ETF Cost Obfuscation

A Study of The Relationship Between Fees and Tracking Errors of Index-Replicating Funds

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ABSTRACT

Index-tracking ETFs have gained popularity by both retail and institutional investors over the past years while costs in the form of fees have declined due to competitive pressures. Index-tracking funds are relatively homogenous products with only the goal of replicating an index as close as possible. However, the funds differ in their levels of costs. We question why competitive pressure has not led to fee-convergence and hypothesize that the funds vary in their ability to track their underlying indices. Retail investors might focus on the fund's stated fees without thinking about more complex measures such as tracking ability. Thus, fund managers might be able to lower fees by putting less effort into tracking their benchmarks. In order to test this hypothesis, we study the relationship between costs and tracking errors for American and European ETFs during the period 2012-2021. Failing to find evidence of a negative relationship for American ETFs, we turn to ETFs listed in Germany tracking European indices. There, we observe a negative relationship between fees and tracking errors for ETFs tracking the STOXX 50 Net Return Index, suggesting lower tracking errors for higher levels of Total Expense Ratios. The finding supports the hypothesis that passive ETF managers obfuscate costs by putting less resources into tracking their benchmark. We extend our analysis to also include other determinants of expense ratios. Fund size is found to have varied effects on expense ratios, while the synthetic ETFs tracking the STOXX 600 Net Return Index are found to have significantly lower expense ratios and a weaker relationship between expense ratios and tracking errors than the physical ETFs.

Keywords: Exchange Traded Funds, Tracking Errors, Expense Ratios, Index Investing, Asset Management

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1 Introduction

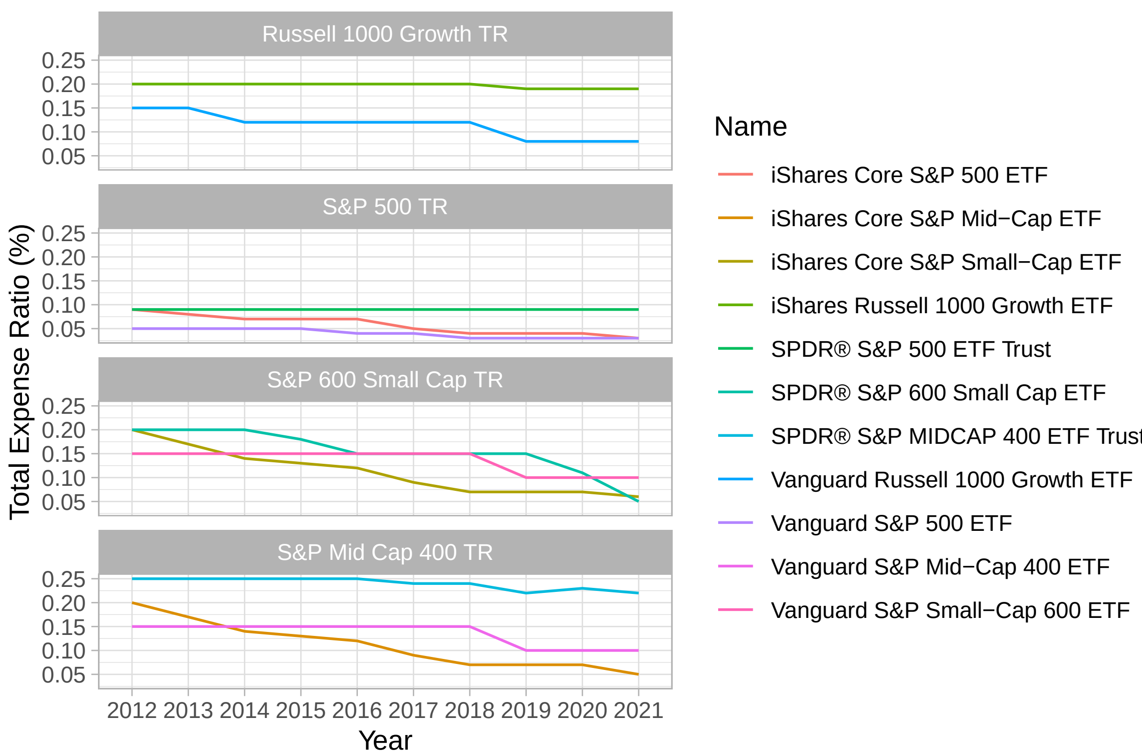
Over the past years, there has been a significant increase in capital inflows to Exchange Traded Funds (ETFs) from both retail and institutional investors (Financial Times (2021b) and Financial Times (2020)). Investments in ETFs have come to represent a significant share of the wealth of retail investors – both directly through their own investments and potentially indirectly through retirement saving schemes (Financial Times, 2021a).

An ETF is a fund that can be traded intraday on an exchange. The fund will typically deploy its capital to purchase and hold a basket of securities, to which each ETF share represents a claim of ownership. In order to invest or divest their holding of the ETF, the investors must conduct transactions on an exchange against other market participants. The ETF sponsor allows Authorized Participants (APs) to exchange baskets of the underlying assets against shares in the ETF, and to redeem ETF shares against the underlying assets. APs can thereby profit from any deviations between the price of the underlying assets of the ETF and the ETF shares. This mechanism keeps the price of the ETF shares from deviating far from the Net Asset Value (NAV) per share. Since ETFs are exchange traded, the fund companies do not have a direct relationship with their investors. This allows passive ETFs to have lower operating costs and, subsequently, lower fees than passive mutual funds (Hill & Hougan, 2015).

Investors may be tempted to invest in ETFs to gain exposure to various indices, while only paying relatively modest fees. Through an ETF, the investor can gain a broad diversification through a single security, rather than building a portfolio of individual stocks, thus incurring lower transaction costs. Investors are often faced with the choice between many potential ETFs - all covering the same reference index. Information related to the individual ETFs are often found to be complex or not readily available. In the choice between several fund options, all covering the same benchmark index, investors might therefore rely heavily on the reported fees of the fund in forming their investment decision.

The influx of capital to ETFs has led to the creation of several prominent ETF sponsors, each of which competes for the favor of potential investors. One of the areas in which the sponsors compete is the level of fees associated with the fund. This has resulted in a decline in the fees of ETFs over the past decade. Investment Company Institute (2022), a trade body, reports that economies of scale and competition between funds has led to downward pressure on index equity ETF expense ratios during the period 2009-2021. The graph below shows the development of fees (measured by total expense ratios) of the American index-tracking ETFs used in our study. We can observe a general trend in which the fees have declined over time. The graph also demonstrates the level differences of fees between funds within each index. The European ETFs included in our analysis show no change in fees over the observation period, but exhibit level differences between funds. As index-tracking funds may be regarded as relatively homogenous products with only the goal of replicating an index as close as possible, we question why competitive pressure does not lead to a fee-convergence within indices.

Figure 1. Development of US Expense Ratios



Carlin (2009) observes that price formation in retail financial markets violates the law of one price. The author notes that producers of retail financial products create ignorance by making their products more complex and notes two ways in which financial institutions may add complexity to their products: Partitioning fees into direct fees and involuntary surcharges, and making it more difficult for consumers to compare prices by using different methods of disclosure.

We hypothesize that, in the competition to lower prices, one way ETF managers can obfuscate costs is by claiming to track a particular index without actually doing so, allowing them to charge lower fees on paper. If there exists a negative relationship between ex-ante fees and tracking errors, meaning that funds with lower fees are worse at tracking their benchmark index, it could support such obfuscation taking place. We analyze the relationship between fund tracking errors and total expense ratios (as a measure of fees) for passive ETFs listed in Germany and the USA. The indices covered in our analysis represent some of the largest and most well-known indices of Europe and the US. The study covers the period 2018-2021 for European ETFs, and the period 2013-2021 for American ETFs.

Our study differs from preceding studies analyzing tracking errors *across* indices. By focusing on the relationships between tracking errors and total expense ratios *within* individual indices, we eliminate the differences between indices that could cloud the potential cost obfuscation. For instance, ETFs following indices covering small-cap stocks can be expected to exhibit larger tracking errors due to the higher price impact of trading illiquid stocks. We further analyze to which extent size and replication method may explain variations in the total expense ratio. Furthermore, our sample period covers the outbreak of the Covid-19 pandemic, a period of high market-volatility which we expect to exhibit larger variation in tracking errors between funds.

2 Literature review

Tsalikis and Papadopoulos (2019) conduct an analysis that compares the tracking errors of American and European ETFs. They utilize 15 ETFs in their study - five of which are American and ten European. The analysis covers the period 2010-2018, and therefore does not include the market turbulence of The Great Financial Crisis nor The Great Pandemic. All ETFs included in the analysis are passive and cover broad equity indices. The analysis is based on the tracking errors across all ETFs, irrespective of reference index, within America and Europe, respectively. The study utilizes the framework of tracking errors as established by Pope and Yadav (1994). The authors find the fund size and the total expense ratio to be important determinants of tracking errors. The tracking errors are found to be negatively associated with the size of a fund, indicating the potential existence of economies of scale. This relationship is significant across all three tracking error metrics. Furthermore, the tracking error is positively associated with the expense ratio of the fund. This relationship is significant only for the absolute tracking errors, and not for the other tracking error metrics. Overall, the authors find the tracking errors of the American ETFs to be lower than that of the European ETFs across all three tracking error metrics. The authors attribute part of this result to the difference in fund sizes between the American ETFs and the European ETFs. The American ETFs, on average, are found to be 29.9x greater, measured by assets under management, than the European ETFs. The paper will serve to provide comparisons for the various causes of tracking errors, and give insight into differences in tracking errors between American and European ETFs.

Pope and Yadav (1994) study the attributes, rationale and drawbacks of three commonly utilized measures of tracking errors. They investigate to what extent the frequency of the observations, that is, the time interval between observations, affects the calculations of tracking errors. The authors find that the difference between the returns of the fund and the reference index (i.e., the tracking difference), are serially correlated in data based on a relatively high frequency of observations (e.g., daily or weekly data). The authors argue that this may lead to a significant estimation bias in the tracking error calculations. To reduce the severity of the estimation bias, the authors suggest employing lower frequency data in the analysis of tracking errors (e.g., monthly observations). The empirical methods proposed by the authors will provide the foundation for our calculations of tracking errors. It also serves to highlight weaknesses inherent in the various tracking error metrics.

Buetow and Henderson (2012) study a large sample of ETFs traded on US exchanges to assess their tracking errors. The ETFs cover a broad range of different asset classes and various indices. The asset classes include, among others, equities, fixed income, real estate and preferred securities. The analysis of tracking errors is conducted within asset classes over the time period 1994-2010. The authors find that the ETFs, on average, tend to closely track the performance of their reference index. Furthermore, the analysis finds that the tracking errors of the ETFs tend to be affected by the liquidity characteristics of the securities comprising the benchmark index. That is, indices consisting of relatively illiquid securities are associated with higher tracking errors. The authors provide an extensive analysis of the causes of tracking errors for ETFs, covering a broader sample than Tsalikis & Papadopoulos (2019). We will rely on their work to compare our relationship between expense ratios and tracking errors.

Ferris and Chance (1987) study how the implementation of a distribution fee (the 12b-1 fee) affects the expense ratios of US mutual funds. The authors seek to identify what factors are influencing the expense ratios of funds in the cross-section. The analysis covers approximately 300 funds in the years 1984 and 1985. The authors find a negative relationship between size and expense ratios, indicating the presence of economies of scale. They also find that funds pursuing certain investment styles, namely "growth" and "income", have lower expense ratios than funds pursuing a strategy of maximum capital gains. Lastly, the age of the funds (i.e., the number of years since its inception) are found to be negatively associated with expense ratios. However, this relationship is only significant for observations in 1984, and not for 1985. Our study builds on the work of Ferris & Chance in order to analyze changes in the Total Expense Ratio over time and within indices. In contrast to the scope of their paper, we analyze ETFs in lieu of mutual funds.

Rea et al. (1999) study the relationship between the operating expense ratio and the assets under management (AUM) of 497 US equity mutual funds. Their findings indicate that funds with a higher AUM generally have lower operating expense ratios than smaller funds. The authors attribute this relationship to economies of scale. They hypothesize that the economies of scale is related to increased efficiency and productivity gains within the operations of the fund, rather than costs being fixed regardless of the AUM of the fund. The level of expense ratios are found to be associated with the fund's approach to investment management. Active funds tend to have higher expense ratios than passive, index tracking funds. The fees also tend to be higher for funds tracking the performance of certain types of indices, for instance small-cap or international indices.

One of the components included in the operating expense ratios is the custodial fees paid by the fund. The authors find this fee to be related to both the size of the fund and the volume of security transactions.

Kuok-Kun Chu (2013) studies the determinants of tracking errors for ETFs listed on the Hong Kong stock exchange. The author finds that synthetic ETFs exhibit higher tracking errors and that expense ratios have a negative impact on tracking errors. The author speculates that this is because the sample consisted of both synthetic and physical ETFs, with synthetic ETFs exhibiting both higher tracking errors and lower expense ratios. The study finds that the magnitude of tracking errors is negatively related to size, but positively related to dividend yields, trading volumes of funds, and market risk. The paper will serve as a comparison for our findings on synthetic ETFs traded on German exchanges.

3 Data

Our data is based on passive equity ETFs listed in the United States and in Germany. We have used information from Morningstar Direct Data, Eikon, the index providers' webpages and the websites of Boerse Frankfurt and Xetra to determine which funds track each respective index. When we have encountered conflicting information regarding the reference index of a security, we have relied on the information supplied by Boerse Frankfurt/Xetra or the fund's own web pages.

We use Total Expense Ratios as the cost measure for the funds. The Total Expense Ratio (TER), sometimes called Net Expense Ratio, is calculated as the operating expenses of the fund divided by the assets under management. This figure is reported on an ex-ante basis in the fund's prospectus, KIID, or other documentation. Operating expenses include management fees and all administrative costs of running the fund, such as marketing expenses, index licensing, and auditing. TER does not include the direct transaction costs of trading the underlying portfolio, such as brokerage fees and market impact. However, larger trading activity can be associated with increased administrative costs as the fund must put more effort into tracking the respective index, along with increased custodian fees.

For the US analysis, we focus on ETFs denominated in US dollars tracking the following indices: *S&P 500 Total Return*, *Russell 1000 Growth Total Return*, *S&P 600 SmallCap Total Return*, and *S&P 400 MidCap Total Return*. The indices are selected based on the number of ETFs that track the given index. The ETFs are all listed on the NYSE Arca exchange.

For the European analysis, we focus on ETFs denominated in Euros tracking the indices *EURO STOXX 50 EUR Net Return Index* and *STOXX EUROPE 600 Net Return Index*. We select the indices with the highest number of following ETFs, but exclude indices specifically related to foreign markets (e.g., S&P 500 NR), including global indices such as emerging markets indices and world benchmarks, in order to avoid issues related to currency effects. We obtain information on replication methods from Xetra/Frankfurt Boerse. The European analysis is limited to the period (2018-2021) as this allows us to cover more funds and maximizes the number of observations given the available data.

We use the data vendor Eikon to retrieve data on monthly Net Asset Value (NAV) returns, total net asset values, and total expense ratios for each fund in our sample. Our size variable is the yearly average of total net assets. We calculate index returns manually using monthly closing quotes obtained from Eikon. We are careful to use the appropriate version of each index in our calculation of tracking errors, discerning between *"Total Return"*, *"Net Total Return"*, and *"Price"* indices. An overview of the funds in our sample is provided in the Appendix.

4 Methodology

4.1 Hypothesis development

We perform regressions with TER as a dependent variable and different measures of tracking errors (TE) as independent variables. We do this in order to test Carlin's theory about whether there is a tradeoff between cost and some quality aspect of the ETFs. The cost of the ETF will be reflected in its Total Expense Ratio, whereas the performance will be linked to how well the ETF manages to track the performance of its benchmark index, given by the tracking error metrics. Our hypothesis is that ETF managers might be lowering fees by putting less effort into tracking their benchmark index. Based on this hypothesis, we expect to see a negative relationship between TER and tracking errors.

It can be reasoned that fund size has an effect on tracking errors. For instance, a large fund might experience larger transaction costs in the form of market impact when rebalancing. Because it is likely that size has an effect on TER via economies of scale and because size might be correlated with tracking errors, we include it as an independent variable to control for this effect.

Analyzing scatterplots of TER against tracking errors for the different indices, we notice a nonlinear relationship and find that tracking errors in log form better fits the data. A negative coefficient on the log of tracking errors would suggest that the effect of TE on TER is lower for higher levels of TE. An economic explanation for this is that when tracking errors are already high, there is less opportunity of reducing costs associated with tracking. We start our analysis by calculating the tracking errors for all ETFs included in our sample. We use two different measures of tracking errors, as proposed by Pope and Yadav (1994), in order to capture aspects related to both levels and fluctuations of tracking errors. The tracking errors will be based on the NAV returns of the funds, as we wish to only analyze the tracking abilities of the fund managers. If we instead had relied on price returns, the tracking errors would be exposed to factors that to some extent are outside the control of the fund managers.

We run a fund fixed-effects regression to control for differences between funds that are constant through time. American ETFs have experienced declining fees over the period we cover. We control for this trend by also running a separate time fixed-effect regression.

In our European analysis, we include terms related to fund size and replication strategy to our regressions. Past research has found fund size to be an important determinant of expense ratios, which is assumed to be due to economies of scale (Rea et al., 1999). Increased fund size is also linked to lower tracking errors (Kuok-Kun Chu, 2013). We expect the fund's size to be negatively associated with the Total Expense Ratio both due to economies of scale and the suspected motivation to lower total expense ratios in order to attract more capital.

We believe funds using synthetic replication display elements of both cost partitioning and more complicated cost and performance structures disclosures. Our reasoning is based on the Total Expense Ratio not including the swap fee associated with the synthetic replication strategy. As this represents a significant part of the costs associated with the ETF, the expense ratio will not accurately reflect the true costs of the product, and the investors may therefore be misled. In turn, we believe the investors might have unrealistic expectations related to the tracking errors of the ETF, due to the fees (reflected through the Total Expense Ratio) seemingly being low and the investors not incorporating costs not included in the TER in their expectations of tracking errors. Furthermore, we also suspect that investors may have limited understanding of the counterparty risks associated with this replication method.

Overall, we suspect that synthetic replication leads to added complexity (Carlin, 2009) and worse outcomes for the investor in terms of tracking errors (Kuok-Kun Chu, 2013). As supported by the findings of Kuok-Kun Chu (2013), we believe our results will reflect synthetic replication to yield a lower Total Expense Ratio and higher tracking errors.

4.2 Measurement of Tracking Errors

The fund returns used in our calculations of tracking errors are based on the Net Asset Value (NAV) of the fund. Past research has used total returns based on prices as a basis for tracking errors, as this more closely reflects what investors will experience. Prices of ETFs will occasionally differ across the various exchanges at which the funds are traded, which in turn causes the returns to vary between exchanges. Furthermore, the quoted prices of ETFs tend to swing around the NAV per share. The return based on fund prices will therefore tend to deviate from the return based on NAV. The magnitude of the deviations between the quoted prices and the NAV will depend on the ability of the APs to exploit arbitrage opportunities, in addition to demand and supply factors. The efficacy of the APs, and thus the discrepancy between price and NAV, will depend on the liquidity characteristics of the market in which the underlying assets are traded, as well as the minimum size of the block trades the APs are permitted to undertake.

Buetow and Henderson (2012) note that since APs need to transact in both ETF shares and the underlying assets, incurring transaction costs, they will only do so when the market price deviates far enough from the value of the underlying. Thus, the liquidity of the underlying securities has an impact on the size of the difference between the market price of the ETF and the value of the underlying basket necessary to induce the AP to create or redeem shares.

Because prices will deviate from NAV values due to factors that to some extent are outside the fund manager's control, we believe NAV returns better reflect management's performance and will be more appropriate in determining whether cost obfuscation takes place. Since prices, in contrast to NAV values, will vary between exchanges, the use of NAV returns will allow us to include ETFs listed in Germany but managed elsewhere. We have utilized monthly returns in our calculations of tracking errors, as high-frequency data have been found to lead to tracking error estimation bias due to returns being serially correlated at shorter intervals (Pope & Yadav, 1994).

We employ two of the methodologies proposed by Pope and Yadav (1994) to calculate the tracking errors. The methods are used to calculate the tracking error for each calendar year for every fund included in our sample. The tracking errors are calculated in the following manner:

Average absolute return difference:

The absolute tracking difference is computed as the arithmetic average of monthly absolute return differences between the fund and the reference index for each calendar year.

$$TE_{1,p} = \frac{\sum_{t=1}^{n} |e_{p,t}|}{n} \tag{1}$$

Where $e_{p,t} = R_{p,t} - R_{b,t}$

$R_{pt} =$ NAV return of ETF p in period t

$R_{bt} =$ return of the benchmark index b in period t,

$n =$ number of observations in the period

This method provides a measure of the extent to which the returns of the fund deviates from that of the benchmark index. The method does not differentiate between the fund outperforming or underperforming its benchmark, and thus considers any deviation from the index return as tracking error. This method follows the notion that the purpose of an index replicating security should not be to outperform the benchmark, but rather to imitate the returns of its benchmark index as closely as possible. The security should therefore not outperform its benchmark, as any such deviation constitutes a violation of its purpose. The absolute value of the deviation is employed as positive and negative return deviations will tend to cancel each other out in the long run, underestimating the tracking error. In order to achieve true performance replication, however, it is not sufficient that the return differences averages out to zero in the long run. Rather, the return of the ETF must approximate that of the underlying index consistently.

Standard deviation of return differences:

This measure of tracking error is computed as the standard deviation of monthly return differences.

$$TE_{2,p} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(e_{p,t} - \bar{e}_p)^2} \tag{2}$$

This method of calculating the tracking error is often used in conjunction with the method based on absolute return differences. The two measures reflect different aspects of a fund's ability in tracking its benchmark.. Whereas the method of absolute return differences measure the *level* of the tracking differences (i.e., the return differences between the fund and the index in percentage points), the method of standard deviations captures the *fluctuations* of tracking differences. Investors seeking to emulate the returns of a benchmark index do not only want an instrument able to closely match the return of the index in individual years, they want an instrument that is able to match it consistently. A potential weakness of the method is that a fund that consistently under- or outperforms its benchmark index will obtain a tracking error of zero. This would result in differing conclusions with regards to the fund's tracking abilities relative to the method using absolute tracking errors. The combination of the two aforementioned measures of tracking error should therefore offer an accurate depiction of the funds' tracking abilities. The resulting tracking error metrics will function as an independent variable in the subsequent regression analyses.

4.3 Factors affecting Total Expense Ratio

Total Net Asset Value is hypothesized to be negatively associated with the Total Expense Ratio. This is related to the assumption that the operating costs of the fund, and thus the Total Expense Ratio, will be subject to benefits of scale. For instance, the marketing and reporting expenses will likely not increase linearly with the net asset value of the fund. An increase in the Net Asset Value of the fund would therefore be expected to allow for a lower Total Expense Ratio.

For the analysis of European ETFs, we include a term that indicates the replication strategy of a given ETF. An ETF may employ either a full-, partial-, or synthetic replication strategy. In the former strategy, the ETF sponsor "physically" holds all securities of the reference index in the same weights as the index. While this offers fluctuations in prices equal to that of the benchmark index, the fund will be subject to relatively high transaction costs, as it will regularly need to undertake market transactions in order to keep the underlying assets of the ETF equal to that of the index portfolio. The full replication strategy will most often be utilized for funds tracking indices with relatively few and liquid securities. The fund may lend securities held in its portfolio to investors seeking a short-position against a fee. The income generated through securities lending can compensate for some of the fund's expenses.

Under a partial replication strategy, on the other hand, the ETF sponsors will hold what they deem to be a representative sample of the securities of the benchmark index. The ETF portfolio will therefore deviate from the index portfolio either in the securities included in the portfolio, or the weighting of the various securities. This strategy will often be employed when the reference index contains many and illiquid securities. Under such circumstances, a full replication strategy would be expensive or infeasible. As the partial replication strategy does not entail holding all securities of the index, the fund will, all else being equal, incur relatively low transaction costs compared to a full replication strategy. However, as the ETF portfolio and the index portfolio are not identical, the values of the portfolio and the index will not perfectly covariate, and will thus lead to tracking errors in the long term.

A synthetic replication strategy involves the use of financial derivatives to imitate the performance of an index. With this strategy, the ETF sponsor holds no “physical” shares of the underlying securities in the index, but rather gains its exposure to the index from the derivative contract. The most commonly utilized approach for synthetic replication involves the use of total return swap contracts. Under such an arrangement, the ETF sponsor will use the capital of its investors to purchase a basket of securities, which may or may not equal the index portfolio composition at the time. The basket of securities will be pledged as collateral, and the return of this portfolio will be awarded to the counterparty of the swap. The ETF sponsor will also pay a fee to the counterparty of the swap contract. In return, the ETF will receive the performance of the benchmark index from the swap counterparty. The investors of synthetic ETFs will thus be exposed to counterparty risk, as they will be subject to losses if the counterparty should fail in upholding the terms of the swap agreement. However, under the UCITS directive, the value of the collateral portfolio must at all times equal or exceed 90% of the NAV of the fund (Fassas, 2012). If the counterparty should fail to deliver according to the specifications of the contract, the ETF investors will seize control of the pledged collateral. The investors of the ETF are therefore subject to a counterparty risk equal to 10% of the fund’s NAV (Fassas, 2012).

4.4 Models

Initially, the Total Expense Ratio is regressed on the tracking errors for the funds of a given index. The purpose of the regression is to assess to which extent the expense ratio of a fund is associated with its tracking abilities.

For each index within our American data, we perform one regression with fund fixed effects and one with time fixed effects.

$$TER = \alpha + \beta_0 log(TE) + \beta_1 SIZE + Fixed\ Effects(FUND) + \epsilon \tag{3}$$

$$TER = \alpha + \beta_0 log(TE) + \beta_1 SIZE + Fixed\ Effects(YEAR) + \epsilon \tag{4}$$

The regression with fund-fixed effects will explain TER variations in the time-series, while the time fixed-effects regression will control for the general decline in expense ratios experienced over the period and explain variations in the cross-section. We perform regression analyses of several different functional forms, and base our formulation of the final model on the expression that yields the highest coefficient of determination.

The explanatory variables include: the natural logarithm of tracking errors ("TE"), constituting the two different measures of tracking error (i.e., the absolute return difference and the standard deviation of return differences), ETF size ("SIZE") defined as the average total net assets of the fund for the given year in USD 100 billions. The interpretation of the coefficient β_1 in this model is the change in total expense ratio in *percentage points* stemming from one *percent* change in the tracking error. The regressions do not include replication method as a variable as there are too few funds in the samples.

For the European indices, we run the regression:

$$\begin{aligned} TER = \alpha + \beta_1 log(TE) + \beta_2 SIZE + \beta_3 SYNTHETIC \\ + \beta_4 SYNTHETIC * log(TE) + \epsilon \end{aligned} \tag{5}$$

In which the variable "synthetic" denotes whether a given ETF utilizes a full or synthetic replication strategy. No ETFs in our sample used a partial replication strategy, and the "synthetic" variable is therefore binary. Due to the lack of variation in Total

Expense Ratio through time, we do not employ fixed effects for the regression analyses of European ETFs. We do not include the synthetic dummy-variable or interaction-term for ETFs tracking STOXX 50 as only one of these are synthetic. The "SIZE" variable is defined as the average total net assets of the fund for a given year in EUR billions.

Lastly, in order to assess the presence of heteroskedasticity in our models, we perform a Breusch-Pagan test for each individual regression. If heteroskedasticity is present, we employ the framework of robust standard errors in our models (White, 1980).

5 Empirical Results

5.1 Descriptive statistics

Summary statistics related to the two different metrics of tracking error are reported in the Table below. We find that the European indices exhibit a greater interdecile range of tracking errors than the American indices, both in terms of the absolute and the standard deviation tracking error metrics. We find that the median tracking error, both Absolute TE and SD TE, is higher for the European indices than for the American indices. These findings indicate that both the level and fluctuations of tracking errors generally tend to be lower for the American indices. Interestingly, we observe that the observations at the 90th percentile of the American indices are lower than the observations at the 10th percentile of the European indices (with the exception of Absolute TE for the S&P 400 index). Our results support the findings of Tsalikis and Papadopoulos (2019), who found that the tracking errors of American ETFs tended to be lower than those of European ETFs. However, Pope and Yadav (1994) argues that tracking errors should not be compared across indices, as each index is subject to different liquidity and size characteristics.

For the European indices, the observations in the first and tenth decile occurred primarily in 2020 and 2021. Based on the findings of Frino and Gallagher (2002), we would expect the tracking errors to increase with market volatility. This is in line with our observations, as the highest decile of tracking errors occurred during the volatile markets caused by the Covid-19 pandemic. However, we find it surprising that the bottom decile also primarily contains observations from this period. This would seem to indicate that some of the funds have lower tracking errors in volatile markets than under more "normal" market conditions. We find this observation puzzling, and suspect it may be due to reduced cash drag caused by a reduction of dividend payments during this period.

During the 2020 - 2021 period, the equity markets faced an increase of volatility due to the Covid-19 pandemic (Investment Company Institute, 2020), which may have exacerbated the tracking errors of some European ETFs. The data suggests that the American ETFs were not affected by the market turbulence to the same extent, and the outermost deciles do not systematically contain observations from any given time period.

Table 1: Descriptive Statistics

		Absolute TE			**SD TE**		
Index	N	10th Percentile	Median	90th Percentile	10th Percentile	Median	90th Percentile
European							
STOXX 50 NR	56	0.037	0.068	0.242	0.054	0.134	0.567
STOXX 600 NR	32	0.021	0.060	0.227	0.029	0.097	0.362
American							
S&P 500 TR	30	0.003	0.005	0.014	0.002	0.004	0.011
S&P 600 Small Cap TR	30	0.008	0.012	0.018	0.006	0.013	0.023
S&P Mid Cap 400 TR	30	0.006	0.010	0.026	0.005	0.007	0.016
Russell 1000 Growth TR	20	0.009	0.013	0.018	0.005	0.006	0.008

Description:
European ETFs 2018-2021, American ETFs 2012-2021. Descriptive statistics for the average monthly ETF tracking errors (TE). The Absolute TE is defined as the monthly average absolute return difference between the ETF and its benchmark index. The SD TE metric is the standard deviation of the monthly return differences between the ETF and its benchmark. Both metrics are calculated per ETF per calendar year (an "ETF-year"). The table presents the total number of observations per index, where the unit of observation is an ETF-year. The table also depicts the 10th, 50th and 90th percentile values for the distribution of both metrics of tracking errors for each respective index.

5.2 American ETFs listed on the NYSE Arca Exchange

In the fund fixed-effect model, we observe a statistically significant positive relationship between TER and absolute tracking errors for all indices except S&P 600. As the coefficient of the absolute tracking error variable (hereby "Abs. TE") is given in logarithmic form, the interpretation is that a 1% increase in Abs. TE is associated with a change in TER of β_1 percentage points. For instance, for the S&P 500 index, we find an increase in Abs. TE of 1% would be associated with an increase in TER of 0.015 percentage points. The positive relationship indicates that the tracking errors increase with the TER. This can be explained by fees lowering the return of the fund, causing it to deviate from the benchmark return. Therefore, we also look at the relationship between TER and the standard deviation of return differences (hereby “SD TE”). The regression does not show any statistically significant relationship between TER and SD TE. We fail to find evidence of a tradeoff between fees and tracking errors.

We observe a negative relationship between size and TER, suggesting that larger funds have lower expense ratios. This is consistent with our expectation that the funds experience economies of scale, achieving lower operational costs as a percentage of fund assets as AUM grows. The observation adheres to the findings of Rea et al. (1999), which indicated a negative relationship between expense ratios and fund assets of US equity mutual funds. Further, the results show significant differences in TER between funds within some of the indices.

In the time fixed-effects regression, we observe weaker significance levels for the Abs. TE variable. The ETFs tracking S&P 500 exhibit a positive, but lower coefficient on tracking errors than in the fund fixed regression. This could indicate that some of the change in TER is explained by other factors that have changed over time, not related to size or tracking errors. This could, for instance, be caused by increased competition for investors, improved operational efficiency of fund management, increased automatization of operations, outsourcing of parts of operations, or increased income from security lending. It could also be caused by economies of scope on the fund provider level, with internal functions shared across an increasing number of funds. However, the coefficient is not found to be significant at the 5% level. For S&P 400, however, we observe a higher coefficient on tracking errors in the time-fixed effect model than in the fund-fixed effect model.

Interestingly, the size coefficient is positive for S&P 500. This counterintuitively indicates that larger ETFs have higher expense ratios. SPY is an ETF with both higher TER and size than the other funds tracking S&P 500, which might skew our results. The size and TER characteristics could be related to the fund structure of SPY, which differs from that of the other ETFs. Additionally, SPY is the only of the three funds that employs a full replication strategy. We have excluded funds tracking Russell 1000 from the time-fixed effects regression since only two funds in our sample track this index.

Table 2: American ETFs (2012-2021). Fixed effects regression using fund fixed effects.
The dependent variable is the Total Expense Ratio for each ETF by year. Independent variables are log of Tracking Errors (Absolute or SD), and size. Size is the yearly average of total net assets in 100 billions of USD. Heteroskedasticity-robust Standard Errors in parantheses. P-stats are based on robust standard errors.

	Total Expense Ratio							
	S&P 500	S&P 400	S&P 600	Russell 1000	S&P 500	S&P 400	S&P 600	Russell 1000
Constant	0.154***	0.409***	0.210	0.473***	0.096***	0.184***	0.118**	0.134
	(0.028)	(0.074)	(0.136)	(0.106)	(0.022)	(0.039)	(0.055)	(0.106)
log(Absolute TE)	0.015***	0.042**	0.007	0.064**				
	(0.005)	(0.016)	(0.030)	(0.025)				
log(SD TE)					0.004	−0.006	−0.015	−0.017
					(0.003)	(0.008)	(0.013)	(0.023)
SIZE	−0.009***	−0.254***	−0.230***	−0.037*	−0.011***	−0.295***	−0.225***	−0.053**
	(0.003)	(0.045)	(0.064)	(0.021)	(0.003)	(0.029)	(0.038)	(0.023)
Fund 2	0.023**	−0.080***	−0.024	−0.061***	0.037***	−0.078***	−0.029	−0.106***
	(0.009)	(0.017)	(0.024)	(0.017)	(0.008)	(0.013)	(0.019)	(0.016)
Fund 3	−0.024***	0.030	−0.043**		−0.026***	0.078***	−0.049***	
	(0.004)	(0.019)	(0.020)		(0.005)	(0.007)	(0.016)	
N	30	30	30	20	30	30	30	20
Adjusted R^2	0.877	0.947	0.406	0.876	0.855	0.935	0.435	0.831

Notes: *Significance at the 10 percent level, **Significance at the 5 percent level,***Significance at the 1 percent level

Table 3: American ETFs (2012-2021). Fixed-effects regression using Time Fixed Effects. The dependent variable is the Total Expense Ratio for each ETF by year. Independent variables: log of Tracking Errors(Absolute or SD), and size. Size is the yearly average of total net assets in 100 billions of USD. Heteroskedasticity-robust Standard Errors in parantheses. P-stats are based on robust standard errors.

	Total Expense Ratio					
	S&P 500	S&P 400	S&P 600	S&P 500	S&P 400	S&P 600
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.109***	0.676***	0.161	0.070***	0.679***	0.098
	(0.024)	(0.045)	(0.107)	(0.019)	(0.082)	(0.068)
log(Absolute TE)	0.009*	0.106***	−0.005			
	(0.005)	(0.010)	(0.022)			
log(SD TE)				0.002	0.095***	−0.019
				(0.003)	(0.019)	(0.014)
SIZE	0.026***	0.007	−0.093**	0.032***	−0.126**	−0.077**
	(0.004)	(0.023)	(0.035)	(0.003)	(0.056)	(0.035)
year2013	−0.007	−0.033	−0.007	−0.009	−0.029	−0.001
	(0.014)	(0.037)	(0.025)	(0.013)	(0.042)	(0.024)
year2014	−0.014	−0.049*	−0.017	−0.018	−0.050	−0.021
	(0.013)	(0.026)	(0.026)	(0.012)	(0.054)	(0.026)
year2015	−0.015	−0.030	−0.026	−0.021*	−0.035	−0.017
	(0.013)	(0.027)	(0.023)	(0.012)	(0.049)	(0.023)
year2016	−0.022	−0.052*	−0.039*	−0.027**	−0.034	−0.036*
	(0.014)	(0.026)	(0.019)	(0.013)	(0.039)	(0.019)
year2017	−0.036**	−0.045	−0.044*	−0.046***	−0.024	−0.035
	(0.014)	(0.026)	(0.023)	(0.012)	(0.058)	(0.022)
year2018	−0.052***	−0.057*	−0.047*	−0.062***	−0.065	−0.042*
	(0.014)	(0.028)	(0.023)	(0.012)	(0.045)	(0.020)
year2019	−0.055***	−0.049*	−0.065**	−0.067***	−0.044	−0.066***
	(0.015)	(0.027)	(0.026)	(0.013)	(0.053)	(0.023)
year2020	−0.063***	−0.053*	−0.074**	−0.076***	−0.077*	−0.059**
	(0.015)	(0.030)	(0.026)	(0.012)	(0.040)	(0.023)
year2021	−0.086***	−0.061*	−0.094***	−0.105***	−0.033	−0.098***
	(0.017)	(0.031)	(0.028)	(0.014)	(0.060)	(0.031)
N	30	30	30	30	30	30
Adjusted R^2	0.799	0.846	0.656	0.779	0.282	0.684

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

5.3 European ETFs listed on the Xetra Exchange in Germany:

We observe a significant negative relationship between TER and Abs. TE for ETFs tracking the STOXX 50 index. The coefficient indicates that a 1% increase in Abs. TE is associated with a decrease in TER of 0.021 percentage points. We also find the coefficient of the standard deviation tracking error variable to be negative. This indicates that the fluctuations in the return difference between the ETF and its index are decreasing as TER increases. Together, these results indicate that both the level and the fluctuations of the tracking errors are reduced for higher levels of TER, thus offering better tracking performance. This relationship suggests a potential tradeoff between low tracking errors and low fees.

Our results contradict the findings of previous research, which found tracking errors to be positively associated with TER (Buetow and Henderson (2012) and Tsalikis and Papadopoulos (2019)). However, these studies did not run regressions within indices. The explanation of the observed relationship may be linked to the portfolio management of the fund. We hypothesize that the funds employing a higher TER can dedicate more resources to tracking their underlying indices closer. For example, both the size and the volume of portfolio transactions will affect the custodial fees of the ETF (Rea et al., 1999). This cost is included in the TER, which may incentivize funds to limit their rebalancing efforts. The funds may also employ different structures for distributing securities lending income. ETF managers may allocate part of the security lending income to themselves as compensation for the efforts required to conduct the securities lending. However, the share of the income attributable to the managers differ between funds.

The negative relationship between TER and tracking errors may also be linked to the operational efficiency of the fund. The managers of an ETF are dependent on sophisticated computing solutions in order to manage their portfolio, undertake transactions and meet reporting requirements. Some fund managers may have conducted larger investments into their computing solutions, which may have aided them in holding their costs down while maintaining low tracking errors. Some fund managers may also have the opportunity to utilize a centralized staff and/or computing solutions to undertake back-office tasks across various funds the firm is managing. This may reduce the operating costs associated with each fund, which in turn could result in lower required TER for each individual fund. It should be noted that the adjusted coefficient of determination for the STOXX 50 index is rather low (5.6%). This would imply that there are other factors also affecting the variability in the data, and that we may be limited in our abilities to draw general inferences from the analysis.

We observe a significant positive relationship between TER and both tracking error measures for the STOXX 600 index. This suggests that tracking errors increase with higher values of TER, which is in accordance with the findings of both Buetow and Henderson (2012) and Tsalikis and Papadopoulos (2019). The relationship between TER and Abs. TE may to an extent be expected, as the TER is subtracted from the NAV of the fund, thus reducing the returns attributable to the investors. As an equivalent fee is not subtracted from the returns of the reference index, the TER will, all else being equal, lead to tracking errors. However, as the TER constitutes a relatively flat fee that is deducted daily, it would not be expected to lead to an increase in the *fluctuations* of the tracking differences. The relationship between TER and SD TE therefore seems to be the result of factors *associated* with TER, rather than through the payment of the fee itself. Potential reasons for the observed positive relationship may stem from funds with high TER having less efficient portfolio management (e.g., relatively low frequency of portfolio rebalancing), higher transaction costs, or a different replication strategy.

The total net assets of a fund (i.e., the "SIZE" variable) is found to be positively related to TER for the STOXX 50 index. This indicates that the Total Expense Ratio would increase as the fund's assets grew. This would contradict the findings of Ferris and Chance (1987), which indicated that the expense ratios were negatively associated with the size of the fund. However, the variable in our regression is not found to be significant. We observe a different result with the STOXX 600 index, however, where the assets of the ETF are found to be negatively associated with TER. The relationship is significant, and suggests that the TER of a fund tends to be reduced by 0.033 percentage points for every 1 bn EUR increase of fund assets (0.035 based on the SD TE regression). This suggests the presence of economies of scale within the funds, which is in line with the observations made by Rea et al. (1999).

Table 4: European ETFs (2018-2021). OLS regression.
The dependent variable is the Total Expense Ratio for each ETF by year. The dependent variable in the regressions is the Total Expense Ratio ("TER"). Independent variables: log of Tracking Errors(Absolute or SD) and SIZE measured as the yearly average of total net assets in billions of EUR, Heteroskedasticity-robust Standard Errors in parantheses. P-stats are based on robust standard errors.

	Total Expense Ratio			
	STOXX Europe 600	STOXX Europe 50	STOXX Europe 600	STOXX Europe 50
	(1)	(2)	(3)	(4)
Constant	0.280***	0.062**	0.263***	0.079***
	(0.012)	(0.025)	(0.013)	(0.018)
log(Absolute TE)	0.027***	−0.021**		
	(0.005)	(0.009)		
log(SD TE)			0.023***	−0.018**
			(0.005)	(0.007)
SIZE (in 1 bn EUR)	−0.033***	0.002	−0.035***	0.002
	(0.008)	(0.003)	(0.008)	(0.003)
N	32	56	32	56
Adjusted R^2	0.622	0.056	0.623	0.063

Notes: *Significance at the 10 percent level, **Significance at the 5 percent level,***Significance at the 1 percent level

We find it somewhat puzzling that we do not observe the same relationship between TER and TE for the two indices. We suspect that the differences may, in part, be explained by the replication strategies employed by the ETFs of the two indices. The STOXX 600 index is tracked by a higher number of synthetic ETFs, while the STOXX 50 index is tracked primarily by ETFs utilizing full replication. We suspect that the synthetic ETFs have less control over the gross tracking errors (i.e., before fees), as the index performance would be provided by the swap counterparty. We believe the inclusion of such ETFs may skew our results, and therefore conduct a sub-sample analysis of the ETFs tracking the index to further examine the potential determinants of TER. The sample of ETFs tracking STOXX 50, nor any of the US indices, includes enough synthetic funds for a similar analysis.

In the table below, the variable "SYNTHETIC" indicates whether a given fund utilizes a synthetic replication strategy. The variable is found to be significant and negatively associated with the total expense ratio. This would indicate that the total expense ratio tends to be 0.13 percentage points lower for ETFs utilizing a synthetic replication strategy than for ETFs using a full replication strategy. This is in line with the findings of Mateus and Rahmani (2017), which indicated that synthetic ETFs traded at the London Stock Exchange that tracked European indices exhibited lower total expense ratios. The TER of ETFs using synthetic replication is likely found to be lower than for ETFs using full replication due to the swap fee not being included in the total expense ratio. The TER therefore does not reflect the full costs related to the swap agreement. As a synthetic fund does not hold the underlying shares of the index portfolio itself, but rather relies on the swap counterparty, the fund will not engage in active trading and portfolio rebalancing. We therefore hypothesize that the operating costs of a synthetic fund, excluding the swap fee, are lower than for a fund utilizing full- or partial replication. This, in turn, is reflected in the relatively low TER of the fund.

The coefficient of the interaction term implies that the relationship between TER and Abs TE is weaker for synthetic ETFs than physical ETFs. This indicates that the tracking errors still increase with TER, but at a lower rate for synthetic ETFs than for those based on a full replication strategy. This relationship may be due to the inherent characteristics of a synthetic replication strategy. As stated above, the swap fee is not included in the TER, and it therefore only includes operating expenses related to overhead, marketing, licensing fees, etc. The swap counterparty is responsible for delivering the performance of the underlying index, and the fund itself is therefore not responsible for the tracking performance (before fees). Therefore, all costs that the fund managers of the synthetic ETF inflict upon the investors through the TER will be expected to inflate tracking errors. However, as the TER is not as high as for funds using full replication, the slope coefficient will be relatively lower.

Interestingly, the size of a synthetic fund is found to be significant and positively related to its TER. This would indicate that the Total Expense Ratio increases as the size of the fund increases. This could imply a lack of economies of scale for synthetic funds, in that the overhead and marketing expenses become increasingly large relative to the fund's assets as its AUM grows. For the physical ETFs, however, we observe no significant relationship between size and TER.

Table 5: Sub-sample analysis of physical and synthetic ETFs tracking STOXX 600.
The “Synthetic” sample contains all ETFs within the STOXX 600 index that utilizes a synthetic replication strategy, while the “Physical” sample includes all ETFs using either a full or partial replication strategy. “STOXX 600” includes all ETFs, regardless of replication strategy. The dependent variable in the regressions is the Total Expense Ratio (“TER”) Independent variables: log of Tracking Errors(Absolute or SD), SIZE measured as the yearly average of total net assets in billions of EUR, and SYNTHETIC indicating whether the ETF is synthetic. The regression also includes an inteaction term between SYNTHETIC and Tracking Errors. Heteroskedasticity-robust Standard Errors in parantheses. P-stats are based on robust standard errors.

	Total Expense Ratio					
	Synthetic	Physical	STOXX 600	Synthetic	Physical	STOXX 600
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.215***	0.345***	0.344***	0.207***	0.309***	0.309***
	(0.003)	(0.013)	(0.012)	(0.002)	(0.011)	(0.010)
log(Absolute TE)	0.008***	0.076***	0.074***			
	(0.001)	(0.009)	(0.006)			
log(SD TE)				0.007***	0.066***	0.067***
				(0.001)	(0.010)	(0.008)
SIZE	0.008**	0.014	0.012	0.009**	−0.0002	0.003
	(0.003)	(0.017)	(0.009)	(0.003)	(0.010)	(0.007)
synthetic			−0.130***			−0.100***
			(0.013)			(0.012)
log(abs_te):synthetic			−0.066***			
			(0.006)			
log(sd_te):synthetic						−0.061***
						(0.008)
N	20	12	32	20	12	32
Adjusted R^2	0.730	0.874	0.883	0.627	0.930	0.930

Notes: *Significance at the 10 percent level, **Significance at the 5 percent level,***Significance at the 1 percent level

Structural differences in the ETF markets between the US and Europe might explain some of the differing results between the two markets. The US ETF market is far greater than the European market in terms of assets under management (Tsalikis & Papadopoulos, 2019). Furthermore, retail investors are more active in the US ETF market than in the European market. The Financial Times (2016) states that approximately 40% of US households invest in funds (not necessarily ETFs), while the reported figure for Europe is at 11%. This is suspected in part to be caused by US citizens generally having a greater responsibility in investing for their own retirement, whereas European citizens relay such responsibilities to their government or their employer. As they to a greater extent are reliant on producing returns for their retirement on their own, they might also be more cost conscious than European retail investors. As a consequence of this, the US retail investors may be more "skilled" in choosing funds that accurately track an index at attractive fee terms, allowing for less cost obfuscation to take place.

The ETF trades in Europe, especially outside the UK, are found to often be conducted through banks, and not specialized brokers. This may create higher transaction costs for the investors, as the banks can charge a fee for intermediating in the transaction. Such fees may also make comparisons between funds harder for investors (Financial Times, 2016). Lastly, the European ETF market is found to be somewhat fragmented relative to that of the US. There are more exchange traded products (ETP) on the European market, and these are offered by a higher number of providers and sold through a higher number of exchanges than for the US ETPs. Combined, the aforementioned qualities could indicate that there are more opportunities for ETF managers, and associated parties, to obfuscate costs within the European market.

6 Conclusion

ETFs have grown in popularity over the past years, and now constitute an important part of the portfolio of retail and institutional investors alike. Expense ratios have been declining the past decade, seemingly benefitting the investors with unencumbered index replication for lower fees. We do not observe a tradeoff between total expense ratios and tracking errors for ETFs tracking the US indices included in our sample, nor do we observe this form of tradeoff for European ETFs tracking the STOXX 600 index. However, we find a significant negative relationship between Total Expense Ratios and tracking errors for ETFs tracking the STOXX 50 index. While this observation supports our hypothesis that ETF managers obfuscate costs, the explanatory power of our regression model is relatively low. We also find that ETFs utilizing a synthetic replication strategy tend to be subject to lower expense ratios than full replication funds covering the same index. We observed a positive relationship between expense ratios and tracking errors for synthetic ETFs, but to a lesser extent than for full replication funds.

The study is limited to only equity ETFs tracking European and American indices. The study is also limited by a small sample size, especially for the American funds. This limits the statistical power of our tests, as well as our ability to draw inferences from our observations. As we can see from our results, there might exist differences between indices so that our results may not apply to other indices or markets than those we study.

Our data for German ETFs covers a relatively short time-span, and includes little variation in TER over time, which can adversely impact the statistical power of our analysis. Future studies may broaden their scope to also include ETFs with other underlying asset classes and funds in different geographical markets. Such studies would benefit from covering a longer time-horizon, which would yield additional data points and likely more time-series variation in the TER. They may also investigate other forms of cost obfuscation, such as increased complexity of prospectuses or fee partitioning.

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7 Appendix

Table 6: ETFs analyzed in this study

Name	Ticker	Benchmark Index	Total Expense Ratio (%)*	Size (billion)*	Curency	Inception year
European						
UBS(Lux)FS EURO STOXX 50 EUR Adis	UIM1	EURO STOXX 50 EUR NET Return Index	0.15	0.425	EUR	2001
BNPP Easy Euro Stoxx 50 ETF EUR C/D	ETBB	EURO STOXX 50 EUR NET Return Index	0.18	0.234	EUR	2015
BNPP Easy Euro Stoxx 50 ETF EUR C	ETDD	EURO STOXX 50 EUR NET Return Index	0.18	0.178	EUR	2015
HSBC EURO STOXX 50 ETF	H4ZA	EURO STOXX 50 EUR NET Return Index	0.05	0.303	EUR	2009
iShares Core EURO STOXX 50 ETF EUR Dist	EUN2	EURO STOXX 50 EUR NET Return Index	0.10	4.256	EUR	2000
Lyxor Euro Stoxx 50 DR ETF Acc	LYSX	EURO STOXX 50 EUR NET Return Index	0.20	3.926	EUR	2001
Lyxor Core Europe Stoxx 50 DR ETF Acc	MSED	EURO STOXX 50 EUR NET Return Index	0.07	0.098	EUR	2001
Invesco EURO STOXX 50 ETF	SC0D	EURO STOXX 50 EUR NET Return Index	0.05	0.313	EUR	2009
iShares Core EURO STOXX 50 ETF (DE)	EXW1	EURO STOXX 50 EUR NET Return Index	0.10	5.812	EUR	2000
iShares Core EURO STOXX 50 ETF EUR Acc	SXRT	EURO STOXX 50 EUR NET Return Index	0.10	3.934	EUR	2010
Amundi IS EURO STOXX 50 ETF-C EUR	V50A	EURO STOXX 50 EUR NET Return Index	0.15	2.358	EUR	2018
Amundi IS EURO STOXX 50 ETF-D EUR	V50D	EURO STOXX 50 EUR NET Return Index	0.15	0.089	EUR	2018
Xtrackers Euro Stoxx 50 ETF 1C	DXET	EURO STOXX 50 EUR NET Return Index	0.09	4.428	EUR	2008
Xtrackers Euro Stoxx 50 ETF 1D	DBXE	EURO STOXX 50 EUR NET Return Index	0.09	2.995	EUR	2007
Amundi IS STOXX Europe 600 ETF-C EUR	AME6	STOXX EUROPE 600 EUR NET Return Index	0.18	0.179	EUR	2018
Lyxor STOXX®Europe 600 NR ETF	C060	STOXX EUROPE 600 EUR NET Return Index	0.20	0.315	EUR	2008
BNPP Easy Stoxx Europe 600 ETF EUR C/D	ETSA	STOXX EUROPE 600 EUR NET Return Index	0.20	0.089	EUR	2013
BNPP Easy Stoxx Europe 600 ETF EUR C	ETSZ	STOXX EUROPE 600 EUR NET Return Index	0.20	0.695	EUR	2013
Lyxor Core STOXX Europe 600(DR) ETF Acc	LYP6	STOXX EUROPE 600 EUR NET Return Index	0.07	2.781	EUR	2013
Invesco STOXX Europe 600 ETF	SC0C	STOXX EUROPE 600 EUR NET Return Index	0.19	0.319	EUR	2009
Xtrackers Stoxx Europe 600 ETF 1C	DX2X	STOXX EUROPE 600 EUR NET Return Index	0.20	1.598	EUR	2009
Xtrackers Stoxx Europe 600 ETF 2C EUR H	XSXE	STOXX EUROPE 600 EUR NET Return Index	0.25	0.007	EUR	2018
American						
iShares Russell 1000 Growth ETF	IWF	Russell 1000 Growth TR	0.19	70.194	USD	2000
Vanguard Russell 1000 Growth ETF	VONG	Russell 1000 Growth TR	0.08	6.773	USD	2010
iShares Core S&P 500 ETF	IVV	S&P 500 TR	0.03	287.167	USD	2005
SPDR® S&P 500 ETF Trust	SPY	S&P 500 TR	0.09	379.012	USD	1993
Vanguard S&P 500 ETF	VOO	S&P 500 TR	0.03	235.173	USD	2010
iShares Core S&P Small-Cap ETF	IJR	S&P 600 Small Cap TR	0.06	69.302	USD	2000
SPDR® S&P 600 Small Cap ETF	SLY	S&P 600 Small Cap TR	0.05	1.754	USD	2005
Vanguard S&P Small-Cap 600 ETF	VIOO	S&P 600 Small Cap TR	0.10	1.704	USD	2010
iShares Core S&P Mid-Cap ETF	IJH	S&P Mid Cap 400 TR	0.05	62.837	USD	2000
Vanguard S&P Mid-Cap 400 ETF	IVOO	S&P Mid Cap 400 TR	0.10	1.420	USD	2010
SPDR® S&P MIDCAP 400 ETF Trust	MDY	S&P Mid Cap 400 TR	0.22	20.856	USD	1995

Note. *As of 2021. European ETFs 2018-2021, American ETFs 2012-2021