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The determinants of a European Exchange-Traded Fund's tracking error

Manuel Gonçalo Gomes de Almeida Pinho Valente

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Abstract

The main goal of this dissertation was to find the main determinants of an ETF's tracking error. We selected a sample of 43 ETFs with 21 different underlying indexes while using specified criteria. The sample will run from June 2003 to June 2020.

The dissertation's research question is relevant, due to the importance given to the ETF market by investors. These, when looking at an ETF, expect it to work as intended, meaning, obtaining the exact returns as its benchmarks. Thus, as an ETFs tracking performance worsens, the investors' interest will also dampen.

We started by selecting the methodology to compute the ETFs and indexes returns, and for the measurement of the tracking error. In the end, we selected three different tracking error-related methodologies to be used. With the methodologies selected, we analysed the tracking error of the sample's ETFs. In the initial phase of the sample, before 2008, the ETFs, in general, presented good tracking performances, but this was not the case for the periods affected by the 2008 international financial crisis, and the subsequent European sovereign debt crisis.

We found evidence of statistical significance for most of the selected variables: market value, number of shares, historical volatility, and associated expense ratio. In terms of possible literature contributions, contrary to what has been reported in other studies, we found that as an ETF's management-related fees increase, its ability to replicate the underlying index also increases, suggesting that tracking performance improves as more resources are used in its management.

JEL codes: G10 G11 G12 G14

Keywords: Exchange-Traded Funds; Tracking performance; Tracking error

Resumo

O principal objetivo desta dissertação é a análise do erro de acompanhamento (*tracking error*) presente nos *Exchange-Traded Funds* da amostra, de forma a encontrar os seus possíveis determinantes. A amostra é composta por 43 *ETFs* e os seus respetivos 21 índices, selecionados através de critérios devidamente identificados. Esta amostra será analisada durante o período de 2003 até 2020.

O estudo do erro de acompanhamento dos *ETFs* tem importância, pois quando alguém investe neste produto financeiro, espera receber um retorno igual ao do índice subjacente.

Em termos metodológicos, escolhemos três métricas de *tracking error* já testadas na literatura. Constatou-se que, numa fase inicial da amostra, anterior a 2008, os *ETFs* apresentavam um bom desempenho no que toca a replicar os seus respetivos índices. Porém, nos períodos seguintes, este desempenho deteriorou-se drasticamente.

Concluímos que as variáveis capitalização bolsista (*market value*), número de unidades de participação (*number of shares*), volatilidade histórica (*historical volatility*) e rácio de despesas *(expense ratio*) são estatisticamente significativas na determinação do erro de acompanhamento. Em termos de contributos para a literatura, destaca-se o facto de, ao contrário do reportado em outros estudos, à medida que as despesas referentes à gestão das *ETFs* aumentam, a capacidade de replicar o índice subjacente também aumenta, sugerindo que o desempenho de acompanhamento melhora à medida que mais recursos são alocados à sua gestão.

Códigos JEL: G10 G11 G12 G14

Palavras-chave: *Exchange-Traded Funds*; Capacidade de replicar índices; Erro de Acompanhamento

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Abbreviations

400E: Historical Volatility

AP: Authorised Participants

AUM: Assets Under Management

CEO: Chief Executive Officer

EMH: Efficient Market Hypothesis

ER: Expense Ratio

ETF: Exchange-Traded Fund

MV: Market Value

NAV: Net Asset Value

NOSH: Number of Shares

OECD: Organisation for Economic Cooperation and Development

RI: Return Index

SEC: Securities and Exchange Commission

SME: Small and medium-sized enterprises

SPDR: Standard & Poor's 500 Depository Receipts

TE: Tracking Error

VO: Turnover by Volume

1. Introduction

Passive investing has been increasing over the last couple of decades. There has been a consistent movement, from active to passive investing, in which exchange-traded funds participate. Passive investment usually consists of a rules-based type of investing, meaning it intends to replicate a known index by tracking it. In general, there are relatively lower associated management costs. Several variables have contributed to this shift's appearance, but the efficient markets hypothesis is usually considered as the trigger for society to question the efficiency of active investing. The EMH strongly argues that, due to the nature of the hypothesis, an investor is incapable of beating the market over the long run. These topics will be further discussed in detail in the upcoming Chapter 3.

An ETF represents a security that, hopefully, efficiently tracks its benchmark index, using a portfolio of stocks to replicate it. This type of fund has many characteristics associated with an index fund, with the addition of being traded on stock exchanges. Due to their nature, ETFs offer an investor the ability, with one single trade, to obtain exposure to a full index composed of a diversified portfolio. A process that previously had presented high inaccessibility and was only attainable with much higher associated fees. This makes ETFs an efficient solution for an individual investor looking to diversify his portfolio, avoiding higher exposure to idiosyncratic risk.

Bogle (2017) describes the invention of exchange-traded funds as a particular variant of an index fund, affirming that the ETF represents a traditional index fund with the additional ability to trade its shares.

Looking at this referred expansion, as seen in Madhavan (2016), ETFs have registered considerable growth, showcased in 2015, where assets in global ETFs exceeded the 3 trillion US dollar mark, surpassing hedge funds. On the one hand, the US inflows to ETFs were 25% and above annually throughout the past decade. Meanwhile, on the other hand, looking at a traditional active mutual fund, these have registered a negative inflow. Nevertheless, there is still clear evidence of continuous registered growth when looking at more recent data. In 2020, the worldwide number of ETFs reached 7602, meanwhile the ETFs accounted for a staggering 7736 billion US dollars in assets under management.

The main goal of our dissertation is to find at what length certain selected variables affect the tracking performance of an ETF. In other words, what are the determinants of an ETF's

tracking error? We reached this research question because, even though an ETF replicates an underlying index, its tracking performance is not always optimal. This discrepancy leaves room for the so-called tracking error, a divergence between the returns of both (the fund and the underlying index), meaning that there is an opportunity to research the determinants that lead to this happening. The study of this phenomenon has more value than one might realize, because investors, big or small, private or public, when looking to invest in an ETF, expect to obtain the same returns as its underlying indexes. Thus, as an ETFs tracking performance worsens, the investors' interest fades due to its inability to replicate its respective benchmark.

To start the research related to an ETF's tracking error, we selected a sample of 43 ETFs with 21 different underlying indexes, meaning that some of the ETFs track the same index. This sample complies with specific selection criteria, presented in Chapter 5, and it ranges from the period of 2003 to 2020.

After having the sample, we selected the methodology to compute the returns of the ETFs and indexes, and afterward the tracking error methodology. From reviewing the literature, we identified three different commonly used procedures, opting, in the end, to use them all while showcasing some reservations related to the third method (M3).

The first tracking error methodology, classified through the dissertation as M1, corresponds to the sheer daily return differences, meaning the difference between the ETF's returns and its underlying index. The second method, M2, now takes only absolute values. In other words, the tracking error corresponds to the fundamental difference between both returns. As for the last method, M3, the tracking error is now represented by the standard deviation.

As other studies concluded, we have also found clear evidence for the presence of tracking errors throughout ETFs. Looking at the tracking error's historical behavior, prior to the subprime crisis, the average daily tracking errors were relatively small. But, both the 2008 financial crisis and the subsequent European sovereign debt crisis seemingly acted as a negative accelerator, worsening the tracking errors. It is also important to mention that, by the end of the sample, June 2020, there are already clear signs of the tracking errors being affected by the SARS-CoV-2 pandemic.

In terms of the determinants, most of the results also coincide with the other ETF-related literature mentioned throughout the paper. We found evidence of statistical significance for the ETF's market value, the number of shares, historical volatility, and associated expense

ratio. Obtaining a negative effect to the ETF's tracking error for the market value, meanwhile for the NOSH, evidence of a positive effect was found. The historical volatility presented a positive effect and the expense ratio, the only divergence compared to other studies, registered a negative effect on the tracking error.

To conclude this first chapter, we will briefly present the rest of this dissertation's structure. The second chapter presents a brief description of the ETF. The third chapter corresponds to the literature review. This chapter concludes with the literature's most commonly identified determinants of an ETF's tracking error. The methodology used corresponding to the tracking errors and returns computation is presented in the fourth chapter. Chapter 5 first shows the criteria behind the selected ETFs and the corresponding final data sample. The last part (5.3) contains a brief collection of the descriptive statistics related to the three tracking error methodologies and the selected variables. Chapter 6 presents the main results obtained in the dissertation. While also presenting a collection of what were the main results registered throughout the literature (while using the same methodology but different samples). Chapter 7 concludes the dissertation.

2. Exchange-Traded Funds: a brief overview

Before exploring the history behind the ETF movement's appearance and its predecessors, this second chapter provides a description of ETFs. Going on to their unique origination process (creation and redemption) and some of their most identifiable pros and cons. It concludes with a brief overview of how the ETF market looks at new financial trends, more precisely, how is it looking to incorporate cryptocurrency into its business.

ETFs are none other than a type of security that tracks an underlying index or a market benchmark while, at the same time, being traded. Therefore, ETFs can be purchased or sold on a stock exchange, just like a regular stock. As we previously mentioned, ETFs share a lot of qualities with mutual funds, with the addition of this financial product being traded.

But it was this simple difference that made ETFs so interesting for investors. There is a famous saying that many investors, no matter their size, religiously follow: "Don't put all your eggs in one basket.". Investors try to construct a diversified investment portfolio, to avoid their exposure to idiosyncratic risk as much as possible, leaving them only exposed to the market risk. This was usually achieved by purchasing a wide range of diversified assets individually or investing in mutual funds. ETFs appeared as the perfect alternative to follow that saying, allowing for international and sector diversification. Because of their core nature, ETFs will enable an investor with a single trade to diversify its portfolio due to its underlying index. ETFs also work, usually, with lower associated fees, due to their passive management and offer intraday trading.

The process that led to the ETF creation will be explored in Chapter 3, Literature Review, but the first ETF appeared in 1993, named Standard & Poor's 500 Depository Receipts. The SPDRs, also called spiders, are classified as Unit Investment Trusts because they have a fixed portfolio and offer ownership units in the trust to investors. SPDRs utilize the process of indexation by replicating the S&P 500 index, presented as a single security trading like a normal stock. In general, ETFs tend to replicate their underlying index's daily profits. To do so, ETFs either invest all their assets into the securities of the respective index, replicating their composition entirely, or opt only for a sampling of the benchmark.

Looking now at how ETFs work, we will briefly describe how they come to fruition via the so-called Creation and Redemption process, as seen in Kosev and Williams (2011). ETFs are built similar to open-ended companies, allowing the number of shares to fluctuate over time.

Before an ETF can be traded, first, it needs to go through the creation process within the primary market. To do so, an ETF is compartmentalized into large blocks containing shares, typically referred to as creation units. These units are only available to be acquired by Authorised Participants, which usually consist of market-makers or institutional investors. For the APs to purchase these units, cash is not traditionally used in the transaction. Instead, the preferred method is to transfer ownership of a portfolio containing securities that are part of the ETF's underlying index. So, the creation units work as a jumpstart for the ETF, directly providing the resources to its portfolio. After this first step, the APs have the freedom to make deals with their units on the secondary market via a stock exchange. They can also start the redemption process, where they can redeem their units back to the fund, basically doing the opposite of the creation process. This process is represented in Figure 6, retrieved from Kosev and Williams (2011), located in Annex 2.

As we previously mentioned, one of the ETF's most appreciated virtues is its ability to diversify an investor's portfolio. This diversification is achieved through a simple process, with an associated low cost, and the ability to be traded daily. Another virtue is, due to its trading nature, an ETF also attracts risk-averse investors. An ETF can apply risk-management strategies to investments, and they might also attract investors looking to short a specific index replicated in an ETF, looking to repurchase them later at a lower fee.

As for frequent concerns, as seen in Kosev and Williams (2011), ETFs have been classified as a financial instrument whose associated complexity is increasing, while simultaneously losing transparency. This is due to the appearance of new variants of ETFs using complicated structures. In its origin, an ETF was characterized by simplicity, where these were backed by the assets contained in the underlying index. Another concern is the liquidity present in ETFs because, as it is previously mentioned, this liquidity originates in the primary market, and is directly linked to the underlying index.

To conclude this chapter, we will explore now how ETFs are looking at new financial trends. There has been increasing demand for the appearance of the first Bitcoin-related ETF. There have been calls for the appearance of this financial product since 2013. But besides the inherent volatility of a cryptocurrency and multiple known situations of obvious price manipulation, this type of currency is not yet seen as its other big brothers. Even though increasing, cryptocurrency is not yet treated as a solid option for institutional investors or government sovereign funds. As seen in Bain and Schmidt (2021), the U.S. Securities and

Exchange Commission Chair, Gary Gensler, opened the doors for the first Bitcoin-related ETF in his first statement regarding cryptocurrencies. Since this SEC's signal, several financial firms have applied to launch Bitcoin-related futures products.

3. Literature review

To start the literature review, we will begin by showcasing some of the critics of actively managed investments that paved the way for the appearance of passive investing. Then, the first appearances of publications referring to passively managed financial instruments, particularly, indexation. Finally, concluding with the surge and development of ETFs and the studies regarding them.

3.1 Active management criticism

As we mentioned previously, passive investing and subsequently ETFs were created to answer the highly criticized actively managed strategies. This type of investment first appeared in the 70s (there were previous attempts, even successful ones, but never long-lasting) when John C. Bogle, acting as The Vanguard Group's CEO, created the first-ever index fund. This creation was a needed answer to the ever-growing EMH movement that defended that an individual investor couldn't predict and consistently beat the market in the long run.

Therefore, to start this review, we will begin with the critics of actively managed investments that paved the way for the appearance of passive investing, trying to follow a brief chronologic pattern. Passing on to the first appearances of publications referring to indexation and concluding with the surge and development of ETFs and their studies.

First and foremost, none other than the frequently called father of the EMH, Eugene Francis Fama. In Fama (1965), he concluded that his Random Walk Hypothesis, where he defends that asset pricing travels a random road, meaning that it cannot be predicted, validates the principles of the EMH. Following this publication, Fama (1965) published three other reviews of it, the last in 1998.

The first review came five years later. In Fama (1970), the author concluded that the EMH argued for a market whose prices were directly related to the available information. On the one hand, Jensen (1978), in a direct analysis, affirmed that the EMH was the most robust hypothesis. On the other hand, Grossman and Stiglitz (1980) argued that the market's prices could never reflect all the available information. All the financial incentives to gather this

information would be gone if this were the case. Thus, prices can only reflect part of the information so that those whose job is to acquire it, will still be compensated. In a more recent publication, Sewell (2011) also reaches the same conclusion as the previous, stating that a market can never be completely efficient. In that case, its prices can never fully reflect all the available information.

In his second review, Fama (1991), the author used a view previously presented in Jensen (1978) to appease his critics. He suggested that in a less radical version of the EMH, there would exist transaction costs. Meaning that prices would reflect the available information, but only until the marginal cost of this information equals its marginal usefulness. This review was also met with critics. Ippolito (1993) states that if this is the case, then a skilled investor can beat passively managed instruments, making the argument for the EMH and passive investing, as a whole, obsolete.

At last, the final review article on efficient markets, Fama (1998). The author disregards the identified anomalies made by his critics due to what he classifies as an incorrectly used methodology. Stating that efficient markets may generate random events that lead to a pricing over-reaction to information. Once again, the latest review brought many defendants and critics between several publications. On the one hand, Malkiel (2003) affirmed, while analysing the relation between efficiency and predictability in investing, that the markets are indeed efficient, supporting the EMH. Degutis and Novickytė (2014) also reached the same conclusion, stating that individual investors cannot beat the market consistently due to the randomness associated with stock returns while working in an efficient market. On the other hand, Deng (2007) stated that the efficient market theory was deeply flawed. The author claimed that the EMH backers presented a lack of knowledge regarding the relationship between investors and stock price behaviour.

3.2 The surge of passive management

We will move along now to the literature review regarding passive investment, particularly indexation. The first argument for an investment process, whose description is as close as possible to this day and age indexation, was made by Renshaw and Feldstein (1960). The authors defended that an individual should invest in the Dow Jones Industrial Average. The

reason is that, even though it would eliminate the possibility for one to beat the market, it would also, at the same time, assure one would never get bitten by it. As we previously mentioned, John C. Bogle brought to life, in 1975, the Vanguard 500 Index Fund, with the goal of turning it into the leading low-cost supplier of mutual funds in the entire globe. The success of indexation accompanied the following years. Sorensen, Miller, and Samak (1998) report that indexing achieved equity market returns with much higher efficiency and lower operation costs than its counterparts, making it much more sought after. It also states that in 1998, the total amount deployed to index funds surpassed the 1 trillion US dollars mark. Looking at more recent publications, Bogle (2016) states, once again, that the lower costs associated to indexation and the continuous incapability of active investors to consistently beat their counterparts paved the way for the rise of indexation.

We will look now at two of the most recent Morningstar's published active/passive barometers. These barometers measure the performance of active funds against their passive peers in the United States. Johnson and Bryan (2017) conclude that actively managed funds are still unable to beat their counterparts when looking at longer periods. In other words, the average dollar invested in passively managed funds can outperform its counterpart. In the following year barometer, Johnson and Bryan (2018), the authors report an increased success rate for actively managed funds, higher than the former year. However, this improvement still made the actively managed funds underperform and be incapable of beating their benchmarks. Elton, Gruber, and de Souza (2019) stated that from 2013 to 2018, passively managed mutual funds rose from 16,4% to a staggering 26%. This increase in AUM, indicates that investors continue to find this type of vehicle as a more than capable replacement for actively managed investments.

To conclude the literature review regarding the surge of passive investment, particularly the indexation type, we used a figure presented in Bogle (2017), located in Annex 3. Figure 7 shows that, as previously mentioned, an actively managed portfolio's odds of beating its counterpart drop drastically when looking at a longer time horizon. For example, when using 25 years, there are only 5% odds of an actively managed portfolio beating its counterpart.

3.3 The rise and development of ETFs

The last part of the literature review will focus solely on the type of passive investing used in this dissertation, ETFs. They refer to what triggered their appearance, how they developed, and studies regarding its performance determinants.

As it is previously stated, ETFs first came to market in 1993, making it possible for an investor to obtain exposure to a diversified range of asset classes, while paying low fees for its asset management. If passive investing was an answer to the highly criticized actively managed portfolios, ETFs, or its initial form, were an answer to the SEC's demand for a single product able to trade baskets of stocks. Balchunas (2016) stated that this demand is present in the paper "The October 1987 Market Break" which acted as the SEC's analysis and response to the 1987 stock market crash. This report triggered the creation of an innovative product that later would be called an ETF. It called for the creation of a less volatile product. ETFs that, ironically, originated from a regulators' paper that financiers saw as a proposal, are in 2015, a three trillion-dollar global industry, reaching in the United States, a staggering twenty trillion US dollars' worth of shares in trades.

ETFs also surfed the same wave as other passive investing instruments, becoming ever more popular with time passing. Hill (2016) finds a logical explanation for this rapid growth. The author states that before the appearance of fixed-income ETFs, indexing was present only at a smaller scale in the realm of fixed-income mutual funds. But once this instrument, seen as an efficient and transparent vehicle, became available, indexing investment grew considerably. This explanation is also corroborated by the previously mentioned Elton et al. (2019). It also states that due to their unique nature, sector-based ETFs also represents an important argument for the positive development of this passively managed investment option. Other factors that helped its growth are presented in Hill (2016), such as, ETFs being available through exchanges; their costs being constant (whether a large or small investor is purchasing it); and due to the ETFs characteristics, it is now possible to commit to a wide range of investment exposure, something that was only previously available to the largest financial institutions.

If Eugene Fama is usually known as the father of the EMH, John C. Bogle can be called, for motives previously mentioned, the father of passive investing. In Bogle (2017), the author

expressed his concerns about the rise of investment in ETFs. Bogle (2017) sees ETFs as an outlier from the original concept of indexing, being used for short-term purposes. The author feared this would lead to an excess in trading, resulting in a short-term approach to investing, in a field that usually works in longer-term plans. However, again Hill (2016) states that this fear present in economists is part of the core nature of an ETF, meaning that to ensure that the fund's valuation is replicating the prices of its securities, it results in a higher than usual trading activity.

3.4 ETFs' performance determinants

Looking now at various studies that observed the performance of ETFs and tried to find what variables significantly affect their tracking performance, by looking at their associated tracking error (which represents, as previously mentioned, the return difference between the ETF and its corresponding benchmark).

First, when looking at an ETF tracking performance, Elton, Gruber, Comer, and Li (2002) studied an ETF's tracking ability by comparing the returns from the first-ever ETF, SPDR, with the returns of its underlying index, S&P 500. The results showcased a lower tracking performance associated with the ETF, in other words, the existence of tracking errors when replicating the index. Rompotis (2011), using a different methodology, and looking now at more than one passively managed ETF, reaches the same conclusion as the previous paper. Both papers found evidence that ETFs cannot perfectly replicate their underlying index.

Regarding differences present due to an ETFs geographic location, Tsalikis and Papadopoulos (2019) concluded that American ETFs register lower tracking errors when compared to European ETFs. A possible explanation could be the sheer size difference between these two, meaning that larger ETFs register lower tracking errors. Kanuri and McLeod (2015) also corroborate the previous results showing a better performance from ETFs originating from the US. The authors' study shows that these ETFs have, on average, higher returns and lower associated risk when compared to international ETFs. Also, Blitz, Huij, and Swinkels (2012) concluded that ETFs originating from developed countries would track their underlying indexes better.

Several papers found the expense ratio (an annual fee charged to the ETF's investors that represents a percentage of the contained assets) as an essential factor for a tracking error in ETFs. For example, Elton et al. (2002) also showcased that ETFs with higher expense ratios (higher associated costs) are likelier to underperform, which was also corroborated by Rompotis (2011).

An ETF's associated risk is also frequently used to determine for the tracking error. In Rompotis (2011), the risk was represented as the standard deviation from the ETFs' returns, so in other words, a higher variation in returns translates to a higher associated risk. The author concluded that the variable risk could be deemed an important determinant of the tracking error, positively affecting it. Rompotis (2011) concluded also that there is a predictability factor regarding an ETF's performance. Since that the yearly top-performing ETFs tend to continue to do well in the subsequent years and, at the same time, keep on outperforming their peers.

Looking now at papers studying the dividend yield (represents the dividend per share as a percentage of the share price). Chu (2011) found a positive effect of this variable, related to an ETF's tracking error. This, as the author stated, may cause some surprise, since, in theory, the referred dividends, distributed by the stocks present in the index, are expected to be immediately reinvested, usually in the next available business day.

The author concluded that the reason for the negative effect on the tracking performance, is that this process is coupled with a constant lag. This lag leads to create a domino effect, experienced when investors see their payments delayed, resulting in the funds' managers also facing a delay when trying to reinvest back into the stocks.

There is also interest regarding the possibility of seasonality affecting an ETF's returns. Specifically, it is interesting to know if seasonal patterns identified throughout the years in studies involving typical stock market returns are also present in ETFs. In terms of seasonal similarities, Mohamad, Jaafar, and Goddard (2016) concluded that these do not match, indicating that stock market and ETFs returns do not have the same seasonal patterns.

Looking now at papers that tested for the existence of specific seasonal effects in ETFs, Agrrawal, and Skaves (2015), using US only ETFs, tested for four different effects: the January effect (where it is expected that, in January, the registered average returns will be higher than the rest of the year); the Halloween effect (the period post-Halloween, starting from November till April is expected to be characterized by higher average returns than the

rest of the year); the Santa Claus rally effect (higher average returns expected to be registered on the first days after the festivities); and the Mark Twain[1] effect (higher average returns expected to be registered in October).

The authors concluded that for ETFs, both the January and the Mark Twain effect are not present. But the other two effects were.

Lastly, we have Alves and Reis (2019) observing US equity ETFs and testing whether the verified seasonality was idiosyncratic (meaning that the same patterns were not present in the ETFs' underlying index) or induced. The authors observed, for April, an above-average performance, with the presence of induced seasonality, due to the same outperformance in the ETF's index. The authors also found evidence for idiosyncratic seasonality throughout their paper.

[1] The name for the effect comes from the famous American novelist himself, retrieved from one of his novels: "October: This is one of the peculiarly dangerous months to speculate in stocks. The others are July, January, September, April, November, May, March, June, December, August and February", Twain (1986).

4. Methodology

In this chapter, we will briefly describe the methodology used in this paper and why. First, we describe some of the various methods used throughout the literature to compute the tracking error. Then we describe the methodology used to achieve the ETFs and Indexes returns, a key component in achieving our desired dependent variable, the tracking error.

4.1 Tracking error estimation methodology

Our goal is to evaluate how is the tracking ability of an ETF affected. We will use the tracking error as our dependent variable to identify its determinants while testing different independent variables for statistical significance. Thus, as we mentioned previously in Chapter 3, we gathered different estimation methodologies used to compute the tracking error present throughout various ETF performance-related papers. Afterward, we also present the main results some papers achieved using those tracking error estimation methodologies.

The tracking error methodologies that we retrieved from the literature, having in mind that the data used is, in a vast majority, daily reported, were:

First Method (M_1):

The first method is the literal mathematical application of what a tracking error is defined as. As it is previously mentioned, the tracking error simply represents the discrepancy between the ETF's registered returns and the underlying benchmark. This method is present in the vast majority of the related studies, and the following formula represents it:

$$\boldsymbol{TE = R_{ETFi,t} - R_{Ii,t}} \quad (1)$$

Where TE means Tracking Error, $\boldsymbol{R_{ETFi,t}}$ represents the daily return of the i ETF and $\boldsymbol{R_{Ii,t}}$ the underlying index's i daily return.

Second Method (M_2):

This method consists in computing the average absolute difference between the returns. Therefore, this method does not distinguish between positive and negative returns. This method was also utilized by a wide range of authors, such as, per example, Frino and Gallagher (2001), and the following formula represents it:

$$TE = \frac{\sum_{t=1}^{n} |e_{p,t}|}{n} \qquad (2)$$

Where $e_{p,t}$ represents the difference between the returns; $e_{p,t} = R_{ETFi,t} - R_{Ii,t}$

Third Method (M_3):

The third and last method is present in Pope and Yadav (1994), but also in both already mentioned Frino and Gallagher (2001) and Chu (2011). This method assumes the standard deviation of the return differences as ETF's tracking error. The tracking error is literally measured by the standard deviation formula (applied to the daily return differences between the fund and index). The third method is expressed as:

$$TE = \sqrt{\frac{\sum_{t=1}^{n} (e_{p,t} - \bar{e}_{p,t})^2}{n-1}} \qquad (3)$$

Where $\bar{e}_{p,t}$ represents the average difference between the returns.

There are however some reservations considering this third method presented throughout the literature. As seen in Pope and Yadav (1994), this method is not recommended when treating data reported with high frequency, such as when being daily reported. The authors concluded that due to the annualized standard deviation, this methodology would not be able to correctly estimate the expected standard deviation of the return's differences. According to the authors, those returns are autocorrelated. Another important aspect to refer is due to this method's core nature, the standard deviation. Suppose an ETF, while using the standard deviation as its tracking error, is consistent in its tracking by either outperforming

or underperforming its benchmark by the same amount. In that case, this methodology will not be able to correctly identify the existent disparity, resulting in a tracking error equal to zero. Therefore, when confronted with ETFs with these characteristics, the M3 will understate the actual tracking error present.

4.2 Returns methodology

With this subchapter, we intend to show what methodology we will use to obtain the tracking error performance. There are many different options when calculating the return. Some papers opt to use the market price as the primary source. Another significant part of the literature uses the NAV, which in ETFs, translates the value of each share's portion related to the fund's underlying assets and cash at the end of the trading day.

We used the Return Index to calculate the returns for two reasons. First, it is easily attainable and explained in great detail via Datastream (part of Thomson's Reuters Eikon). The second reason is the core nature of the variable. When using the RI, the obtained return values will provide more accurate information to compute the returns, resulting in a more accurate tracking error. As described in Datastream's database, the RI represents the growth in value of a share holding, over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price. The following expression represents it:

$$\boldsymbol{RI_t = RI_{t-1} * \frac{PI_t}{PI_{t-1}} * \left(1 + \frac{DY_t}{100} * \frac{1}{N}\right)} \quad (4)$$

Where $\boldsymbol{RI_t}$ is the return index on day t, $\boldsymbol{RI_{t-1}}$ represents the return index the previous day, $\boldsymbol{PI_t}$ is the price index on day t, $\boldsymbol{PI_{t-1}}$ is the price index the previous day, $\boldsymbol{DY_t}$ refers to the dividend yield's percentage registered on a specific day t and $\boldsymbol{N}$ refers to the annual number of working days.

Therefore, instead of simply using the market prices to compute the respective returns, we will use the RI (which, as mentioned above, also incorporates the prices on its formula). With the RI in mind, the ETF's returns and those of the underlying indexes are now obtained through the subsequent formulas:

$$\boldsymbol{Returns_{ETF,t}} = \frac{\boldsymbol{RI_{ETF,t} - RI_{ETF,t-1}}}{\boldsymbol{RI_{ETF,t-1}}} \qquad (5)$$

$$\boldsymbol{Returns_{I,t}} = \frac{\boldsymbol{RI_{I,t} - RI_{I,t-1}}}{\boldsymbol{RI_{I,t-1}}} \qquad (6)$$

4.3 Explanatory variables

This chapter will identify what variables were chosen with the belief to be the dependent's main determinants. When describing these, we will also look at some of the results obtained throughout the ETFs literature. Some of the results were previously stated in Chapter 3. Afterward, we will define the econometric model used to run three different regressions for each tracking error method.

4.3.1 Selected variables

We have already mentioned some of the most commonly accepted determinants of an ETF's associated tracking error in Chapter 3. Therefore, it is with no surprise that we ended up choosing variants or some of the same determinants as the independent variables for this dissertation's econometric model. The explanatory variables that we selected are:

- **Market Value (MV)**
- **Number of Shares (NOSH)**
- **Historical Volatility (400E)**
- **Expense Ratio (ER)**
- **Turnover by Volume (VO)**

MV:

As the first variable, we chose the market value to assess if an ETF's value influences its tracking performance. The MV is expressed in millions of euros. As we previously mentioned, authors such as Tsalikis and Papadopoulos (2019) believe that a market's size can influence the tracking error of the ETFs associated with it. Still, in this case, we are looking at the sheer value size of the actual ETF. Chu (2011) concluded that this variable negatively influences the ETF's tracking error, meaning that as an ETF expands, its tracking error should decrease. The reasons appointed by the author were that, in general, larger ETFs

would have a better capacity to track their underlying benchmark due to, for example, having a bigger and/or more qualified management team.

NOSH:

We picked the number of shares to have an alternative to the size-related variable market value as the second variable. This variable represents the total number of ordinary shares present in an ETF, and its amount varies whenever new tranches of stock are issued. It is expected to have the same influence as the MV, but while the MV expresses the ETF's size using its financial valuation, NOSH uses its sheer share size. Therefore, as it was previously mentioned, Chu (2011) corroborated the negative relation between the size of an ETF and its tracking error. Its value is expressed in the thousands.

400E:

We opted for the ETF's Historical Volatility, as it seemed of capital importance to assess if an ETF's inherent risk has any evidence of influence on an ETF's tracking error. An ETF's risk is usually related to its returns' standard deviation, meaning that more unstable returns (higher presence of volatility) are expected to bring with it higher tracking errors. So, the variable related to risk should positively affect the dependent variable. As we previously mentioned, Rompotis (2011) concluded that the variable risk could be an important determinant of the tracking error, positively affecting it. When testing the risk's significance, estimated as the ETF's returns standard deviation, using a sample entirely made of only Blackrock's iShares, the author found evidence of a positive impact on the tracking error. For Datastream, this variable is estimated as the standard deviation of the returns over the past five years, and its given abbreviation is 400E.

ER:

As it is previously mentioned in Chapter 3, the expense ratio is widely regarded as one of the most common determinants of the tracking error. It corresponds to an annual fee, charged to the ETF's investors, representing a percentage of the value of the contained assets. Several papers found its positive influence on an ETF's tracking error. For example, Elton et al.

(2002) and Rompotis (2011) showcased that ETFs with higher expense ratios are likelier to underperform due to registering higher tracking errors.

It is also important to mention that, besides being reported annually, the expense ratio-related variable data was not available to be obtained via the Datastream. The ER was retrieved from either the ETF's website (www.ishares.com, for example) or from global aggregating third-party ETF-related websites (such as www.justetf.com). In some particular cases we had to obtain these values through a website, typically known as the Wayback Machine, located at www.archive.org/web/, which allows its users access to previous archived websites from a past date as long as they are available.

VO:

The VO variable, turnover by volume, expressed in thousands, shows us the number of shares traded for the ETF on a particular day. An ETF's tradability, measured by volume, should be an important determinant for its tracking error. Expecting an ETF with higher trading action to negatively influence its tracking error, meaning that with greater cashflows, the ETF's associated trading costs will be lowered, hence also improving its tracking performance. Therefore, we used this variable to control an ETF's liquidity, studying the impact between the trading volume and the correspondent ETF's tracking error.

4.3.2 Econometric model

After referring the three methodologies used to obtain the ETF's tracking error, how the returns' computation will be achieved, and the determinants selection criteria, it is time to define what will glue all these factors together. This equation will be used to assess how exactly the explanatory variables affect the tracking error.

The regression that will be used, in compliance with ETF literature, is presented in equation 7:

$$TE_{Mi} = \beta_0 + \beta_1 * MV + \beta_2 * NOSH + \beta_3 * 400E + \beta_4 * VO + \beta_5 * ER + \varepsilon_i \qquad (7)$$

Where $\boldsymbol{TE_{Mi}}$ represents the estimation i for the different methods of the tracking error previously mentioned; **MV** refers to the market value; **NOSH** refers to the Number of Shares; **400E** refers to the Historical Volatility; **ER** refers to the expense ratio; and **VO** refers to the Turnover by Volume. All variables, besides ER (annual), are reported with daily data.

5. Data

At first, we will present the selection criteria used to identify the sample of ETFs collected to build the database. The second point presents the results from applying the referred criteria, the final ETF sample. Concluding with a brief analysis to the descriptive statistics related to the ETFs and index returns, but also of the selected variables.

5.1 ETF selection criteria

To select which ETFs would be the object of analysis and ensure that this selection was made with objective criteria, we used the Fund Screener available in Thomson's Reuters Eikon, which access has been provided by the Faculty of Economics of the University of Porto. The selected data filters were:

- The asset universe composed of ETFs is the financial product that this dissertation will focus on.
- ETFs focussed on index tracking, meaning the use of indexation.
- ETFs that are currently active. Omitting from this study ETFs that are either inactive or dead. The goal of this dissertation is to identify what variables can be considered as determinants of the tracking error corresponding to ETFs that are currently available on the market. Therefore, we are only looking at active ETFs.
- European ETFs, even though it is widely known that ETFs are more present and diversified in the US market, we opted to focus on the European region. The reason is that most of the available papers have already focussed their studies only on US ETFs, so we hope to add up to the available European ETF research by taking this route. To achieve this, we used a combination of different parameters: European domicile; European geographical focus; Classified as EU equity by the Lipper Global.
- Launch date before 31st of June 2019 to ensure that there is sufficient historical data available to observe.
- Euro as the asset's currency.

- Primary flag, designated by the Lipper. Only the primary version of the ETF will be selected. Some ETFs offer two different variants, while replicating the same index, distributing ETFs, or accumulating ETFs.

5.2 The sample

With these criteria, the number of ETFs selected to start creating the database reached 64. Afterward, we gathered information relative to the ETF itself and its underlying index from Datastream. This process ended up being harder than expected due to either some indexes being unavailable in the database; some ETFs or indexes' tracking being classified as dead; and some of the underlying indexes being only available in a different currency than the ETF's. Thus, the total number of ETFs present in the final sample is 43 with the respective 21 underlying indexes. Table 15 (Appendix 1) represents what would the original sample be if no associated deficiencies were encountered while gathering the corresponding data. The ETFs that were discarded are highlighted with the color red.

It is also important to mention that not all the ETFs' data could be retrieved from the same exchange lister. In some cases, there was some discrepancy between the ETF's launch date and the first entry of the date available from these in Datastream.

Table 14, also located in the Appendix, represents the final version of this dissertation's sample. It is organized in alphabetical order, referring to the ETFs. On the first column lies the ETF's most common ticker (for an easier identification process); the second column presents the name of the ETFs; the third column presents the ETF's domicile; the fourth column shows the index's corresponding ticker; the last column presents the benchmark's name.

Once again, it is essential to mention that some of the corresponding indexes were not available through the Lipper Database, being retrieved from either the ETF's own website (www.ishares.com, for example) or from global aggregating third-party ETF-related websites (such as www.justetf.com).

The final sample contains 43 ETFs and 21 different underlying indexes. The sample will run from June 2003, when the oldest ETF of the group launched, iShares STOXX Europe 50 UCITS ETF, until June 2020. The youngest ETF of the sample is the iShares MSCI Europe SRI UCITS ETF, launched just in June 2019. It is also important to mention that this period was characterized by important economic catastrophes, which effects also surely rippled to the ETF market, such as the initial US subprime crisis that paved the way for the subsequent international financial crisis of 2008, which in its turn originated the 2010 European sovereign debt crisis. The effects of these on the ETFs' tracking errors are presented in Chapter 6.

The ETFs have two favorite indexes that they replicate, the STOXX Europe 600 and the MSCI Europe, both present nine different times.

With the final sample in mind, we then collected the returns data for the ETFs and their underlying indexes, with the determination to compute the RI. We also gathered the ETFs' corresponding market value, number of shares, historical volatility, turnover by volume, and expense ratio.

5.3 Descriptive statistics

This chapter will provide the descriptive statistics related to the returns of the ETFs and their underlying benchmarks and those of the explanatory variables. Descriptive statistics refer to the process of analysing a brief statistical summary that quantitatively weighs a database.

Table 1 - Summary statistics – ETF, index, and determinants

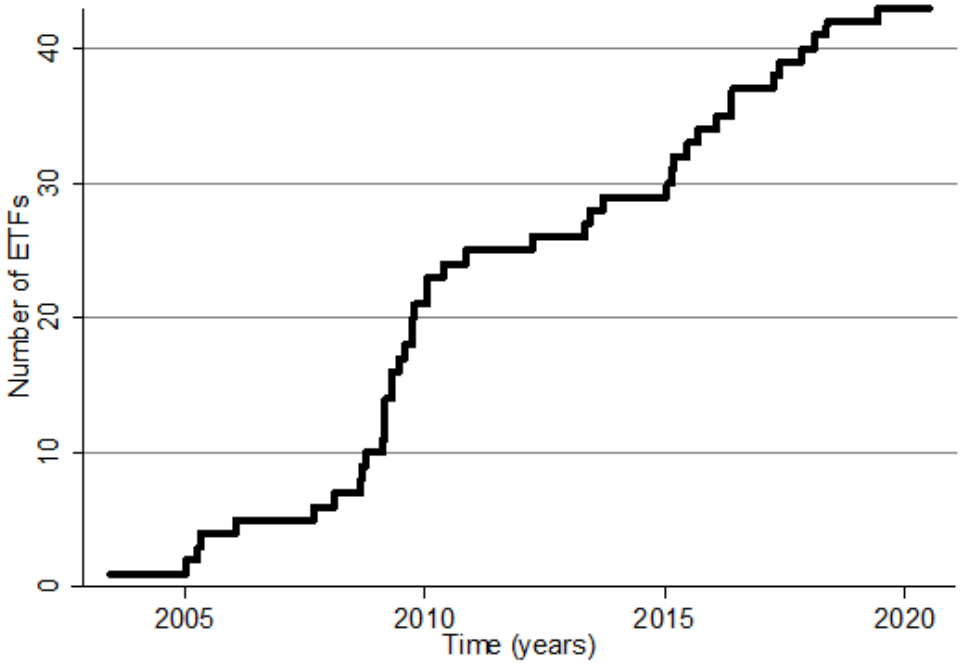
Variables	N	Mean	SD	Min	Max
ETF Returns	99898	0.000240	0.011227	-0.421	0.232
Index Returns	83363	0.000324	0.011177	-0.136	0.110
MV	89192	448.2028	352.3123	0.93	28823.04
NOSH	100008	15875.92	14211.17	1	1252358
400E	99019	0.149894	0.036378	0	0.5594
VO	72331	55.00373	330.4946	0	153733.8

Where N represents the number of observations (fewer for the indexes due to some ETFs tracking the same benchmark); Mean represents the average value of the returns; SD stands for standard deviation; Min and Max correspond, respectively, to the minimum and maximum values encountered for both valuables.

The table shows that both the average value for the returns and the standard deviation of these present comparable values. The data shows that the average daily returns for ETFs and their underlying indexes are the values 0.000240 and 0.000324. The standard deviation also presents similar values for the two, 0.011227 and 0.011177.

Looking at the ETFs' growth in sheer numbers, represented in Figure 1, we can see that the number of ETFs from the sample increased throughout the period (from 2003 to 2020). This correlates with an annexed figure (Figure 4, located in Annex 1) that shows the worldwide number of ETFs for the same period.

Figure 1 - ETFs growth (numbers)



Looking now at the determinants descriptive statistics presented in Table 1. We can see that the sample's average market value was around 448 million euros. The MV also showcased a

high standard deviation level, meaning a high dispersion of amounts corresponding to an ETF's MV, verified in the large gap presented by the minimum (nearly 1 million euros) and the maximum (28823 million). As for the numbers of shares, expressed in thousands, the same discrepancies are present, indicating that the sample has ETFs of various dimensions. The NOSH also registered the highest number of observations, meaning a high frequency of change in an ETF's NOSH. The historical volatility, 400E, as was previously mentioned, is estimated as a standard deviation of the returns over the past five years, usually associated with the historical beta variable. Lastly, the turnover by volume variable, also expressed in the thousands, showcases the lowest observations of the group, indicating that the number of shares traded for the selected ETFs represents a lower frequency than any of the other variables.

To avoid confusion, we omitted the expense ratio variable, ER, because it represents an annual charged fee. Preventing comparing the statistics of one annually reported variable with other daily ones.

The detailed statistics tables corresponding to each determinant are located in Appendix 2. For the MV we have Table 16, Table 17 for the NOSH, Table 18 for 400E, and for the VO, Table 19.

The detailed returns statistics are in Appendix 4, Tables 22 and 23. Table 22 represents the returns and descriptive statistics of each ETF in the sample. Meanwhile, the latter presents the corresponding 21 underlying indexes, where, in both tables, older financial instruments will have a higher number of observations (N).

6. Results

This chapter will contain all of this dissertation's results, first related to the tracking error performance (computed with three different previously detailed methods) and the determinants of the tracking error. Also, we will present the results obtained by some of the literature already mentioned when estimating with the same methods as ours, but with a different sample.

6.1 Tracking performance statistics

As already mentioned, the tracking error variable provides information on how the ETFs are tracking their underlying benchmark, in other words, how is their tracking performance behavior. Therefore, a lower tracking error will translate to a better ability to replicate the ETFs.

The following table, Table 2, presents the descriptive statistics for the three methods used for achieving the tracking error, previously described in Chapter 4.

Table 2 - Tracking error summary statistics

TE	N	Mean	SD	Min	Max
M1	4448	-0.0000139	0.001104	-0.0117962	0.0116955
M2	4448	0.0011697	0.001244	0	0.0153275
M3	4448	0.0042711	0.0051555	0	0.1330838

Each row corresponds to a different estimation method for the tracking error. It is important to remember that the second method, M2, considers absolute numbers only, hence the present discrepancy in obtained results, in the table above. Its usefulness will be explained later in this chapter.

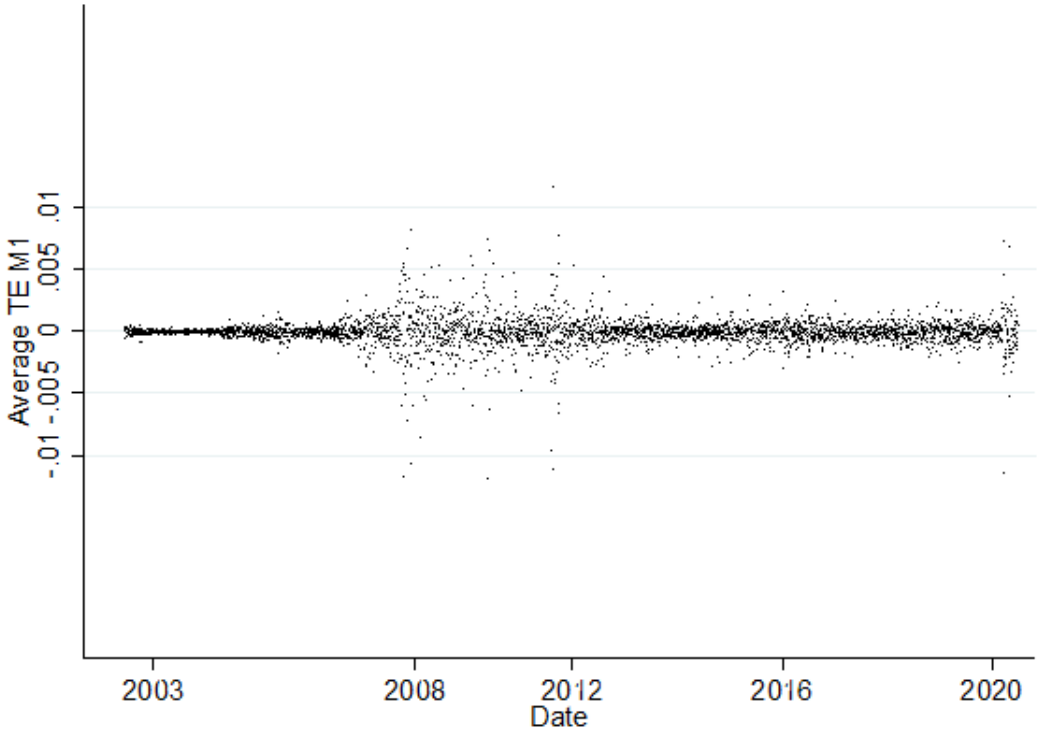
The results for the differences between ETF returns and their respective indexes returns, M1, are present in Table 2. In addition, the average tracking error presented a negative value

(-0.0000139) indicating that, on average, there is a presence of a lagging tracking performance, which means that an ETF's tracking performance is, on average, unable to track its underlying index correctly. There is, however, a significant amount of standard deviation, as it is verified by comparing the lowest and highest value for the tracking error.

With this method, the average tracking error value is to be taken with a grain of salt because it corresponds to a simple mathematical difference, and as it is previously stated, tracking errors with different signals will cancel each other out. This means that if there is, per example, a significant positive tracking error (meaning that, in this case, the returns for the ETF were higher than the index) coupled with a negative tracking error, this will result in a flattening to the tracking error's real value. Indicating a value of tracking error much lower than the real one because it just experienced two consecutive tracking errors with two different signals.

Figure 2 presents the development of the average tracking error while using the first method. Prior to 2008, the graph is almost scatter-free. It is clear that after 2008, there was a visible graphical explosion, and now it presents clear dispersion. The sample's data range involves a significant economic crisis, and its effects are very clear in Figure 2. It is visible that the start of the burst coincided with the 2008 international financial crisis, and it went on till the European sovereign debt crisis in 2011. Even though there is visible flattening post-2012, the average registered tracking error could not recover the likes of its former glory years. This recovery trend was also recently abandoned, being affected by the notorious worldwide health crisis, the pandemic, showing signs of a roughening scatter at the end of the sample's date (June 2020).

Figure 2 - Average Tracking Error (M1)

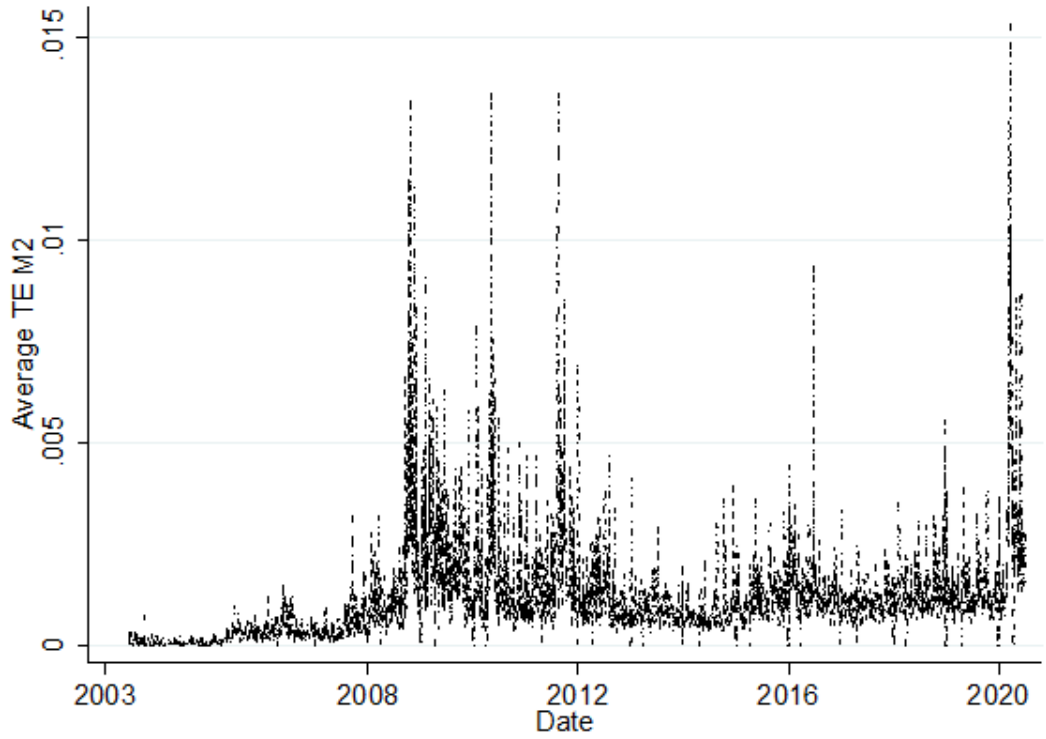


As mentioned in Chapter 4, the second method makes no distinction between negative or positive tracking error values, meaning that it just measures the flow of the tracking performance. As seen again in Frino and Gallagher (2001), the absolute value method represents a more precise indicator of the ETF's tracking capacity due to its core methodologic nature. This method only considers the tracking capacity and not if this tracking was negative or positive during the period, surpassing the problem evidenced in the previous method. As seen in the second row of Table 2, this method's average value is significantly higher by being, obviously, positive. On the other hand, the associated standard deviation values do not present a significant deviation.

The same graphical bursts are now visible for the M2, as seen in Figure 3, showing a significant recovery in tracking performance. However, while reaching the end of the sample, we can already see a clear scatter increase, coinciding with the appearance, in Europe, of the

first pandemic fears, due to the appearance of the first SARS-CoV-2 cases of European origin.

Figure 3 - Average Tracking Error (M2)



The third and final method, M3, approaches the tracking error as the standard deviation of return differences. Its statistics are presented in the third row of Table 2, and all the values presented are significantly higher when dealing with the standard deviation, but show similar behavior to the M2's.

6.2 Tracking error literature results

As previously mentioned, a vast majority of ETF-related studies, while analysing its tracking performance, have found evidence for tracking errors, no matter the methodology used. There is, however, evidence that what influences the most for discovering a tracking error's behavior is not the specific methodology but the sample used, as seen in Frino and Gallagher (2001 and 2002). Hence, we opted to use the previously mentioned criteria (Chapter 5) to

select the ETFs. In the referred papers, the authors applied the same methodologies to two different samples, the US and Australian markets, resulting in two very different outputs.

As we mentioned in Chapter 4, Frino and Gallagher (2001) used as one of their methodologies the M2, corresponding to the average absolute difference between returns. The authors found an average monthly tracking error of 5,9 basis points for a cross-sectional estimation. They concluded that an ETF's tracking error is intrinsic to its performance, meaning that, due to the core nature of an ETF, performing with a tracking error is practically inevitable. Frino and Gallagher (2002) now used a sample corresponding to the Australian market while applying the same exact methodologies (being M2 one of them). However, the authors achieved different conclusions when comparing the results from the Australian market to the US ones.

Once again, as it is mentioned in Chapter 4, Chu (2011) also found evidence of a subpar tracking performance for ETFs (in this case, the sample was relative to 21 ETFs domiciled in Hong Kong) using the M2. For this methodology, the author found that the daily tracking error ranged from 0.2495% to 2.1311%.

6.3 Estimation results

As previously mentioned, to estimate the tracking errors' determinants, we computed three different regressions, each one corresponding to a different tracking error methodology, acting as the dependent variable. As for the selected explanatory variables, these were also previously identified in equation 7.

Table 3, located below, presents an abbreviated version of the results from the estimation of the three versions.

Table 3 - Regression results (M1, M2 and M3)

Variables	TE M1	TE M2	TE M3
MV	-0.000197	-0.00520***	-0.0106***
	(-0.39)	(-10.17)	(-4.74)
NOSH	0.00000440	0.000132***	0.000344***
	(0.33)	(9.90)	(-5.97)
400E	-0.000396	0.0132***	0.0148***
	(-0.71)	(23.29)	(-6.04)
VO	0.0000619	0.000331	0.00109
	(0.35)	(1.84)	(-1.4)
ER	0.0221	-0.208**	-3.655***
	(0.35)	(-3.27)	(-11.57)
R^2	0.00	0.19	0.123

Obs.: Where the standard errors are represented in parenthesis; significance levels are outlined with: * for p<0.1, ** for p<0.05, and *** for p<0.01; All models include a constant, which was omitted to show only the possible determinants data; computed using the reg command available in the Stata software, which uses the ordinary least squares, obtained via the esttab command included in Stata's estout user generated package. The variables' scale was changed for presentation purposes, the MV is now expressed in thousands of euros (instead of millions), NOSH presents its shares (instead of thousands), and the VO is value also reporting the shares' turnover (instead of thousands).

Looking at Table 3 for explanatory power, R^2, the M1 method shows a value of approximately 0%, meaning that the p-value for the f test is higher than 0.1. In other words, for the M1, we cannot reject the test's null hypothesis that the R^2 equals 0. Furthermore, none of the explanatory variables for M1 could have been classified as statistically significant. Hereafter, we will not consider this regression's results for my conclusions.

As for the M2's coefficient of determination, it is possible to say that the variables explain 19.02% of the tracking error's variation. It is also visible in Table 3 that all independent variables are significant at any level except for the expense ratio, ER (significant only at the 5 and 10 % level), and the turnover by volume, VO, which was deemed non-significant statistically.

The results obtained using the M2 methodology coincide with those from other studies mentioned in the previous chapter. Showing for the MV a negative effect on the ETF's tracking error, as was expected. As for the other size-related variable, the NOSH, which weighs the sheer size of an ETF, evidence of a slim positive effect was found. The volatility, 400E, also showed, as expected, a positive effect. The expense ratio was the only divergence in comparison with other studies. It registered a negative effect on the tracking error.

In conclusion, the MV variable shows that as the market value of an ETF increases, its tracking error will decrease. As for the NOSH, the opposite, when the number of shares present in an ETF increase, its tracking error will also increase. As for the volatility, 400E, its results are also expected. It means that when an ETF's risk increases, its tracking performance will decrease, meaning a higher tracking error. At last, the expense ratio's result, ER, correlates that while an ETF may be more costly, its replication ability is superior to others with lower fees, meaning a lower associated tracking error. So, when an ETF's expense ratio increases, its tracking capacity will also increase.

When interpreting the obtained results, the expense ratio caught our attention due to its obtained regressions values being peculiar compared to the other variables. For example, it is possible to say that when the expense ratio of an ETF increases by 0.1 percentage points, its tracking error will decrease by approximately 0.021 percentage points.

M3's results share similarities with the prior methodology, with all variables presenting the same signals, resulting in the same interpretations. The independent variables were also deemed statistically significant for all levels, including the ER, with only the VO variable failing. For this methodology, we obtained an explanatory power of approximately 12.3%.

6.4 Additional testing

We decided to run additional tests to complement some of the previous results. First, we started by fixing the sample regarding the ETF's country of origin. In our sample, we have four countries present: France, Germany, Ireland, and Luxembourg. With that in mind, we split our ETFs into three other groups, French, German, and Tax Haven (corresponding to Ireland and Luxembourg).

The decision was taken to create this group to capture a possible influence on an ETF's tracking ability if it is domiciled in a so-called tax haven country. Our original sample (Table 15) shows that 47 of the 64 selected ETFs are either in Ireland or Luxembourg. This fact shows a clear sign of attractiveness to the jurisdiction practiced in this type of domicile.

A tax haven refers to a country that, with the jurisdiction in practice, allows for low tax rates, meaning large amounts of corporate profits. It is also important to notice that there has been a search for a universal solution to fight back against this type of situation, spearheaded by the Organisation for Economic Cooperation and Development. As seen in Thomas (2021), the OECD announced on the 1st of July 2021 that 130 countries, representing more than 90% of the planet's GDP, converged in agreement on the idea of a universal minimum corporate tax of 15%. Unfortunately, with its ever more attractive 12,5% corporate tax, (a value that, for example, in Portugal is only applicable for an SME's first taxable 25000€) Ireland was not part of the 130 in agreement.

- **France (FR)**

Starting with French-only ETFs, representing only 5 out of the sample's 43. Before running the tracking error methodologies, we present these ETF's statistics and compare them to the original statistics. The following table, Table 4, shows us the detailed statistics only related to French ETFs.

Table 4 - FR summary statistics

Variables	N	Mean	SD	Min	Max
MV	8922	592.6969	195.102	0.97	6103.04
NOSH	11761	11711.46	11112.51	1	129466
400E	11646	0.121097	0.024731	0	0.2361
VO	9524	29.25101	55.67172	0	4389.1
M1	3764	-0.0000173	0.0014591	-0.0222774	0.0329523
M2	3764	0.0009831	0.0014844	0	0.0340713
M3	3764	0.0016119	0.0028387	0	0.0515144

When compared with Table 1 (located in chapter 5), presenting similar statistics for the entire sample, we can see that French ETFs present, on average, a higher market value. However, the maximum registered value is still far behind the original table. Meanwhile, the other three variables present lower means. The same happens in terms of deviation, but in this case, for all four variables.

Looking now at the tracking error statistics, compared to Table 2, when using only French ETFs to calculate the daily tracking error, we can see higher discrepancies in the minimum and maximum registered values. In terms of deviation, all methodologies also present higher values. However, for the second methodology (using only absolute values to calculate the tracking error), its mean is lower than the one shown in Table 2. The same is observed for the M3's mean value.

Lastly, we will run the tracking error-related regressions only for French ETFs. Table 5 presents the results.

Table 5 - FR regression results (M1, M2 and M3)

Variables	TE M1	TE M2	TE M3
MV	-0.000105 (-0.53)	-0.00148*** (-8.13)	-0.00313*** (-8.76)
NOSH	-0.00000135 (-0.19)	0.0000389*** (6.04)	0.0000450*** (-3.44)
400E	-0.00193 (-1.10)	-0.0113*** (-6.92)	-0.0220*** (-4.93)
VO	-0.000307 (-0.39)	0.00367*** (5.00)	0.00471** (-3.27)
ER	0.101 (0.83)	1.108*** (9.77)	2.560*** (-10.65)
R^2	0.001	0.164	0.15

Obs.: Where the standard errors are represented in parenthesis; significance levels are outlined with: * for p<0.1, ** for p<0.05, and *** for p<0.01; All models include a constant, which was omitted to show only the possible determinants data; computed using the reg command available in the Stata software, which uses the ordinary least squares, obtained via the esttab command included in Stata's estout user generated package. The variables' scale was changed for presentation purposes, the MV is now expressed in thousands of euros (instead of millions), NOSH presents its shares (instead of thousands), and the VO is value also reporting the shares' turnover (instead of thousands).

When comparing the results presented above with the ones from Table 3, we can see no significant changes for the first methodology (M1). But for the second methodology, turnover by volume (VO) is now deemed statistically significant, within all significance levels. The ER is now significant at all three levels, which means that all five variables were considered statistically significant. There are also, for the M2, two signal changes when compared to Table 3. The historical volatility (400E) now presents a surprisingly negative

impact, meaning that as a French ETF becomes more volatile, its tracking error is expected to decrease. The ER variable has also seen a change in signal, being now positive, meaning that for French ETFs there is a direct connection between an ETFs expense ratio and its tracking capacity.

On the other hand, there is a slight loss of explanatory power. When looking only at French ETFs and using these independent variables, the R^2 value dropped to 0.164, when looking at the M2.

As for the M3, the VO variable is also now deemed statistically significant, but only for two significance levels. The same behaviour was observed for the 400E and ER variable. The historical volatility now presents a negative signal, while the expense ratio has a positive signal when looking only at French ETFs. In terms of explanatory power, we can conclude that when dealing with the standard deviation methodology, M3, for these 5 ETFs there is an improvement compared to when looking at the full sample. We now have a R^2 of 0.15.

- **Germany (DE)**

German ETFs were the second least represented in the final sample, accounting for 7 out of 43 ETFs. Next, we present their related statistics and their regressions' results.

Table 6 - DE summary statistics

Variable	N	Mean	SD	Min	Max
MV	17480	439.8166086	430.781876	9.44	8190.59
NOSH	18831	13473.95211	11863.5145	1	302791
400E	18670	0.157910243	0.039212929	0	0.4178
VO	12862	54.78358681	91.52565743	0	8417.7
M1	3972	-0.0000142	0.0028883	0	0.04237
M2	3972	0.0016973	0.0027427	0	0.04336
M3	3972	0.0031296	0.0057939	0	0.08950

Comparing now the values from Table 6 with the ones presented in Table 1, German ETFs present, on average, a lower market value when compared to the entire sample. The same happens when looking at the NOSH and VO variables. As for the historical volatility, German ETFs appear to be slightly more volatile. In terms of the tracking error, the most significant discrepancy is present in the maximum registered values for the three methodologies when compared to Table 2.

Table 7 - DE regression results (M1, M2 and M3)

Variables	TE M1	TE M2	TE M3
MV	-0.0000257 (-0.02)	-0.000578 (-0.55)	0.000436 (0.20)
NOSH	0.0000000162 (0.00)	-0.0000671 (-1.78)	-0.000191* (-2.48)
400E	-0.000316 (-0.20)	0.00221 (1.6)	-0.0263*** (-9.17)
VO	0.000244 (0.33)	0.00300*** (4.55)	0.00446*** (3.31)
ER	-0.00639 (-0.12)	-0.376*** (-7.94)	-1.027*** (-10.53)
R^2	0.00	0.115	0.174

Obs.: Where the standard errors are represented in parenthesis; significance levels are outlined with: * for p<0.1, ** for p<0.05, and *** for p<0.01; All models include a constant, which was omitted to show only the possible determinants data; computed using the reg command available in the Stata software, which uses the ordinary least squares, obtained via the esttab command included in Stata's estout user generated package. The variables' scale was changed for presentation purposes, the MV is now expressed in thousands of euros (instead of millions), NOSH presents its shares (instead of thousands), and the VO is value also reporting the shares' turnover (instead of thousands).

For the German only regression results, presented in Table 7, there are several discrepancies compared to Table 3. For the second methodology, M2, only two variables (VO and ER) were found statistically significant (in all levels), with their associated signals remaining the same. As for the explanatory power of these variables, it stands now at 11,5%.

For the M3, only the MV variable loses its full statistical significance, and the NOSH variable now only retains one significance level. There are also two signal changes among the significant variables, when looking at German ETFs. The NOSH and 400E variable switched from being positive to a negative signal. As for the explanatory power, when looking at only German ETFs the M3, registers an increase at 17,40%.

- **Tax Haven (TH)**

In this last part, we are fixing the sample to the last two countries present in our study. These were classified as tax haven countries, Ireland and Luxembourg. They correspond to most of our final sample, accounting for 31 out of 43 ETFs.

Table 8 - TH summary statistics

Variables	N	Mean	SD	Min	Max
MV	62790	426.7909	359.9498505	0.93	28823.04
NOSH	69416	17089.99	15241.07006	1	1252358
400E	68703	0.152729	0.037615971	0	0.5594
VO	49945	59.2071	428.7815908	0	153733.8
M1	4448	-0.000014	0.0010203	-0.0097262	0.0081878
M2	4448	0.001146	0.0011975	0	0.0167819
M3	4448	0.0040436	0.0055167	0	0.1728415

As was expected, in terms of statistics, the values obtained do not vary from those in the full sample, presented in Table 1. Besides the market value variable, all the other variables present averages higher than the original ones, but none of the values present a significant

discrepancy. All the maximum values were also part of Tax Haven domiciled ETFs. The same could be said about the tracking error-related statistics.

Table 9 presents the regression results related to the tracking error methodologies, with ETFs domiciled either in Ireland or Luxembourg.

Table 9 - TH regression results (M1, M2 and M3)

Variables	TE M1	TE M2	TE M3
MV	0.000216	-0.00245***	-0.0107***
	(0.60)	(-6.63)	(-5.59)
NOSH	-0.00000475	0.0000526***	0.000193***
	(-0.55)	(5.96)	(-4.21)
400E	-0.000227	0.0156***	0.0268***
	(-0.35)	(23.64)	(-7.6)
VO	0.0000396	0.0000529	0.000206
	(0.33)	(0.44)	(-0.33)
ER	-0.0083	-0.248***	-1.476***
	(-0.15)	(-4.27)	(-4.91)
R^2	0.00	0.248	0.105

Obs.: Where the standard errors are represented in parenthesis; significance levels are outlined with: * for p<0.1, ** for p<0.05, and *** for p<0.01; All models include a constant, which was omitted to show only the possible determinants data; computed using the reg command available in the Stata software, which uses the ordinary least squares, obtained via the esttab command included in Stata's estout user generated package. The variables' scale was changed for presentation purposes, the MV is now expressed in thousands of euros (instead of millions), NOSH presents its shares (instead of thousands), and the VO is value also reporting the shares' turnover (instead of thousands).

When compared to Table 3, we can see very similar results. Focusing mainly on the second methodology, M2, all variables maintain the same signal from the original regression. The VO variable remains statistically insignificant, but the expense ratio (ER) has now been upgraded to a significance in all three levels. Finally, our obtained R^2 is the highest in the entire dissertation, meaning that the selected independent variables can better explain the tracking error's behavior when looking at tax haven countries. Therefore, for the M2's coefficient of determination, it is possible to say that the variables explain 24.80% of the tracking error's variation.

As for the M3, all variables retain the same statistical significance, levels, and signals. In terms of the explanatory power, 10.05%, there is a decrease.

We have also tested the determinants on their own, using all three methodologies, to measure each determinant's individual explanatory power. This process is presented in the following three tables.

Table 10 - Individual regression using M1

Variables	Value	R^2
MV	-0.0000327 (-0.53)	0.00
NOSH	-0.000000857 (-0.49)	0.00
400E	-0.000254 (-0.80)	0.00
VO	0.0000376 (0.22)	0.00
ER	-0.0115 (-0.54)	0.00

Table 11 - Individual regression using M2

Variables	Value	R^2
MV	0.000653*** (9.44)	0.02
NOSH	0.0000212*** (10.90)	0.026
400E	0.00902*** (27.34)	0.144
VO	0.000928*** (4.76)	0.005
ER	0.335*** (14.27)	0.044

Table 12 - Individual regression using M3

Variables	Value	R^2
MV	-0.00537*** (-18.60)	0.079
NOSH	-0.000140*** (-17.17)	0.068
400E	-0.0185*** (-11.13)	0.03
VO	-0.00185* (-2.28)	0.001

ER	-2.362*** (-21.53)	0.103

Obs.: Where, for all three tables, the standard errors are represented in parenthesis; significance levels are outlined with: * for p<0.1, ** for p<0.05, and *** for p<0.01; All models include a constant, which was omitted to show only the possible determinants data; computed using the reg command available in the Stata software, which uses the ordinary least squares, obtained via the esttab command included in Stata's estout user generated package. The variables' scale was changed for presentation purposes, the MV is now expressed in thousands of euros (instead of millions), NOSH presents its shares (instead of thousands), and the VO is value also reporting the shares' turnover (instead of thousands).

While regressing each independent variable using the first methodology, M1, none of the variables could obtain any statistical significance. On the other hand, for M2, all regressions determined each different variable to be statistically significant at all levels. The same happened when using the M3. Again, all regressions determined each variable to be statistically significant, with the exception that the VO variable was found to be statistically significant only for the first level.

For the M2, we can see that the variable Historical Volatility (400E) is by far the variable with more explanatory power while using the second methodology. This variable alone has more power than all the others combined, showcasing how important the role of volatility is while studying the tracking ability of an ETF. This proves the hypothesis previously stated while presenting the chosen determinants to be studied (Chapter 4), which means that an ETF's inherent risk influences its tracking ability, positively affecting the dependent variable. The higher the volatility is, the higher the expected associated tracking error. This also corroborates the findings present in Rompotis (2011), where the author found evidence of its risk variable having a positive impact on the tracking error. As for the M3, the expense ratio bares the most individual explanatory power.

In Table 13, we present the correlation matrix between the three tracking error estimations previously described.

Table 13 – Tracking error methodology correlation matrix

	M1	**M2**	**M3**
M1	1		
M2	-0.0604	1	
M3	-0.0321	0.7271	1

From the table's analysis, we can conclude that there is a strong and positive correlation between M2 and M3 (0.7271), and with that, we can also conclude that there will be a close similarity between these two tracking error measures in terms of given results. We should also note that M1 has a weak and negative correlation with the other two methodologies of an ETFs' tracking error.

7. Conclusion

This dissertation aimed to find the main determinants of an ETF's tracking error. We started by selecting a sample of 43 ETFs with 21 different underlying indexes. The sample ran from June 2003, since that is when the oldest ETF of the group launched, till June 2020.

First, we selected the methodology to compute the ETFs and index returns. Afterward, to measure the tracking error, we identified from reviewing the literature three different commonly used methodologies.

Like many other studies, we have also found clear evidence for the presence of tracking errors throughout ETFs, suggesting that this discrepancy is almost intrinsic to an ETF. As for the tracking error's historical behavior, before 2008, the average daily tracking errors presented good results. However, the 2008 international financial crisis and the subsequent European sovereign debt crisis devastated these. It is also important to mention that, by the end of the sample, June 2020, there are already clear signs of the tracking errors being affected by SARS-CoV-2 ripple effects.

We then test our determinants and what hypothesis these might validate. For example, could an ETF with a high market value translate to a lower tracking error? This means that it gets more management attention than its less valuable alternatives. Conversely, does volatility make it harder for an ETF to track its index correctly, or even the sheer number of shares present in an ETF. Is there a quality trade-off present in ETFs? Better tracking performing ETFs will also present a higher expense ratio, perhaps due to them being better looked after, with a bigger management team. Finally, how does an ETF's liquidity impact its tracking ability?

Regarding the tracking error determinants, for the second tracking error methodology, M2, a majority of the results coincide with other ETF-related literature. For example, we found evidence of statistical significance for the ETF's market value, the number of shares, historical volatility, and associated expense ratio. The same could be said for the standard deviation methodology, the M3.

Obtaining a negative effect on the market value on the ETF's tracking error and a positive impact on the number of shares. Showcasing that higher valuable ETFs tend to track their index better. The NOSH's result correlates with one of the ETF-related fears presented

earlier in the dissertation (Chapter 3). In Bogle (2017), the author expressed his concerns about the rise of investment in ETFs. The author feared that this increase in investment would lead to a high trading frequency, with higher associated costs, damaging the ETF's performance.

The historical volatility, 400E, presented a positive effect, meaning that more volatile ETFs are less efficient with their tracking.

The expense ratio, the only divergence compared to other studies, registered a negative effect on the tracking error. It is here where the most exciting result of this dissertation lies. When an ETF's associated fees increase, its tracking performance will also increase, demonstrating the existence of a premium that an investor must face when investing in better tracking ETFs for his portfolio. This can be explained, for example, by these ETFs having a larger management team than their counterparts or even being monitored more frequently, resulting in higher maintenance fees. This came as a surprise because as previously mentioned, the general expectation is to have a positive relationship between the ER and an ETF's tracking error. Our result directly contradicts papers such as Elton et al. (2002) and Rompotis (2011), who concluded that ETFs with higher expense ratios are likelier to underperform.

For future research, this study suggests further investigation of the expense ratio as a determinant for an ETF's tracking error. With the aim to find the reasons that lead to this behavior from the expense ratio when looking at this sample. Furthermore, since our sample has presented a survivorship bias, there is the opportunity to study the tracking error determinants for inactive or liquidated ETFs, and if the results differ when looking at active ones. Finally, another possibility is to conduct another study for the remaining markets, such as the US, or even limit the study to only French domiciled ETFs to understand why these have a positive relationship with the ER variable.

8. Appendix

Appendix 1 – Final and Original ETF sample

Table 14 – Final sample of selected ETFs

ETF Ticker	Asset Name	Domicile	Index Ticker	Underlying Index
CU9	Amundi ETF MSCI Europe Ex Emu UCITS ETF	France	MSEXEME	MSCI EUROPE ex EMU NR EUR
C5E	Amundi ETF Stoxx Europe 50 UCITS ETF	France	DJSTO50	STOXX Europe 50 NR EUR
SMRE	Amundi Erp Eqy Mlt Smt Alctn Scnfc BETA-UCT ETF-EC	Luxembourg	SBEXDHE	Scientific Beta Ext Dev Eur M-Beta Stra ERC NR EUR
CG9	Amundi MSCI Europe Growth UCITS ETF - EUR (C)	Luxembourg	MSGEURE	MSCI Europe Growth TR EUR
MIVO	Amundi MSCI Europe Min Vol Factor UCITS ETF-EC	Luxembourg	MSURMVL	MSCI Europe Minimum Volatility NR EUR
MCEU	Amundi MSCI Europe Momentum Factor UCITS ETF - EUR (C)	Luxembourg	MSMOURL	MSCI Europe Momentum NR EUR
QCEU	Amundi MSCI Europe Quality Factor UCITS ETF-EUR(C)	Luxembourg	MSURQAL	MSCI Europe Quality NR EUR
CEU	Amundi MSCI Europe UCITS ETF - EUR (C)	Luxembourg	MSEROPE	MSCI Europe TR EUR

CV9	Amundi MSCI Europe Value Factor UCITS ETF - EUR (C)	Luxembourg	MSVEURE	MSCI Europe Value NR EUR
C6E	Amundi STOXX Europe 600 UCITS ETF	Luxembourg	DJSTOXX	STOXX Europe 600
MKTN	AmundiETF iStoxxEurope MultiFct MrktNtrl UCITS ETF	France	ISXEMFE	iSTOXX Europe Multi-Factor Market Neutral
ETZ	BNP Paribas Easy Stoxx Europe 600 UCITS ETF	France	DJSTOXX	STOXX Europe 600
ECN	BNPP Easy Low Carbon 100 Europe PAB UCITS ETF	Luxembourg	SXELC1E	Low Carbon 100 Europe PAB
EL4H	Deka MSCI Europe LC UCITS ETF	Germany	MSLEURE	MSCI Europe Large Cap
EL42	Deka MSCI Europe UCITS ETF	Germany	MSEROPE	MSCI Europe
ELF5	Deka MSCI Europe ex EMU UCITS ETF	Germany	MSEXEME	MSCI Europe ex EMU
EL4Y	Deka STOXX Europe 50® UCITS ETF	Germany	DJSTO50	STOXX Europe 50
ES5R	Europe SectorTrend UCITS ETF	Luxembourg	DJSTOXX	STOXX Europe 600
HMEU	HSBC MSCI Europe UCITS ETF	Ireland	MSEROPE	MSCI Europe
PEF	Invesco FTSE RAFI Europe UCITS ETF	Ireland	FTREUPE	FTSE RAFI Europe
SC0E	Invesco MSCI Europe UCITS ETF	Ireland	MSEROPE	MSCI Europe
EMSV	Invesco MSCI Europe Value UCITS ETF Acc	Ireland	MSVEURE	MSCI Europe Value
SC0C	Invesco STOXX Europe 600 UCITS ETF Acc	Ireland	DJSTOXX	STOXX Europe 600

E960	Lyxor 1 Stoxx Europe 600 UCITS ETF	Germany	DJSTOXX	STOXX Europe 600
MEUD	Lyxor Core STOXX Europe 600 (DR) - UCITS ETF Acc	Luxembourg	DJSTOXX	STOXX Europe 600
MEU1	Lyxor MSCI Europe (DR) UCITS ETF - Acc	France	MSEROPE	MSCI Europe
C060	Lyxor STOXX® Europe 600 UCITS ETF	Luxembourg	DJSTOXX	STOXX Europe 600
EROT	SPDR MSCI Europe UCITS ETF	Ireland	MSEROPE	MSCI Europe
EUREUA	UBS LFS MSCI Europe UCITS ETF (EUR) Adis	Luxembourg	MSEROPE	MSCI Europe
VEUR	Vanguard FTSE Developed Europe UCITS ETF EUR Dist	Ireland	AWDVERE	FTSE Developed Europe
XZEU	Xtrackers MSCI Europe ESG UCITS ETF 1C	Ireland	MSURCDL	MSCI Europe Low Carbon Leaders
D5BL	Xtrackers MSCI Europe Value UCITS ETF 1C	Luxembourg	MSEUEVL	MSCI Europe Enhanced Value
DX2X	Xtrackers Stoxx Europe 600 UCITS ETF 1C	Luxembourg	DJSTOXX	STOXX Europe 600
SMEA	iShares Core MSCI Europe UCITS ETF EUR (Acc)	Ireland	MSEROPE	MSCI Europe
IMEU	iShares Core MSCI Europe UCITS ETF EUR Dist	Ireland	MSEROPE	MSCI Europe
IEVl	iShares Edge MSCI Eu Val Factor UCITS ETF EUR Acc	Ireland	MSEUEVL	MSCI Europe Enhanced Value
IEMO	iShares Edge MSCIEuMomentumFactor UCITS ETF EUR A	Ireland	MSMOURL	MSCI Europe Momentum

IBC0	iShares EdgeMSCIEuropeMultifactorUCITS ETF EUR Acc	Ireland	MSURMFL	MSCI Europe Diversified Multiple-Factor
EUMD	iShares MSCI Europe Mid Cap UCITS ETF EUR (Acc)	Ireland	MSMEURE	MSCI Europe Mid Cap
IMES	iShares MSCI Europe SRI UCITS ETF EUR (Acc)	Ireland	MSURSRL	MSCI Europe SRI Select Reduced Fossil Fuel
EUN	iShares STOXX Europe 50 UCITS ETF EUR (Dist)	Ireland	DJSTO50	STOXX Europe 50
EXSA	iShares STOXX Europe 600 UCITS ETF (DE)	Germany	DJSTOXX	STOXX Europe 600
EXSC	iShares STOXX Europe Large 200 UCITS ETF (DE)	Germany	DJSLARG	STOXX Europe Large 200

Table 15 - Original ETF sample (discarded highlighted in red)

ETF Ticker	Asset Name	Domicile	Index Ticker	Underlying Index
CU9	Amundi ETF MSCI Europe Ex Emu UCITS ETF	France	MSEXEME	MSCI EUROPE ex EMU
C5E	Amundi ETF Stoxx Europe 50 UCITS ETF	France	DJSTO50	STOXX Europe 50
SMRE	Amundi Erp Eqy Mlt Smt Alctn Scnfc BETA-UCT ETF-EC	Luxembourg	SBEXDHE	Scientific Beta Ext Dev Eur M-Beta Stra ERC
CG9	Amundi MSCI Europe Growth UCITS ETF - EUR (C)	Luxembourg	MSGEURE	MSCI Europe Growth

MIVO	Amundi MSCI Europe Min Vol Factor UCITS ETF-EC	Luxembourg	MSURMVL	MSCI Europe Minimum Volatility
MCEU	Amundi MSCI Europe Momentum Factor UCITS ETF - EUR (C)	Luxembourg	MSMOURL	MSCI Europe Momentum
QCEU	Amundi MSCI Europe Quality Factor UCITS ETF-EUR(C)	Luxembourg	MSURQAL	MSCI Europe Quality
CEU	Amundi MSCI Europe UCITS ETF - EUR (C)	Luxembourg	MSEROPE	MSCI Europe TR EUR
CV9	Amundi MSCI Europe Value Factor UCITS ETF - EUR (C)	Luxembourg	MSVEURE	MSCI Europe Value
C6E	Amundi STOXX Europe 600 UCITS ETF - EUR (C)	Luxembourg	DJSTOXX	STOXX Europe 600
MKTN	AmundiETF iStoxxEurope MultiFct MrktNtrl UCITS ETF	France	ISXEMFE	iSTOXX Europe Multi-Factor Market Neutral
ETZ	BNP Paribas Easy Stoxx Europe 600 UCITS ETF C	France	DJSTOXX	STOXX Europe 600
EDEU	BNPP Easy Equity Dividend Europe UCITS ETF C	Luxembourg		Index is not available on Lipper Database
EVOE	BNPP Easy Equity Low Vol Europe UCITS ETF Cap	Luxembourg		Index is not available on Lipper Database
EMOM	BNPP Easy Equity Momentum Europe UCITS ETF Cap	Luxembourg		Index is not available on Lipper Database
EQUA	BNPP Easy Equity Quality Europe UCITS ETF Cap	Luxembourg		Index is not available on Lipper Database
EVAE	BNPP Easy Equity Value Europe UCITS ETF Cap	Luxembourg		Index is not available on Lipper Database

ECN	BNPP Easy Low Carbon 100 Europe PAB UCITS ETF C	Luxembourg	SXELC1E	Low Carbon 100 Europe PAB
EL4H	Deka MSCI Europe LC UCITS ETF	Germany	MSLEURE	MSCI Europe Large Cap
EL42	Deka MSCI Europe UCITS ETF	Germany	MSEROPE	MSCI Europe
ELF5	Deka MSCI Europe ex EMU UCITS ETF	Germany	MSEXEME	MSCI Europe ex EMU
EL4Y	Deka STOXX Europe 50® UCITS ETF	Germany	DJSTO50	STOXX Europe 50
EL4C	Deka STOXX® Europe Strong Growth 20 UCITS ETF	Germany	DJSG20E	STOXX Europe Strong Growth 20
EL4E	Deka STOXX® Europe Strong Style Comp 40 UCITS ETF	Germany	DJSS40E	STOXX Europe Strong Style Composite 40
EL4D	Deka STOXX® Europe Strong Value 20 UCITS ETF	Germany	DJSV20E	STOXX Europe Strong Value 20
ES5R	Europe SectorTrend UCITS ETF R	Luxembourg	DJSTOXX	STOXX Europe 600
FVUE	Franklin LibertyQ European Eq UCITS ETF EUR Acc	Ireland		Index is not available on Lipper Database
HMEU	HSBC MSCI Europe UCITS ETF	Ireland	MSEROPE	MSCI Europe
PEF	Invesco FTSE RAFI Europe UCITS ETF Dist	Ireland	FTREUPE	FTSE RAFI Europe
EFIE	Invesco Goldman Sachs Eq Fac Idx Eur UCITS ETF Acc	Ireland		Index is not available on Lipper Database
SC0E	Invesco MSCI Europe UCITS ETF Acc	Ireland	MSEROPE	MSCI Europe
EMSV	Invesco MSCI Europe Value UCITS ETF Acc	Ireland	MSVEURE	MSCI Europe Value
SC0C	Invesco STOXX Europe 600 UCITS ETF Acc	Ireland	DJSTOXX	STOXX Europe 600

E960	Lyxor 1 Stoxx Europe 600 UCITS ETF	Germany	DJSTOXX	STOXX Europe 600
MEUD	Lyxor Core STOXX Europe 600 (DR) - UCITS ETF Acc	Luxembourg	DJSTOXX	STOXX Europe 600
MEU1	Lyxor MSCI Europe (DR) UCITS ETF - Acc	France	MSEROPE	MSCI Europe
C060	Lyxor STOXX® Europe 600 UCITS ETF	Luxembourg	DJSTOXX	STOXX Europe 600
S6EW	OSSIAM Stoxx Europe 600 EqualWeightNR UCITS ETF 1C	Luxembourg		STOXX Europe 600 Equal Weight
CAPE	Ossiam ShillerBarclaysCAPE EuSectValTR UCITSETF1CE	Luxembourg		Index is not available on Lipper Database
OSX4	Ossiam iSTOXX Europe Minimum Variance NR 1C (EUR)	Luxembourg	SEUMVIN	iSTOXX Europe Minimum Variance
EROT	SPDR MSCI Europe UCITS ETF	Ireland	MSEROPE	MSCI Europe
ZPRW	SPDR MSCI Europe Value UCITS ETF	Ireland		MSCI Europe
EHEF	SciBeta HFE Europe Equity 6F EW UCITS ETF	Ireland		Scientific Beta DevEu HFIMBMS
EUREUA	UBS LFS MSCI Europe UCITS ETF (EUR) Adis	Luxembourg	MSEROPE	MSCI Europe
TEET	VanEck Vectors™ European Equal Weight UCITS ETF	Netherlands		Solactive European Equity
VEUR	Vanguard FTSE Developed Europe UCITS ETF EUR Dist	Ireland	AWDVERE	FTSE Developed Europe
XZEU	Xtrackers MSCI Europe ESG UCITS ETF 1C	Ireland	MSURCDL	MSCI Europe Low Carbon Leaders
D5BL	Xtrackers MSCI Europe Value UCITS ETF 1C	Luxembourg	MSEUEVL	MSCI Europe Enhanced Value

DX2X	Xtrackers Stoxx Europe 600 UCITS ETF 1C	Luxembourg	DJSTOXX	STOXX Europe 600
SMEA	iShares Core MSCI Europe UCITS ETF EUR (Acc)	Ireland	MSEROPE	MSCI Europe
IMEU	iShares Core MSCI Europe UCITS ETF EUR Dist	Ireland	MSEROPE	MSCI Europe
IEVl	iShares Edge MSCI Eu Val Factor UCITS ETF EUR Acc	Ireland	MSEUEVL	MSCI Europe Enhanced Value
IEFS	iShares Edge MSCI EuSizeFactor UCITS ETF EUR A	Ireland		Index is not available on Lipper Database
IMVU	iShares Edge MSCI Europe Min Vol UCITS ETF EUR Acc	Ireland		MSCI Europe Minimum Volatility
IEMO	iShares Edge MSCIEuMomentumFactor UCITS ETF EUR A	Ireland	MSMOURL	MSCI Europe Momentum
IEFQ	iShares Edge MSCIEuropeQltyFactorUCITS ETF EUR Acc	Ireland		Index is not available on Lipper Database
IBC0	iShares EdgeMSCIEuropeMultifactorUCITS ETF EUR Acc	Ireland	MSURMFL	MSCI Europe Diversified Multiple-Factor
SAEU	iShares MSCI Europe ESG Screened UCITS ETF EUR Acc	Ireland		MSCI Europe ESG Screened
EUMD	iShares MSCI Europe Mid Cap UCITS ETF EUR (Acc)	Ireland	MSMEURE	MSCI Europe Mid Cap
IMES	iShares MSCI Europe SRI UCITS ETF EUR (Acc)	Ireland	MSURSRL	MSCI Europe SRI Select Reduced Fossil Fuel
EXW3	iShares STOXX Europe 50 UCITS ETF (DE)	Germany		STOXX Europe 50 USD
EUN	iShares STOXX Europe 50 UCITS ETF EUR (Dist)	Ireland	DJSTO50	STOXX Europe 50

EXSA	iShares STOXX Europe 600 UCITS ETF (DE)	Germany	DJSTOXX	STOXX Europe 600
EXSC	iShares STOXX Europe Large 200 UCITS ETF (DE)	Germany	DJSLARG	STOXX Europe Large 200

Appendix 2 – Detailed Determinants statistics

Table 16 - MV statistics

ETF Ticker	N	Mean	SD	Min	Max
CU9	2727	142.2752	118.8084	5.22	456.93
C5E	2806	111.8341	95.71125	4.63	321.63
SMRE	1151	258.8951	102.1993	0.98	412.71
CG9	2955	17.0835	14.18597	4.2	64.6
MIVO	2955	108.7963	137.3537	3.88	486.19
MCEU	1071	147.0128	96.78065	1.01	401.72
QCEU	1071	201.5192	161.6128	1.13	669.26
CEU	3062	501.6024	864.4694	2.8	2711.59
CV9	2955	159.1472	261.4952	3.71	1034.32
C6E	2806	142.5671	141.62	5.16	436.64
MKTN	691	293.0151	172.6625	0.97	627.39
ETZ	1772	779.935	382.0356	95.49	6103.04
ECN	847	438.2766	257.8092	54.52	847.17
EL4H	2710	33.73691	4.599969	22.75	52.18
EL42	2489	206.9798	183.8408	21.84	3766.72
ELF5	1396	57.22741	322.3039	26.97	7260.23

EL4Y	2490	37.6453	29.22444	9.44	782.03
ES5R	1312	12.02989	9.35279	6.39	56.08
HEU	1783	162.2522	50.20715	36.05	271.32
PEF	803	8.236526	2.275997	0.93	11.89
SC0E	2217	514.1214	148.0581	288.08	1201.45
EMSV	1783	236.8918	124.8875	50.12	547.92
SC0C	1783	326.2279	98.52722	181.93	674.19
E960	619	17.6411	4.230863	9.45	28.56
MEUD	1869	489.9462	656.3664	4.75	2161.36
MEU1	926	1636.425	206.292	990.79	1936.64
C060	2736	275.6911	83.4519	130.33	474.64
EROT	4041	589.8929	110.7236	328.93	985.2
EUREUA	2758	143.0246	125.1042	10.77	436.6
VEUR	989	1474.56	423.3435	564.69	2182.55
XZEU	558	17.83919	10.63689	5.5	40.3
D5BL	2641	257.0936	2334.181	5.06	28823.04
DX2X	2968	696.2771	662.4826	3.72	1818.28
SMEA	2727	506.3203	506.3886	10.07	2173.58
IMEU	3342	2930.385	2127.816	3.18	6289.44
IEVl	1423	679.0091	547.58	9.56	1565.93
IEMO	1392	169.2239	185.9674	25.07	800.65
IBC0	1255	236.9659	108.1664	4.7	427.44
EUMD	812	357.4007	219.9677	19.42	570.54
IMES	276	982.1757	272.0484	668.09	1645.55
EUN	4449	190.0537	313.3858	1.62	963.22
EXSA	3972	2676.327	2435.985	198.14	8190.59
EXSC	3804	49.15874	35.28816	16.77	1532.68

Table 17 - NOSH statistics

ETF Ticker	N	Mean	SD	Min	Max
CU9	2727	661.4173	552.9876	45	2217
C5E	2806	1706.648	1395.553	130	4366
SMRE	1151	6809.923	2473.526	31	10375
CG9	2955	105.3936	70.44175	51	349
MIVO	2955	1184.897	1386.595	130	4740
MCEU	1071	2375.965	1384.166	20	5603
QCEU	1071	2974.189	2126.316	20	8965
CEU	3062	2306.846	3928.594	40	11500
CV9	2955	748.778	1193.16	49	4410
C6E	2806	1912.377	1792.738	140	5700
MKTN	691	12432.52	7104.735	40	25681
ETZ	1772	40559.69	40863.97	4903	129466
ECN	847	2618.564	1456.684	361	4807
EL4H	3088	367.9058	150.7888	1	617
EL42	2881	14442.84	14737.75	1	302791
ELF5	1396	431.7414	2446.127	207	54088
EL4Y	2916	1133.861	1053.069	1	25290
ES5R	1312	164.5526	124.5145	106	705
HEU	2519	9128.22	6715.25	1	19000
PEF	3230	223.4139	401.9929	1	1200
SC0E	2922	2139.799	1396.72	1	6793

EMSV	2158	985.0941	756.6321	1	2770
SC0C	2922	2799.719	2542.444	1	8957
E960	619	463.2456	112.542	250	745
MEUD	1869	3256.936	4338.768	50	12596
MEU1	3765	3197.01	5645.285	1	15254
C060	3082	4266.393	2610.603	1	7450
EROT	4041	4349.827	1149.187	2125	6350
EUREUA	2796	2328.108	1992.184	1	6223
VEUR	1846	26565.56	26773.12	1	71605
XZEU	558	916.0753	544.6016	330	1980
D5BL	2641	12816.5	102823	317	1252358
DX2X	2968	9324.975	8561.662	150	22829
SMEA	2727	10875.75	9738.751	400	43711
IMEU	3345	134398.2	87277.54	1	282159
IEV1	1423	118506.2	92844.35	2000	259500
IEMO	1392	26590.57	29062.45	4500	122864
IBC0	1255	41302.53	17492.63	1000	70500
EUMD	812	69863.34	42989.36	3864	115633
IMES	276	21815.68	6460.621	15305	35957
EUN	4449	6135.327	10064.57	100	28800
EXSA	3972	76113.19	63643.16	7636	208200
EXS	3959	1364.881	901.1647	1	39104

Table 18 - 400E statistics

ETF Ticker	N	Mean	SD	Min	Max
CU9	2704	0.124616	0.028493	0	0.1833
C5E	2783	0.147304	0.017984	0	0.1867
SMRE	1128	0.113253	0.026076	0	0.2044
CG9	2932	0.142121	0.016515	0	0.1791
MIVO	2932	0.18042	0.044285	0	0.2808
MCEU	1048	0.108406	0.021819	0	0.1775
QCEU	1048	0.118532	0.018726	0	0.1786
CEU	3039	0.209725	0.095782	0	0.5005
CV9	2932	0.185223	0.03679	0	0.3056
C6E	2783	0.147453	0.019223	0	0.1979
MKTN	668	0.031343	0.006209	0	0.0387
ETZ	1749	0.133487	0.027812	0	0.198
ECN	824	0.102864	0.036145	0	0.2052
EL4H	3065	0.208012	0.079417	0	0.4178
EL42	2858	0.150811	0.015121	0	0.1977
ELF5	1373	0.141499	0.02672	0	0.1841
EL4Y	2893	0.153314	0.014316	0	0.2144
ES5R	1289	0.152013	0.023804	0	0.2175
HEU	2496	0.150202	0.026872	0	0.2024
PEF	3207	0.23514	0.115007	0	0.5594
SC0E	2899	0.150918	0.016184	0	0.2065
EMSV	2135	0.145999	0.021925	0	0.2263
SC0C	2899	0.152509	0.017113	0	0.206

E960	596	0.130167	0.046159	0	0.2472
MEUD	1846	0.137605	0.01912	0	0.1977
MEU1	3742	0.168738	0.043158	0	0.2361
C060	3059	0.197817	0.06685	0	0.3848
EROT	4018	0.158551	0.043917	0	0.2244
EUREUA	2773	0.155879	0.021503	0	0.2037
VEUR	1823	0.132803	0.027516	0	0.1983
XZEU	535	0.122901	0.052799	0	0.244
D5BL	2618	0.159543	0.02272	0	0.2307
DX2X	2945	0.165016	0.027043	0	0.3185
SMEA	2704	0.15165	0.01833	0	0.2051
IMEU	3322	0.186456	0.04845	0	0.2819
IEV1	1400	0.1651	0.032565	0	0.2323
IEMO	1369	0.126357	0.024279	0	0.1764
IBC0	1232	0.143584	0.025036	0	0.204
EUMD	789	0.115567	0.049483	0	0.2475
IMES	253	0.171062	0.109458	0	0.3468
EUN	4426	0.149935	0.040764	0	0.2187
EXSA	3949	0.16207	0.045099	0	0.2262
EXSC	3936	0.159499	0.047658	0	0.2325

Table 19 - VO statistics

ETF Ticker	N	Mean	SD	Min	Max
CU9	1587	2.336988	4.730801	0	60
C5E	2381	4.208484	8.684432	0	156.9
SMRE	813	3.817958	12.87426	0	288.4
CG9	1402	0.513766	1.313952	0	13
MIVO	1804	2.82755	8.3155	0	135.1
MCEU	551	1.343376	5.188332	0	95.4
QCEU	572	2.949126	11.31526	0	177.3
CEU	2765	8.720253	20.93613	0	828.2
CV9	1857	0.974313	3.699045	0	86.4
C6E	2336	8.109375	13.11503	0	194.7
MKTN	450	8.522222	16.10106	0	150.7
ETZ	1681	100.3225	203.7852	0	4389.1
ECN	711	1.367932	2.404377	0	24.8
EL4H	1666	1.232653	6.271159	0	166.7
EL42	2190	45.12982	112.064	0	1939.3
ELF5	382	0.578534	1.922012	0	23.5
EL4Y	1876	3.412154	19.28064	0	697.2
ES5R	292	1.007534	1.769621	0	15.8
HEU	2071	14.91902	35.56983	0	770.6
PEF	433	8.138799	39.8942	0	617.5
SC0E	1727	5.448176	11.65189	0	199.4
EMSV	1543	0.588983	1.684178	0	29.9
SC0C	2349	15.47739	50.53199	0	1507.9
E960	369	0.8729	2.481031	0	29.4

MEUD	1119	5.82109	13.79912	0	211.4
MEU1	3425	30.86488	45.05712	0	1285.3
C060	2916	6.21773	16.24367	0	333.7
EROT	3164	11.73948	19.62777	0	243.3
EUREUA	2162	5.722849	14.9655	0	290.5
VEUR	1782	59.66835	73.68023	0	720.3
XZEU	317	3.258991	9.532922	0	131.2
D5BL	1541	4.456522	14.8613	0	304.8
DX2X	2761	39.93271	67.48007	0	1400.3
SMEA	2060	10.77087	31.45487	0	974.3
IMEU	3191	243.9891	512.1156	0	21297.1
IEVl	1110	479.3935	2923.585	0	91297.9
IEMO	326	19.45798	42.3642	0	426.1
IBC0	1039	29.17863	54.42999	0	570.1
EUMD	710	798.9904	9213.388	0	153733.8
IMES	208	2.035577	8.962977	0	112.4
EUN	4313	38.58268	55.4745	0	1182.5
EXSA	3694	327.4605	477.1698	0	8417.7
EXSC	2685	4.798547	21.49096	0	797.6

Appendix 3 – Detailed Tracking Error statistics

Table 20 - Tracking error statistics using M1, per ETF

ETF Ticker	N	Mean	SD	Min	Max
CU9	2726	-2.6E-05	0.003173	-0.05377	0.048123
C5E	2805	-2E-05	0.001509	-0.02606	0.028433
SMRE	1150	-7.2E-05	0.003424	-0.06068	0.041036
CG9	2954	-3E-05	0.001542	-0.02284	0.02345
MIVO	2954	1.36E-05	0.006196	-0.06235	0.051017
MCEU	1070	-7.4E-05	0.002337	-0.02812	0.00996
QCEU	1070	-7.7E-05	0.002423	-0.02984	0.011518
CEU	3061	-3.2E-05	0.0073	-0.25873	0.075613
CV9	2954	-3.6E-05	0.00168	-0.02318	0.034631
C6E	2805	-1.7E-05	0.001304	-0.01553	0.016067
MKTN	690	-0.00015	0.011814	-0.07539	0.117125
ETZ	1771	-1.7E-05	0.00198	-0.02931	0.036389
ECN	846	-6.1E-05	0.003654	-0.02626	0.023246
EL4H	3087	-2.2E-05	0.009275	-0.10248	0.120758
EL42	2880	-2.7E-05	0.005818	-0.08948	0.097802
ELF5	1395	-2.3E-05	0.001954	-0.01555	0.017638
EL4Y	2848	-2E-05	0.005338	-0.08308	0.080448
ES5R	1311	-9.7E-05	0.007319	-0.15645	0.114653
HEU	2518	-2.1E-05	0.00186	-0.03173	0.032783
PEF	3229	-2.3E-05	0.013064	-0.39878	0.207524
SC0E	2921	-2.4E-05	0.005491	-0.06086	0.062726

EMSV	2157	-4E-05	0.00367	-0.04439	0.061619
SC0C	2921	-1.9E-05	0.005651	-0.07949	0.046351
E960	618	-3.4E-05	0.003109	-0.05393	0.029745
MEUD	1868	-2.5E-05	0.003057	-0.03543	0.031872
MEU1	3764	-1.8E-05	0.002855	-0.02502	0.030687
C060	3081	-2.2E-05	0.005261	-0.04643	0.060054
EROT	4040	-2.3E-05	0.002684	-0.02145	0.030687
EUREUA	2795	-5.18E-06	0.010433	-0.18627	0.246289
VEUR	1845	-1.4E-05	0.001327	-0.00923	0.009152
XZEU	557	0.000113	0.002502	-0.01056	0.013654
D5BL	2640	-2.6E-05	0.004446	-0.05158	0.053418
DX2X	2967	-2.5E-05	0.004038	-0.06576	0.055632
SMEA	2726	-2.1E-05	0.008709	-0.0708	0.086192
IMEU	3344	-2.8E-05	0.004837	-0.04463	0.048029
IEVl	1422	-5.4E-05	0.002594	-0.01918	0.016988
IEMO	1391	-4.5E-05	0.01127	-0.07805	0.062412
IBC0	1254	-8.5E-05	0.002464	-0.02439	0.011917
EUMD	811	-2.3E-05	0.002926	-0.02708	0.019813
IMES	275	-3.2E-05	0.007679	-0.03334	0.046606
EUN	4448	-2.8E-05	0.004167	-0.03293	0.030254
EXSA	3971	-1.5E-05	0.003421	-0.02675	0.018991
EXSC	3958	-2.1E-05	0.009263	-0.10321	0.115616

Table 21 - Tracking error statistics using M2, per ETF

ETF Ticker	N	Mean	SD	Min	Max
CU9	2726	0.00136	0.002867	0	0.053773
C5E	2805	0.000826	0.001263	0	0.028433
SMRE	1150	0.001883	0.002859	0	0.060683
CG9	2954	0.000831	0.001299	0	0.02345
MIVO	2954	0.003746	0.004934	0	0.062351
MCEU	1070	0.001489	0.001801	0	0.028119
QCEU	1070	0.001668	0.001759	0	0.029843
CEU	3061	0.001633	0.007115	0	2.59E-01
CV9	2954	0.000865	0.00144	0	3.46E-02
C6E	2805	0.00075	0.001067	0	0.016067
MKTN	690	0.00727	0.009309	0	0.117125
ETZ	1771	0.000861	0.001783	0	0.036389
ECN	846	0.002563	0.002603	0	0.026259
EL4H	3087	0.00308	0.008749	0	0.120758
EL42	2880	0.002037	0.00545	0	0.097802
ELF5	1395	0.001267	0.001487	0	0.017638
EL4Y	2848	0.00188	0.004996	0	0.083079
ES5R	1311	0.002946	0.0067	0	0.156452
HEU	2518	0.000952	0.001598	0	0.032783
PEF	3229	0.003882	0.012474	0	0.398777
SC0E	2921	0.001869	0.005163	0	0.062726
EMSV	2157	0.001329	0.003421	0	0.061619
SC0C	2921	0.001965	0.005299	0	0.079494
E960	618	0.001111	0.002904	0	0.053927

MEUD	1868	0.001303	0.002765	0	0.035427
MEU1	3764	0.001578	0.002379	0	0.030687
C060	3081	0.001983	0.004873	0	0.060054
EROT	4040	0.001539	0.002199	0	0.030687
EUREUA	2795	0.005593	0.008807	0	0.246289
VEUR	1845	0.000905	0.00097	0	0.009233
XZEU	557	0.001699	0.001839	0	0.013654
D5BL	2640	0.002327	0.003788	0	0.053418
DX2X	2967	0.00154	0.003732	0	0.065759
SMEA	2726	0.004725	0.007316	0	0.086192
IMEU	3344	0.002138	0.004338	0	0.048029
IEVl	1422	0.001796	0.001872	0	0.019184
IEMO	1391	0.007552	0.008364	0	0.078045
IBC0	1254	0.001777	0.001708	0	0.024386
EUMD	811	0.00155	0.002481	0	0.027079
IMES	275	0.005028	0.005796	0	0.046606
EUN	4448	0.002832	0.003057	0	0.032926
EXSA	3971	0.002075	0.002719	0	0.026752
EXSC	3958	0.003984	0.008362	0	0.115616

Appendix 4 – Detailed Returns statistics

Table 22 - ETF returns statistics

ETF Ticker	N	Mean	SD	Min	Max
CU9	2726	0.0002918	0.009858	-0.0707	0.082751
C5E	2805	0.0002571	0.010697	-0.11067	0.075164
SMRE	1150	0.0002008	0.010794	-0.11929	0.081491
CG9	2954	0.0004673	0.010344	-0.1004	0.071101
MIVO	2954	0.0004551	0.011282	-0.10549	0.079692
MCEU	1070	0.0003504	0.010282	-0.10768	0.078619
QCEU	1070	0.0002956	0.009775	-0.09582	0.072926
CEU	3061	0.0002935	0.011928	-0.2323	0.090945
CV9	2954	0.0003479	0.012452	-0.13383	0.101384
C6E	2805	0.0003121	0.010979	-0.11946	0.074705
MKTN	690	-0.0001906	0.003093	-0.01719	0.017646
ETZ	1771	0.0002452	0.010897	-0.11234	0.08817
ECN	846	0.0002039	0.010504	-0.10952	0.07203
EL4H	3087	0.0002384	0.012415	-0.17413	0.115521
EL42	2880	0.0003373	0.010914	-0.11494	0.094945
ELF5	1395	0.0000853	0.010946	-0.10865	0.082744
EL4Y	2848	0.0002801	0.010535	-0.11152	0.075716
ES5R	1311	0.0000242	0.011168	-0.12617	0.073432
HEU	2518	0.0002679	0.010513	-0.10504	0.062801
PEF	3229	0.0001863	0.01449	-0.42061	0.171729
SC0E	2921	0.0003752	0.010994	-0.11587	0.089071
EMSV	2157	0.0001927	0.011737	-0.14117	0.093332

SC0C	2921	0.0003935	0.01125	-0.12981	0.088661
E960	618	0.0001085	0.011471	-0.1183	0.04918
MEUD	1868	0.0002602	0.010538	-0.10972	0.085406
MEU1	3764	0.0002137	0.012429	-0.1164	0.094468
C060	3081	0.0002684	0.012402	-0.11997	0.084472
EROT	4040	0.0002529	0.011861	-0.11798	0.092746
EUREUA	2795	0.0003142	0.012345	-0.20164	0.232242
VEUR	1845	0.0002572	0.010692	-0.11415	0.084106
XZEU	557	0.0001355	0.011881	-0.10422	0.080315
D5BL	2640	0.0002072	0.012066	-0.1354	0.105253
DX2X	2967	0.0003856	0.011209	-0.11039	0.080745
SMEA	2726	0.00028	0.010969	-0.13788	0.094456
IMEU	3344	0.0001626	0.012334	-0.11273	0.08424
IEV1	1422	0.0000837	0.012684	-0.13209	0.097099
IEMO	1391	0.0002402	0.009423	-0.11576	0.065556
IBC0	1254	0.0001635	0.011187	-0.11907	0.094954
EUMD	811	0.0000784	0.011178	-0.11125	0.061021
IMES	275	0.0002606	0.014988	-0.112	0.068128
EUN	4448	0.000232	0.011452	-0.11132	0.103952
EXSA	3971	0.000264	0.012047	-0.12261	0.089975
EXSC	3958	0.0002544	0.011751	-0.08728	0.13973

Table 23 - Index returns statistics

Index Ticker	N	Mean	SD	Min	Max
MSEXEME	4448	0.000312	0.011142	-0.10588	0.096449
DJSTO50	4448	0.00026	0.011671	-0.10865	0.107596
SBEXDHE	4312	0.000354	0.010828	-0.12798	0.085893
MSGEURE	4448	0.00035	0.01065	-0.09788	0.100287
MSURMVL	4448	0.000368	0.008625	-0.10213	0.083804
MSMOURL	4448	0.000458	0.010944	-0.10648	0.089794
MSURQAL	4448	0.000403	0.01004	-0.09047	0.097882
MSEROPE	4448	0.000308	0.011504	-0.11562	0.100474
MSVEURE	4448	0.000264	0.012881	-0.13587	0.110499
DJSTOXX	4448	0.00032	0.011513	-0.11465	0.098735
ISXEMFE	911	8.21E-05	0.00985	-0.11295	0.066787
SXELC1E	1145	0.000405	0.010395	-0.10616	0.079065
MSLEURE	4448	0.000293	0.011579	-0.11502	0.102478
FTREUPE	4448	0.000311	0.012661	-0.13046	0.102824
AWDVERE	4448	0.000313	0.011558	-0.11573	0.101781
MSURCDL	2500	0.000317	0.010226	-0.11032	0.076246
MSEUEVL	4448	0.000328	0.012493	-0.13293	0.098855
MSURMFL	4448	0.000428	0.01111	-0.11599	0.086573
MSMEURE	4448	0.000364	0.011608	-0.11793	0.088504
MSURSRL	3327	0.00027	0.011843	-0.10557	0.100363
DJSLARG	4448	0.000301	0.011595	-0.11377	0.103208

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10. Annex

Annex 1 – Graphs showcasing ETF growth

Figure 4 - Worldwide number of ETFs

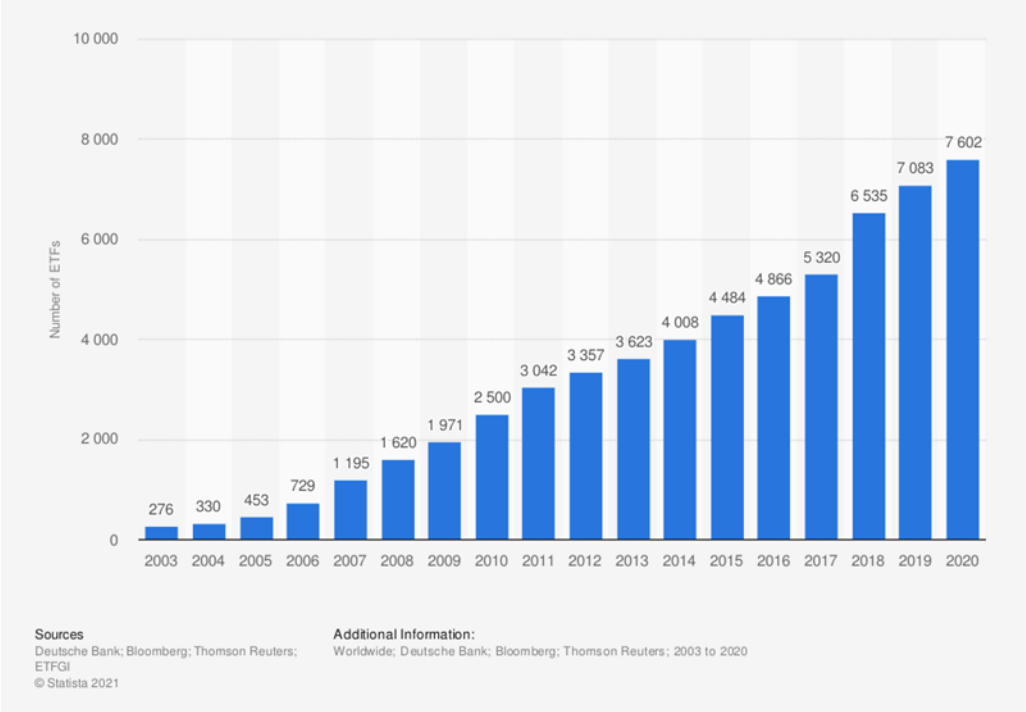
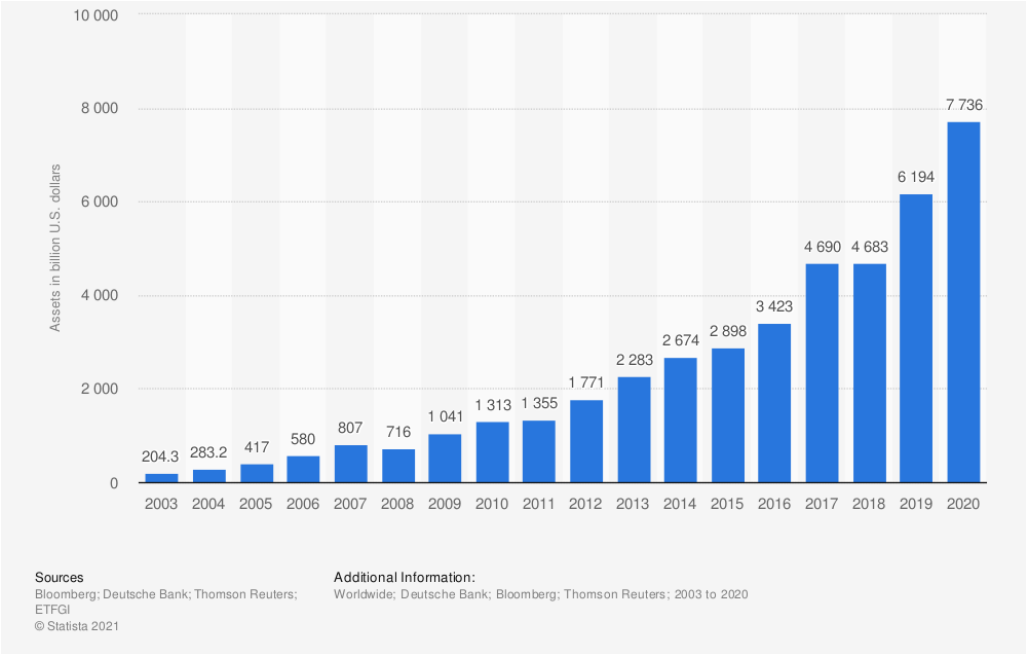
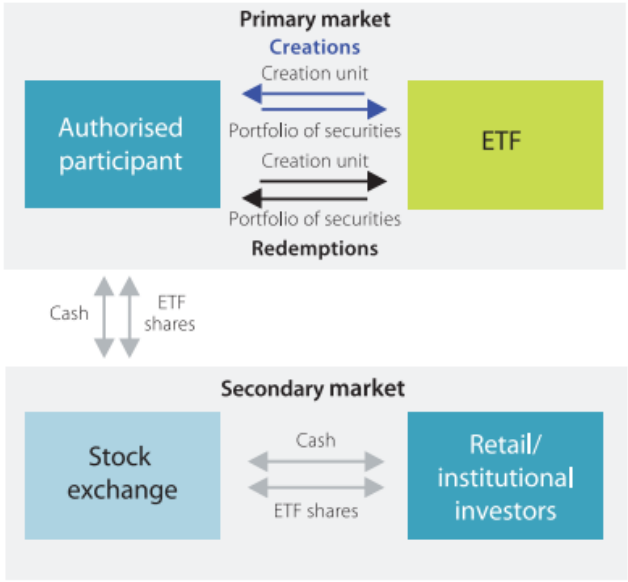


Figure 5 - ETF's AUM



Annex 2 – ETF origination

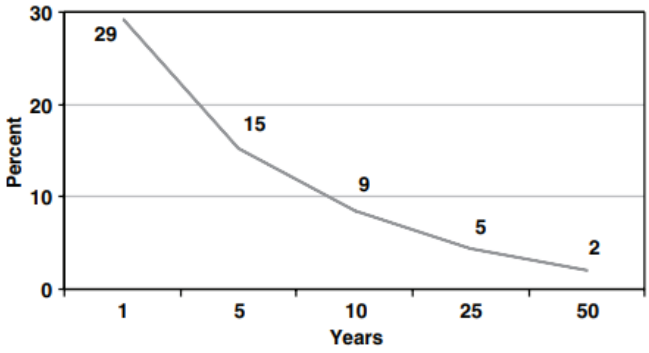
Figure 6 - Creation and Redemption Mechanism of ETFs



Source: RBA

Annex 3 – Active vs Passive efficiency

Figure 7 - Odds of Actively Managed Portfolio Outperforming Passive Index Fund



Bogle (2017) (p.124)

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