5)	0.996710 (5)	0.997245 (5)	0.999427 (5)	0.998569 (8)	0.998447 (5)	0.996827 (7)
iShares Core S&P Small Cap (IJR)	Developed	0.961267 (11)	0.997621 (9)	0.999572 (3)	0.997495 (3)	0.998046 (4)	0.998129 (2)	0.998103 (3)	0.999445 (4)	0.998952 (4)	0.998805 (3)	0.996449 (9)
iShares Russell 3000 (IWV)	Developed	0.989907 (6)	0.998909 (5)	0.998313 (8)	0.993938 (8)	0.995778 (7)	0.993298 (8)	0.996352 (8)	0.999311 (7)	0.998636 (7)	0.997569 (8)	0.997727 (6)
iShares S&P 100 (OEF)	Developed	0.995224 (5)	0.998460 (6)	0.997236 (9)	0.991340 (9)	0.994664 (9)	0.990152 (9)	0.995922 (9)	0.999202 (8)	0.998811 (5)	0.997017 (9)	0.997416 (5)
iShares Russell 2000 Value (IWN)	Developed	0.996068 (4)	0.999348 (4)	0.998873 (6)	0.993966 (7)	0.995619 (8)	0.995895 (7)	0.996465 (7)	0.999339 (6)	0.997733 (1)	0.997739 (7)	0.998322 (3)
iShares Russell 2000 Growth (IWO)	Developed	0.996992 (2)	0.999855 (2)	0.999840 (1)	0.998202 (2)	0.999495 (1)	0.999154 (1)	0.999641 (1)	0.999941 (1)	0.999772 (2)	0.999596 (1)	0.999538 (1)
iShares S&P Mid Cap 400 Growth (IJK)	Developed	0.965118 (8)	0.999893 (1)	0.999830 (2)	0.998673 (1)	0.998734 (2)	0.998037 (3)	0.998784 (2)	0.999837 (2)	0.999361 (3)	0.999275 (2)	0.997762 (4)
iShares MSCI Eurozone (EZU)	Developed	0.792955 * (12)	0.991069 (10)	0.994626 (10)	0.985041 (10)	0.988928 (10)	0.985012 (11)	0.967988 ** (11)	0.961478 *** (10)	0.697079 *** (11)	0.909756 *** (11)	0.942581 * (11)
iShares S&P Mid Cap Value (IJJ)	Developed	0.965037 (9)	0.997771 (8)	0.998789 (7)	0.995847 (6)	0.996119 (6)	0.996213 (6)	0.996794 (6)	0.999046 (9)	0.997934 (9)	0.997902 (6)	0.996465 (8)
iShares S&P Small Cap 600 Value (IJS)	Developed	0.998402 (1)	0.999461 (3)	0.999456 (4)	0.996984 (5)	0.997520 (3)	0.997897 (4)	0.997689 (4)	0.999489 (3)	0.998772 (6)	0.998675 (4)	0.999007 (2)
Average TE4 for stratified sampled ETFs	-	**0.967277 (8)**	**0.992535 (3)**	**0.996917 (1)**	**0.990523 (6)**	**0.992784 (2)**	**0.991989 (4)**	**0.990678 (5)**	**0.975931 * (9)**	**0.922177 * (11)**	**0.966970 * (10)**	**0.979753 (7)**

*Note: Test of R^2 of R^2 equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_4 significance and magnitude for each column, and across the row for the average TE_4. (Author's own construction, 2024)*

Table 5-16: R^2 of the Regression (TE_4) for Optimized ETFs

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
iShares MSCI Emerging Markets (EEM)	Emerging	0.770280 *** (8)	0.814998 *** (7)	0.953679 * (6)	0.987501 (8)	0.985691 (10)	0.988303 (7)	0.980423 (9)	0.910803 *** (11)	0.536732 *** (12)	0.862337 *** (11)	0.842393 *** (6)
Vanguard FTSE Emerging Markets (VWO)	Emerging	0.606430 *** (7)	0.564751 *** (8)	0.663398 *** (7)	0.725396 *** (12)	0.739274 *** (12)	0.720141 *** (12)	0.633387 *** (12)	0.740294 *** (12)	0.553879 *** (11)	0.686187 *** (12)	0.626326 *** (8)
iShares Core S&P500 (IVV)	Developed	0.994197 (2)	0.988698 (4)	0.997594 (3)	0.992427 (5)	0.994291 (6)	0.990807 (6)	0.995236 (6)	0.998978 (5)	0.998266 (6)	0.996766 (5)	0.993972 (3)
iShares Russell 1000 Growth (IWF)	Developed	0.991224 (3)	0.989483 (3)	0.998825 (1)	0.995757 (1)	0.997583 (1)	0.996162 (1)	0.998965 (1)	0.999825 (1)	0.999722 (1)	0.998981 (1)	0.995958 (2)
iShares S&P500 Growth (IVW)	Developed	0.996021 (1)	0.992681 (2)	0.998517 (2)	0.994592 (3)	0.997318 (2)	0.995347 (2)	0.997925 (3)	0.999776 (2)	0.999567 (2)	0.998629 (2)	0.996776 (1)
SPDR Portfolio S&P500 Growth (SPYG)	Developed	0.961159 (6)	0.986057 (6)	0.994425 (5)	0.994659 (2)	0.997190 (3)	0.994812 (3)	0.998119 (2)	0.999309 (3)	0.999451 (3)	0.998412 (3)	0.992566 (4)
SPDR Portfolio S&P500 Value (SPYV)	Developed	0.978196 (5)	0.987708 (5)	0.995308 (4)	0.991226 (6)	0.992218 (8)	0.983478 (8)	0.991737 (7)	0.997039 (7)	0.996017 (7)	0.994172 (7)	0.990486 (5)
Vanguard Total Stock Market (VTI)	Developed	0.989421 (4)	0.998917 (1)	0.360006 *** (8)	0.992602 (4)	0.995185 (5)	0.992259 (5)	0.996020 (5)	0.999162 (4)	0.998436 (4)	0.997169 (4)	0.811921 *** (7)
iShares MSCI World UCITS (IWRD)	Developed	-	-	-	0.980740 (10)	0.986284 (9)	0.973586 (10)	0.979883 (10)	0.988403 (10)	0.981820 (100	0.983811 (9)	-
iShares Core MSCI World UCITS (SWDA)	Developed	-	-	-	0.989018 (7)	0.993055 (7)	0.981735 (9)	0.986147 (8)	0.988897 (9)	0.983943 (8)	0.987360 (8)	-
Schwab International Equity (SCHF)	Developed	-	-	-	0.967276 (11)	0.954364 *** (11)	0.963737 * (11)	0.936012 *** (11)	0.988962 (8)	0.982344 (9)	0.972218 (10)	-
Schwab US Broad Market (SCHB)	Developed	-	-	-	0.987133 (9)	0.995313 (4)	0.992445 (4)	0.996062 (4)	0.998974 (6)	0.998400 (5)	0.996686 (6)	-
Average TE4 for optimized ETFs	-	**0.910866 *** (9)**	**0.915412 *** (8)**	**0.870219 *** (11)**	**0.966527 (1)**	**0.968980 ** (3)**	**0.964401 * (2)**	**0.957493 *** (6)**	**0.967535 ** (4)**	**0.919048 *** (7)**	**0.956061 ** (5)**	**0.906300 *** (10)**

*Note: Test of R^2 of R^2 equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_4 significance and magnitude for each column, and across the row for the average TE_4. (Author's own construction, 2024)*

Table 5-17: R^2 of the Regression (TE_4) for Synthetic ETFs.

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
Amundi MSCI India II UCITS (INR)	Emerging	-	-	-	0.980801 (6)	0.964869 *** (6)	0.947634 ** (7)	0.972338 * (7)	0.988067 (6)	0.938810 ** (8)	0.971740 (7)	-
Amundi MSCI Emerging Markets III UCITS (LEM)	Emerging	-	-	-	0.948072 ** (7)	0.947708 *** (9)	0.939332 *** (9)	0.959951 *** (8)	0.978180 (9)	0.943498 ** (7)	0.955540 ** (8)	-
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	Emerging	-	-	-	0.940006 *** (9)	0.945477 *** (10)	0.925180 *** (10)	0.848694 *** (12)	0.944968 *** (11)	0.907866 *** (12)	0.921272 *** (12)	-
Amundi MSCI Brazil UCITS (BRZ)	Emerging	-	-	-	0.998140 (2)	0.999989 (3)	0.999751 (5)	0.999992 (2)	0.999999 (1)	0.993499 (5)	0.998919 (3)	-
Amundi MSCI Emerging Markets Asia (AASU)	Emerging	-	-	-	0.998550 (1)	0.999996 (2)	0.999998 (1)	0.999998 (1)	0.999997 (2)	1.000000 (1)	0.999798 (1)	-
Xtrackers MSCI Africa Top 50 Swap UCITS (XMKA)	Emerging	-	-	-	0.932695 *** (10)	0.958219 *** (7)	0.950773 ** (6)	0.853441 *** (11)	0.961657 *** (10)	0.911272 *** (11)	0.929918 *** (11)	-
Amundi NASDAQ-100 II (ANXU)	Developed	-	-	-	0.989960 (5)	0.999999 (1)	0.999960 (3)	0.996113 (4)	0.988090 (5)	0.999999 (2)	0.994697 (4)	-
Amundi FTSE 100 (L100)	Developed	-	-	-	0.992468 (4)	0.994441 (5)	0.999681 (4)	0.995901 (5)	0.987091 (7)	0.999999 (3)	0.993787 (5)	-
Amundi MSCI Europe Banks UCITS (CB5)	Developed	-	-	-	0.995620 (3)	0.999981 (4)	0.999978 (2)	0.999926 (3)	0.999896 (3)	0.999965 (4)	0.999239 (2)	-
Amundi Dow Jones Industrial Average UCITS (DJE)	Developed	0.672177 ***	0.945337 ***	0.929156 ***	0.919298 *** (12)	0.935162 *** (11)	0.890507 *** (12)	0.949739 *** (9)	0.933536 *** (12)	0.930543 *** (9)	0.931313 *** (10)	0.921302 ***
Amundi NASDAQ-100 UCITS (ANX)	Developed	-	-	-	0.947735 ** (8)	0.957380 *** (8)	0.939473 *** (8)	0.980566 (6)	0.989434 (4)	0.977000 (6)	0.974144 (6)	-
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	Developed	-	-	-	0.925874 *** (11)	0.913398 *** (12)	0.924541 *** (11)	0.866062 *** (10)	0.982538 (8)	0.919283 *** (10)	0.940016 *** (9)	-
Average TE4 for synthetic ETFs	-	**0.672177 *** (11)**	**0.945337 *** (8)**	**0.929156 *** (9)**	**0.964102 * (4)**	**0.968052 ** (6)**	**0.959734 * (5)**	**0.951893 *** (7)**	**0.979454 (1)**	**0.960144 (3)**	**0.967532 (2)**	**0.921302 *** (10)**

*Note: Test of R^2 of R^2 equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_4 significance and magnitude, and across the row for the average TE_4. (Author's own construction, 2024)*

In summary, we find that the R^2 (TE_4) estimates conform with the results derived from TE_1, TE_2 and TE_3, suggesting that partial physical replication (stratified and optimized) show the highest level of tracking performance, while full physical ETFs do not replicate their benchmark index accurately. Additionally, we conclude that while synthetic ETFs underperform their benchmark index more than partial physical ETFs, they show better levels of tracking performance and can minimize tracking errors to a greater extent than the full physical ETFs.

5.2.1.1. (e) Beta of the Regression

In conjunction with the standard error estimates (TE_3) and R^2 measure (TE_4), we analyse the beta estimates (slope coefficients) from the regression; to determine to what extent the ETF replicates the movements in the index. Ideally the slope coefficient should equal 1 which is suggestive of perfect replication. However, studies such as Strydom, Charteris and McCullough (2015) have deemed that simply analysing how closely the beta estimates approximate 1 is not sufficient, therefore we test the relationship statistically. The slope coefficient estimates are provided in tables 5-18 to 5-21.

The overarching observation for the beta estimates is that across all four replication strategies and periods, most ETFs exhibit beta estimates that are not significantly different from 1, suggesting that the ETFs in this sample track their benchmarks relatively well. However, in the case of full physical ETFs we find that the average beta estimates across all periods except 2020-2021 are statistically significant at the 1% level. Additionally, we observe that the full physical ETF sample show more ETFs that have beta estimates that are statistically significant at the 1% level in comparison to the stratified, optimized and synthetic samples. These results support the observations made under all four methods of tracking error estimation.

The average slope coefficient/beta estimates for the stratified and optimized ETFs closely mirror those observed for the R^2 (TE_4) values, suggesting that partially replicated ETFs minimize tracking error and replicate their underlying benchmarks more satisfactorily than their full physical and synthetic counterparts. The average slope coefficient/beta estimates for the full physically replicated ETFs differ significantly from 1 at a 1% level of significance across five of the six sub periods and the full period, with values that depart further below 1 than the partial physical and synthetic ETFs. This suggests that full physical replication demonstrates the weakest level of tracking performance. The beta estimates of the synthetic ETFs approximate 1 closer than the full physical ETFs, suggesting that synthetic ETFs better replicate their benchmark indices.

These results contradict Rompotis (2012b) who found that ETFs that do not adopt full replication strategies exhibit beta estimates that significantly differ from 1. However, in this study we find that the ETFs that follow partial physical (stratified and optimized) and synthetic replication have beta estimates closer to 1 than the full physical sample. This indicates that partial physical and synthetic replication track their benchmarks more accurately than full physical ETFs. The slope coefficient/beta results for full physical ETFs found here are consistent with Meinhardt, Mueller and Schoene (2015), whose beta coefficients for physical ETFs significantly differed from unity signalling the presence of tracking error.

Table 5-18: Beta of the Regression for Full Physically Replicated ETFs

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
iShares MSCI Mexico (EWW)	Emerging	0.976654 **	0.990867	0.993324	0.993309	0.992726 *	1.001014	0.998681	0.958989 ***	0.942689 ***	0.977408	0.982897
iShares MSCI South Africa (EZA)	Emerging	1.252222 ***	1.401835 ***	1.478102 ***	1.295895 ***	1.196787 ***	0.029211 ***	0.996076	0.992431 ***	0.885133 ***	0.228414 ***	0.329002 ***
iShares MSCI BIC (BFK)	Emerging	-	-	-	0.981004	0.994786	0.997225	1.003738	0.980729 ***	0.800765 ***	0.944580 ***	-
Colombia Research Enhanced Emerging Economies (ECON US)	Emerging	-	-	-	0.994529	0.999803	1.005390	0.998806	0.998935	0.994871	0.998791	-
Colombia India Consumer (INCO US)	Emerging	-	-	-	1.001120	0.996733	0.997020	1.000161	1.009869 ***	0.990140	1.000971	-
First Trust Emerging Markets Alpha Dex Fund (FEM)	Emerging	-	-	-	0.906552 ***	1.033068 ***	0.727745 ***	0.902361 ***	0.991321 ***	0.892839 ***	0.915842 ***	-
SPDR S&P500 ETF Trust (SPY)	Developed	0.994432	0.995712	0.996964	0.998144	1.001891	0.997351	1.001100	1.000871	1.000291	1.000436	0.998092
Invesco S&P500 Equal Weight (RSP)	Developed	0.990426	0.999431	0.996563	0.997691	1.001501	0.997246	1.003275	1.002572	0.998700	1.000969	0.999345
Vanguard Growth (VUG)	Developed	0.992680	1.000307	0.999809	0.081930 ***	1.001318	1.002007	1.002149	0.998596	1.000156	0.570900 ***	0.699094
SPDR Portfolio S&P500 (SPLG)	Developed	0.982941	0.987403	1.002062	1.004276	0.999159	1.012399	1.003292	1.001357	0.997732	1.001508	0.995941
Vanguard FTSE Developed Markets (VEA)	Developed	-	-	-	0.888339 ***	0.935478 ***	0.865418 ***	0.816104 ***	1.021257 ***	0.847886 ***	0.915446 ***	-
Vanguard S&P500 (VOO)	Developed	-	-	-	1.004051	0.995586	1.002576	0.998165	0.997069	0.998262	0.998229	-
Average beta for full physical ETFs	-	**1.031559 *****	**1.062592 *****	**1.077804 *****	**0.928903 *****	**1.012403 *****	**0.886217 *****	**0.976992 *****	**0.996166**	**0.945789 *****	**0.879458 *****	**0.834062 *****

*Note: Test of beta of beta equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-19: Beta of the Regression for Stratified Sampled ETFs

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
iShares Latin America 40 (ILF)	Emerging	0.967429 ***	0.991156	0.964208	0.948077 ***	0.958700 ***	0.955710 **	0.951758 ***	1.009474 ***	1.010593	0.982149	0.982147
iShares China Large Cap (FXI)	Emerging	0.997410	0.977050	0.992603	0.991631	0.996954	1.001677	0.999072	0.893979 ***	0.666240 ***	0.865631 ***	0.929677 ***
iShares Core S&P Mid Cap (IJH)	Developed	0.966937 ***	0.996724	0.997452	0.998984	1.001875	1.004792	1.005305	0.999430	1.002040	1.001150	0.997564
iShares Core S&P Small Cap (IJR)	Developed	0.964383 ***	0.996907	0.998159	0.996087	1.001017	1.004118	1.003910	0.999847	1.001581	1.000747	0.997198
iShares Russell 3000 (IWV)	Developed	0.993507	0.997534	0.997476	0.998876	0.999999	1.004380	1.006122	0.999889	1.001580	1.001263	0.999134
iShares S&P 100 (OEF)	Developed	0.999729	0.995540	0.994673	0.997138	1.002166	1.007852	1.005360	1.000917	1.001494	1.001905	0.998891
iShares Russell 2000 Value (IWN)	Developed	0.998792	0.998551	0.998399	0.995511	1.001332	1.003406	1.005258	0.998794	1.002170	1.000294	0.999367
iShares Russell 2000 Growth (IWO)	Developed	0.998409	0.998740	0.998919	0.998427	1.000530	1.001465	1.001233	0.999765	1.000066	1.000113	0.999466
iShares S&P Mid Cap 400 Growth (IJK)	Developed	0.965426 ***	0.998887	0.998595	0.998072	1.000912	1.003380	1.002894	0.999758	1.000950	1.000583	0.997953
iShares MSCI Eurozone (EZU)	Developed	0.901016 ***	0.994208	0.995645	0.999391	1.001844	0.999293	1.006430	0.973857 ***	0.831849 ***	0.956082 **	0.971902
iShares S&P Mid Cap Value (IJJ)	Developed	0.970597 **	0.996131	0.996593	0.997227	1.001582	1.005202	1.007190	0.998862	1.002990	1.001001	0.997485
iShares S&P Small Cap 600 Value (IJS)	Developed	1.000259	0.997639	0.997978	0.996277	1.001423	1.004878	1.004233	0.999786	1.001838	1.000849	0.999424
Average beta for stratified sampled ETFs	-	**0.976991 ****	**0.994922**	**0.994225**	**0.992975**	**0.997361**	**0.999680**	**0.999897**	**0.989530 *****	**0.960283 *****	**0.984314**	**0.989184**

*Note: Test of beta of beta equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-20: Beta of the Regression for Optimized ETFs

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
iShares MSCI Emerging Markets (EEM)	Emerging	0.966972 ***	1.022909	1.005634	0.999081	0.999752	0.998957	1.006382	0.984973 ***	0.763063 ***	0.948773 ***	0.983513
Vanguard FTSE Emerging Markets (VWO)	Emerging	0.900260 ***	0.938101 ***	1.008284	0.966422 *	0.952080 ***	0.901367 ***	0.896225 ***	1.008994 ***	0.776592 ***	0.923419 ***	0.935831 **
iShares Core S&P500 (IVV)	Developed	0.999030	0.990001	0.995543	0.998404	1.002516	1.006863	1.006264	1.000013	1.002566	1.001950	0.996926
iShares Russell 1000 Growth (IWF)	Developed	0.992517	0.993648	0.998116	0.999894	1.000597	1.003327	1.002386	0.999789	1.000496	1.000622	0.998030
iShares S&P500 Growth (IVW)	Developed	0.999173	0.993731	0.996347	0.997573	1.001678	1.004446	1.001754	1.000062	1.000311	1.000593	0.998070
SPDR Portfolio S&P500 Growth (SPYG)	Developed	1.006172	1.012735	1.017316	0.998156	1.000866	0.998159	1.001893	0.997959	0.997879	0.998770	1.005191
SPDR Portfolio S&P500 Value (SPYV)	Developed	0.959154 ***	0.945644 ***	0.979185	0.998987	1.001552	0.993724	1.006430	1.001305	0.995809	1.000248	0.974392
Vanguard Total Stock Market (VTI)	Developed	0.995047	1.000555	0.359633 ***	1.003248	1.000694	1.003658	1.005899	0.996337	1.002176	1.000345	0.813697 ***
iShares MSCI World UCITS (IWRD)	Developed	-	-	-	1.011236	0.995707	0.999605	0.995781	0.999902	0.993894	0.998857	-
iShares Core MSCI World UCITS (SWDA)	Developed	-	-	-	1.005071	0.998549	0.995364	0.998251	0.994155 **	0.991749	0.995726	-
Schwab International Equity (SCHF)	Developed	-	-	-	0.997015	0.997541	0.987277	0.969796 ***	1.002265	1.001034	0.995808	-
Schwab US Broad Market (SCHB)	Developed	-	-	-	0.995561	0.997736	0.994871	0.997655	1.001022	1.003150	0.999874	-
Average beta for optimized ETFs	-	**0.977291 ***	**0.987166**	**0.920007 *****	**0.997554**	**0.995772**	**0.990635**	**0.990726 *****	**0.998898**	**0.960727 *****	**0.988749**	**0.963206**

*Note: Test of beta of beta equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-21: Beta of the Regression for Synthetic ETFs

ETF Name and Ticker	Fund Domicile	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
Amundi MSCI India II UCITS (INR)	Emerging	-	-	-	0.993510	1.011506 ***	0.991329	0.984819 ***	0.992186 ***	0.982112 *	0.992864	-
Amundi MSCI Emerging Markets III UCITS (LEM)	Emerging	-	-	-	0.962899 *	1.006998	0.968552	0.995877	0.987078 ***	0.984776	0.984767	-
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	Emerging	-	-	-	0.961741 *	1.006762	0.955657 **	0.956561 ***	0.968371 ***	0.969030 ***	0.969573 *	-
Amundi MSCI Brazil UCITS (BRZ)	Emerging	-	-	-	0.997825	1.000023	1.000325	1.000149	0.999993	1.007637	1.000922	-
Amundi MSCI Emerging Markets Asia (AASU)	Emerging	-	-	-	0.999799	1.000182	0.999955	0.999975	1.000000	1.000028	0.999980	-
Xtrackers MSCI Africa Top 50 Swap UCITS (XMKA)	Emerging	-	-	-	0.944225 ***	1.003597	0.947406 ***	0.936855 ***	0.967921 ***	0.967303 ***	0.961723 **	-
Amundi NASDAQ-100 II (ANXU)	Developed	-	-	-	0.990557	1.000080	1.000279	0.997346	0.991555 ***	0.999984	0.996101	-
Amundi FTSE 100 (L100)	Developed	-	-	-	0.994656	0.998494	1.000452	0.998417	0.995702 *	0.999931	0.997700	-
Amundi MSCI Europe Banks UCITS (CB5)	Developed	-	-	-	0.997346	0.999899	0.999807	1.000267	0.999882	0.999912	0.999497	-
Amundi Dow Jones Industrial Average UCITS (DJE)	Developed	0.876886 ***	0.987419	1.006917	1.009456	1.001871	0.997031	1.000610	0.987434 ***	1.027011 **	0.999293	0.990410
Amundi NASDAQ-100 UCITS (ANX)	Developed	-	-	-	1.013472	0.990633 **	0.994790	1.003397	0.983660 ***	1.022478 **	1.000958	-
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	Developed	-	-	-	0.988584	0.992898	1.011157	1.006884	1.001345	0.996897	0.999456	-
Average beta for synthetic ETFs	-	**0.876886 *****	**0.987419**	**1.006917**	**0.987839**	**1.001078**	**0.988895**	**0.990096 ****	**0.989594 *****	**0.996425**	**0.991903**	**0.990410**

*Note: Test of beta of beta equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

In summary, the beta estimates further support the claim from the four methods of tracking error applied, that ETFs following partial physical replication demonstrate the highest level of tracking performance, while full physical ETFs suffer from a higher level of tracking error predisposition. Synthetic ETFs show lower levels of tracking error than full physical ETFs, despite being less favourable than partial physical ETFs in respect to tracking error.

5.2.1.1. (f) Alpha of the Regression

The intercept of the regression, which captures Jensen's alpha (α), provides an overview of the performance of the ETF in respect to risk adjusted returns. The alpha estimates are shown in tables 5-22 to 5-25. The results show that all ETFs in the sample underperform their benchmark index consistently. However, the alpha estimates conflict with the observations made under TE_1, TE_2, TE_3, TE_4 and the beta estimates, suggesting that partially physically replicated ETFs (stratified and optimized) show higher levels of benchmark index underperformance, than the synthetic ETFs across all the sub periods and the full period. However, consistent with the results obtained for the tracking error and beta estimates, the partial physical ETFs show lower levels of underperformance than the full physical ETFs, for most of the sub periods and the full period. Additionally, and consistent with the findings from the tracking error and beta estimates, we find that synthetic ETFs underperform their index to a lesser extent than full physical ETFs

From the results of the average alpha values across all four replication strategies and five out of the six sub periods and the full period of study, we find that all the ETFs in the sample consistently underperform their benchmark index as indicated by the negative alpha estimates. The application of the t-tests of significance to the alpha estimates confirm the underperformance of the funds. The magnitude of the results obtained for the average alpha estimates in this study are mixed, with full physical replication showing the lowest levels of underperformance during 2012-2013 and 2016-2017, and synthetic ETFs showing the lowest levels of underperformance during 2014-2015, 2018-2019, 2020-2021, 2022-2024 and the full period, 2012-2024.

The partial physical ETFs show lower underperformance than the full physical ETFs during 2014-2015, 2018-2019, 2020-2021, 2022-2024 and the full period, 2012-2024.The average alpha estimates for the full physical ETFs are statistically significant during 2014-2015 and 2018-2019 at 1% and 5% levels respectively, signalling significant underperformance. For the stratified sampled ETFs, the alpha estimate is statistically significant at a 5% level during 2016-2017, and the optimized ETFs show statistically significant alpha estimates during 2012-2013 and 2016-2017 at a 5% level. The synthetic ETFs do not demonstrate any alpha estimates that are statistically significant at a level of 5% or 1%. Therefore, suggesting that under the alpha estimations, synthetic ETFs track their benchmark index most accurately in comparison to the other replication strategies.

The greater levels of underperformance inherent to the stratified sampled and optimized ETFs is reflective of the higher costs and increased passiveness associated with them as discussed in chapter two of this study (*see 2.2.2. and 2.2.3.*). The results observed in this study in respect to the alpha estimates reflect the findings of international studies such as Blitz and Huij (2012) and Rompotis (2009) who found that passive funds tend to underperform the benchmark more frequently. Rompotis (2012b) further provides justification for our findings as they state that ETFs that are passively managed possess none or low trading flexibility that could enhance their performance relative to the benchmark therefore resulting in negative alphas/underperformance.

Table 5-22: Alpha of the Regression for Full Physically Replicated ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares MSCI Mexico (EWW)	Emerging	-0.000128	-0.003934	-0.002324	-0.004473	-0.007691 **	-0.008974 **	-0.011693 **	-0.007845	-0.009512	-0.008839	-0.006722
iShares MSCI South Africa (EZA)	Emerging	-0.029758	-0.025219	-0.035736	-0.071798 *	-0.083673 **	0.068683	-0.033269	-0.016301	-0.015650	-0.029580	-0.022903
iShares MSCI BIC (BFK)	Emerging	-	-	-	-0.012714	-0.013312 **	-0.009364 **	-0.009566 **	-0.010481	-0.018546	-0.010420	-
Colombia Research Enhanced Emerging Economies (ECON US)	Emerging	-	-	-	-0.006184 **	-0.010438 ***	-0.005875 *	-0.008712 **	-0.006316 **	-0.007800	-0.007511 ***	-
Colombia India Consumer (INCO US)	Emerging	-	-	-	-0.007573	-0.006734 **	-0.005583 ***	-0.004846	-0.023706 *	-0.038851 *	-0.014909 ***	-
First Trust Emerging Markets Alpha Dex Fund (FEM)	Emerging	-	-	-	0.004555	-0.012655	-0.000106	-0.017467	-0.018329	-0.026973	-0.016219	-
SPDR S&P500 ETF Trust (SPY)	Developed	0.000066	0.000086	-0.000092	-0.000011	-0.000090	-0.000093	-0.000080	-0.000199	0.000016	-0.000118	-0.000006
Invesco S&P500 Equal Weight (RSP)	Developed	-0.006112 *	-0.010767 ***	-0.007458 ***	-0.007805 ***	-0.007881 ***	-0.007026 ***	-0.008167 ***	-0.007994 ***	-0.007828 ***	-0.007837 ***	-0.007923 ***
Vanguard Growth (VUG)	Developed	0.000045	0.000278	-0.000175	0.084158 **	-0.005378 ***	-0.005516 ***	-0.004688 ***	-0.002721 ***	-0.002704 ***	0.031378 **	0.018676 *
SPDR Portfolio S&P500 (SPLG)	Developed	-0.009339 *	-0.008421 *	-0.007372 **	-0.008928 **	-0.009788 ***	-0.008905 ***	-0.007871 **	-0.006418 ***	-0.006466 ***	-0.007885 ***	-0.007805 ***
Vanguard FTSE Developed Markets (VEA)	Developed				0.000428	-0.012580	-0.005928	-0.010548	-0.011560	-0.012605	-0.008956	-
Vanguard S&P500 (VOO)	Developed				-0.008900 ***	-0.008005 ***	-0.008271 ***	-0.007867 ***	-0.006180 ***	-0.006602 ***	-0.007538 ***	-
Average alpha for full physical ETFs	-	**-0.007538 *****	**-0.007996 *****	**-0.008860 ****	**-0.003271**	**-0.014852 *****	**0.000254**	**-0.010398 ****	**-0.009837**	**-0.012793**	**-0.007369**	**-0.004447 *****

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-23: Alpha of the Regression for Stratified Sampled ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares Latin America 40 (ILF)	Emerging	0.003205	0.003480	-0.004224	-0.004466	-0.005215	0.004503	-0.000920	-0.002209	-0.001739	-0.001649	-0.001030
iShares China Large Cap (FXI)	Emerging	0.006328	-0.003331	-0.000452	-0.000263	-0.001224	-0.001253	-0.000136	-0.004522	-0.029880	-0.002468	0.000072
iShares Core S&P Mid Cap (IJH)	Developed	-0.004466	-0.006421	-0.005433 ***	-0.006000 ***	-0.006066 ***	-0.006551 ***	-0.006764 ***	-0.006025 ***	-0.006592 ***	-0.006327 ***	-0.006044 ***
iShares Core S&P Small Cap (IJR)	Developed	-0.003215	-0.005043	-0.004799 ***	-0.005225 **	-0.005564 ***	-0.005728 ***	-0.005764 ***	-0.006423 ***	-0.005957 ***	-0.005813 ***	-0.005319 ***
iShares Russell 3000 (IWV)	Developed	-0.006571 *	-0.008458 **	-0.007624 ***	-0.008166 ***	-0.007848 ***	-0.008013 ***	-0.008177 ***	-0.006166 ***	-0.006390 ***	-0.007451 ***	-0.007437 ***
iShares S&P 100 (OEF)	Developed	-0.007960 ***	-0.010909 ***	-0.008831 ***	-0.009322 ***	-0.008799 ***	-0.009361 ***	-0.008928 ***	-0.006768 ***	-0.006333 ***	-0.008242 ***	-0.008460 ***
iShares Russell 2000 Value (IWN)	Developed	-0.007836 **	-0.008233 ***	-0.008102 ***	-0.009127 ***	-0.008076 ***	-0.008238 ***	-0.008069 ***	-0.007886 ***	-0.009365 ***	-0.008505 ***	-0.008335 ***
iShares Russell 2000 Growth (IWO)	Developed	-0.002380	-0.002809 **	-0.002702 **	-0.003924 **	-0.002568 **	-0.003349 **	-0.002920 ***	-0.002279 ***	-0.003112 ***	-0.003036 ***	-0.002888 ***
iShares S&P Mid Cap 400 Growth (IJK)	Developed	-0.001549	-0.003043 ***	-0.003395 ***	-0.004469 ***	-0.004755 ***	-0.005483 ***	-0.005244 ***	-0.003643 ***	-0.005039 ***	-0.004780 ***	-0.004130 ***
iShares MSCI Eurozone (EZU)	Developed	0.000148	-0.017995 *	-0.012872 *	-0.012206	-0.009680 *	-0.010457 *	-0.012354 *	-0.007397	-0.009913	-0.009243	-0.010938 **
iShares S&P Mid Cap Value (IJJ)	Developed	-0.007028	-0.010331 *	-0.007640 ***	-0.007680 ***	-0.007522 ***	-0.008165 ***	-0.008182 ***	-0.008849 ***	-0.008257 ***	-0.008115 ***	-0.008182 ***
iShares S&P Small Cap 600 Value (IJS)	Developed	-0.006459 ***	-0.007165 **	-0.005816 ***	-0.006665 ***	-0.006743 ***	-0.006617 ***	-0.007391 ***	-0.006659 ***	-0.007103 ***	-0.006889 ***	-0.006712 ***
Average alpha for stratified sampled ETFs	-	**-0.003149**	**-0.006688 *****	**-0.005991 ****	**-0.006459 ***	**-0.006172**	**-0.005726 ****	**-0.006237**	**-0.005735**	**-0.008307**	**-0.006043**	**-0.005784 *****

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-24: Alpha of the Regression for Optimized ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
iShares MSCI Emerging Markets (EEM)	Emerging	-0.010559	-0.001365	-0.012787	-0.010664 **	-0.011355 **	-0.010109 **	-0.012197 **	-0.010254	-0.019586	-0.010612	-0.010508
Vanguard FTSE Emerging Markets (VWO)	Emerging	-0.003979	-0.018182	-0.006207	-0.011956	-0.020515	0.000393	-0.011100	-0.011142	-0.020815	-0.011713	-0.011663
iShares Core S&P500 (IVV)	Developed	-0.000001	0.000047	0.000002	0.000438	-0.000283	-0.000129	-0.000858	-0.000134	0.000094	-0.000143	0.000102
iShares Russell 1000 Growth (IWF)	Developed	-0.004239	-0.006534	-0.006242 ***	-0.006985 ***	-0.006223 ***	-0.006237 ***	-0.005428 ***	-0.003533 ***	-0.003788 ***	-0.005344 ***	-0.005359 ***
iShares S&P500 Growth (IVW)	Developed	-0.005536 **	-0.006415	-0.006748 ***	-0.007430 ***	-0.006695 ***	-0.006830 ***	-0.006572 ***	-0.003859 ***	-0.004529 ***	-0.005978 ***	-0.005959 ***
SPDR Portfolio S&P500 Growth (SPYG)	Developed	-0.004269	-0.003638	-0.003681	-0.007583 ***	-0.006757 ***	-0.006729 ***	-0.006012 ***	-0.003630 *	-0.004537 ***	-0.005858 ***	-0.005398 ***
SPDR Portfolio S&P500 Value (SPYV)	Developed	-0.007454	-0.014149	-0.008923 **	-0.010237 ***	-0.010059 ***	-0.011095 ***	-0.010770 ***	-0.010234 **	-0.008309 ***	-0.010173 ***	-0.009242 ***
Vanguard Total Stock Market (VTI)	Developed	-0.000046	0.000257	0.044964	-0.008320 ***	-0.007609 `***	-0.007934 ***	-0.007829 ***	-0.005772 ***	-0.006320 ***	-0.007234 ***	0.008686
iShares MSCI World UCITS (IWRD)	Developed	-	-	-	-0.009646 **	-0.007464 **	-0.007275	-0.007650	-0.005907	-0.006394	-0.007228 ***	-
iShares Core MSCI World UCITS (SWDA)	Developed	-	-	-	-0.001047	0.000459	0.000708	0.000342	0.000614	0.000386	0.000395	-
Schwab International Equity (SCHF)	Developed	-	-	-	-0.010716	-0.010897	-0.009658	-0.011887	-0.011069 *	-0.011800 *	-0.011067 ***	-
Schwab US Broad Market (SCHB)	Developed	-	-	-	-0.007728 *	-0.007259 ***	-0.007186 ***	-0.007576 ***	-0.006761 ***	-0.006178 ***	-0.007237 ***	-
Average alpha for optimized ETFs	-	**-0.004511 ****	**-0.006247 *****	**0.000047**	**-0.007656 ****	**-0.007888 ***	**-0.006007 ****	**-0.007295**	**-0.005974**	**-0.007648**	**-0.006850**	**-0.004918 *****

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-25: Alpha of the Regression for Synthetic ETFs

ETF Name and Ticker	Fund Domicile	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Amundi MSCI India II UCITS (INR)	Emerging	-	-	-	-0.004302	-0.006067	-0.005422	-0.006740	-0.005797	-0.005510	-0.005608	-
Amundi MSCI Emerging Markets III UCITS (LEM)	Emerging	-	-	-	-0.001952	-0.002698	0.000428	-0.003393	-0.001875	-0.002399	-0.002425	-
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	Emerging	-	-	-	-0.002736	-0.002943	0.000805	-0.000980	-0.001947	-0.001691	-0.002050	-
Amundi MSCI Brazil UCITS (BRZ)	Emerging	-	-	-	-0.000459	-0.002758 ***	-0.002933 **	-0.003189 ***	-0.003315 ***	-0.002902	-0.002477 **	-
Amundi MSCI Emerging Markets Asia (AASU)	Emerging	-	-	-	-0.002927 *	-0.002212 ***	-0.002029 ***	-0.001941 ***	-0.001427 ***	-0.000665 ***	-0.001866 ***	-
Xtrackers MSCI Africa Top 50 Swap UCITS (XMKA)	Emerging	-	-	-	0.000729	-0.003719	-0.004390	-0.003658	-0.007606	-0.004940	-0.004604	-
Amundi NASDAQ-100 II (ANXU)	Developed	-	-	-	0.000228	-0.000708 ***	-0.000120	-0.000194	0.000965	0.000138	-0.000030	-
Amundi FTSE 100 (L100)	Developed	-	-	-	-0.000525	-0.000315	-0.000137	-0.000738	-0.000928	-0.001003 ***	-0.000625	-
Amundi MSCI Europe Banks UCITS (CB5)	Developed	-	-	-	-0.000032	-0.000331	-0.000231	0.000231	-0.000076	0.001109 **	0.000072	-
Amundi Dow Jones Industrial Average UCITS (DJE)	Developed	-0.000123	-0.008413	-0.008501	-0.006805	-0.007878	-0.007515	-0.006305	-0.005205	-0.005173	-0.006431	-0.006478
Amundi NASDAQ-100 UCITS (ANX)	Developed	-	-	-	-0.001436	-0.000289	0.000427	-0.000736	0.002095	-0.000142	-0.000297	-
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	Developed	-	-	-	-0.021639 *	-0.022388 *	-0.020560 *	-0.021123	-0.019092 *	-0.025479	-0.021695 ***	-
Average alpha for synthetic ETFs	-	**-0.000123**	**-0.008413 *****	**-0.008501 ****	**-0.003488**	**-0.004359**	**-0.003473**	**-0.004064 ***	**-0.003684**	**-0.004055**	**-0.004003**	**-0.006478 *****

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

In summary, we find that the alpha estimates suggest that ETFs following synthetic replication underperform their benchmark index the least, while partial and full physical ETFs are more predisposed to benchmark underperformance due to their structure and passive nature.

5.2.1.2. Tracking Error and Leveraged Replication

The subsequent tables 5-26 to 5-31, present the results of the TE_1, TE_2, TE_3, TE_4, beta and alpha estimates for the leveraged ETF sample. The estimates for the leveraged ETFs are shown for the subperiods between and the full period of 2012-2024, since none of the leveraged ETFs considered in this sample have an inception date prior to 2012. In this section we find that, as expected, leveraged ETFs demonstrate tracking errors that are considerably higher than the ETFs following stratified, optimized, synthetic, and full physical replication. The average TE_1, TE_2 and TE_3 estimates are observed to be statistically significant at the 1% level of significance, further substantiating the existence and persistence of tracking error in leveraged ETFs. These observations are consistent with that of Bansal and Marshall (2015) and Rompotis (2016), both of which found that leveraged ETFs exhibit sizable and persistent tracking errors that are statistically significant at the 1% level.

When considering leveraged ETFs that track the same benchmark index (the S&P500), those with lower leverage multipliers minimize tracking error to a greater extent. When considering leveraged ETFs that track differing benchmark indices, those with higher leverage multipliers show lower tracking errors. In respect to the inverse leveraged ETFs, we find that those with multipliers of -1x show lower tracking errors in comparison to those with multipliers of -2x and -3x. Further to that, we find leveraged ETFs deliver their promised ratios while inverse leveraged ETFs do not.

The average R^2 values (TE_4) are statistically significant at the 1% level across all periods, suggesting that the estimates differ from 1, showing persistence of tracking errors in the leveraged ETF sample. The R^2 estimates are provided in table 5-29. The average alpha estimates are all negative and higher in magnitude in comparison with the other replication strategies, and statistically significant at the 1% level which demonstrates that the leveraged ETFs underperform their indices significantly and to a considerable extent, as observed in table 5-31.

We further consider the differences in tracking error persistence between the leveraged, (positive multipliers of 2x (EET and SSO) and 3x (UPRO)) and inverse leveraged ETFs, (negative multipliers of -1x (SH) , -2x (SDS) and -3x (SPXU)), with the leveraged ETFs being presented in rows 2, 3 and 4 and the inverse leveraged ETFs being presented in rows 5, 6 and 7 of the respective tables. Leveraged ETFs demonstrate smaller individual tracking errors than the inverse leveraged ETFs under TE_1, TE_2, TE_3 and TE_4, across most of the sub periods and during the full period of study. Additionally, we observe that as the leverage multiplier is increased for ETFs that track the same index (in the context of this study, the SPX) the tracking error is increased.

This result is inconsistent with the findings of Bansal and Marshall (2015) who observed an indirect linkage between the leverage multiplier and tracking error, suggesting that, although the tracking error estimations are sizable and significant in all leveraged ETFs, as the leverage multiplier is increased, the tracking errors are lessened. We observe that the ETF tracking the SPX with a 2x leverage multiplier (SSO) is ranked higher in respect to the ETF tracking the SPX with a 3x multiplier (UPRO). For comparison purposes SSO (2x) exhibits tracking errors that while statistically significant (therefore tracking error exists) are lower than that of UPRO (3x). The range of estimates for these two ETFs are SSO [TE_1: from 0.754013% (2012-2013) to 3.504195% (2020-2021); TE_2: from 0.441967% (2016-2017) to 1.129535% (2020-2021); TE_3: from 0.031071% (2016-2017) to 3.087929% (2020-2021)] and UPRO [TE_1: from 1.316903% (2016-2017) to 3.442273% (2020-2021) ; TE_2: from 0.878721% (2016-2017) to 2.002387% (2020-2021); TE_3: from 0.042947% (2016-2017) to 0.362236% (2020-2021)].

In respect to the R^2 (TE_4) values between SSO (2x) and UPRO (3x), SSO exhibits R^2 values that are closer in magnitude to 1 and not statistically significant for five out of the six sub periods (ranges from 0.742102 (2012-2024 to 0.999754 (2022-2024)) whereas UPRO exhibits R^2 values that are not statistically significant for any period (range from 0.994940 (2020-2021) to 0.999527 (2016-2017)), therefore the results for the R^2 (TE_4) measure is conflicting to the results of first three methods of tracking error estimation.

In analysing the beta estimates from the regression, we test whether the beta estimates are equal to or differ significantly from their respective multipliers, this is done in accordance with Charupat and Miu (2011) who stated that for leveraged ETFs to deliver their promised ratios, their beta estimates should be equal to their leverage multipliers. For, all three (positively) leveraged ETFs, EET (2x), SSO (2x) and UPRO (3x) this observation is confirmed as the results for their respective betas across all periods of study are not significantly different from 2 and 3, respectively.

The alpha estimates for SSO (2x) and UPRO (3x) show mixed results in respect to magnitude, however in terms of statistical significance three and four out of the seven estimates for SSO and UPRO, respectively are statistically significant at the 1% level suggesting that the mean of the estimates differ from zero (those that are significant are small and unlikely to be economically significant), which is consistent with the expectations of Charupat and Miu (2011) who found that for leveraged ETFs to deliver their promised ratios, the alpha estimates should be close to zero. In respect to under/over performance for the whole sample across all periods, the results are mixed, however the average alpha estimates exhibit significant and consistent underperformance.

An interesting finding is that when we compare leveraged ETFs that have different multipliers and track different indices namely, UPRO (3x the SPX) against that of EET (2x the MXEF), we find that the tracking error estimates across all three methods and R^2 conform to the findings of Bansal and Marshall (2015), therefore suggesting that when we consider different positive leveraged multiples of ETFs that track the same benchmark index, those with lower leverage multipliers minimize tracking error, however when considering ETFs with differing positive leverage multipliers that track different benchmark indices, the ETFs with higher leverage multipliers exhibit lower levels of tracking error.

In looking at the inverse ETFs, SH (-1x), SDS (-2x) and SPXU (-3x), we observe that under TE_1, TE_2 and TE_3, the results conform with the findings of Bansal and Marshall (2015), as SH shows the lowest levels of tracking error across all periods in comparison to SDS and SPXU, and SDS shows lower tracking error across all periods compared to SPXU, with SPXU showing the highest level of tracking error in comparison to SH and SDS.

The R^2 (TE_4) estimates conform to these observations, with all inverse leveraged ETFs' estimates not being statistically significant and SH demonstrating R^2 values closest to 1 in comparison to SDS and SPXU. The beta test of equality against the inverse leveraged multipliers show that for SH (-1x), SDS (-2x) and SPXU (-3x) the estimates differ significantly from their multipliers at the 5% or 1% levels across at least four of the seven periods of study. The alpha estimates for all inverse ETFs across all periods are negative and statistically significant at the 1% level suggesting significant underperformance for inverse leveraged ETFs. The results obtained from the alpha and beta estimates suggest that the inverse leveraged ETFs do not deliver their promised ratios for most of the periods of study, whereas the positive leveraged ETFs deliver their promised ratios across all periods of study.

Table 5-26: The Standard Deviation of the Active Return (TE_1) for Leveraged ETFs

ETF Name and Ticker	Fund Domicile	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)
ProShares Ultra MSCI Emerging Markets (EET)	Emerging	1.909528 *** (4)	1.869067 *** (4)	1.765256 *** (4)	1.856717 *** (2)	2.669638 *** (1)	2.023329 *** (2)	2.037780 *** (2)
ProShares Ultra S&P500 (SSO)	Developed	0.754013 *** (1)	0.858897 *** (1)	0.659024 *** (1)	0.949202 *** (1)	3.504195 *** (4)	1.230581 *** (1)	1.656508 *** (1)
ProShares Ultra Pro S&P500 (UPRO)	Developed	1.511244 *** (3)	1.720351 *** (3)	1.316903 *** (3)	1.904602 *** (4)	3.442273 *** (3)	2.465905 *** (4)	2.181248 *** (4)
ProShares Short S&P500 (SH)	Developed	1.505335 *** (2)	1.714100 *** (2)	1.307638 *** (2)	1.886931 *** (3)	3.287801 *** (2)	2.441655 *** (3)	2.131175 *** (3)
ProShares Ultra Short S&P500 (SDS)	Developed	2.263136 *** (5)	2.567144 *** (5)	1.963628 *** (5)	2.824701 *** (5)	4.927891 *** (5)	3.666123 *** (5)	3.196086 *** (5)
ProShares Ultra Pro Short S&P500 (SPXU)	Developed	3.024041 *** (6)	3.421073 *** (6)	2.616661 *** (6)	3.762487 *** (6)	6.588273 *** (6)	4.893929 *** (6)	4.267163 *** (6)
Average TE1 for leveraged ETFs	-	**1.827883 *** (2)**	**2.025105 *** (3)**	**1.604851 *** (1)**	**2.197440 *** (4)**	**4.070012 *** (7)**	**2.786920 *** (6)**	**2.578327 *** (5)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_1 significance and magnitude for each column, and across the row for the average TE_1. (Author's own construction, 2024)*

Table 5-27: The Mean Absolute Deviation (MAD) of the Active Return (TE_2) for Leveraged ETFs

ETF Name and Ticker	Fund Domicile	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021	2022-2024 (%)	2012-2024
ProShares Ultra MSCI Emerging Markets (EET)	Emerging	1.502710 *** (4)	1.453035 *** (4)	1.302823 *** (4)	1.386647 *** (4)	1.722239 *** (2)	1.558379 *** (2)	1.487973 *** (4)
ProShares Ultra S&P500 (SSO)	Developed	0.567458 *** (1)	0.624029 *** (1)	0.441967 *** (1)	0.657883 *** (1)	1.129535 *** (1)	0.922680 *** (1)	0.724213 *** (1)
ProShares Ultra Pro S&P500 (UPRO)	Developed	1.135880 *** (3)	1.248829 *** (3)	0.878721 *** (3)	1.316487 *** (3)	2.002387 *** (4)	1.847241 *** (4)	1.405357 *** (3)
ProShares Short S&P500 (SH)	Developed	1.133993 *** (2)	1.248289 *** (2)	0.876533 *** (2)	1.310680 *** (2)	1.986945 *** (3)	1.830606 *** (3)	1.398269 *** (2)
ProShares Ultra Short S&P500 (SDS)	Developed	1.704444 *** (5)	1.870581 *** (5)	1.315764 *** (5)	1.965141 *** (5)	2.982488 *** (5)	2.750104 *** (5)	2.098728 *** (5)
ProShares Ultra Pro Short S&P500 (SPXU)	Developed	2.278296 *** (6)	2.494130 *** (6)	1.758183 *** (6)	2.620402 *** (6)	3.982056 *** (6)	3.671012 *** (6)	2.801534 *** (6)
Average TE2 for leveraged ETFs	-	**1.387130 *** (2)**	**1.489816 *** (3)**	**1.095665 *** (1)**	**1.542873 *** (4)**	**2.300942 *** (7)**	**2.096670 *** (6)**	**1.652679 *** (5)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_2 significance and magnitude for each column, and across the row for the average TE_2. (Author's own construction, 2024)*

Table 5-28: The Standard Error of the Regression (TE_3) for Leveraged ETFs

ETF Name and Ticker	Fund Domicile	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)
ProShares Ultra MSCI Emerging Markets (EET)	Emerging	1.754283 *** (6)	1.689892 *** (6)	1.611006 *** (6)	1.714967 *** (6)	2.273842 *** (5)	1.972789 *** (6)	1.862024 *** (6)
ProShares Ultra S&P500 (SSO)	Developed	0.036519 (2)	0.034142 (2)	0.031071 (2)	0.041622 (1)	3.087929 *** (6)	0.038561 (1)	1.262461 *** (5)
ProShares Ultra Pro S&P500 (UPRO)	Developed	0.092109 ** (4)	0.061362 * (4)	0.042947 (4)	0.077931 ** (3)	0.362236 *** (3)	0.088272 * (2)	0.169036 *** (3)
ProShares Short S&P500 (SH)	Developed	0.019977 (1)	0.024929 (1)	0.020677 (1)	0.054555 * (2)	0.106269 (1)	0.121423 ** (3)	0.071955 (1)
ProShares Ultra Short S&P500 (SDS)	Developed	0.068347 * (3)	0.052705 (3)	0.042828 (3)	0.086359 ** (4)	0.318981 *** (2)	0.151678 *** (4)	0.155736 *** (2)
ProShares Ultra Pro Short S&P500 (SPXU)	Developed	0.127819 *** (5)	0.095598 *** (5)	0.071590 * (5)	0.144929 *** (5)	0.638226 *** (4)	0.221906 *** (5)	0.295032 *** (4)
Average TE3 for leveraged ETFs	-	**0.349842 *** (3)**	**0.326438 *** (2)**	**0.303353 *** (1)**	**0.353394 *** (4)**	**1.131247 *** (7)**	**0.432438 *** (5)**	**0.636041 *** (6)**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_3 significance and magnitude for each column, and across the row for the average TE_3. (Author's own construction, 2024)*

Table 5-29: R^2 of the Regression (TE_4) for Leveraged ETFs

ETF Name and Ticker	Fund Domicile	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024
ProShares Ultra MSCI Emerging Markets (EET)	Emerging	0.468860 *** (6)	0.497884 *** (6)	0.498086 *** (6)	0.462643 *** (6)	0.581445 *** (5)	0.381893 *** (6)	0.489131 *** (6)
ProShares Ultra S&P500 (SSO)	Developed	0.999413 (1)	0.999604 (1)	0.999442 (2)	0.999517 (1)	0.535704 *** (6)	0.999754 (1)	0.742102 *** (5)
ProShares Ultra Pro S&P500 (UPRO)	Developed	0.998345 (3)	0.999434 (2)	0.999527 (1)	0.999253 (2)	0.994940 (2)	0.999429 (2)	0.997292 (1)
ProShares Short S&P500 (SH)	Developed	0.999299 (2)	0.999157 (3)	0.998997 (3)	0.996666 (4)	0.995800 (1)	0.990095 (5)	0.995428 (2)
ProShares Ultra Short S&P500 (SDS)	Developed	0.997960 (4)	0.999053 (4)	0.998930 (4)	0.997897 (3)	0.990571 (3)	0.996149 (4)	0.994654 (3)
ProShares Ultra Pro Short S&P500 (SPXU)	Developed	0.996844 (5)	0.998614 (5)	0.998670 (5)	0.997363 (5)	0.983390 (4)	0.996351 (3)	0.991514 (4)
Average TE4 for leveraged ETFs	-	**0.910120 *** (3)**	**0.915624 *** (1)**	**0.915609 *** (2)**	**0.908890 *** (4)**	**0.846975 *** (7)**	**0.893945 *** (5)**	**0.868353 *** (6)**

*Note: Test of R^2 of R^2 equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF as per TE_4 significance and magnitude for each column, and across the row for the average TE_4. (Author's own construction, 2024)*

Table 5-30: Beta of the Regression for Leveraged ETFs

ETF Name and Ticker	Fund Domicile	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024
ProShares Ultra MSCI Emerging Markets (EET)	Emerging	1.853550	1.912537	1.826034	1.818760	2.100039	1.419681	1.834361
ProShares Ultra S&P500 (SSO)	Developed	2.001642	2.002154	2.004117	2.004682	2.006566	2.003343	2.003995
ProShares Ultra Pro S&P500 (UPRO)	Developed	3.006184	3.007601	3.007653	3.016173	3.072929	3.010253	3.035357
ProShares Short S&P500 (SH)	Developed	-1.001879	-1.001366	-0.994338 **	-0.998304	-0.989900 ***	-0.989299 ***	-0.993493 **
ProShares Ultra Short S&P500 (SDS)	Developed	-2.008540 **	-1.997056	-1.994481	-1.991278 **	-1.977854 ***	-1.988050 **	-1.987760 **
ProShares Ultra Pro Short S&P500 (SPXU)	Developed	-3.018306 **	-2.993275	-2.989796	-2.983272 **	-2.970823 ***	-2.988080 *	-2.984210 **
Average beta for leveraged ETFs	-	**0.138775**	**0.155099**	**0.143198**	**0.144460**	**0.206826**	**0.077975**	**0.151375**

*Note: Test of beta of beta equal to leverage multipliers (2, 3, -1, -2, -3) with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-31: Alpha of the Regression for Leveraged ETFs

ETF Name and Ticker	Fund Domicile	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)
ProShares Ultra MSCI Emerging Markets (EET)	Emerging	0.002481	-0.016006	0.009711	-0.016703	-0.029962	-0.052351	-0.014104
ProShares Ultra S&P500 (SSO)	Developed	0.006092 ***	0.002293	0.002077	-0.010851 ***	-0.160695	-0.023907 ***	-0.030916
ProShares Ultra Pro S&P500 (UPRO)	Developed	0.000926	-0.006842 **	-0.001577	-0.031938 ***	-0.082782 ***	-0.066640 ***	-0.031848 ***
ProShares Short S&P500 (SH)	Developed	-0.016851 ***	-0.017643 ***	-0.011148 ***	-0.008360 ***	-0.035869 ***	-0.009233 *	-0.016657 ***
ProShares Ultra Short S&P500 (SDS)	Developed	-0.036074 ***	-0.039230 ***	-0.024841 ***	-0.025557 ***	-0.096703 ***	-0.032439 ***	-0.042761 ***
ProShares Ultra Pro Short S&P500 (SPXU)	Developed	-0.061354 ***	-0.068295 ***	-0.043097 ***	-0.051867 ***	-0.184157 ***	-0.072280 ***	-0.080581 ***
Average alpha for leveraged ETFs	-	**-0.017463 *****	**-0.024287 *****	**-0.011479 *****	**-0.024213 *****	**-0.098361 *****	**-0.042808 *****	**-0.036145 *****

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

5.2.2. Tracking Error and Fund Domicile

The subsequent tables 5-32 to 5-36 present the average TE_1, TE_2, TE_3, TE_4, alpha and beta estimates for the Emerging and Developed ETFs, across four replication strategies (full physical, stratified, optimized and synthetic) and for each sub period of study and the full period, 2012-2024 (*not* 2006-2024, as explained previously as being due to data availability, however we include the time periods between 2006 and 2012 and 2006-2024, due to referring to these tables in the crisis period discussion *(see 5.2.3.)*). This timeline is then split into six 2-year sub periods. The leveraged ETF sample have been excluded from this section of the study due to its extreme values and activeness in comparison to other replication strategies that would skew the resultant estimates. This analysis considers 16 ETFs that track emerging market indices and 32 ETFs that track developed market indices. The highest ranked ETFs in respect to magnitude and statistical significance for the emerging and developed samples under each period is highlighted in the columns of the respective tables.

The results observed in this section are in accordance with previous studies such as Zawadzki (2020) who found that emerging market ETFs show higher levels of tracking error than developed ETFs, under all methods of tracking error estimation. The results from the alpha and beta estimates suggest that emerging ETFs underperform their benchmark index to a greater extent than developed ETFs. Additionally, we find that, in respect to emerging market indices, synthetic replication minimizes tracking error to the greatest extent. Further to that, when tracking developed market indices, partial physical ETFs minimize tracking error the most.

Table 5-32 presents the results of the average standard deviation of the return difference between the ETF and its benchmark index (TE_1). The results from TE_1 show that across the complete samples of emerging and developed ETFs, the emerging market sample exhibits significantly higher levels of tracking error than the developed market sample across all six sub periods and the full period. The TE_1 estimates for the emerging ETFs range from 0.244806% (2014-2015) to 0.678004% (2022-2024), with a full period estimate of 0.518469%. The emerging sample estimates are statistically significant at the 1% level across all periods, which suggests that tracking error is present and persistent. The TE_1 estimates for the developed ETFs are significantly lower in comparison ranging from 0.097234% (2016-2017) to 0.221699% (2012-2013). The developed ETFs estimates are significant at a 1% level for only three out of the seven periods of study. The results obtained in this study closely replicate that of Blitz and Huij (2012) who found that emerging ETFs exhibit significantly higher levels of tracking error than developed ETFs under the standard deviation method of estimation. These results also mirror that of Zawadzki (2020), who used seven ETFs that are common to our study. Zawadzki (2020), also found that emerging ETFs exhibit higher levels of significant tracking errors than developed ETFs with TE_1 estimates ranging from -0.027% to -0.030% for developed ETFs and from -0.047 to -0.059 for emerging ETFs. The absolute magnitude of the TE_1 estimates in Zawadzki (2020) closely mirror the results obtained in this study.

The average estimates obtained for the mean absolute deviation (MAD) in the return difference between the ETF and its benchmark (TE_2) and the standard error of the regression (TE_3) are presented in tables 5-33 and 5-34 respectively. These estimates exhibit the same results as TE_1, with the emerging ETFs demonstrating significantly higher levels of tracking error than the developed ETFs, across all subperiods and the full period. The average TE_2 and TE_3 estimates for the emerging ETFs are observed to be statistically significant at the 1% level, ranging from 0.127330% (2018-2019) to 0.456314% (2022-2024) and from 0.242644% (2014-2015) to 0.645066% (2022-2024), respectively.

The TE_2 and TE_3 estimates for the developed ETFs are statistically significant at the 5% level for the TE_2 (2012-2013) estimate only and at either the 5% or 1% level across all periods for the TE_3 estimates. The average estimates range from 0.037259% (2018-2019) to 0.963443% (2022-2024) for TE_2 and from 0.127102% (2014-2015) to 0.231813% (2022-2024) for TE_3. The estimates obtained in this study are consistent with those of Zawadzki (2020) and Blitz and Huij (2012), who used the same methods of tracking error quantification.

The average estimates for R^2 (TE_4) are presented in table 5-35. We observe that the average R^2 values for the emerging ETFs are statistically significant at the 1% level for the test of R^2 is equal to unity, across all periods. This observation suggests that the R^2 estimates for emerging ETFs differ significantly from 1, which is suggestive of emerging ETFs not being able to closely and accurately replicate their benchmark index. The R^2

estimates for the developed ETFs are observed to better approximate 1 in comparison to the emerging ETFs, with only the 2012-2013 estimate being statistically significant at the 5% level. These findings are closely related to the results obtained in Blitz and Huij (2012) and Khan, Bacha and Masih (2015), who found that the R^2 estimates for emerging ETFs exhibit a significant departure from 1. The results obtained for TE_4 further justify the observations made for TE_1, TE_2 and TE_3 which suggests that emerging ETFs suffer from a higher predisposition to tracking error in comparison to developed ETFs.

The results for the alpha and beta estimates are displayed in tables 5-36 and 5-37 respectively. The findings from these complementary measures are consistent with the findings of Khan, Bacha and Masih (2015). We observe in table 5-36 that the average alpha estimates for the emerging and developed ETFs are negative across all periods, which depicts underperformance of the ETF against its benchmark index.

The emerging ETF average alpha estimates are statistically significant at either the 5% or 1% level for six out of the seven periods of study. While the average alpha estimates for the developed ETFs are statistically significant at the 1% level across all periods. However, in respect to magnitude, the emerging ETFs show a higher level of underperformance for six out of the seven periods when conducting a period versus period comparison between emerging and developed ETFs. This observation is consistent with Zawadzki (2020) who attributed the presence of tracking errors in emerging ETFs to their underperformance against the benchmark index as observed in the results of their alpha estimates.

The results obtained from the beta estimates mimic that of what was observed for the R^2 analysis, with emerging ETFs showing a significant departure from 1 as derived from the results of the test of beta equal to unity, suggesting inefficient index replication. The observations made from the results of the alpha and beta estimates are complementary to and consistent with the tracking error observations across all four methods of tracking error estimation, therefore enabling us to conclude that emerging ETFs exhibit higher tracking errors and weaker tracking performance in comparison to developed ETFs, consistent with the findings of Blitz and Huij (2012), Khan, Bacha and Masih (2015) and Zawadzki (2020).

Elia (2012) and Meinhardt, Mueller and Schoene (2015) found that synthetic ETFs exhibit lower tracking errors for emerging markets. With those findings in mind, we observe from the results of the TE_1, TE_2 and TE_3 estimates that within the emerging market panel of tables 5-32, 5-33 and 5-34, synthetic ETFs are ranked first in respect to the magnitude of their tracking error, suggesting that out of the four replication strategies that the emerging ETFs follow, synthetic ETFs that track emerging indices exhibit the lowest level of tracking error.

The average R^2 estimates (table 5-35) for synthetically replicated emerging ETFs further justify this observation, as the average estimates for six out of the seven periods do not significantly differ from 1 at a 5% or 1% level of significance, suggesting close tracking of the underlying benchmark index. The complementary beta and alpha estimates further substantiate the findings that synthetically replicated emerging ETFs exhibit lower tracking errors in comparison to other forms of replication applied to emerging indices. The average alpha estimates, while statistically significant at either the 5% or 1% level for four out of the seven periods are extremely small and economically insignificant, therefore demonstrating insignificant levels of underperformance against the benchmark index. The beta estimates do not significantly differ from 1 for four out of the seven periods of study, suggesting close tracking of the benchmark index during most periods. The findings in this study in respect to the linkage between synthetic replication of emerging indices and tracking error minimization are consistent with Elia (2012) and Meinhardt, Mueller and Schoene (2015).

In respect to the developed ETFs, we find that the results from all four tracking error measures and the complementary alpha and beta analyses conform with that of the fund replication strategy and tracking error analysis, as partial physical (stratified and optimized) ETFs demonstrate the lowest levels of tracking error when tracking developed market indices. This observation was consistent across all sub periods and the full period. Therefore, with the goal of minimizing tracking error in mind, we can deduce that when using ETFs to replicate developed market indices, it is advised to use partial physical replication, and when aiming to track emerging market indices, the most suitable choice is synthetic ETFs.

Table 5-32: The Standard Deviation of the Active Return (TE_1) for Emerging and Developed ETFs

Replication Strategy	Fund Domicile	Number of ETFs	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Full physical	Emerging	6	0.569977	0.851847	0.554487	0.334440 *** (4)	0.307556 *** (4)	1.364656 *** (4)	0.233225 *** (4)	0.519000 *** (2)	0.594710 *** (2)	0.825904 *** (4)	1.499745
Stratified Sampled	Emerging	2	0.170781	0.585182	0.177991	0.212209 *** (2)	0.221900 *** (2)	0.219141 (2)	0.232148 *** (2)	0.643528 *** (4)	1.103328 *** (4)	0.574159 *** (3)	0.517811
Optimized	Emerging	2	0.753028	1.429580	0.575287	0.304312 *** (3)	0.307282 *** (3)	0.283763 ** (3)	0.348337 *** (3)	0.562794 *** (3)	0.778426 *** (3)	0.489141 *** (2)	0.699803
Synthetic	Emerging	6	-	-	-	0.161071 *** (1)	0.142488 *** (1)	0.162908 (1)	0.191787 *** (1)	0.162667 ** (1)	0.235552 * (1)	0.184670 ** (1)	-
All Emerging ETFs	**Emerging**	**16**	**0.497928**	**0.955536**	**0.435922**	**0.253008 *** (3)**	**0.244806 *** (1)**	**0.507617 *** (5)**	**0.251374 *** (2)**	**0.471997 *** (4)**	**0.678004 *** (7)**	**0.518469 *** (6)**	**0.905786**
Full physical	Developed	6	0.079827	0.071040	0.055770	0.576211 *** (4)	0.135171 *** (4)	0.131127 (4)	0.139128 *** (4)	0.171875 ** (3)	0.157239 (3)	0.320601 *** (4)	0.265635
Stratified Sampled	Developed	10	0.158062	0.091556	0.055170	0.066061 (1)	0.055089 * (1)	0.057389 (1)	0.060872 * (1)	0.072444 (1)	0.129016 (2)	0.083587 (2)	0.097333
Optimized	Developed	10	0.096239	0.204955	0.364190	0.080307 (2)	0.070292 ** (2)	0.075752 (2)	0.075305 ** (2)	0.077132 (2)	0.073173 (1)	0.076639 (1)	0.184220
Synthetic	Developed	6	0.486795	0.475812	0.325067	0.164217 *** (3)	0.132393 *** (3)	0.124667 (3)	0.138489 *** (3)	0.215841 ** (4)	0.161584 (4)	0.171623 * (3)	0.340770
All Developed ETFs	**Developed**	**32**	**0.205231**	**0.210841**	**0.200049**	**0.221699 *** (7)**	**0.098236 *** (5)**	**0.097234 (1)**	**0.103449 *** (6)**	**0.134323 * (3)**	**0.130253 (2)**	**0.163113 * (4)**	**0.221989**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF set as per TE_1 significance and magnitude for the emerging and developed samples in each column, and across the rows for the average TE_1.*
(Author's own construction, 2024)

Table 5-33: The Mean Absolute Deviation (MAD) of the Active Return (TE_2) for Emerging and Developed ETFs

Replication Strategy	Fund Domicile	Number of ETFs	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Full physical	Emerging	6	0.417710	0.626727	0.404494	0.220429 *** (4)	0.204850 *** (4)	0.236009 *** (4)	0.080026 *** (1)	0.195295 *** (2)	0.384448 *** (2)	0.220121 *** (2)	0.378154
Stratified Sampled	Emerging	2	0.106301	0.171728	0.098277	0.101854 *** (1)	0.116816 *** (2)	0.125967 *** (2)	0.113925 *** (3)	0.293285 *** (3)	0.697876 *** (4)	0.241660 *** (3)	0.202920
Optimized	Emerging	2	0.545580	0.943048	0.392430	0.205387 *** (3)	0.198799 *** (3)	0.173428 *** (3)	0.208931 *** (4)	0.357598 *** (4)	0.597127 *** (3)	0.290254 *** (4)	0.402665
Synthetic	Emerging	6	-	-	-	0.109205 *** (2)	0.105411 *** (1)	0.113021 *** (1)	0.106439 *** (2)	0.102391 ** (1)	0.145806 *** (1)	0.113760 *** (1)	-
All Emerging ETFs	**Emerging**	**16**	**0.356530**	**0.580501**	**0.298400**	**0.159219 *** (3)**	**0.156469 *** (2)**	**0.162107 *** (4)**	**0.127330 *** (1)**	**0.237142 *** (6)**	**0.456314 *** (7)**	**0.216449 *** (5)**	**0.327913**
Full physical	Developed	6	0.024646	0.028914	0.017883	0.108458 *** (4)	0.076737 *** (4)	0.070500 ** (4)	0.073555 *** (4)	0.093357 ** (4)	0.097591 (4)	0.086661 ** (4)	0.020890
Stratified Sampled	Developed	10	0.033175	0.018336	0.009788	0.010723 (1)	0.010019 (1)	0.010368 (1)	0.010157 (1)	0.020955 (2)	0.069905 (2)	0.022020 (2)	0.021485
Optimized	Developed	10	0.046198	0.085368	0.038487	0.017496 (2)	0.013926 (2)	0.012681 (2)	0.013755 (2)	0.013792 (1)	0.013490 (1)	0.014351 (1)	0.025679
Synthetic	Developed	6	0.298021	0.311252	0.245413	0.061603 ** (3)	0.057982 ** (3)	0.057676 ** (3)	0.051570 ** (3)	0.059383 (3)	0.072785 (3)	0.060190 (3)	0.203058
All Developed ETFs	**Developed**	**32**	**0.100510**	**0.110968**	**0.077893**	**0.049570 ** (7)**	**0.039666 (2)**	**0.037806 (1)**	**0.037259 * (4)**	**0.046872 (3)**	**0.063443 * (6)**	**0.045806 * (5)**	**0.067778**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF set as per TE_2 significance and magnitude for the emerging and developed samples in each column, and across the rows for the average TE_2.*
(Author's own construction, 2024)

Table 5-34: The Standard Errors of the Regression (TE_3) for Emerging and Developed ETFs

Replication Strategy	Fund Domicile	Number of ETFs	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Full physical	Emerging	6	0.537526	0.756162	0.482843	0.326959 *** (4)	0.30269 *** (3)	0.448774 *** (4)	0.232358 *** (3)	0.518778 *** (2)	0.581002 *** (2)	0.591528 *** (4)	1.080961
Stratified Sampled	Emerging	2	0.166277	0.583354	0.173623	0.208425 *** (2)	0.218668 *** (2)	0.214785 *** (2)	0.227635 *** (2)	0.633670 *** (4)	1.024018 *** (4)	0.559866 *** (3)	0.510785
Optimized	Emerging	2	0.749130	1.427900	0.575785	0.304209 *** (3)	0.306678 *** (4)	0.280482 *** (3)	0.345361 *** (4)	0.563078 *** (3)	0.740445 *** (3)	0.485286 *** (2)	0.697978
Synthetic	Emerging	6	-	-	-	0.159322 *** (1)	0.142532 *** (1)	0.160919 *** (1)	0.190547 *** (1)	0.161497 ** (1)	0.234800 ** (1)	0.183742 ** (1)	-
All Emerging ETFs	**Emerging**	**16**	**0.484311**	**0.922472**	**0.410751**	**0.249729 *** (3)**	**0.242644 *** (1)**	**0.276240 *** (4)**	**0.248975 *** (2)**	**0.469256 *** (6)**	**0.645066 *** (7)**	**0.455106 *** (5)**	**0.763242**
Full physical	Developed	6	0.079336	0.070008	0.055714	0.268729 *** (4)	0.134922 *** (4)	0.129183 *** (4)	0.136941 *** (3)	0.173378 ** (3)	0.154443 (3)	0.276914 *** (4)	0.230348
Stratified Sampled	Developed	10	0.155935	0.091358	0.055049	0.066068 ** (1)	0.055129 * (1)	0.057316 (1)	0.060723 * (1)	0.072222 (1)	0.125336 (2)	0.083180 (2)	0.097056
Optimized	Developed	10	0.095410	0.199308	0.240992	0.080327 ** (2)	0.070343 ** (2)	0.075729 * (2)	0.075163 ** (2)	0.077124 (2)	0.073138 (1)	0.076632 (1)	0.173537
Synthetic	Developed	6	0.477719	0.475616	0.325285	0.164159 *** (3)	0.132472 *** (3)	0.124744 *** (3)	0.138596 *** (4)	0.215449 ** (4)	0.161079 (4)	0.171620 ** (3)	0.340620
All Developed ETFs	**Developed**	**32**	**0.258542**	**0.351752**	**0.217558**	**0.165802 *** (4)**	**0.127102 ** (1)**	**0.132642 ** (3)**	**0.132080 ** (2)**	**0.201486 *** (5)**	**0.231813 *** (7)**	**0.212690 *** (6)**	**0.320961**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF set as per TE_3 significance and magnitude for the emerging and developed samples in each column, and across the rows for the average TE_3.*
(Author's own construction, 2024)

Table 5-35: R^2 of the Regression (TE_4) for Emerging and Developed ETFs.

Replication Strategy	Fund Domicile	Number of ETFs	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021	2022-2024	2012-2024	2006-2024
Full physical	Emerging	6	0.881084	0.893622	0.884990	0.876301 *** (3)	0.896874 *** (3)	0.775799 *** (4)	0.932997 *** (3)	0.897460 *** (2)	0.631607 *** (3)	0.765676 *** (4)	0.578574
Stratified Sampled	Emerging	2	0.991499	0.964833	0.988532	0.968739 (1)	0.975598 (1)	0.976684 (1)	0.971578 (1)	0.877328 *** (3)	0.690250 *** (2)	0.854432 *** (2)	0.917472
Optimized	Emerging	2	0.688355	0.689875	0.808538	0.856448 *** (4)	0.862482 *** (4)	0.854222 *** (3)	0.806905 *** (4)	0.825548 *** (4)	0.545305 *** (4)	0.774262 *** (3)	0.734359
Synthetic	Emerging	6	-	-	-	0.966377 (2)	0.969377 * (2)	0.960445 (2)	0.939069 *** (2)	0.978811 (1)	0.949157 (1)	0.962864 (1)	-
All Emerging ETFs	**Emerging**	**16**	**0.853646**	**0.849443**	**0.894020**	**0.916967 *** (2)**	**0.926083 *** (1)**	**0.891787 *** (5)**	**0.912637 *** (3)**	**0.894787 *** (4)**	**0.704080 *** (7)**	**0.839309 *** (6)**	**0.743469**
Full physical	Developed	6	0.991798	0.998913	0.998238	0.779795 *** (4)	0.935013 *** (4)	0.938862 ** (4)	0.914627 *** (4)	0.950245 ** (4)	0.934352 (4)	0.866409 *** (4)	0.922304
Stratified Sampled	Developed	10	0.962433	0.998075	0.998593	0.994880 (1)	0.996221 (1)	0.995050 (1)	0.994498 (1)	0.995652 (2)	0.968562 (3)	0.989478 (2)	0.992210
Optimized	Developed	10	0.985036	0.990591	0.890779	0.988543 (2)	0.990280 (2)	0.986437 (2)	0.987611 (2)	0.995932 (1)	0.993797 (1)	0.992421 (1)	0.963613
Synthetic	Developed	6	0.672177	0.945337	0.929156	0.961826 (3)	0.966727 ** (3)	0.959023 * (3)	0.964718 * (3)	0.980097 (3)	0.971131 (2)	0.972199 (3)	0.921302
All Developed ETFs	**Developed**	**32**	**0.902861**	**0.983229**	**0.954192**	**0.931261 ** (7)**	**0.972060 * (5)**	**0.969843 (2)**	**0.965363 * (6)**	**0.980482 (1)**	**0.966960 (3)**	**0.955127 (4)**	**0.949857**

*Note: Test of R^2 of R^2 equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (#) indicates ranking of each ETF set as per TE_4 significance and magnitude for the emerging and developed samples in each column, and across the rows for the average TE_3. (Author's own construction, 2024)*

Table 5-36: Alpha of the Regression for Emerging and Developed ETFs

Replication Strategy	Fund Domicile	Number of ETFs	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Full physical	Emerging	6	-0.014943	-0.014576	-0.019030	-0.016365 ***	-0.022417 ***	0.006463 ***	-0.014259 ***	-0.013829 ***	-0.019555 ***	-0.014580 ***	-0.014813
Stratified Sampled	Emerging	2	0.004766	0.000075	-0.002338	-0.002364 ***	-0.003219	0.001625	-0.000528	-0.003365 **	-0.015809 **	-0.002059	-0.000479
Optimized	Emerging	2	-0.007269	-0.009773	-0.009497	-0.011310	-0.015935 ***	-0.004858 ***	-0.011649 ***	-0.010698 ***	-0.020200 ***	-0.011163 ***	-0.011086
Synthetic	Emerging	6	-	-	-	-0.001941	-0.003399	-0.002257	-0.003317 **	-0.003661 ***	-0.003018 **	-0.003172 **	-
All Emerging ETFs	**Emerging**	**16**	**-0.001251**	**-0.004849**	**-0.005917**	**-0.005205 ****	**-0.007518 *****	**-0.001830**	**-0.005165 *****	**-0.005908 *****	**-0.013009 *****	**-0.005464 *****	**-0.005782**
Full physical	Developed	6	-0.003835	-0.004706	-0.003774	0.009823 ***	-0.007287 ***	-0.005956 ***	-0.006537 ***	-0.005845 ***	-0.006031 ***	-0.000159	0.000736
Stratified Sampled	Developed	10	-0.004732	-0.008041	-0.006721	-0.007278 **	-0.006762 ***	-0.007196 ***	-0.007379 ***	-0.006209 ***	-0.006806 ***	-0.006840 ***	-0.006845
Optimized	Developed	10	-0.003591	-0.005072	0.003229	-0.006925 **	-0.006279 ***	-0.006237 ***	-0.006424 ***	-0.005029 ***	-0.005137 ***	-0.005987 ***	-0.002862
Synthetic	Developed	6	-0.000123	-0.008413	-0.008501	-0.005035 **	-0.005318 **	-0.004689 ***	-0.004811 ***	-0.003707 ***	-0.005092 ***	-0.004834 ***	-0.006478
All Developed ETFs	**Developed**	**32**	**-0.003070**	**-0.006558**	**-0.003942**	**-0.002354**	**-0.006411 *****	**-0.006020 *****	**-0.006288 *****	**-0.005198 *****	**-0.005767 *****	**-0.004455 *****	**-0.003862**

*Note: Test of significance with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

Table 5-37: Beta of the Regression for Emerging and Developed ETFs

Replication Strategy	Fund Domicile	Number of ETFs	2006-2007 (%)	2008-2009 (%)	2010-2011 (%)	2012-2013 (%)	2014-2015 (%)	2016-2017 (%)	2018-2019 (%)	2020-2021 (%)	2022-2024 (%)	2012-2024 (%)	2006-2024 (%)
Full physical	Emerging	6	1.114438	1.196351	1.235713	1.028735	1.035650 ***	0.792934 ***	0.983304 **	0.988712 *	0.917740 ***	0.844334 ***	0.655949
Stratified Sampled	Emerging	2	0.982420	0.984103	0.978406	0.969854	0.977827 ***	0.978693	0.975415 ***	0.951727 ***	0.838417 ***	0.923890 ***	0.955912
Optimized	Emerging	2	0.933616	0.980505	1.006959	0.982752	0.975916 ***	0.950162 **	0.951303 ***	0.996984	0.769828 ***	0.936096 ***	0.959672 *
Synthetic	Emerging	6	-	-	-	0.976666	1.004844 ***	0.977204	0.979039 ***	0.985925 **	0.985148	0.984971	-
All Emerging ETFs	**Emerging**	**16**	**1.010158**	**1.053653**	**1.073692**	**0.989502**	**0.998559**	**0.924748 *****	**0.972265 *****	**0.980837 *****	**0.877783 *****	**0.922323 *****	**0.857178**
Full physical	Developed	6	0.990120	0.995713	0.998849	0.829072 ***	0.989155 *	0.979499	0.970681 ***	1.003620	0.973838	0.914581 ***	0.923118
Stratified Sampled	Developed	10	0.975906	0.997086	0.997389	0.997599	1.001268	1.003877	1.004794	0.997091	0.984656	0.996399	0.995838
Optimized	Developed	10	0.991849	0.989386	0.891023	1.000514	0.999744	0.998729	0.998611	0.999281	0.998906	0.999279	0.964384
Synthetic	Developed	6	0.876886	0.987419	1.006917	0.999012	0.997312	1.000586	1.001154	0.993263	1.007702	0.998834	0.990410
All Developed ETFs	**Developed**	**32**	**0.958690**	**0.992401**	**0.973545**	**0.956549 ****	**0.996870**	**0.995673**	**0.993810**	**0.998314**	**0.991276**	**0.977273**	**0.968438**

*Note: Test of beta of beta equal to unity with ***, **, * indicating significance at the 1%, 5%, and 10% levels. (Author's own construction, 2024)*

5.2.3. Tracking Error and Total Expense Ratio (TER)

Various studies such as, Frino and Gallagher (2001) and Chu (2010) have found that the tracking errors of funds are positively related to expenses, which suggest that an ETFs lower total expense ratio (TER) results in lower tracking error. Therefore, this section of the analysis looks at the average TERs of each replication strategy and fund domicile to determine whether the magnitude of their TERs conform with the results observed for their tracking error predispositions.

5.2.3.1. Fund Replication Strategy and TER

The average TER estimates for the different replication strategies are presented in the subsequent tables 5-38 to 5-42. The first finding that we observe is that the leveraged ETF sample demonstrates the highest level of TER (0.912%), this is expected as studies such as Rompotis (2012c) have highlighted the high costs and as a result high expense ratios associated with leveraged ETFs. The high costs associated with leveraged ETFs arise from their frequent rebalancing and the additional costs associated with evaluating their portfolios (Murphy and Wright, 2010; Rompotis, 2012c). In linking the tracking error estimates to the average TER, we find that the leveraged ETFs which demonstrate the highest TER, also exhibit the largest tracking error estimates across all methods of tracking error employed in this study. This observation conforms with the findings of previous studies such as Frino and Gallagher (2001) and Chu (2011), as we deduce that the replication strategy with the highest TER has also exhibited large significant tracking errors.

We find that when considering the other four forms of replication strategy, the average TER is the highest for the synthetic ETF sample (0.411%) and the lowest for the optimized ETF sample (0.173%). This contradicts with the results observed for the tracking error estimations, as we had observed that synthetic ETFs demonstrate lower levels of tracking errors than full physical ETFs, however in the case of the TER the full physical ETF sample shows an average TER of 0.356%. This result conforms with the findings of Charteris and McCullough (2020) who found that TER does not play a significant role in the tracking performance of funds as it yields conflicting results to that of the tracking error analysis.

However, when comparing the TERs of partial physically replicated ETFs with full physical ETFs, we find that the stratified (TER: 0.271%) and optimized ETF samples demonstrate lower TER magnitudes than the full physical sample. In this case, we find that our results conform with Frino and Gallagher (2001) and Chu (2010), as the partially replicated samples demonstrate lower tracking error and TER than the full physical sample. Overall, our comparison between the tracking error and TER of different replication strategies yields conflicting results. However, this is expected due to the large variety of ETFs following different replication strategies and tracking different benchmarks of various sizes included in this sample.

5.2.3.2. Fund Domicile and TER

Figures 5-1 and 5-2 present the average TER estimates for the emerging and developed market ETFs respectively. We observe that the average TER for developed ETFs (0.268%) is lower than that of emerging ETFs (0.593%). This observation conforms with our results under the tracking error analysis where we found that emerging market ETFs demonstrate higher levels of tracking error than developed ETFs. These results are consistent with Naumenko and Chystiakova (2015) and Saunders (2018) who both observed that the TER has a large and significant impact on the tracking errors of ETFs across various markets. Further to that, several studies such as Blitz and Huij (2012) and Hilliard and Dat Le (2022) found that emerging market ETFs have higher expense ratios and tracking errors compared to developed market ETFs.

It is integral to note that in this section of the study, we have conducted a simple comparative analysis between the average tracking error and TER across replication strategies and fund domiciles to add an additional analytical element to justify the tracking error results However, for a more accurate picture on the relationship between tracking performance and TER, it would be advised to conduct a regression analysis on ETF tracking performance using TER as a dependant variable. This was beyond the scope of this study.

Table 5-38: TER% for Full Physical ETFs

ETF Name and Ticker	TER %
iShares MSCI Mexico (EWW)	0.500
iShares MSCI South Africa (EZA)	0.590
iShares MSCI BIC (BFK)	0.700
Colombia Research Enhanced Emerging Economies (ECON US)	0.490
Colombia India Consumer (INCO US)	0.750
First Trust Emerging Markets Alpha Dex Fund (FEM)	0.800
SPDR S&P500 ETF Trust (SPY)	0.095
Invesco S&P500 Equal Weight (RSP)	0.200
Vanguard Growth (VUG)	0.040
SPDR Portfolio S&P500 (SPLG)	0.020
Vanguard FTSE Developed Markets (VEA)	0.060
Vanguard S&P500 (VOO)	0.030
Average TER% for full physical ETFs	**0.356**

(Author's own construction, 2024; Bloomberg, 2024)

Table 5-39: TER% for Stratified ETFs

ETF Name and Ticker	TER%
iShares Latin America 40 (ILF)	0.480
iShares China Large Cap (FXI)	0.740
iShares Core S&P Mid Cap (IJH)	0.050
iShares Core S&P Small Cap (IJR)	0.060
iShares Russell 3000 (IWV)	0.200
iShares S&P 100 (OEF)	0.200
iShares Russell 2000 Value (IWN)	0.240
iShares Russell 2000 Growth (IWO)	0.240
iShares S&P Mid Cap 400 Growth (IJK)	0.170
iShares MSCI Eurozone (EZU)	0.510
iShares S&P Mid Cap Value (IJJ)	0.180
iShares S&P Small Cap 600 Value (IJS)	0.180
Average TER% for stratified sampled ETFs	**0.271**

(Author's own construction, 2024; Bloomberg, 2024)

Table 5-40: TER% for Optimized ETFs

ETF Name and Ticker	TER%
iShares MSCI Emerging Markets (EEM)	0.700
Vanguard FTSE Emerging Markets (VWO)	0.080
iShares Core S&P500 (IVV)	0.030
iShares Russell 1000 Growth (IWF)	0.190
iShares S&P500 Growth (IVW)	0.180
SPDR Portfolio S&P500 Growth (SPYG)	0.040
SPDR Portfolio S&P500 Value (SPYV)	0.040
Vanguard Total Stock Market (VTI)	0.030
iShares MSCI World UCITS (IWRD)	0.500
iShares Core MSCI World UCITS (SWDA)	0.200
Schwab International Equity (SCHF)	0.060
Schwab US Broad Market (SCHB)	0.030
Average TER% for optimized ETFs	**0.173**

(Author's own construction, 2024; Bloomberg, 2024)

Table 5-41: TER% for Synthetic ETFs

ETF Name and Ticker	TER%
Amundi MSCI India II UCITS (INR)	0.850
Amundi MSCI Emerging Markets III UCITS (LEM)	0.550
Xtrackers MSCI Emerging Markets Swap UCITS (XMEM)	0.490
Amundi MSCI Brazil UCITS (BRZ)	0.550
Amundi MSCI Emerging Markets Asia (AASU)	0.200
Xtrackers MSCI Africa Top 50 Swap UCITS (XMKA)	0.650
Amundi NASDAQ-100 II (ANXU)	0.220
Amundi FTSE 100 (L100)	0.140
Amundi MSCI Europe Banks UCITS (CB5)	0.250
Amundi Dow Jones Industrial Average UCITS (DJE)	0.500
Amundi NASDAQ-100 UCITS (ANX)	0.230
Amundi Stoxx Europe Select Dividend 30 UCITS (SELD)	0.300
Average TER% for synthetic ETFs	**0.411**

(Author's own construction, 2024; Bloomberg, 2024)

Table 5-42: TER% for Leveraged ETFs

ETF Name and Ticker	TER%
ProShares Ultra MSCI Emerging Markets (EET)	0.960
ProShares Ultra S&P500 (SSO)	0.910
ProShares Ultra Pro S&P500 (UPRO)	0.920
ProShares Short S&P500 (SH)	0.880
ProShares Ultra Short S&P500 (SDS)	0.900
ProShares Ultra Pro Short S&P500 (SPXU)	0.900
Average TER% for leveraged ETFs	**0.912**

(Author's own construction, 2024; Bloomberg, 2024)

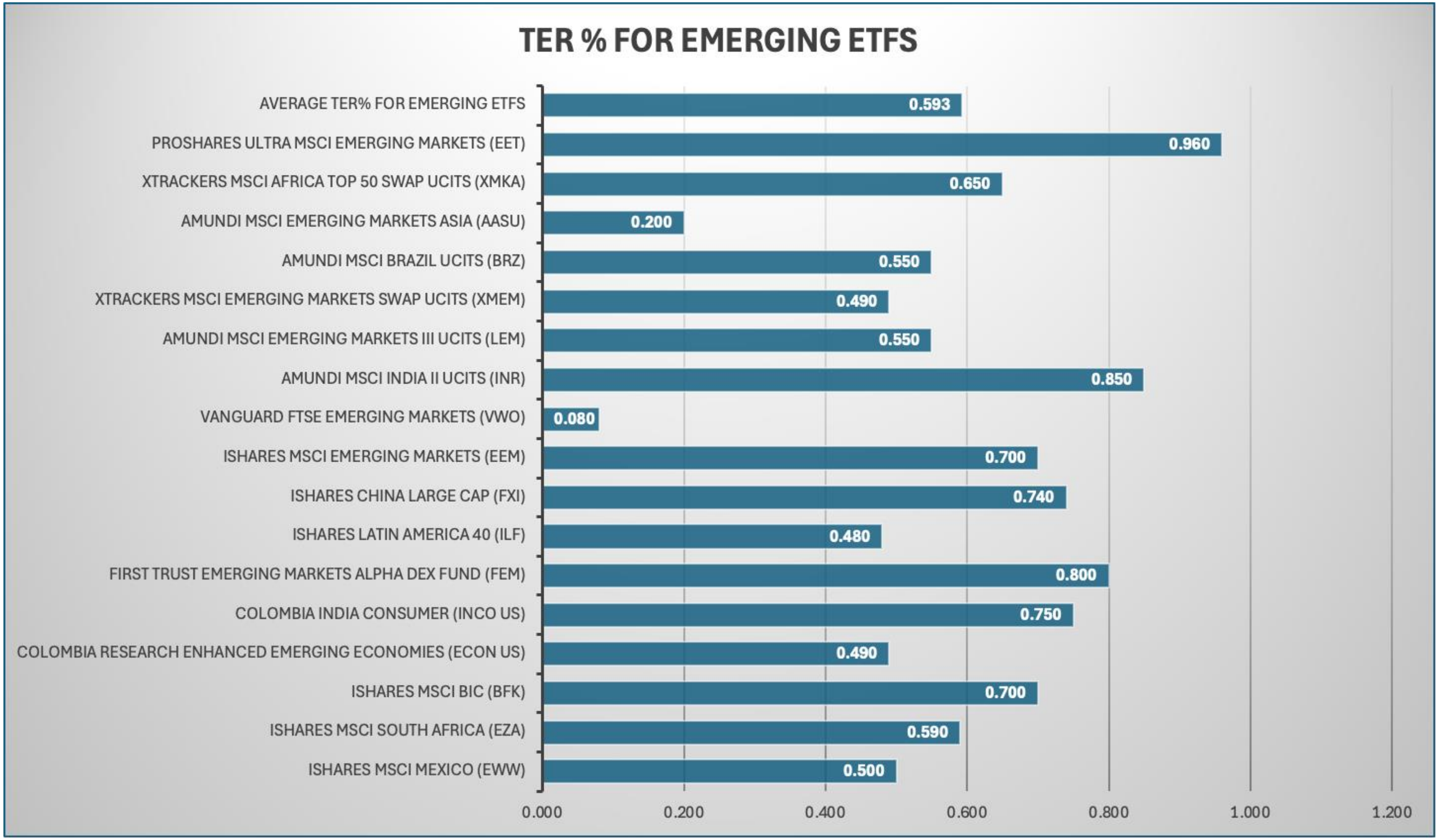

Figure: 5-1: TER% for Emerging ETFs

(Author's own construction, 2024; Bloomberg, 2024)

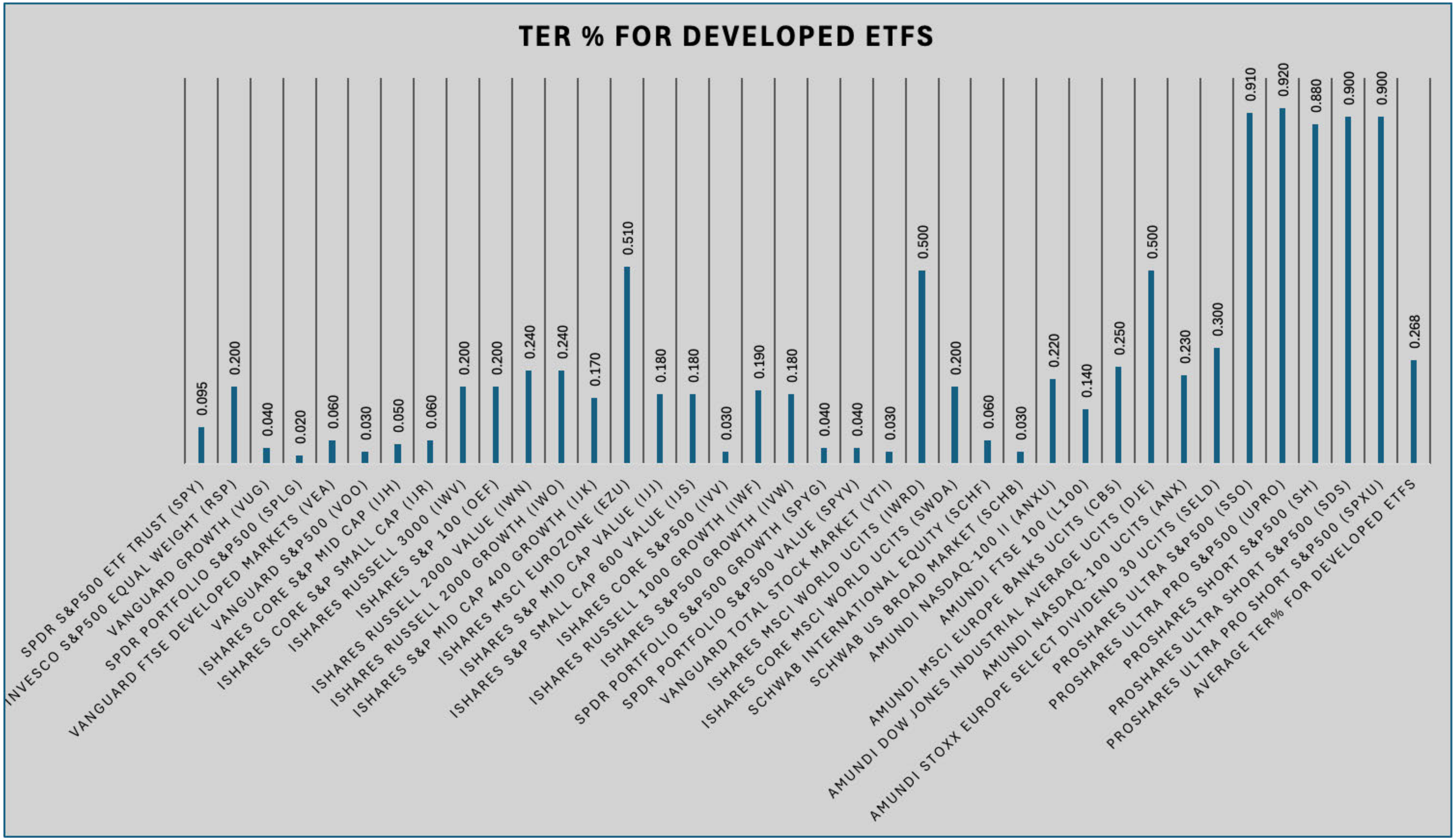

Figure: 5-2: TER% for Developed ETFs

(Author's own construction, 2024; Bloomberg, 2024)

5.2.4. Tracking Error and Crisis Period

This section of the study looks at the effects of crisis periods on the tracking error of ETFs. The period of study is extended to 2006 to 2024 to account for the effect of the Global Financial Crisis of 2008/2009. The leveraged ETFs are excluded from this analysis due to their extreme values as a result of their activeness that would affect the reliability and accuracy of the crisis period results, additionally, none of the leveraged ETFs used in the sample have an inception date prior to 2006. Further, we exclude synthetic ETFs from the analysis for the Global Financial Crisis periods of interest due to the sample consisting of only one synthetic ETF with sufficient data for 2006 to 2011. The lack of sufficient synthetic ETFs with an inception date before 2006, is expected as studies have shown that synthetic ETFs mostly gained traction post-GFC. The two crises under consideration in this section is the Global Financial Crisis of 2008/2009 (hereafter referred to as the GFC) and the COVID-19 pandemic, due to them having two of the largest impacts on global financial markets in the last two decades.

To account for the effect of the Global Financial Crisis (GFC) and the COVID-19 pandemic on the tracking performance of ETFs, the full period of study, 2006 – 2024 (18 years), was further divided into 9 two-year sub periods, 2006-2007, 2008-2009, 2010-2011, 2012-2013, 2014-2015, 2016-2017, 2018-2019, 2020-2021 and the full period 2022-2024. The Global Financial Crisis is represented by the sub period of 2008-2009, as previous studies, such as Arestad and Broström (2011) and Goltz and Schröder (2011), use 2008-2009 as the period most affected by the GFC.

The sub period of 2020-2021 represents the COVID-19 pandemic as informed by the first confirmed case of COVID-19 being recorded in January 2020 (World Health Organisation, 2024) and as used by previous studies such as Tsai (2024). The period 2020-2021 is also marked as the epitome of the pandemic, with the highest number of cases being recorded during this period (World Health Organisation, 2024) and the most severe lockdowns occurring worldwide, which had significant economic and financial implications for the global economy (Tsai, 2024). The sub period of 2022-2024 represents the aftermath of the emergency period of the COVID-19 pandemic, as restrictions were eased, and global markets began to recover.

The main sub periods of interest are 2006-2007 (pre-GFC), 2008-2009 (GFC), 2010-2011 (post-GFC), 2018-2019 (pre-COVID19), 2020-2021 (COVID19), 2022-2024 (post-COVID19). The subsequent figures 5-3 to 5-6 in conjunction with tables 5-2 to 5-13, 5-22 to 5-25 under the replication strategy analysis, present the results obtained from the TE_1, TE_2, TE_3 and alpha estimations in respect to ETFs categorized by different fund replication strategies and across the periods of interest. For the R^2 (TE_4) and beta estimates we refer to tables 5-14 to 5-21, found under the replication strategy analysis.

From these estimation methods we observe that across three of the replication strategies under consideration (full physical, stratified sampling and optimization), the tracking error estimates increase from 2006-2007 (pre-GFC) to 2008-2009 (GFC), with optimized ETFs showing the largest increase in tracking error across all three methods. In referencing the appropriate tables, we find that the 2008-2009 tracking error estimates across TE_1, TE_2 and TE_3 and the three replication strategies are significant at either the 5% or 1% level, which indicates that the existence of tracking errors are significant. The R^2 estimates (TE_4) show that during the 2008-2009 period, the estimates for full physical (0.963816) and optimized (0.915412) ETFs are statistically different from 1 at a 1% level of significance as indicated by the results of the test of unity. This observation indicates that during 2008-2009 full physical and optimized ETFs failed to accurately replicate their benchmark index to a greater extent, therefore predisposing them to a higher level of tracking error.

Figure 5-6 depicts the alpha estimates for ETFs of different replication strategies during the crisis periods. From these results we observe that all three methods of replication under consideration show increased levels of underperformance during 2008-2009 in comparison to 2006-2007. In reference to the appropriate tables, we observe that the underperformance is significant as the alpha estimates are statistically significant at the 1% level during 2006-2007 and 2008-2009. This observation suggests that during the GFC full physical, stratified and optimized ETFs suffered from increased levels of underperformance against their benchmark index. As with the tracking error estimates, the optimized ETFs showed the highest increase in underperformance from 2006-2007 to 2008-2009. The beta estimates however do not provide a clear indication of the tracking ability of the replication strategies during the GFC. However, we can conclude from the results of the four methods of tracking error estimation and the alpha estimates, that the optimized ETFs exhibited the highest level of tracking error during the GFC and suffered from the largest predisposition to the GFC in respect to increased tracking error in comparison to the pre-GFC period.

The results observed from the TE_1, TE_2, TE_3 and alpha estimates suggest that the full physically replicated ETFs exhibited the smallest increase in tracking error from the pre-GFC period to the GFC period. However, the TE_4 estimates suggest that the stratified ETFs showed the most resilience as their R^2 (TE_4) estimates remained statistically insignificant and approximated 1 the closest. These findings conclude that partial physical replication exhibits higher increases in tracking errors during periods of market crisis in comparison to full physical replication. In the recovery period of the GFC (2010-2011), we observe from figures 5-3 to 5-5, sharp declines in the estimates of all three methods of tracking error across all three replication strategies, with optimized ETFs showing the highest magnitude in the decline. We further observe a substantial decrease in the underperformance of all three methods of replication in figure 5-4, which suggests that during the post-GFC period, the ETFs' tracking performance began to recover.

In analysing the tracking error predisposition of ETFs following different replication strategies during the COVID-19 periods of interest, we refer to figures 5-3 to 5-5 and the appropriate tables. The results under the three methods of tracking error estimation (TE_1, TE_2 and TE_3) show increased levels of tracking error across all four replication strategies (full physical, stratified, optimized and synthetic) from 2018-2019 to 2020-2021. Figure 5-6 which depicts the alpha estimates corresponds with the tracking error results as we observe significant increases in ETF underperformance from 2018-2019 to 2020-2021. We further observe that the full physical ETFs exhibit the largest increase in TE_1, TE_2, TE_3 and alpha estimates, while the synthetic ETFs demonstrate the smallest increase. These findings are statistically significant at either the 5% or 1% levels as observed in the relevant tables.

The R^2 (TE_4) and beta estimates, however, did not yield conclusive results to justify the observations made under the first three methods of tracking error estimation and the alphas. However, under the TE_1, TE_2, TE_3 and alpha results we can conclude that, while all replication strategies suffered from a significant increase in tracking error during the height of the COVID-19 pandemic (2020-2021), full physical ETFs exhibited the highest increase in tracking error and the synthetic ETFs showed the lowest predisposition to increased tracking error.

This conclusion is consistent with that of Saffi and Zheng (2023), whose findings suggested that synthetic ETFs exhibited tracking errors that were 63.6% (relative to the mean) lower than those of physical ETFs during the COVID-19 outbreak. Saffi and Zheng (2023) justified this observation with the finding that, during liquidity shocks (COVID19 caused short-term losses in liquidity throughout financial markets globally), the tracking performance of synthetic ETFs are better protected than physical ETFs, due to the ability of synthetic ETFs to better control counterparty risk.

Interestingly, when we analyse the 2022-2024 period in figures 5-3 to 5-6 which is deemed the “recovery” period from the COVID19 pandemic (due to the abandonment of restrictions and decreased confirmed cases), we find that the results from the TE_1, TE_2, TE_3 and alpha estimates show no significant levels of recovery in the tracking performance of the ETFs across all replication strategies. This observation indicates that despite the decrease in the severity of the pandemic between January 2022 and January 2024, ETFs have not demonstrated significant improvements in tracking performance. Pre-existing literature such as Cao, Woo, Li and Liu (2020) attributes the lagged recovery of the ETF market to decreased investor sentiment because of the pandemic, which has resulted in reduced alphas and betas of ETFs.

In analysing the tracking error (TE_1, TE_2, TE_3) and alpha estimates of emerging and developed ETF samples during the crisis periods of interest, we refer to the subsequent figures 5-7 to 5-10 and tables 5-26 to 5-28 and 5-31 under the fund domicile analysis. We observe that the TE_1, TE_2, TE_3 and complementary alpha estimates show significant increases in tracking errors and ETF underperformance against the benchmark from 2006-2007 to 2008-2009, which is indicative of the GFC, and from 2018-2019 to 2020-2021, which reflects the COVID19 pandemic for both emerging and developed ETFs. However, the emerging ETFs show significantly higher increases in tracking error and underperformance (represented by alpha) during both periods of crises.

As with the analysis of replication strategy and crisis period, the R^2 (TE_4) and beta estimates, shown in tables 5-29 and 5-30 under the fund domicile analysis, provide conflicting results regarding the tracking performance dynamics of the ETF samples of interest during the crisis periods. These observations are consistent with the findings of Khan, Bacha and Masih (2015) who stated that emerging market ETFs exhibit higher tracking errors and less efficient index replication compared to developed market ETFs. In respect to the post-crisis periods of 2010-2011 (post-GFC) and 2022-2024 (post-COVID19), we observe that while both developed and emerging ETFs show significant levels of post-GFC recovery in 2010-2011 as demonstrated by observably lower TE_1, TE_2 and TE_3 estimates and lower levels of underperformance, emerging ETFs showed more extreme tracking error declines (depicted by steeper declines in figures 5-7, 5-8 and 5-9). As with the preceding analysis, the estimates obtained for 2022-2024 showed no significant recovery post-COVID19.

Therefore, we can conclude in this section of the study, that during the GFC partial physical ETFs suffered from a higher predisposition to increased tracking error than full physical ETFs, however they also showed the quickest recovery in respect to sharp declines in tracking error post-GFC. In respect to the COVID-19 pandemic, we observe that synthetic ETFs showed more resilience to increased tracking errors than full physical and partial physical ETFs. However, none of the replication strategies showed substantial recoveries in respect to decreased tracking errors post-COVID-19. In respect to the emerging and developed market ETFs, we observe that emerging market ETFs showed larger increases in tracking error during both crisis periods, and more extreme recovery than the developed ETFs in respect to decreased tracking error for the post-GFC period. The emerging and developed samples, like the replication strategies showed no substantial recovery during the post-COVID-19 period. From these observations, we find that in regard to both the replication strategies and fund domiciles, the ETF samples (partial replication/emerging) that showed larger increases in tracking error during the GFC, also showed more substantial recovery than their counterparts post-GFC. In comparing the recovery from the post-GFC period to the post-COVID-19 period, we find that across all replication strategies and fund domiciles of interest, the ETFs in the sample showed better levels of recovery (decrease in tracking errors) post-GFC than post-COVID-19.

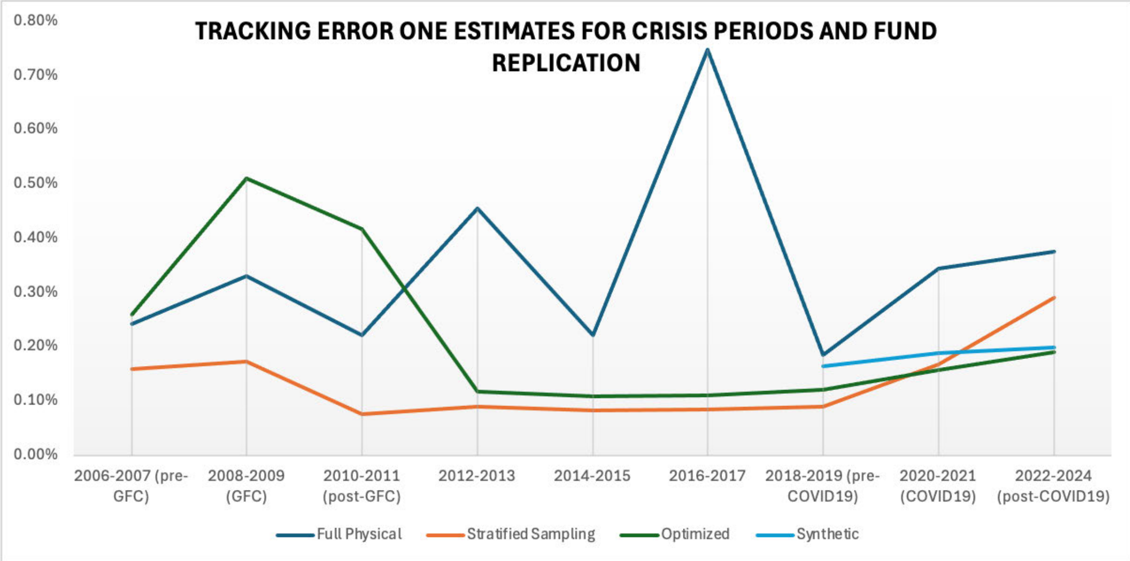

Figure 5-3: Standard Deviation of the Active Return (TE_1) for Crisis Periods and Fund Replication

(Author's own construction, 2024)

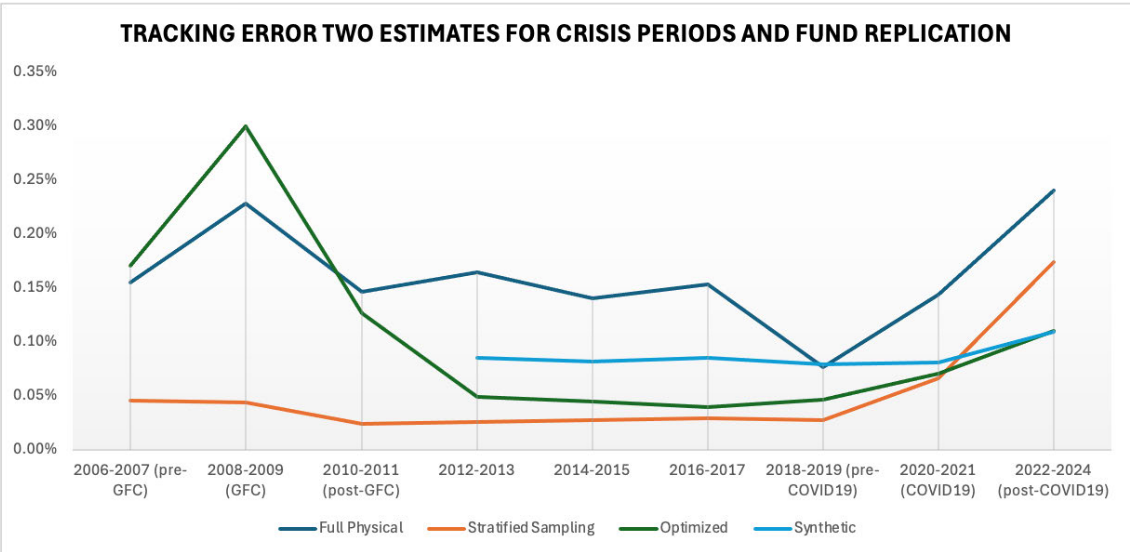

Figure 5-4: Mean Absolute Deviation of the Active Return (TE_2) Estimates for Crisis Periods and Fund Replication

(Author's own construction, 2024)

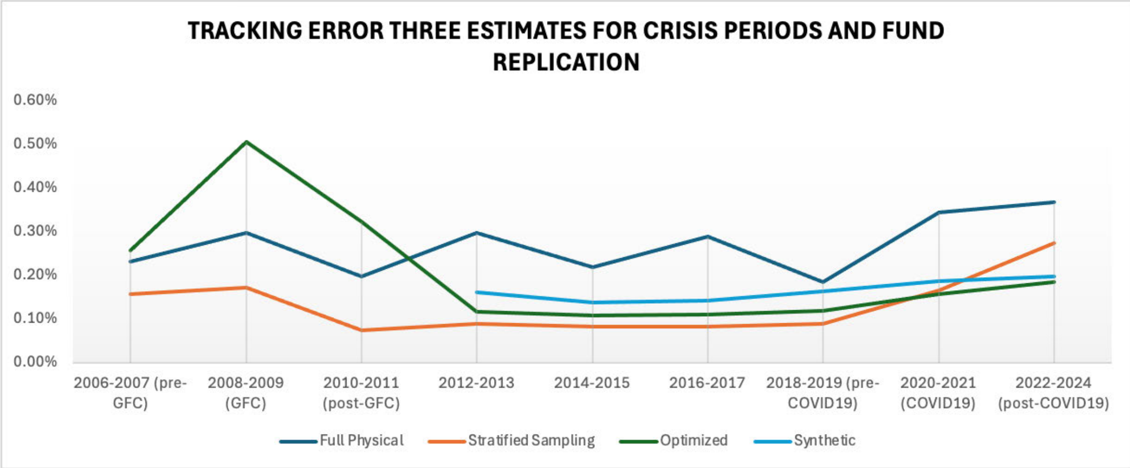

Figure 5-5: Standard Errors (TE_3) for Crisis Period and Fund Replication

(Author's own construction, 2024)

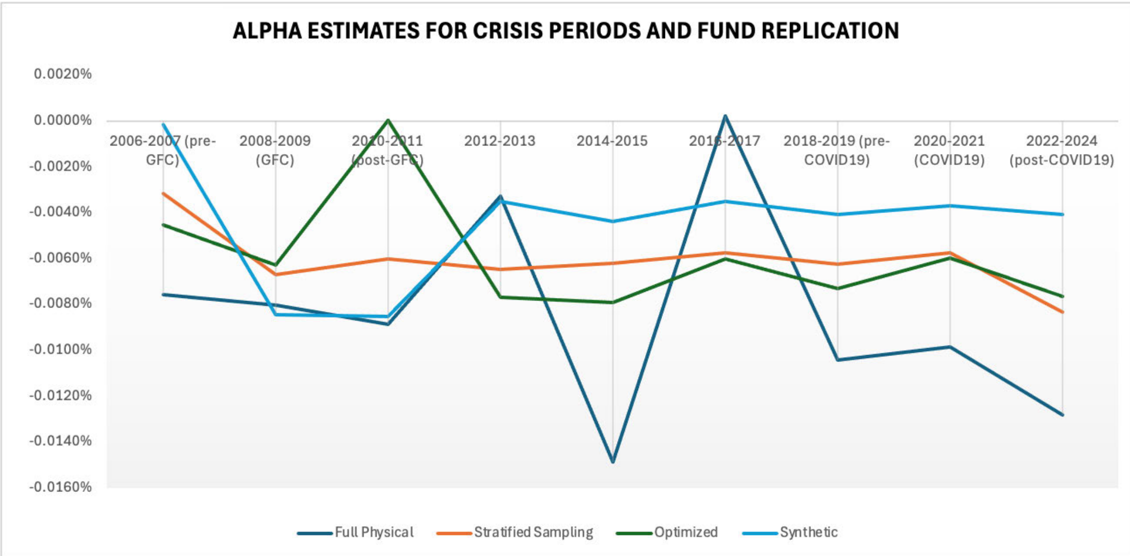

Figure 5-6: Alpha Estimates for Crisis Periods and Fund Replication

(Author's own construction, 2024)

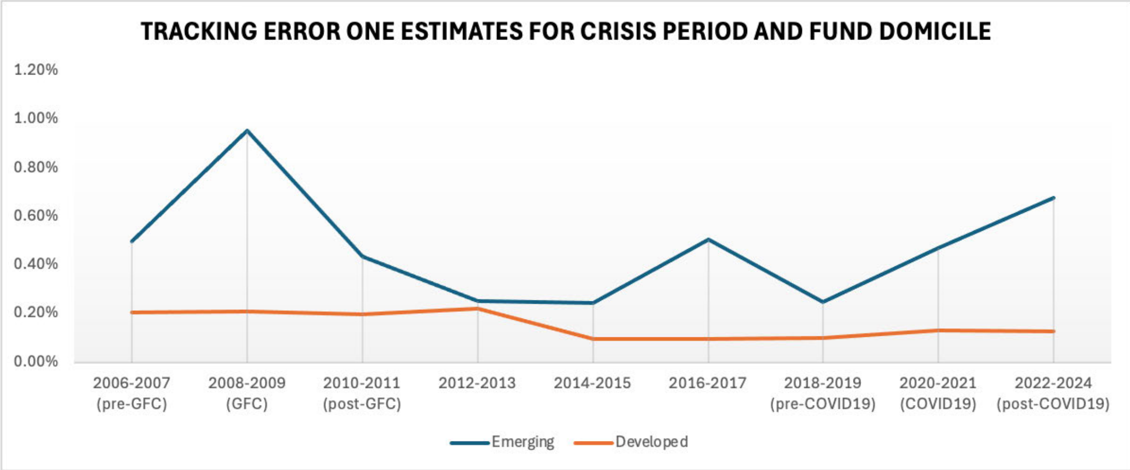

Figure 5-7: Standard Deviation of the Active Return (TE_1) for Crisis Periods and Fund Domicile

(Author's own construction, 2024)

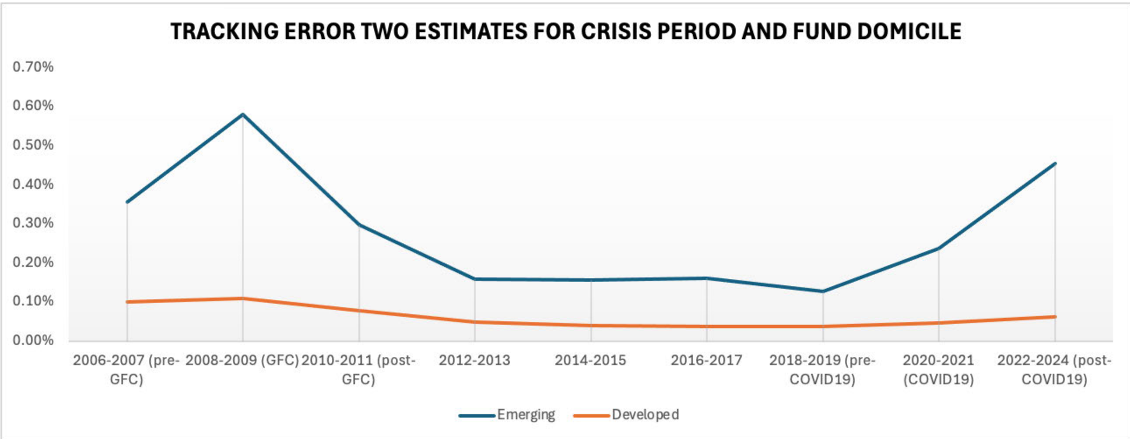

Figure 5-8: Mean Absolute Deviation (MAD) of the Active Return (TE_2) for Crisis Periods and Fund Domicile

(Author's own construction, 2024)

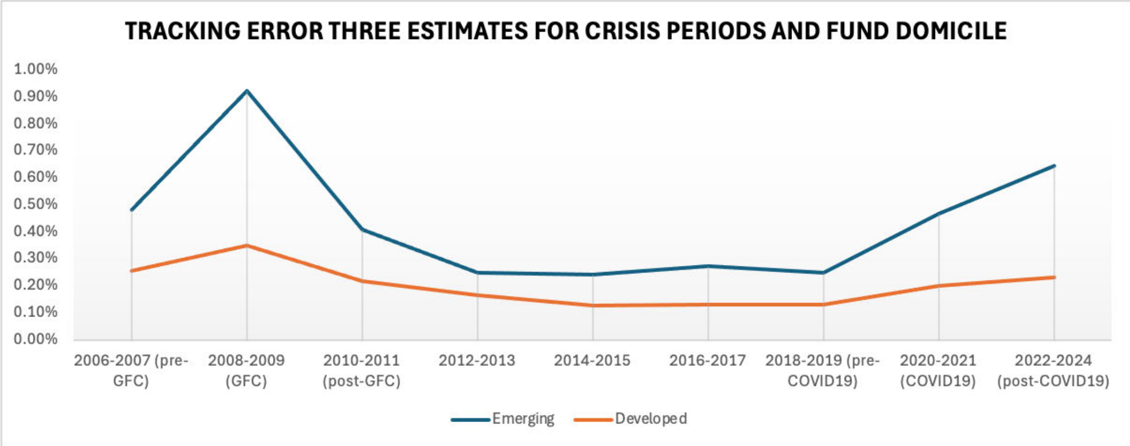

Figure 5-9: Standard Errors (TE_3) for Crisis Periods and Fund Domicile

(Author's own construction, 2024)

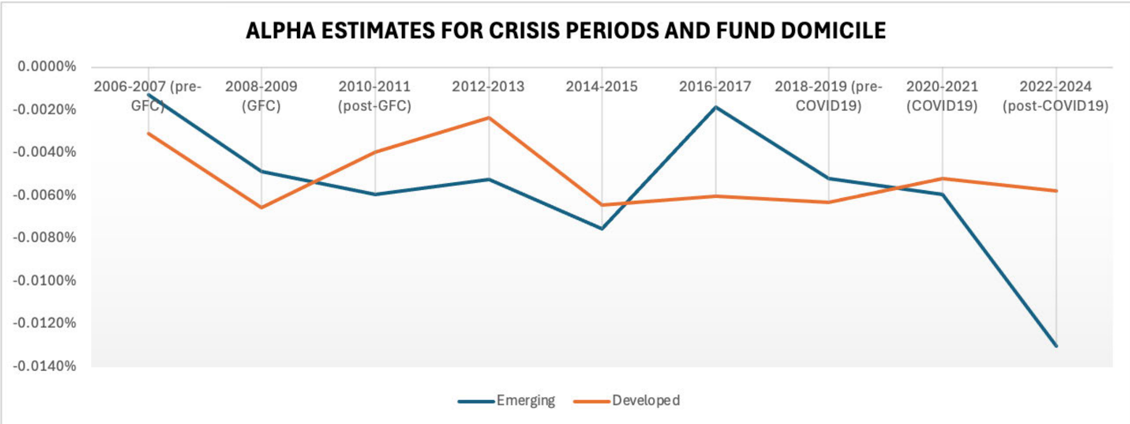

Figure 5-10: Alpha Estimates for Crisis Period and Fund Domicile

(Author's own construction, 2024)

6. Conclusion and Summary

The proliferation of ETFs into the investment market has resulted in increased interest around their nature, structure, functioning and their ability to effectively track their underlying benchmark index. As a result, the main aim of this study was to conduct a comprehensive analysis on a sample of 52 ETFs to determine how their adopted fund replication strategy and fund domicile impact their level of tracking error predisposition. Further to that we aimed to determine how the tracking errors of the ETFs in the sample fluctuated during periods of notable crisis such as the 2008/2009 Global Financial Crisis and the COVID-19 pandemic. The findings from this study were obtained by using four commonly adopted methods of tracking error estimation and obtaining the alpha and beta estimates derived from Sharpe's Single Index Market Model (1963). We further conducted a complementary analysis of the TER and tracking error linkage for the replication strategy and fund domicile analyses.

The existence of tracking errors is expected as ETFs are frequently predisposed to deviations in performance in comparison to their underlying benchmark indices because of the frictions that exist within markets. Due to the observation that tracking errors almost always persists, we focused our study on the variations in the magnitudes of the ETFs' tracking error across the different factors of study.

The first analysis performed in this study, focused on the isolated effect fund replication has on tracking error, considering five forms of ETF replication as found on Bloomberg Terminal, namely full physical, stratified sampling, optimized, synthetic and leveraged ETF replication. The findings obtained suggest that partial physical replication (stratified sampling and optimization) exhibit the lowest levels of tracking error under all methods of tracking error quantification used, in comparison to the other forms of replication considered. Further findings also demonstrated that the synthetic ETFs used in the sample demonstrate lower levels of tracking error in comparison to the full physically replicated ETFs under the methods of estimation used, which conform with the findings of Elia (2012) and contradict those of Mateus and Rahmani (2017). In this study we also considered a sample of six leveraged ETFs which produced results that suggest, when an identical benchmark index is being tracked by leveraged ETFs, the leveraged ETFs that have lower leverage multipliers minimize tracking error. Additionally, in comparing leveraged and inverse leveraged ETFs and applying a test of equality of beta is equal to the respective multiplier, we found that leveraged ETFs demonstrate better tracking performance and deliver their promised ratios more effectively than inverse leveraged ETFs. These findings conformed with that of Bansal and Marshall (2015).

The second analysis undertaken in this study focused on the effect of a fund's domicile on tracking error. In this study we categorized a fund's domicile as either an emerging or developed market. The findings of this analysis were consistent with Johnson (2009); Khan, Bacha and Masih (2015); Saunders (2018), as the results suggested that developed market ETFs exhibit lower levels of tracking error in comparison to emerging market ETFs. In addition, we looked at the combined effect fund replication (excluding leveraged) and fund domicile have on tracking errors. We found that synthetic replication exhibits the lowest tracking errors when tracking emerging market indices, while partial physical replication is preferred for tracking developed market indices, this observation was consistent with the findings of Elia (2012) and Meinhardt, Mueller and Schoene (2015).

In respect to the results of the complementary TER and tracking error comparative analysis conducted for the fund replication strategy and domicile analyses, we found mixed results. We observed that the TER and tracking error exhibit conflicting results for the ETFs following different replication strategies, which we attribute to the consideration of various replication strategies in this study, and the differing costs associated with each of them. However, for the fund domicile analysis, we observed that higher TER is associated with higher tracking error, which is consistent with Saunders (2018).

The last analysis performed in this study looked at the deviations in the tracking error of ETFs following different replication strategies (leveraged excluded) and those domiciled in emerging and developed markets, during notable crisis periods such as the GFC and the COVID19 pandemic. We observed that during the GFC optimized ETFs exhibited the largest increase in tracking errors, while the full physical ETFs exhibited the smallest increase. During the COVID19 pandemic the full physical ETFs exhibited the most significant increase in tracking error, while the synthetic ETFs showed the most resilience. Overall, however, ETFs following all replication strategies considered exhibited increases in tracking error during both periods of crisis.

The emerging ETFs demonstrated significantly higher levels of tracking error in comparison to the developed ETFs, during both crises. Therefore, our findings in this analysis are suggestive of the observation that increased market volatility, and the presence of market frictions results in increased levels of tracking error due to decreased investor sentiment and sharp declines in financial markets. However, while the post-GFC period showed significant declines of tracking error across all ETF categorisations indicating tracking performance recovery, the tracking error estimations showed no significant decline during 2022-2024, which was considered the post-COVID period. This observation was suggestive of the ETF markets having not recovered post-2021 because of decreased investor sentiment as a consequence of the pandemic.

Overall, the findings in this study were conclusive that the replication strategy employed by an ETF, the ETF's domicile of origin and the market frictions caused by crisis periods, all collectively impact the tracking performance of equity ETFs. This study is the first to assess the collective effects of replication strategy, fund domicile and crisis period on ETF tracking performance. From the findings in this study, we were able to deduce that tracking error persists across all the ETFs used in the study and across all periods of study. It is conclusive from our results and preexisting literature such as Rompotis (2006; 2009; 2012 a, b, c) and Strydom, Charteris and McCullough (2015), that due to various factors that have been thoroughly discussed in the sections of this study, tracking error exists indefinitely, therefore we placed focus on the magnitude of the tracking errors across the different subjects of study.

The implications of the preceding findings, suggest that sampling and optimization techniques can improve tracking performance by reducing the costs associated with full replication, such as transaction fees and liquidity constraints. In respect to the findings associated with leveraged ETFs, the implication is that the compounding effects and rebalancing inefficiencies that higher leverage multipliers introduce lead to higher tracking error. The fund domicile analysis indicates that synthetic replication may be more effective in emerging markets where liquidity constraints and market inefficiencies make full physical replication challenging. The implication that follows from partial physical ETFs performing better in developed markets is that ETFs in well-established markets may benefit from efficient sampling techniques while avoiding the high costs of full replication. Overall, the finding that developed market ETFs show superior tracking performance to emerging market ETFs, aligns with expectations, as developed markets generally have higher liquidity, lower trading costs, and fewer market frictions, reducing tracking errors. The finding under the market crisis analysis underscores that extreme market conditions lead to higher volatility, liquidity constraints, and price dislocations, making it challenging for ETFs to track their benchmarks accurately.

The findings of this study strongly align with its objectives which was to determine whether fund replication strategy, fund domicile, and crisis periods impact the tracking performance of equity ETFs. Under the replication strategy analysis, the preceding findings and implications confirm that replication strategy significantly affects tracking performance. In respect to the fund domicile analysis, the preceding findings show that fund domicile plays a role in tracking error predisposition. Lastly, the findings under the crisis period analysis supports the objective of this study by demonstrating that market disruptions lead to higher tracking errors.

This study has contributed significantly to the literature on equity ETFs, providing valuable insights for both academics and portfolio managers alike. By examining how different replication strategies affect tracking performance, this study adds nuance to existing ETF literature. It aids in clarifying how fund structure influences tracking error, an area of interest for researchers exploring ETF efficiency and investor outcomes. The findings in this study, further helps academics and investors to understand the trade-offs inherent to specific replication strategies and their impact on the ability of an ETF to accurately mimic the returns of its underlying benchmark index. The findings in the replication strategy analysis of this study can assist portfolio managers in better understanding the trade-offs between cost, accuracy, and risk. An example that highlights the significance of the prior statement is that while the findings show synthetically replicated ETFs exhibit lower levels of tracking error than full physical ETFs, they do introduce counterparty risk, which is a consideration portfolio managers must weigh when selecting specific ETFs for their portfolios.

Investigating the influence a fund’s domicile has on tracking performance addresses an identified gap in ETF literature as highlighted in preceding sections. It sheds light on the importance of regulatory environments, taxation, and operational factors that are country-specific and the impact they may have on tracking error. The insight from the fund domicile analysis is crucial to portfolio managers when applying multinational investment strategies where regional variations could affect returns. The consideration of the impact of the Global Financial Crisis and COVID-19 on tracking performance, advances knowledge about ETF resilience during periods of market stress and provides critical insights into how systematic risk impacts ETF performance, which adds to financial research on stability and the interconnection between ETFs, liquidity, and market volatility. By highlighting how crises influence ETF tracking performance, this study is helpful to portfolio managers when stress-testing portfolios and optimizing asset allocation under extreme conditions.

Overall, this study bridges gaps in ETF literature, equipping academics with a deeper understanding of ETF performance drivers and assisting portfolio managers in making more informed decisions regarding fund selection, regional considerations, and crisis management. It is also the first study to investigate all five Bloomberg replication classifications with the consideration of regional and crisis factors. This study further enhances investor confidence, building trust in ETFs as efficient vehicles for exposure to equity markets, even during times of crisis.

While this study exhibits originality and casts a wide net over various classifications of ETFs and has included both broad market and country-specific equity ETFs by using a data sample of significant size, it is not free from shortcomings. In that, we were unable to find sufficient data on ETFs with inception dates prior to 2006, which led to subdividing the data sample across the different subjects. Possible bias that this study may have been subject to is the survivorship bias as the study included ETFs that survived both crisis periods, having omitted funds that would have liquidated due to poor tracking or financial distress. To address any bias in the sample size we tried to ensure that all replication strategies beside the leveraged (which did not pose an issue as it was analysed separately) had an equivalent number of ETFs, however we were unable to ensure this for the emerging and domicile samples, therefore a possibility exists in that the dataset could have been skewed toward the developed ETF sample. Possible market structure and liquidity bias in that ETFs in emerging markets or following synthetic structures might suffer from wider bid-ask spreads, affecting tracking performance. The introduction of crisis-specific bias from volatility differences as the GFC and COVID-19 crises had different volatility dynamics, affecting tracking error in different ways.

Additionally, index changes and index composition changes had to be accounted for due to the identified unavailability of closing price data on certain indices. We addressed these shortcomings by performing an extensive data collection analysis via the Bloomberg Terminal, where we individually sifted through the ETF universe to find funds that were suitable to this study and would result in an extensive and representative sample for our subject of study. Thorough and careful research and collection were done to ensure that a large enough and appropriate data sample was chosen which resulted in a selection of 52 ETFs that covered all five replication strategies and provided us with enough price and NAV data to carry out an analysis that spanned a significant number of years to obtain unbiased and representative results.

The prior mentioned biases and limitations in this study could be addressed in future research by expanding the dataset to include both active and liquidated funds to avoid survivorship bias. Weighting ETFs more extensively to avoid overrepresentation of developed markets possibly through including ETFs with inception dates after 2012. Controlling for bid-ask spreads and trading volume in tracking error calculations. Apply further criteria for crisis period comparability by clearly defining crisis start and end dates based on volatility spikes and market conditions as opposed to reported dates.

Further recommendations for future study include extending the data sample and the period of study to gather further insight into the dynamics of tracking error in respect to a fund's replication strategy and domicile. The inclusion of more leveraged and inverse leveraged ETFs would result in more light being shed on the performance dynamics of those types of funds. The inclusion of additional documented crisis periods would also result in further observations regarding the behaviour of ETF tracking errors during volatile markets. Additional recommendations for further study, that were beyond the scope of this study, is to perform a regression analysis on factors that measure financial metrics such as economic development, exchange rate fluctuations and time variations between US trading hours and international trading hours to determine the isolated effect each factor has on tracking error magnitude to deduce the full extent to which developed market ETFs outperform their emerging market counterparts, as a result of market specific differences.

An additional recommendation is to conduct a regression analysis on factors that provide a measure for investor sentiment to determine its isolated effect on tracking performance/tracking errors during notable crisis periods. In respect to the TER analysis, including TER as a dependant variable regressed against the tracking performance of ETFs following different replication strategies and existing in different domiciles would provide further clarity on the linkage between TER and tracking performance. The robust work of this study can further pave the way for future research on fund replication strategies by conducting a granular analysis on how the effectiveness of different replication strategies vary across specific asset classes such as large-cap versus small-cap ETFs. Investigating how liquidity constraints and transaction costs impact tracking performance for different replication strategies. The fund domicile analysis could be further expanded to include the impact of market microstructure and liquidity by examining the role of bid-ask spreads, market depth and trading volume in influencing tracking error. The crisis period analysis can be further extended to compare tracking error behaviour during short-term volatility shocks versus prolonged financial downturns. The inclusion of analyzing ETF performance in different interest rate environments may add a relevant and fresh perspective to ETF literature by analyzing how shifts in monetary policy regimes, low versus high-interest rate environments, affect tracking performance, and whether replication strategies behave differently in rising interest rate environments.

A further interesting perspective that would increase the depth of this study in the future is the addition of sector-specific/thematic ETFs and ESG-compliant ETFs. The inclusion of ETFs such as the Health Care Select Sector SPDR Fund (XLV) which tracks the Health Care Select Sector Index (IXV) and the Vanguard Information Technology ETF (VGT) which tracks the MSCI US Investable Market Technology 25/50 Index, would provide insight into the unique tracking challenges faced by sector-specific funds in the health care and technology industries due to increased industry-specific volatility, specifically during periods such as the COVID-19 pandemic where the health care industry faced significant strain. Additionally, due to the growing popularity of sustainable investing, the inclusion of funds such as the iShares MSCI Global Sustainable Development Goals ETF (SDG) which tracks the MSCI ACWI Sustainable Impact Index would add an interesting layer to the study whereby the gap in literature surrounding ESG investing can be filled.

It is integral to note that due to the observed breaks in the daily closing price of the benchmark indices tracked by certain ETFs, we had to account for index and index composition changes, during the period of study. Careful research and selection were conducted to ensure the suitable indices were located and included to ensure representativeness and remove bias. Data transparency was ensured throughout this study by disclosing all data collection tools used and methodologies applied. The raw NAV, price, ADF, KPSS, VIF test results, and tracking error calculation data are readily available and can be requested from the author.

7. References

Aber, J. W., Li, D., & Can, L. (2009). Price volatility and tracking ability of ETFs. *Journal of Asset Management*, *10*(4), 210-221. https://doi.org/10.1057/jam.2009.13

Ackert, L. F., & Tian, Y. S. (2008). Arbitrage, liquidity, and the valuation of exchange-traded funds. *Financial Markets, Institutions & Instruments*, *17*(5), 331-362. https://doi.org/10.1111/j.1468-0416.2008.00144.x

Agapova, A. (2011). Conventional mutual index funds versus exchange-traded funds. *Journal of Financial Markets*, *14*(2), 323-343.https://doi.org/10.1016/j.finmar.2010.10.005

Aggarwal, R., & Huang, D. (2021). Withdrawal of high-frequency traders and intraday ETF volatility during the COVID19 crisis. *SSRN Electronic Journal*, *1*(1), 2-42. http://dx.doi.org/10.2139/ssrn.3992113

Aggarwal, R., & Schofield, L. (2014). The growth of global ETFs and regulatory challenges. *Advances in Financial Economics, 16*(1), 77-102. Emerald Group Publishing Limited. https://doi.org/10.1108/S1569-3732(2013)0000016003

Alexander, G. J., & Baptista, A. M. (2003). Portfolio performance evaluation using value at risk. *The Journal of Portfolio Management*, *29*(4), 93-102. https://doi.org/10.3905/jpm.2003.319898

Ali, M. M., & Thalheimer, R. (1983). Stationarity tests in time series model building. *Journal of Forecasting*, *2*(3), 249-257. https: //doi.org/10.1002/for.3980020307

Alighanbari, M., & Chia, C. P. (2016). Multifactor indexes made simple: A review of static and dynamic approaches. *The Journal of Index Investing*, *7*(2), 87-99. https://doi.org/10.3905/jii.2016.7.2.087

Amenc, N., Ducoulombier, F., Goltz, F., & Tang, L. (2012). What are the risks of European ETFs. *EDHEC Risk Institute, 1*(2)*, 1-70*. https://www. edhec-risk.com

Amenc, N., Goltz, F., & Grigoriu, A. (2010). Risk Control through dynamic core-satellite portfolios of ETFs: Applications to absolute return funds and tactical asset-allocation. *The Journal of Alternative Investments*, *13*(2), 47-57. https://www.proquest.com/scholarly-journals/risk-control-through-dynamic-coresatellite/docview/758683097/se-2

Andrew, T. (2022). Are investors turning towards country-specific ETFs in emerging markets? *Strategies allowing investors to have more granular exposures are increasing*. Retrieved 1 November 2024, from https://www.etfstream.com/articles /are-investors-turning-towards-country-specific-etfs-in-emerging-markets

Antoniewicz, R. S., & Heinrichs, J. (2014). Understanding exchange-traded funds: How ETFs work. *Jane, Understanding Exchange-Traded Funds: How ETFs Work, 20*(5)*,*1-39. http://dx.doi.org/10.2139/ssrn.2523540

Antoniou, A., Koutmos, G., & Pericli, A. (2005). Index futures and positive feedback trading : evidence from major stock exchanges. *Journal of Empirical Finance*, *12*(2), 219-238. https://doi.org/https://doi.org/10.1016/j.jempfin.2003.11.003

Aramonte, S., Caglio, C., & Tuzun, T. (2017). Synthetic ETFs. *Board of Governors of the Federal Reserve System: FEDS Notes*. Retrieved 12 August 2023, from https://www.federalreserve.gov/econres/notes/feds-notes/synthetic-etfs20170810.html?trk =public_post_comment-text

Arestad, C.-J., & Broström, C. (2011). Performance of exchange-traded funds during the financial crisis. *(No publishing information available)*. Retrieved 23 August 2024, from https://api.semanticscholar.org/CorpusID:167159410

Armour, B. (2024). Active ETFs are soaring. Should you invest? Retrieved 4 August 2024, from https://www.morningstar.com/funds/active-etfs-are-soaring-should-you-invest

Aroskar, R., & Ogden, W. A. (2012). An analysis of exchange traded notes tracking errors with their underlying indexes and indicative values. *Applied Financial Economics*, *22*(24), 2047-2062. https://doi.org/10.1080/09603107.2012.684787

Avdiu, K., & Unger, S. (2023). Index tracking error optimization of equity and fixed-income ETFs. *The Journal of Beta Investment Strategies*, *14*(4), 92-107. https://doi.org/10.3905/jbis.2023.1.050

Avellaneda, M., & Dobi, D. (2012). Structural Slippage of Leveraged ETFs. *Advanced Risk & Portfolio Management® Research Paper Series*, *1*(1), 1-17. http://dx.doi.org/10.2139/ssrn.2127738

Babalos, V., Caporale, G. M., & Spagnolo, N. (2021). Equity fund flows and stock market returns in the USA before and after the Global Financial Crisis: a VAR-GARCH-in-mean analysis. *Empirical Economics*, *60*(2), 539-555. https://doi.org/10.1007/s00181-019-01783-5

Bae, K., & Kim, D. (2020). Liquidity risk and exchange-traded fund returns, variances, and tracking errors. *Journal of Financial Economics*, *138*(1), 222-253. https://doi .org/10.1016/j.jfineco.2019.02.012

Bahadar, S., Gan, C., & Nguyen, C. (2020). Performance dynamics of international Exchange-Traded Funds. *Journal of Risk and Financial Management*, *13*(8), 2-14. https://doi.org/10.3390/jrfm13080169

Bajpai, P. (2021). What are synthetic ETFs? Retrieved 10 June 2023, from https://www.nasdaq.com/articles/what-are-synthetic-etfs-2021-09-22

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bansal, V. K., & Marshall, J. F. (2015). A tracking error approach to leveraged ETFs: Are they really that bad? *Global Finance Journal*, *26*(2015), 47-63. https://doi.org/10.1016 /j.gfj.2015.01.004

Baptista, A., & Alexander, G. (2008). Active portfolio management with benchmarking: Adding a value-at-risk constraint. *Journal of Economic Dynamics and Control*, *32*(3), 779-820. https://doi.org/10.2139/ssrn.686188

Barma, N. H., & Vogel, S. K. (2021). The Global Financial Crisis. In Martinelli, A. & Cavalli, A. (Eds.). *The Political Economy Reader: Contending Perspectives and Contemporary Debates*, 316-334. Routledge. https://doi.org/10.1163/9789004351776_016

Bartram, S. M., & Bodnar, G. M. (2009). No place to hide: The global crisis in equity markets in 2008/09. *History of Finance eJournal*, *28*(8), 1246-1292. https://doi.org/10.1016/j.jimonfin.2009.08.005

Baş, N. K., & Sarioğlu, S. E. (2015). Tracking ability and pricing efficiency of Exchange-Traded Funds: Evidence from Borsa Istanbul. *Business and Economics Research Journal*, *6*(1), 19-33. https://doi.org/1309-2448

Bekaert, G., & Harvey, C. R. (1995). Time-varying world market integration. *The Journal of Finance*, *50*(2), 403-444. https://doi.org/10.1111/j.1540-6261. 1 995.tb04790.x

Belhassine, O., & Karamti, C. (2021). Contagion and portfolio management in times of COVID-19. *Economic Analysis and Policy*, *72*(2021), 73-86. https://doi.org/10.1016/j.eap.2021.07.010

Ben-David, I., Franzoni, F., & Moussawi, R. (2012). ETFs, arbitrage, and shock propagation. *Fischer College of Business Working Paper Series, No. 2012,* 1-73. https: //doi.org/10.2139/ssrn.1967599

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do ETFs increase volatility? *The Journal of Finance*, *73*(6), 2471-2535. https://doi.org/10.1111/jofi.12727

Berg, N., & Lien, D. (2003). Tracking error decision rules and accumulated wealth. *Applied Mathematical Finance*, *10*(2), 91-119. https://doi.org/10.1080/1350486032000088912

Berk, J. B., & Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, *112*(6), 1269-1295. https://doi.org/10.108 6/424739

Bernstein, P. J. (2002). A primer on exchange-traded funds. *Journal of Accountancy*, *193*(1)*,* 38-41. https://www.journalofaccountancy.com/issues/2002/jan/aprimeronexchangetradedfunds.html

Birdthistle, W. A. (2008). The fortunes and foibles of Exchange-Traded Funds: A positive market response to the problems of mutual funds. *The Delaware Journal of Corporate Law*, *33*(1), 69-109. https://ssrn.com/abstract=1267466

Blake, C. R., Elton, E. J., & Gruber, M. J. (1993). The performance of bond mutual funds. *The Journal of Business*, *66*(3), 371-403. http://www.jstor.org/stable/2353206

Blitz, D., & De Groot, W. (2013). Strategic allocation to commodity factor premiums. *The Journal of Alternative Investments*, *17*(2), 103-115. https://doi.org/10.3905/jai.2014.17.2.103

Blitz, D., & Huij, J. (2012). Evaluating the performance of global emerging markets equity exchange-traded funds. *Emerging Markets Review*, *13*(2), 149-158. https://doi.org/10.1016/j.ememar.2012.01.004

Blocher, J., & Whaley, R. E. (2014). *Passive Investing: The Role of Securities Lending*. Vanderbilt Owen Graduate School of Management. *Vanderbilt Owen Graduate School of Management Research Paper*, *No.2474904.* 1-37. https: //acfr.aut.ac.nz/data/assets/pdf_file/0010/29917/WhaleyPassive-Investing.pdf

Bloomberg. (2021). Stigma surrounding synthetic ETFs should be put to rest for good. Retrieved 12 September 2024, from https://www.bloomberg.com/professional/insights/trading/stigma-surrounding-synthetic-etfs-should-be-put-to-rest-for-good/

Bloomberg Professional Terminal. (2024). *ETF and Index NAV and Price Data.* [Data Collection, 21 June 2021-23 August 2024].

Blume, M. E., & Edelen, R. M. (2002). On replicating the S&P 500 index. *The Rodney L. White Center for Financial Research: Working Paper Series, No. 08-02.* 1-32. https://finance.wharton.upenn.edu/~rlwctr

Boersma, A. J. J., L. Todd. (2020). Best practices model portfolio performance. *The CFA Instituite and State Street Global Advisors White Paper*. 1-8. Retrieved 10 June 2024, from https://www.ssga.com/librarycontent/announcement/etfs/au/

Borio, C., Claessens, S., Schrimpf, A., Shin, H. S., & Todorov, K. (2021). The anatomy of bond ETF arbitrage. *BIS Quarterly Review 2021*, *March* (2021). 41-53. https://www.bis.org/publ/qtrpdf/r_qt2103d.htm

Bowes, J., & Ausloos, M. (2021). Financial risk and better returns through Smart Beta Exchange-Traded Funds? *Journal of Risk and Financial Management*, *14*(7), 283-313. https://doi.org/10.3390/jrfm14070283

Braun, P. A. (2018). Smart beta Exchange-Traded Funds and factor investing. *Kellogg School of Management Cases*, *Business Case Series, No. 2018.* 1-39. https://doi.org/10.4135/9781526474995

Brinson, G. P., Hood, L. R., & Beebower, G. L. (1995). Determinants of portfolio performance. *Financial Analysts Journal*, *42*(4), 39-44. https://doi.org/10.2469/faj.v42.n4.39

Broby, D., & Spence, O. (2020). The tracking efficiency of physical and synthetic equity index ETFs. *The Journal of Index Investing*, *11*(3), 34-47. https://doi.org/10.3905/jii.2020.1.097

Brogaard, J., Heath, D., & Huang, D. J. (2020). The heterogeneous effects of passive investing on asset markets. *Capital Markets:Market Microstructure eJournal*, *1*(1), 1-85. http://dx.doi.org/10.2139/ssrn.3510359

Broms, T. J., & Gastineau, G. L. (2006). The development of improved exchange-traded funds (ETFs) in the United States. *Proceedings of the Third Annual Brookings-Tokyo Club Conference: New Financial Instruments and Institutions: Policy Challenges,* The Brookings Institution, Washington, USA. *The Journal of Beta Investments, 2007*(1)*,* 16-26. https://www.nomurafoundation.or.jp/en/wordpress/

Brown, M. (2010). *Total Expense Ratios - Some Explanation.* Retrieved 11 November 2023, from http:// www.etfsa.co.za/news/2010/totalexpenseratiosjul2010.pdf/

Buetow, G. W., & Henderson, B. J. (2012). An empirical analysis of exchange-traded funds. *Journal of Portfolio Management*, *38*(4), 112-127. https://doi.org/10.3905/jpm.2012.38.4.112

Cairns, P. (2014). South Africa's most innovative ETFs. *Personal Finance*, *2014*(403), 4-6. https://doi.org/doi:10.10520/EJC156322

Cao, K. H., Woo, C.-K., Li, Y., & Liu, Y. (2022). Covid-19's effect on the alpha and beta of a US stock exchange-traded fund. *Applied Economics Letters*, *29*(2), 123-128. https://doi.org/10.1080/13504851.2020.1859447

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Cervantes, P., Díaz, A., Esparcia, C., & Huélamo, D. (2022). The impact of COVID-19 induced panic on stock market returns: A two-year experience. *Economic Analysis and Policy*, *76*(2022), 1075-1097. https://doi.org/10.1016/j.eap.2022.10.012

Chai, D., Faff, R., & Gharghori, P. (2013). Liquidity in asset pricing: New Australian evidence using low-frequency data. *Australian Journal of Management*, *38*(2), 375-400. https://doi.org/10.1177/0312896213489143

Charteris, A., Chau, F., Gavriilidis, K., & Kallinterakis, V. (2014). Premiums, discounts and feedback trading: Evidence from emerging markets' ETFs. *International Review of Financial Analysis*, *35*(2014), 80-89. https://doi.org/10.1016/j.irfa.2014.07.010

Charteris, A., & McCullough, K. (2020). Tracking error vs tracking difference: Does it matter? *Investment Analysts Journal*, *49*(3), 269-287. https://doi.org/10.1080/10293523.2020.1806480

Charupat, N., & Miu, P. (2011). The pricing and performance of leveraged exchange-traded funds. *Journal of Banking & Finance*, *35*(4), 966-977. https://doi.org/10.1016/j.jbankfin.2010.09.012

Charupat, N., & Miu, P. (2013). Recent developments in exchange-traded fund literature: Pricing efficiency, tracking ability, and effects on underlying securities. *Managerial Finance*, *39*(5), 427-443. https://doi.org/10.1108/030743513113138

Charupat, N., & Miu, P. (2016). *Leveraged exchange-traded funds. A Comprehensive Guide to Structure, Pricing, and Performance*, 176. Palgrave Macmillan. https://doi.org/10.1057/9781137478214

Chen, J., Chen, Y., & Frijns, B. (2017). Evaluating the tracking performance and tracking error of New Zealand exchange traded funds. *Pacific Accounting Review*, *29*(3), 443-462. https://doi.org/10.1108/PAR-10-2016-0089

Cheng, M., & Madhavan, A. (2009). The dynamics of leveraged and inverse-exchange traded funds. *Journal of Investment Management*, *7*(4), 43-62. https://api.semanticscholar.org/CorpusID:55556779

Cheng, S., Massa, M., & Zhang, H. (2019). The unexpected activeness of passive investors: A worldwide analysis of ETFs. *The Review of Asset Pricing Studies*, *9*(2), 296-355. https://doi.org/10.1093/rapstu/ray011

Chiang, W. (2001). Optimizing performance. In Neubert, A.S. (Eds.) *Indexing for Maximum Investment Results*, 1-30. Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9781315074054-17/

Chlebisz, A. (2018). ETF Efficiency compared to active managed equity investment funds based on the capital market in Poland. *Journal of Organisational Culture and Management* (*Rynek-Społeczeństwo-Kultura*), *1*(27), 46-50. https://kwartalnikrsk .pl/Artykuły/RSK1-2018/RSK1-2018-Chlebisz-Efektywność-EFT.pdf

Chu, P. K.-K. (2011). Study on the tracking errors and their determinants: Evidence from Hong Kong exchange-traded funds. *Applied Financial Economics*, *21*(5), 309-315. https://doi.org/10.1080/09603107.2010.530215

Chu, P. K.-K. (2013). Tracking errors and their determinants: Evidence from Hong Kong exchange-traded funds. *SSRN Electronic Journal, 1*(1), 1-30. http://dx.doi.org/10.2139/ssrn.2303600

Clements, R. (2019). Are ETFs making some asset managers too interconnected to fail? *University of Pennsylvania Journal of Business Law, 22*(4)*,* 1-70. https://ssrn.com/abstract=3516936

Cohen, S. (2023). Global ETF market facts: Three things to know from Q1 2023 [Electronic Article]. Retrieved 24 November 2023, from https://www.nasdaq.com/articles/global-etf-market-facts%3A-three-things-to-know-from-q1-2023

Colon, J. M. (2017). The great ETF tax swindle: The taxation of in-kind redemptions. *Penn State Law Review, 122*(1)*,* 1-68. https://ir.lawnet.fordham.edu/faculty

Converse, N., Levy-Yeyati, E., & Williams, T. (2020). How ETFs amplify the global financial cycle in emerging markets? *Harvard Center for International Development Faculty Working Paper Series, No. 351,* 1-61. https://growthlab.hks.harvard.edu/files/growthlab/files/2019-05-cid-wp-351-etf-amplify.pdf

Corse, M. H., Nusrath; Hsu, David. (2020). An overview of physical and synthetic ETF structures. Retrieved 22 May 2024, from https://www.it.vanguard/content/dam/intl/europe/documents/en/physical-and-synthetic-etf-structures-eu-en-pro1.pdf

Cox, P. W., & Lehrbass, F. B. (2018). Which factors explain the quality of replication of an ETF? *Capital Markets:Asset Pricing & Valuation Journal*, *16*(1), 9-122. http://dx.doi.org/10.2139/ssrn.3453066

Cresson, J. E., Mike Cudd, R., & Lipscomb, T. J. (2002). The early attraction of S&P index funds: Is perfect tracking performance an illusion? *Managerial Finance*, *28*(7), 1-8. https://doi.org/10.1108/03074350210767933

Cutler, D. M., Poterba, J. M., & Summers, L. H. l. (1990). Speculative dynamics and the role of feedback traders. *The American Economic Review, 80*(2)*,* 63-68. http://www.jstor.org/stable/2006544

Darolles, S., Dudek, J., & Le Fol, G. (2016). Gauging liquidity risk in emerging market bond index funds. *Annals of Economics and Statistics, 123(124)*, 247-269. https ://doi.org/10.15609/annaeconstat2009.123-124.0247

Daswa, K. A. (2016). *Perfomance evaluation of the tracking ability and pricing efficiency of exchange-traded funds (ETFs) in South Africa (Masters dissertation). University of the Western Cape*. https://core.ac.uk/download/pdf/92534834.pdf

Dębski, W. (2010). The financial market and its mechanisms. *Warsaw Scientific Publishing House*, *17*(2), 68-74. https://doi.org/10.2478/manment-2013-0072

DeFusco, R. A., Ivanov, S. I., & Karels, G. V. (2011). The exchange traded funds' pricing deviation: analysis and forecasts. *Journal of Economics and Finance*, *35*(2011), 181-197. https://doi.org/10.1007/s12197-009-9090-6

Dellva, W. L. (2001). Exchange-traded funds not for everyone. *Journal of Financial Planning*, *14*(4), 110-124. https://www.proquest.com/trade-journals/exchange-traded-funds-not-everyone/

Deloitte. (2017). Introduction to Section 871 (m) of the International Revenue Code (IRC). *Deloitte Financial Services Review, 2017*(1), 1-12. Retrieved 10 June 2024 from, https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/financial-services/ch-fs-en-introduction-to-irc-section-871(m).pdf

DeMiguel, V., Garlappi, L., & Uppal, R. (2007). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *The Review of Financial Studies*, *22*(5), 1915-1953. https://doi.org/10.1093/rfs/hhm075

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Dimkpah, Y., & Ngassam, C. (2013). The rise in equity exchange-traded funds (ETFs): The case of momentum? *Academy of Accounting and Financial Studies Journal*, *17*(1), 95-102. https://www.proquest.com/openview/980fafe443941ff768d25693

Dobson, P. J. (2020). ETFs tracking errors on global markets with consideration of regional diversity. *MPRA Working Paper Series, No. 103695,* 2-12. https://mpra.ub.uni-muenchen.de/id/eprint/103695

Dorocáková, M. (2017). Comparison of ETFs' performance related to the tracking error. *Journal of International Studies*, *10*(4), 154-165. https://doi.org/10.14254/2071-8330.2017/10-4/12

Drenovak, M., Urošević, B., & Jelic, R. (2014). European Bond ETFs: Tracking errors and the Sovereign Debt Crisis. *European Financial Management*, *20*(5), 958-994. https://doi.org/10.1111/j.1468-036X.2012.00649.x

Ducoulombier, F., & Goltz, F. (2012). The true risks of European ETFs. *ETFs and Indexing*, *2012*(1), 112-117. https://guides.pm-research.com/content/iijetfind/2012/1/112

Ducoulombier, F. d. r., & Goltz, F. (2012). The true risks of European ETFs. *EDHEC-Risk Instituite, 2012*(1), 3-61. https://citeseerx.ist.psu.edu/

Easley, D., Michayluk, D., O'Hara, M., & Putniņš, T. J. (2021). The active world of passive investing. *Review of Finance*, *25*(5), 1433-1471. https://doi.org/10.1093/rof/rfab021

Edey, M. (2009). The Global Financial Crisis and its effects. *Economic Papers: A Journal of Applied Economics and Policy*, *28*(3), 186-195. https://doi.org/10.1111/j.1759-3441.2009.00032.x

Ehnes, R. G., Noman, A., & Rahman, M. (2024). Tracking ability of iShares country ETFs during Covid–19 pandemic. *Journal of Finance Issues*, *22*(1), 1-13. https://doi.org/10.58886/jfi.v22i1.6796

Elia, M. (2012). Tracking error of traditional and synthetic European exchange-traded funds. *Proceedings from the 29th International Conference of the French Finance Association (AFFI)*, 2-22. www.fma.org:80/Atlanta/Papers/

Elton, E. J., & Gruber, M. J. (2020). A review of the performance measurement of long-term mutual funds. *Financial Analysts Journal*, *76*(3), 22-37. https://doi.org/101 1080/0015198X.2020.1738126

Elton, E. J., Gruber, M. J., Comer, G., & Li, K. (2005). Spiders: Where are the bugs? In Hein, E. (Eds.) *Exchange Traded Funds: Structure, Regulation and Application of a New Fund Class*, 37-59. Springer. https://doi.org/10.1007/3-540-27637-8_4

Elton, E. J., Gruber, M. J., & de Souza, A. (2019). Passive mutual funds and ETFs: Performance and comparison. *Journal of Banking & Finance*, *106*(2019), 265-275. https://doi.org/10.1016/j.jbankfin.2019.07.004

Engle, R., & Sarkar, D. (2006). Premiums-discounts and exchange-traded funds. *Journal of Derivatives*, *13*(4), 27-45. https://www.iijournals.com

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and error correction: Representation, estimation, and testing. *Econometrica*, *55*(2), 251-276. https://doi.org/10.2307/1913236

Estrada, J. (2024). Multifactor funds vs. homemade factor diversification strategies. *The Journal of Beta Investment Strategies, 15*(1), 54-65. https://doi.org/10.3905/jbis.2024.1.053

ETFGI. (2018). *ETFGI reports assets invested in ETFs and ETPs listed globally reached a new high of $5.12 trillion at the end of July 2018*. ETFGI. Retrieved 4 March 2024, from https://etfgi.com/news/press-releases/2018/08/etfgi-reports-assets-invested-etfs-and-etps-listed-globally-reached-new

Evans, R. B., Moussawi, R., Pagano, M. S., & Sedunov, J. (2018). ETF Short Interest and Failures-to-Deliver: Naked Short-Selling or Operational Shorting? *Proceedings from Academic Research Colloquium for Financial Planning and Related Disciplines. SSRN Electronic Journal, 1*(1)*,* 1-91. https://doi.org//10.2139/ssrn.2961954

Fabozzi, F. J., Gupta, F., & Markowitz, H. M. (2002). The Legacy of Modern Portfolio Theory. *The Journal of Investing*, *11*(3), 7-22. https://doi.org/10.3905/joi.2002.319510

Fabozzi, F. J., & Markowitz, H. M. (2011). Equity Analysis using traditional and value-based metrics. In Grant, J. L. (Eds.), *Equity Valuation and Portfolio Management*. *(199)*, 25-70. John Wiley & Sons, Inc. https://books.google.co.za/books

Fama, E. F. (1970). Efficient capital markets. *Journal of Finance*, *25*(2), 383-417. https://doi.org/10.7208/9780226426983-007

Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance*, *65*(5), 1915-1947. https://doi.org/10.1111/j.1540-6261.2010.01598.x

Fassas, A. (2014). Tracking ability of ETFs: Physical vs. synthetic replication. *The Journal of Index Investing, 5*(2)*,* 9-20. https://doi.org/10.3905/jii.2014.5.2.009

Fenty, S., & Constantine, D. (2015). Transitioning emerging markets equities. *Proceedings from State Street Global Advisory Conference.* 1-20. Retrieved 1 November 2024, from https://www. statestreet.com/us/en/asset-manager

Fidelity Investments. (2022). *Stocks with high short interest.* Fidelity Investments. Retrieved 19 June 2023, from https://www.fidelity.com/viewpoints/active-investor/using-open-and-short-interest

Fidelity Investements. (2024). *Direct indexing in detail*. Fidelity Investments. Retrieved 10 June 2024, from https://www.fidelity.com/learning-center/trading-investing/direct-indexing

Filippou, I., Gozluklu, A., & Rozental, H. (2024). ETF arbitrage and international diversification. *Journal of Banking & Finance*, *168*(2024), 107-274. https://doi.org/10.1016/j.jbankfin.2024.107274

Fisch, J. E., Hamdani, A., & Davidoff Solomon, S. (2020). The new titans of Wall Street: A theoretical framework for passive investors. *University of Pennsylvania Law Review*, *168*(1), 17-72. http://dx.doi.org/10.2139/ssrn.3192069

Frino, A., & Gallagher, D. (2001). Tracking S&P 500 index funds. *Journal of Portfolio Management*, *28*(1), 44-55. https://doi.org/ 10.3905/jpm.2001.319822

Frino, A., Gallagher, D., Neubert, A., & Oetomo, T. (2004). Index design and implications for index tracking: Evidence from S&P 500 index funds. *Journal of Portfolio Management*, *30*(2), 89-95. http://hdl.handle.net/10453/12245

Frino, A., & Gallagher, D. R. (2002). Is index performance achievable? An analysis of Australian equity index funds. *ABACUS: A Journal of Accounting, Finance and Business Statistics*, *38*(2), 200-214. https://doi.org/10.1111/1467-6281.00105

Fry-McKibbin, R., Greenwood-Nimmo, M., Hsiao, C. Y.-L., & Qi, L. (2022). Higher-order comoment contagion among G20 equity markets during the COVID-19 pandemic. *Finance Research Letters*, *45*(2022), 102-150. https://doi.org/10.1016/j.frl.2021.102150

Gaba, A., & Kumar, R. (2021). Investigating pricing efficiency and price discovery mechanism of world indices ETFs: Evidence from India. *FOCUS*, *23*(3), 26-35. https://publication.iift.ac.in/Articles/198.pdf

Gajurel, D., & Dungey, M. (2023). Systematic contagion effects of the global finance crisis: Evidence from the world's largest advanced and emerging equity markets. *Journal of Risk and Financial Management*, *16*(3), 182-202. https://doi.org/10.3390/jrfm16030182

Gallagher, D. R. (2003). Investment manager characteristics, strategy, top management changes and fund performance. *Accounting & Finance*, *43*(3), 283-309. https://doi.org/10.1111/j.1467-629x.2003.00092.x

Gallagher, D. R., & Segara, R. (2005). The performance and trading characteristics of exchange-traded funds. *Journal of Investment Strategy*, *1*(2), 47-58. http://rain maker -s3 media.s3.amazonaws.com

Galloppo, G., & Aliano, M. (2018). Fund manager performance in emerging market: Factor specialisation and financial crisis impact. *Journal of Emerging Market Finance*, *17*(1), 130-158. https://doi.org/10.1177/0972652717748101

Gastineau, G. L. (2001). Exchange-traded funds: An introduction. *Journal of Portfolio Management*, *27*(3), 88-96. https://doi.org/ 10.3905/jpm.2001.319804

Gastineau, G. L. (2002). Equity index funds have lost their way: A solution to growing problems. *The Journal of Portfolio Management*, *28*(2), 55-64. https://doi.org/10.3905/jpm.2002.319832

Gastineau, G. L. (2004). The Benchmark Index ETF Performance Problem. *The Journal of Portfolio Management*, *30*(2), 96-103. https://doi.org/10.3905/jpm.2004.319 9

Gastineau, G. L. (2010). The history and structure of exchange-traded funds and some of their competitors. In *The Exchange-Traded Funds Manual*, (186), 19-41. John Wiley & Sons. https://doi.org/ 10.1002/9781118266946

Glosten, L., Nallareddy, S., & Zou, Y. (2021). ETF activity and informational efficiency of underlying securities. *Management Science*, *67*(1), 22-47. https://doi.org/10.1287/mnsc.2019.3427

Goltz, F., & Schröder, D. (2011). Passive investing before and after the crisis: Investors' views on exchange-traded funds and competing index products. *Bankers, Markets & Investors*, *110*(1), 1-24. https://eprints.bbk.ac.uk/id/eprint/6818/

Golub, B. W., Ferconi, M., Madhavan, A., & Ulitsky, A. (2018). Factor-based optimisation and the creation/redemption mechanism of fixed income exchange-traded funds. *International Journal of Financial Engineering and Risk Management*, *2*(4), 335-350. https://doi.org/10.1504/ijferm.2018.094020

Grill, M., Lambert, C., Marquardt, P., Watfe, G., & Weistroffer, C. (2018). Counterparty and liquidity risks in exchange-traded funds. *European Central Bank: Financial Stability Review*, *November* (2018). Retrieved 22 August 2024, from https://www.ecb.europa.eu/press/financial-stability

Grinold, R., & Kahn, R. (1999). *Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Selecting Superior Returns and Controlling Risk (2nd ed.)*, 256-596. Mcgraw-hill. ISBN: 13-978-0070248823

Gulko, L. (1999). The entropy theory of stock option pricing. *International Journal of Theoretical and Applied Finance*, *2*(3), 331-355. https://doi.org/10.1142/s0219024999000182

Gunning, W., & Van Vuuren, G. (2019). Exploring the drivers of tracking error constrained portfolio performance. *Cogent Economics & Finance*, *7*(1), 1-15. https://doi.org/10.1080/23322039.2019.1684181

Hajric, V. (2024). BlackRock says active ETFs poised to hit $4 Trillion by 2030. Retrieved 18 August 2024, from https://www.bnnbloomberg.ca/investing/etfs/2024/07/16/blackrock-says-active-etfs-poised-to-hit-4-trillion-by-2030/

Harjoto, M. A., & Rossi, F. (2023). Market reaction to the COVID-19 pandemic: evidence from emerging markets. *International Journal of Emerging Markets*, *18*(1), 173-199. https://doi.org/10.1108/IJOEM-05-2020-0545

Hill, J. M., Nadig, D., & Hougan, M. (2015). A comprehensive guide to exchange-traded funds (ETFs). *CFA Institute Research Foundation*, *2015* (1), 1-181. Retrieved 2 October 2024, from https://rpc.cfainstitute.org/-/media/documents/book/

Hill, J. M., & Teller, S. G. (2009). Rebalancing leveraged and inverse funds. *ETFs and Indexing*, *2009*(1), 67-76. https://guides.pm-research.com/content/

Hilliard, J., & Dat Le, T. (2022). Exchange-traded funds investing in the European emerging markets. *Journal of Eastern European and Central Asian Research (JEECAR)*, *9*(2), 260-270. https://doi.org/10.15549/jeecar.v9i2.804

Holzhauer, H. M., Lu, X., McLeod, R. W., & Mehran, J. (2013). Bad news bears: Effects of expected market volatility on daily tracking error of leveraged bull and bear ETFs. *Managerial Finance*, *39 (12)*, 1169-1187. https://doi.org/10.1108/MF-09-2012-0203

Hougan, M. (2009). How long can you hold leveraged ETFs? *Journal of Indexes*, *12*(2), 36-41. [no doi/url available].

Hu, H. T. C., & Morley, J. T. (2019). The SEC and Regulation of Exchange-Traded Funds: A Commendable Start and a Welcome Invitation. *Southern California Law Review*, *92*(1), 1157-1202. https://papers.ssrn.com/sol3/papers.cfm?abstractid=3

Huang, J. C., & Guedj, I. (2009). Are ETFs replacing index mutual funds? *AFA 2009 San Francisco Meetings Paper*, *2009* (1), 1-41. http://dx.doi.org/10.2139/ssrn.1108728

Huang, M.-Y., & Lin, J.-B. (2011). Do ETFs provide effective international diversification? *Research in International Business and Finance*, *25*(3), 335-344. https://doi.org/10.1016/j.ribaf.2011.03.003

Hui, E. C. M., & Chan, K. K. K. (2022). How does Covid-19 affect global equity markets? *Financial Innovation*, *8*(1), 25-44. https://doi.org/10.1186/s40854-021-00330-5

Hurlin, C., Iseli, G., Pérignon, C., & Yeung, S. (2019). The counterparty risk exposure of ETF investors. *Journal of Banking & Finance*, *102*(2019), 215-230. https://doi.org/10.1016/j.jbankfin.2019.03.014

Invesco. (2024). *Invesco S&P China A 300 Swap UCITS ETF Acc*. Invesco. Retrieved 1 November 2024, from https://www.invesco.com/nl/en/financial-products/etfs/invesco-sp-china-a-300-swap-ucits-etf-acc.html

Ivanov, S. I. (2012). REIT ETFs performance during the Financial Crisis. *Journal of Finance and Accountancy*, *10*(1), 12-30. https://doi.org/10.4236/me.2010.1100

Jaakkola, M. (2022). *How efficient is the pricing of ETFs?: Comparing the pricing of ETFs with the pricing of the underlying stocks and the index (Masters dissertation).* Lappeenrata-Lahti University of Technology. https://lutpub.lut.fi/

Jain, K. (2020). A study of investment opportunities and investors sentiments during COVID-19 Pandemic. *International Journal of Indian Culture and Business Management*, *24*(3), 283-302. https://doi.org/10.1504/IJICBM.2020.10035232

Jeambart, V., & Nakano, M. (2017). The tracking ability of physical and synthetic exchange-traded funds on the Asian market. (Unpublished Work). 2-50. Retrieved 2 August 2024, from https://academia.edu

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2), 231-254. https://doi.org/10.1016/0165-1889(88)90041-3

Johnson B, Bioy H, Kellett A, & L, D. (2013). On the right track: Measuring tracking efficiency in ETFs. *The Journal of Index Investing*, *4*(3), 35-41. https://doi.org/10.3905/jii.2013.4.3.035

Johnson, B., Bioy, H., & Rose, G. (2012). Synthetic ETFs under the Microscope. *ETFs and Indexing*, *2012*(1), 94-100. https://pm-research.com

Johnson, W. F. (2009). Tracking errors of exchange traded funds. *Journal of Asset Management*, *10*(4), 253-262. https://doi.org/10.1057/jam.2009.10

Jorion, P. (1992). Portfolio Optimization in Practice. *Financial Analysts Journal*, *48*(1), 68-74. https://doi.org/10.2469/faj.v48.n1.68

Jorion, P. (2005). Valuation and Risk Models. In Global Association of Risk Professionals (GARP) (Eds.), *Financial Risk Manager Handbook* (3rd ed.), 281-355. Wiley Database.

JP Morgan Management.(2024). *Active ETFs take centre stage.* JP Morgan [Marketing Communication]. Retrieved 1 October 2024, from https://am.jpmorgan.com/content/dam/jpm-am/active-etfs-take-center-stage.pdf

Kadiyala, P. (2022). Response of ETF flows and long-run returns to investor sentiment. *Financial Markets and Portfolio Management*, *36*(4), 489-531. https://doi.org/10.1007/s11408-022-00410-1

Kanuri, S., & McLeod, R. W. (2015). Does it pay to diversify? US vs. international ETFs. *Financial Services Review*, *24*(3), 249-270. https://doi.org/10.61190/fsr.v24i3.3337

Kempf, A., & Memmel, C. (2006). Estimating the Global Minimum Variance Portfolio. *Schmalenbach Business Review*, *58*(4), 332-348. https://doi.org/10.1007/BF03396737

Kenneth, L. K. K., Lai, K. K., & He, K. (2013). Evaluating the performance of exchange-traded funds in the emerging markets.*Proceedings from the 2013 Sixth International Conference on Business Intelligence and Financial Engineering (BIFE)* ,359-363. https://doi. ieeecomputersociety.org /10.1109/BIFE.2013.75

Khan, A. P., Bacha, O. I., & Masih, A. (2015). Performance and trading characteristics of exchange-traded funds: Developed vs emerging markets. *Capital Markets Review*, *23*(1&2), 40-64. http://www.mfa.com.my/wp-content/uploads/2013/12/CMR-2015-003.pdf

Kim, J., Cho, H., & Seok, S. (2023). Liquidity risk, return performance, and tracking error: Synthetic vs. physical ETFs. *Journal of International Financial Markets, Institutions and Money*, *89*(2023), 1-20. https://doi.org/10.1016/j.intfin.2023.101

Kim, J. H., Lee, Y., Kim, W. C., & Fabozzi, F. J. (2021). Mean–variance optimization for asset allocation. *Journal of Portfolio Management Investment Models*, *47*(5), 24-40. https://doi.org/10.3905/jpm.2021.1.219

Kiymaz, H. (2002). An analysis of linkages among equity markets: study of selected Latin American and developed countries. *Journal of Economics and Business Studies*, *1*(1), 16-33. [No doi/url available].

Kompalli, S. K. (2018). A Study on Pricing Efficiency and Replication Strategy of Exchange-Traded Funds. *SDMIMD Journal of Management*, *9*(2), 1-8. https://doi.org/10.18311/sdmimd/2018/21418

Kosev, M., & Williams, T. (2011). Exchange-traded funds. *RBA Bulletin, March*, 51-59. https://www.rba.gov.au/publications/bulletin/2011/mar/pdf/

Kostovetsky, L. (2003). Index mutual funds and exchange-traded funds. *Journal of Portfolio Management*, *29*(4), 80-92. https://doi.org/ 10.3905/jpm.2003.319897

Kumar, K. S. (2018). A Study on pricing efficiency and replication strategy of exchange-traded funds. *SDMIMD Journal of Management*, *9*(2), 1-15. https://doi.org/10.18311/sdmimd/2018/21418

Kunjal, D., & Peerbhai, F. (2021). Investor Overconfidence in the South African Exchange-Traded Fund Market. *Cogent Economics &Finance*, *9*(1), 1-18. https://doi.org/10.1080/23322039.2021.1978190

Larsen, G. A., & Resnick, B. G. (1998). Empirical Insights on Indexing How Capitalization, Stratification and Weighting Can Affect Tracking Error. *Journal of Portfolio Management, 25*(1), 51-60. https://ssrn.com/abstract=1925450

Legal Information Institute. (2015). *15 U.S. Code § 80a-6-Exemptions.* Retrieved 3 August 2024, from www.law.cornell.edu/uscode/text/15/80a-6

León, C., Kim, G.-Y., Martínez, C., & Lee, D. (2017). Equity Markets' Clustering and The Global Financial Crisis. *Quantitative Finance*, *17*(12), 1905-1922. https://doi.org/10.1080/14697688.2017.1357970

Levy, A., & Lieberman, O. (2013). Overreaction of country ETFs to US market returns: Intraday vs. daily horizons and the role of synchronized trading. *Journal of Banking & Finance*, *37*(5), 1412-1421. https://doi.org/10.1016/j.jbankfin.2012.0

Lin, C.-C., Chan, S.-J., & Hsu, H. (2006). Pricing efficiency of exchange traded funds in Taiwan. *Journal of Asset Management*, *7*(1), 60-68. https://doi.org/10.1057/palgrave.jam.2240202

Lin, V., & Mackintosh, P. (2010). ETF mythbuster: Tracking down the truth. *The Journal of Index Investing*, *1*(1), 95-106. https://doi.org/ 10.3905/jii.2010.1.1.095

Lintner, J. (1975). The valuation of risk, assets and the selection of risky investments in stock portfolios and capital budgets. In Ziemba W.T. & Vickson R.G. (Eds.), *Stochastic Optimization Models in Finance*, 131-155. Academic Press. https://doi.org/10.1016/B978-0-12-780850-5.50018-6

Liu, Y.-S., & Lee, L. (2022). Are modifications in the ETF's investment performance and risks during the COVID-19 pandemic event? *Review of Applied Socio Economic Research*, *23*(1), 5-17. https://doi.org/10.54609/reaser.v23i1.202

Lo, A. W. (2002). The statistics of sharpe ratios. *Financial Analysts Journal*, *58*(4), 36-52. https://doi.org/10.2469/faj.v58.n4.2453

Ludden, T. M., Beal, S. L., & Sheiner, L. B. (1994). Comparison of the Akaike Information Criterion, the Schwarz criterion and the F test as guides to model selection. *Journal of Pharmacokinetics and Biopharmaceutics*, *22*(5), 431-445. https://doi.org/10.1007/BF02353864

Luhr, S. (2013). The Growth of ETFs in Emerging Markets. *The Journal of Index Investing*, *4*(3), 115 - 117. https://doi.org/10.3905/jii.2013.4.3.115

Madhavan, A. (2014). Exchange-Traded Funds: An Overview of Institutions, Trading, and Impacts. *Annual Review of Financial Economics*, *6*, 311-341. https://doi.org/10.1146/annurev-financial-110613-034316

Malhotra, P., & Sinha, P. (2023). Exchange-traded funds in India amid COVID-19 crisis: An empirical analysis of the performance. *Metamorphosis*, *22*(1), 38-54. https://doi.org/ 10.1177/09726225221141180

Marszk, A. (2016). Complexity of innovative financial products: The case of synthetic exchange-traded funds in Europe. *Financial Sciences*, *2*(27), 49-64. https://doi.org/10.15611/nof.2016.2.04

Materials, B. E. C. (2024). *Module 4: ETF Structures* [Course Materials]. BlackRock. Retrieved 2 October 2024, from https://www.blackrock.com/americas-offshore/en/education/etf/etf-structures

Mateus, C., & Kuo, T.W. (2008). The performance and persistence of exchange-traded funds: evidence for iShares MSCI country-specific ETFs. *Proceedings from the Swiss Society for Financial Market Research 11th Conference, 11 April 2008, SWX Swiss Exchange, Zürich, Switzerland. (Unpublished).* Retrieved 25 January 2025, from https://gala.gre.ac.uk/id/eprint/2712/

Mateus, C., & Rahmani, Y. (2017). Physical versus synthetic exchange traded funds. Which one replicates better? *Journal of Mathematical Finance, 7*(4), 975-989. https://doi.org/10.4236/jmf.2017.74054

Maurer, F., & Williams, S. O. (2015). Physically versus synthetically replicated trackers: Is there a difference in terms of risk? *Journal of Applied Business Research*, *31*(1), 131-146. https://doi.org/10.19030/jabr.v31i1.8996

Mazumder, I. (2014). Investing in exchange-traded funds. *Applied Finance Letters, 3*(2), 16-23. https://doi.org/10.24135/afl.v3i2.23

Mazza, D. B. (2012). Do ETFs increase correlations? *The Journal of Index Investing*, *3*(1), 45 - 51. https://doi.org/10.3905/jii.2012.3.1.045

Mazzilli, P. J., & Kittsley, D. F. (2003). Low historical tracking error for most ETFs. *Morgan Stanley Equity Research Report*. [No doi/url available].

Meinhardt, C., Mueller, S., & Schoene, S. (2015). Physical and synthetic exchange-traded funds: The good, the bad, or the ugly? *The Journal of Investing*, *24*(2), 35-44. https://doi.org/10.3905/joi.2015.24.2.035

Meziani, A. S. (2015). Active exchange-traded funds: Are we there yet? *The Journal of Index Investing*, *6*(2), 86-98. https://doi.org/10.3905/jii.2015.6.2.086

Michaud, R. O., & Michaud, R. O. (2008). Classic mean-variance optimization In *Efficient Asset Management: A Practical Guide to Stock Portfolio Optimization and Asset Allocation,* (2nd ed.), 7-17. Oxford University Press. https://www.researchgate.net/publication/227466933

Milonas, N. T., & Rompotis, G. G. (2010). Dual offerings of ETFs on the same stock index: U.S. vs. Swiss ETFs. *Journal of Alternative Investments*, *12*(4), 97-113. https://doi.org/10.3905/JAI.2010.12.4.097

Mistry, M. (2013). ETFs bridging the gap to emerging markets. *The Journal of Index Investing*, *4*(3), 118 - 121. https://doi.org/10.3905/jii.2013.4.3.118

Miziołek, T., & Feder-Sempach, E. (2019). Tracking ability of exchange-traded funds: Evidence from emerging markets equity ETFs. *Bank i Kredyt, Narodowy Bank Polski*, *50*(3), 221-248. https://bankikredyt.nbp.pl/content/2019/03/BIK_03_2019_01.pdf

Moriarty, K. H. (2020). The SEC's exchange-traded investment fund rule. *The Journal of Index Investing*, *10*(4), 25-36. https://doi.org/10.3905/jii.2020.1.083

Munusamy, D., Narayanamurthy, V., & Sivanmalaiappan, M. (2016). A study on the relationship between price and net asset value of the exchange traded funds in India. *SMART Journal of Business Management Studies*, *12*(2), 31-39. https://doi.org/10.5958/2321-2012.2016.00011.7

Murphy, R. J., & Wright, C. (2010). An empirical investigation of the performance of commodity-based leveraged ETFs. *The Journal of Index Investing*, *1*(3), 14 - 23. https://doi.org/10.3905/jii.2010.1.3.014

Narend, S., & Thenmozhi, M. (2016). What drives fund flows to index ETFs and mutual funds? A panel analysis of funds in India. *DECISION*, *43*(1), 17-30. https://doi.org/10.1007/s40622-016-0124-6

Naumenko, K., & Chystiakova, O. (2015). An empirical study on the differences between synthetic and physical ETFs. *International Journal of Economics and Finance*, *7*(3), 24-35. http://dx.doi.org/10.5539/ijef.v7n3p24

Nazlı Kalfa Baş, S. E. S. (2015). Tracking ability and pricing efficiency of exchange-traded funds: Evidence from Borsa Istanbul. *Business and Economics Research Journal*, *6*(1), 19-33. https://EconPapers.repec.org/RePEc:ris:buecrj:0174

Neto, A. F. d. C., Klotzle, M. C., & Pinto, A. C. F. (2021). Do market conditions affect the tracking efficiency of exchange-traded funds? Evidence from developed and emerging markets. *Global Business Review*, 1-19. https://doi.org/10.1177/09721509211036798

Nguyen, H. (2023). COVID-19: Performance of ESG ETFS and, ESG ETFS vs. their declared indexes. *Applied Finance Letters*, *12*(1), 33-43. https://ojs.aut.ac.nz/applied-finance-letters/article/view/647

Organisation, W. H. (2024). *Coronavirus disease (COVID-19) pandemic.* Retrieved 11 October 2024, from https://www.who.int/europe/emergencies/situations/covid-19

Osterhoff, F., & Kaserer, C. (2016). Determinants of tracking error in German ETFs – the role of market liquidity. *Managerial Finance*, *42*(5), 417-437. https://doi.org/10.1108/MF-04-2015-0105

Patra, S. (2024). An empirical analysis of the volume-volatility nexus in crude oil markets under structural breaks: Implications for forecasting. *International Review of Economics & Finance*, *94*, 103-434. https://doi.org/10.1016/j.iref.2024.103434

Peltomäki, J. (2017). Beta as a determinant of investor activity in sector exchange-traded funds. *The Quarterly Review of Economics and Finance*, *65*, 137-145. https://doi.org/10.1016/j.qref.2016.06.006

Pinheiro, C. M., & Varela, H. H. (2018). Do exchange-traded funds (ETFs) outperform the market?: Evidence from the Portuguese Stock Index. *GEE Working Papers No. 109*, 1-26. https://www.gee.gov.pt/RePEc/WorkingPapers

Pope, P. F., & Yadav, P. K. (1994). Discovering errors in tracking error. *The Journal of Portfolio Management*, *20*(2), 27-32. https://doi.org/10.3905/jpm.1994.409471

Poterba, J. M., & Shoven, J. B. (2002). Exchange-Traded Funds: A new investment option for taxable investors. *American Economic Review*, *92*(2), 422–427. https://doi.org/10.1257/000282802320191732

Qadan, M., & Yagil, J. (2012). On the dynamics of tracking indices by exchange traded funds in the presence of high volatility. *Managerial Finance*, *38*(9), 804-832. https://doi.org/10.1108/03074351211248162

Qin, N., & Singal, V. (2015). Indexing and stock price efficiency. *Financial Management*, *44*(4), 875-904. https://doi.org/10.1111/fima.12102

Ramaswamy, S. (2011). Market structures and systemic risks of exchange-traded funds. *BIS Working Paper, No. 343*, 1-13. https://ssrn.com/abstract=1859246

Razin, A., & Rosefielde, S. S. (2010). Global Financial Crisis 2008 and beyond: A rude awakening. *Israel Economic Review, 8*(2), 1-8. https://ssrn.com/abstract=2191589

Research, M. S. (2024). The rise of active ETFs: Four reasons to consider active ETFs. Retrieved 10 August 2024, from https://us.etrade.com/knowledge/library/etfs/the-rise-of-active-etfs

Rhee, G., & Wang, C.-J. (1997). The bid-ask bounce effect and the spread size effect: Evidence from the Taiwan stock market. *Pacific-basin Finance Journal*, *5*(2), 231-258. https://doi.org/10.1016/S0927-538X(97)00014-0

Riva, F., Calamia, A., & Deville, L. (2013). Liquidity in European equity ETFs: What really matters? *Bankers, Markets and Investors, 2013*(124), 60-73. https://EconPapers.repec.org/RePEc:hal:journl:halshs-00861646

Roll, R. (1992). A mean/variance analysis of tracking error. *The Journal of Portfolio Management*, *18*(4), 13-22. https://doi.org/10.3905/jpm.1992.701922

Roll, R. (2013). Volatility, correlation, and diversification in a multi-factor world. *The Journal of Portfolio Management*, *39*(2), 11-18. https://doi.org/10.3905/jpm.2013.39.2.011

Rompotis, G. G. (2005). An empirical comparing investigation on exchange-traded funds and index funds performance. *SSRN Electronic Journal, No. 903110,* 1-18. http://dx.doi.org/10.2139/ssrn.90311

Rompotis, G. G. (2009). Interfamily competition on index tracking: The case of the Vanguard ETFs and index funds. *Journal of Asset Management*, *10*(2009), 263-278. https://doi.org/10.1057/jam.2009.11

Rompotis, G. G. (2011). The performance of actively managed exchange-traded funds. *The Journal of Index Investing*, *1*(4), 53-65. https://doi.org/10.3905/jii.2011.1.4.053

Rompotis, G. G. (2012a). An empirical look at Swiss exchange-traded funds market. *Aestimatio: The IEB International Journal of Finance, 4*(2012)*,* 52-81. http://dialnet.unirioja.es/servlet/oaiart?codigo=4158784

Rompotis, G. G. (2012b). The German exchange-traded funds. *IUP Journal of Applied Finance*, *18*(4), 62-82. https://ssrn.com/abstract=2184748

Rompotis, G. G. (2012c). A Survey on leveraged and inverse exchange-traded funds. *The Journal of Index Investing*, *2*(4), 84-95. https://doi.org/10.3905/jii.2012.2.4.084

Rompotis, G. G. (2013a). Active vs. passive management: New evidence from exchange-traded funds. *SSRN Electronic Journal, No. 1337708.* 1-18. http://dx.doi.org/10.2139/ssrn.1337708

Rompotis, G. G. (2013b). Monthly effects on the trading behavior of US exchange-traded funds. *Aestimatio: The IEB International Journal of Finance, 7*(1), 2-35. https://www.ieb.es/wp-

Rompotis, G. G. (2015). A performance evaluation of the Canadian actively managed ETFs. *The Journal of Index Investing*, *6*(2), 57-75. https://doi.org/10.3905/jii.2015.6.2.057

Rompotis, G. (2016). Return and volatility of emerging markets leveraged ETFs. *Journal of Asset Management*, *17*(3), 165-194. https://doi.org/10.1057/jam.2016.2

Rosca, E. R. (2010). Stationary and Non-stationary time series. *The USV Annals of Economics and Public Administration*, *10*(1), 177-186. http://annals.feaa.usv.ro/index.php/annals/article/view/262/270

Rubesam, A., & Hwang, S. (2018). Do smart beta ETFs capture factor premiums? A Bayesian Perspective. *S&P Global Market Intelligence Research Working Paper Series*, *No. 2018-ACF-04,* 1-14. https://EconPapers.repec.org/RePEc:ies:wpaper:f201804

Rudolf, M., Wolter, H.-J. r., & Zimmermann, H. (1999). A linear model for tracking error minimization. *Journal of Banking and Finance*, *23*(1), 85-103. https://doi.org/10.1016/S0378-4266(98)00076-4

Saffi, P., & Zheng, X. (2023). Does the replication method matter?: Comparing tracking performance during market turmoil. *SSRN Electronic Journal, No. 3962470*, 1-41. http://dx.doi.org/10.2139/ssrn.3962470

Saha, K., Madhavan, V., & Chandrashekhar, G. R. (2022). Effect of COVID-19 on ETF and index efficiency: Evidence from an Entropy-based Analysis. *Journal of Economics and Finance*, *46*(1), 347 - 359. https://doi.org/10.1007/s12197-021-09566-4

Saini, C., Sharma, I., Verma, B., & Bharti. (2023). Performance of equity ETFs during COVID-19 pandemic crisis: Evidence from India. *Abhigyan*, *41*(3), 21-31. https://doi.org/10.56401/Abhigyan_41.3.2023.21-31

Saji, T. G. (2017). Performance and tracking efficiency of Exchange Traded Funds : An analysis of Indian equity index funds. *Indian Journal of Research in Capital Markets*, *4*(2), 7-14. https://doi.org/10.17010/ijrcm/2017/v4/i2/116083

Saunders, K. T. (2018). Analysis of international ETF tracking error in country-specific funds. *Atlantic Economic Journal*, *46*(2), 151-160. https://doi.org/10.1007/s11293-018-9574-x

Schizas, P. (2014). Active ETFs and their performance vis-à-vis passive ETFs, mutual funds, and hedge funds. *The Journal of Wealth Management*, *17*(3), 84-98. https://www.proquest.com/scholarly-journals/active-etfs-their-performance-vis-à-passive/docview/1627121022/se-2

Securities and Exchange Commission. Commodity and Securities Rule 22c-1, (1968). https://www.sec.gov/Archives/edgar/data/356476/000119312510291404/dex9928h3.html

Seven, Ü., & Yılmaz, F. (2021). World equity markets and COVID-19: Immediate response and recovery prospects. *Research in International Business and Finance*, *56(COVID Financial Markets)*, 101-349. https://doi.org/10.1016/j.ribaf.2020.101349

Shabri Abd Majid, M., Kameel Mydin Meera, A., Azmi Omar, M., & Abdul Aziz, H. (2009). Dynamic linkages among ASEAN-5 emerging stock markets. *International Journal of Emerging Markets*, *4*(2), 160-184. https://doi.org/10.1108/17468800910945783

Shaikh, I. (2022). Impact of COVID-19 pandemic on the energy markets. *Economic Change and Restructuring*, *55*(1), 433-484. https://doi.org/10.1007/s10644-021-09320-0

Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management Science*, *9*(2), 277-293. https://doi.org/10.1287/mnsc.9.2.277

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, *19*(3), 425-442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Sherrill, D. E., & Stark, J. R. (2018). ETF liquidation determinants. *Journal of Empirical Finance*, *48(2018)*, 357-373. https://doi.org/10.1016/j.jempfin.2018.07.007

Shin, S., & Soydemir, G. (2010). Exchange-traded funds, persistence in tracking errors and information dissemination. *Journal of Multinational Financial Management*, *20(4-5)*, 214-234. https://doi.org/10.1016/j.mulfin.2010.07.005

Shum, P. M., & Kang, J. (2013). Leveraged and inverse ETF performance during the financial crisis. *Managerial Finance*, *39*(5), 476-508. https://doi.org/10.1108/03074351311313825

Sinclair, E. (2013). Stylized Facts about returns and volatility. In *Volatility trading* (2nd ed.), 35-47. John Wiley & Sons. https://doi.org/10.1002/9781118662724

Singh, J., & Kaur, P. (2016). Tracking efficiency of exchange traded funds (ETFs) empirical evidence from Indian equity ETFs. *Paradigm*, *20*(2), 176-190. https://doi.org/10.1177/0971890716670722

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance*, *70*(5), 1903-1948. https://doi.org/10.1111/jofi.12286

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *The Review of Financial Studies*, *30*(4), 1270-1315. https://doi.org/10.1093/rfs/hhw107

Statista. (2024). *Number of ETFs in the U.S. 2003 to 2023*. Statista Research. Retrieved 23 June 2024, from https://www.statista.com/statistics/350525/number-etfs-usa/

Steiner, A. (2012). Risk parity for the masses. *The Journal of Investing*, *21*(3), 129 - 139. https://doi.org/10.3905/joi.2012.21.3.129

Steyn, J. (2019). The tracking efficiency of exchange-traded funds listed on the Johannesburg Stock Exchange. *Management Dynamics: Journal of the Southern African Institute for Management Scientists*, *28*(4), 2-14. https://hdl.handle.net/10520/EJC-1999

Strydom, B., McCullough, K., & Charteris, A. (2015). The relative tracking ability of South African exchange traded funds and index funds. *Investment Analysts Journal*, *44*(2), 117-133. https://doi.org/10.1080/10293523.2014.994454

Suk Kim, B. (2011). Linkages between the US and Asia-Pacific exchange-traded funds (ETF) markets: Evidence from the 2007-2008 Global Financial Crisis. *Asian Academy of Management: Journal of Accounting & Finance*, *7*(1), 53-72. https://ejournal.usm.my/aamjaf/article/view/aamjaf_vol7-no1-2011_3

Trackinsight Global ETF Survey. (2024). *How equity ETFs are shaping in 2024 so Far*. [Electronic Survey]. Trackinsight. Retrieved 2 November 2024, from https://www.trackinsight.com/es/etf-news/new-report-equity-etfs-shaping-2024-far

Thanakijsombat, T., & Kongtoranin, T. (2018). Performance and diversification benefits of foreign-equity ETFs in emerging markets. *Applied Economics Letters*, *25*(2), 125-129. https://doi.org/10.1080/13504851.2017.1302055

Thomaidou, A., & Kenourgios, D. (2020). On financial Contagion Through ETFs. In Zopounidis, C., Kenourgios, D. & Dotsis, G. (Eds.), *Recent Advances and Applications in Alternative Investments*, 82-101. IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-7998-2436-7.ch004

Trainor, W., & Gregory, R. (2016). Leveraged ETF option strategies. *Managerial Finance*, *42*(5), 438-448. https://doi.org/10.1108/MF-12-2014-0305

Travis, D. H., & Fulkerson, J. A. (2023). Commodity ETF arbitrage: Futures-backed versus physical-backed ETFs. *The Journal of Derivatives*, *31*(2), 128-147. https://doi.org/ 10.3905/jod.2023.1.193

Tripathi, V., & Sethi, A. (2022). An evaluation of the tracking performance of exchange-traded funds (ETFs): The case of Indian index ETFs. *Vision: The Journal of Business Perspective*, *26*(3), 339-350. https://doi.org/10.1177/097226292199648

Tsai, I. C. (2024). Features of different asset types and extreme risk transmission during the COVID-19 crisis. *Financial Innovation*, *10*(62), 1-42. https://doi.org/10.1186/s40854-023-00510-5

Tsalikis, G., & Papadopoulos, S. (2019). ETFs performance, tracking errors and their determinants in Europe and the USA. *Risk Governance & Control: Financial Markets & Institutions*, *9*(4), 67-76. https://doi.org/10.22495/rgcv9i4p6

Tse, Y., & Martinez, V. (2007). Price discovery and informational efficiency of international iShares funds. *Global Finance Journal*, *18*(1), 1-15. https://doi.org/10.1016/j.gfj.2007.02.001

Vanguard Asset Management. (2023,). *What you need to know about physical and synthetic ETFs*. Vanguard Asset Management UK. Retrieved 27 May 2023, from https://www.vanguard.co.uk/professional/vanguard-365/investment-knowledge/etf-knowledge/etf-basics

Vardharaj, R., Fabozzi, F. J., & Jones, F. J. (2004). Determinants of tracking error for equity portfolios. *The Journal of Investing*, *13*(2), 37-47. https://doi.org/10.3905/joi.2004.412305

Verma, R., & Dhiman, D. (2020). A causal study on gold, SENSEX, and gold exchange traded funds. *Gold Bulletin*, *53*(2), 121-128. https://doi.org/10.1007/s13404-020-00280-3

Wagalath, L. (2014). Modelling the rebalancing slippage of leveraged exchange-traded funds. *Quantitative Finance*, *14*(9), 1503-1511. https://doi.org/10.1080/14697688.2014.916817

Warne, D. P., & Monika. (2023). ETF tracking errors: Evidence from Indian Stock Market. *IUP Journal of Financial Risk Management*, *20*(2), 51-59. https://www.researchgate.net/publication/378976313

Welch, S. J. (2007). On performance & tracking error in exchange-traded funds and index mutual funds. *College of Saint Benedict: Saint John's University Accounting and Finance Faculty Publications*. *7(1)*, 1-43. https://digitalcommons .csbsju.edu/acct_pubs/7

Woodgate, A., Siegel, A. F., & Mack, B. J. (2015). Practical applications of how much error is in the tracking error: The impact of estimation risk on fund tracking error. *The Journal of Portfolio Management*, *41*(2), 1-4. https://doi.org/10.3905/pa.2015.3.1.116

Wooldridge, J. M. (2020). Advanced time series topics. In *Introductory Econometrics: A Modern Approach* (7th ed.), 605-631. Cengage Learning. ISBN: 978-1-337-55886-0

Yao, S., & Zhang, J. (2011). On economic theory and recovery of the financial crisis. *Microeconomics: Search; Learning; Information Costs & Specific Knowledge; Expectation & Speculation eJournal*, *34*(5), 764-777. https://doi.org/10.1111/j.1467-9701.2011.01347.x

Yavas, B. F., & Rezayat, F. (2016). Country ETF returns and volatility spillovers in emerging stock markets, Europe and USA. *International Journal of Emerging Markets*, *11*(3), 419-437. https://doi.org/10.1108/IJOEM-10-2014-0150

Yiannaki, S. M. (2015). ETFs performance Europe - A good start or not? *Procedia Economics and Finance*, *30*(2015), 955-966. https://doi.org/10.1016/S2212-5671(15)01346-5

Zaimovic, A., & Dedovic, L. (2021, May 2021). The role of large tech companies in the capital market recovery from the Covid-19 Crisis. *Proceedings from the New Technologies and Applications 7th International Conference, New Technologies, Development and Application, 4*(1), 1149-1157. https://doi.org/10.1007/978-3-030-75275-0_127

Zawadzki, K. (2020). The performance of ETFs on developed and emerging markets with consideration of regional diversity. *Quantitative Finance and Economics*, *4*(3), 515-525. https://doi.org/10.3934/QFE.2020024

Zhu, Z., Bai, Z., Vieito, J. P., & Wong, W. K. (2018). The impact of the Global Financial Crisis on the efficiency and performance of Latin American stock markets. *PSN: Global Markets*, *46*(1), 2-22. https://doi.org/10.2139/ssrn.3208090

8. Appendices

Appendix 8.A

8.A.1. KPSS Test Results

Table 8-A.1: Results of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test for Stationarity

ETF/Index	Level	First Difference
EWW NAV	0.806968***	0.069528
EWW NAV Return	0.059046	0.065026
M1MX51M Closing Price	1.529194***	0.077834
M1MX51M Closing Price Return	0.055260	0.048083
IJH NAV	7.898335***	0.065404
IJH NAV Return	0.041215	0.029939
SPTRMDCP Closing Price	7.925918***	0.097510
SPTRMDCP Closing Price Return	0.042263	0.029104
SPYG NAV	7.497564***	0.192704
SPYG NAV Return	0.089201	0.007285
SPTRSGX Closing Price	7.488842***	0.237427
SPTRSGX Closing Price Return	0.096378	0.007125
XMEM NAV	3.533012***	0.182546
XMEM NAV Return	0.333866	0.500013
NDUEEGF Closing Price	4,255496***	0.232599
NDUEEGF Closing Price Return	0.333888	0.500008
SSO NAV	5.386826***	0.029415
SSO NAV Return	0.132200	0.021928
SPX Closing Price	6.560702***	0.048809
SPX Closing Price Return	0.037055	0.018105

*Note: Full physical: EWW (Index:M1MX51M), stratified sampling: IJH (Index: SPTRMDCP), optimized: SPYG (Index: SPTRSGX), synthetic: XMEM (Index: NDUEEGF) and leveraged: SSO (Index: SPX (2x)). Null hypothesis: The time series is stationary. ***, **, * indicates significance at 1%, 5% and 10% levels.*

(Author's own construction, 2025)

8.A.2. VIF Test Results

Table 8-A.2: Results of Variance Inflation Factor (VIF) Test for Multicollinearity in the Regression

Dependent Variable	Independent Variable	Uncentered VIF	Centred VIF
EZA Daily NAV Return	M1CXBAC Daily Return	1.000387	1.000000
SPY Daily NAV Return	SPXT Daily Return	1.000547	1.000000
IWV Daily NAV Return	RU30INTR Daily Return	1.000818	1.000000
IJH Daily NAV Return	SPTRMDCP Daily Return	1.000594	1.000000
EEM Daily NAV Return	NDUEEGF Daily Return	1.000192	1.000000
IWF Daily NAV Return	RU10GRTR Daily Return	1.001166	1.000000
INR Daily NAV Return	NDEUSIA Daily Return	1.000909	1.000000
DJE Daily NAV Return	DJINR Daily Return	1.000841	1.000000
EET Daily NAV Return	MXEF Daily Return	1.000009	1.000000
SSO Daily NAV Return	SPX Daily Return	1.000002	1.000000

Note: Full physical: EZA (Index: M1CXBAC); SPY (Index: SPXT), stratified sampling: IWV (Index: RU30INTR); IJH (Index: SPTRMDCP), optimized: EEM (Index: NDUEEGF); IWF (Index: RU10GRTR), synthetic: INR (Index: NDEUSIA); DJE (Index: DJINR), leveraged: EET (Index: MXEF); SSO (Index: SPX).

(Author's own construction, 2025)

Appendix 8.B

8.B.1. Ethical Clearance Letter

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

16 AUgust 2023

Miss Prianca Naidoo (219008320)
School Of Acc Economics&Fin
Westville

Dear Miss Prianca Naidoo,

Original application number: 00021877
Project title: The tracking performance of equity Exchange Traded Funds: A consideration of fund replication strategy, fund domicile, and crisis period

Exemption from Ethics Review

In response to your application received on 14 August 2023 , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

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

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

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