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An overview of tracking error for ‘Green’ Equity ETFs: Europe vs America.

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Abstract: This study aims to investigate the tracking errors of green ETFs as well as finding the differences in tracking error between American and European funds, two regions with different sustainability policies. This first part of the paper studies this by calculating two forms of yearly tracking errors using daily returns information of the ETFs and their respective index. These tracking error figures are then compared for the two regions using a two-sample t-test. The second part of the analysis uses a tracking performance measure with two controlled variables that influence tracking error based on past literature. The results of the study reflected that tracking error is persistent for all ETFs slightly favouring American firms as they reflect a lower tracking error for the second form of tracking error calculated. This contributes to the research showing that ETFs do not perfectly track their index and that moreover, the American funds have better or more flexible techniques when it comes to achieving as little tracking error as possible, potentially due to less strict environmental policies.

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1.0 Introduction

Our constantly changing economy has in recent times seen many adaptations that have affected every type of investor/market. Most notably, there has been a drastic change in the global stance towards sustainability having led to parts of the world having already made plans, rules and legislations to accompany for a green transition. Secondly, the economy has changed due to the introduction of a security that has seen immense incorporation into the investment world: Exchange-Traded-Funds (ETFs). ETFs are investment securities that can be bought and traded like stocks whilst having great similarities to mutual funds. ETFs almost represented a record $ 11.5 trillion at the end of 2023, having grown by more than 25% since December 2022 (PWC, 2024). This paper aims to bring these two very relevant concepts together. ETFs are generally designed to closely track and replicate the returns of an index allowing for a passive form of investing. Prior to the introduction of ETFs, an investor seeking broad market or sector diversification via a single investment instrument would be limited to mutual funds, which are priced just once a day, unlike ETFs which can be bought and sold on the stock market (Garg et al, 2014). When an ETF is bought, investors do not have actual ownership of the individual security as with a stock, but rather they own a proportional share of the fund's total assets. For example, if you own the SPDR S&P 500 ETF trust, a very popular ETF that aims to track the S&P 500, you do not own all securities in the index but rather a proportion of a portfolio meant to replicate this index. There are multiple steps to construct an ETF so that it can be traded on the market. Firstly, an ETF manager such as Blackrock or Amundi must find incentive to create a fund after which it will seek approval from the Securities & Exchange Commission (SEC). If agreed, the relevant manager will have to find an authorized participant (AP), who exclusively has the right to create or redeem ETFs shares directly with the issuer. The AP will then generally purchase all the securities that constitute the demanded ETF in appropriate proportion to the overall portfolio and will exchange this with the ETF issuer for one or more 'creation units' of the ETF (Charles Schwab AM, 2023). One creation unit can have up to thousands of ETF shares, which are then traded on the market. Antoniewicz et al (2014) document that on average, each ETF provider has 34 APs. This mechanism called 'creation and redemption' can be seen in Appendix C. If an investor wants to sell an ETF and there is no buyer, the AP will have to go into the primary market to create more ETF shares. Inversely, if there's an excess supply of ETF shares the AP can reduce the number of shares by exchanging them for the underlying security (ETF Stream, 2024). This paper will solely focus on passive equity ETFs so there is no need to clarify the numerous types of ETFs. Equity ETFs invest in stocks and as its aim is to replicate the performance of a specific equity index.

Research shows that ETFs generally offer good diversification, liquidity, cost efficiency, flexible access & range and transparency (Blackrock, 2023). These features are often beneficial relative to other more active forms of investing such as stock picking just by the assumption of Sharpe (1991), who shows that it is hard to 'beat' the market showing his preference for passive forms of investing.

With this, themost researched topic in the ETF field is around tracking error. Many papers including Chen et al (2017) find that tracking errors, the most common measure of performance for ETFs are present, resulting in ETFs that do not flawlessly function. Moreover, papers such as Xu et al. (2019), Ben-David et al. (2018) and Marshall et al. (2015) find that the introduction of ETFs has led to changes in volatility and liquidity of the market, with the underlying assets included in the ETFs being impacted the most. Other papers surrounding ETFs such as Borkovec et al. (2010) and Pan et al. (2012) find that the beneficial character traits ETFs are limited during times of financial crisis. ETFs and their impact of price discovery is also a well-researched topic in this field with Madhavan et al. (2016) as well as Glosten et al. (2015) siding with the fact that ETFs increase information efficiency. These are just a small amount of the heaps of research done on this topic and although the focus of this thesis will be primarily on the persistency of tracking error these already researched fields will continue to influence the market as ETFs continue to increase in importance.

A crucial aspect that is missing in the research of ETFs is in the scope of sustainable finance. As research proves that ETFs can have big impacts on the market and their underlying assets, it becomes apparent they will play a crucial role in the general shift towards a more sustainable economy. With high inflows into 'green' ETFs there will be more capital towards sustainable projects and investments that are included in these funds. Limited research has been done on these specific tools and moreover little research has been done how these funds performance in aeras that have different sustainability views and practises. Therefore, this thesis asks: "*How well do 'green' ETFs track their index in locations that have different sustainability policies?*"

To answer the question mentioned above I will take a sample of 14 ETFs from 2019-2024, 7 being from the United States and 7 from Europe that all track sustainable indices. I will first calculate two forms of yearly tracking error using daily data for every ETFs to compare how they perform in the different continents. The ultimate comparison of these two firms of tracjing error will be done using a two sample t-test. Secondly, I will then run a timeseries regression with the excess returns of the ETFs as a dependent variable and the excess returns of the Index as the independent variable including controlled variables that have been proven to impact the performance of ETFs. This will again give a view of how well these funds track their index as well as which factors impact performance. My daily performance data will be collected from the Refinitiv Eikon database for both the Index and the ETF.

This paper looks to find that 'green' ETFs indeed have a statically significant tracking error similarly to previous research done on other types. Moreover, we expect to find that American ETFs will perform better due to the leniency in US regulations when it comes to ethical practises and binding laws in line with sustainable concepts such as Net Nero by 2050.

2.0 Theoretical framework

2.1 ETFs characteristics, performance and effect on the economy

It goes without saying that ETFs were introduced as they offer favourable characteristics for certain investors relative to more traditional forms of investing. These so-called 'superior' characteristics are reflected in the continuously increasing market share of ETFs, partly at the costs of index futures and index mutual funds (Agapova 2011). Within the past 15 years, total assets of ETFs have twenty-folded, whereas active mutual funds grew by only 130%. The first potential reason for this increase is the expense ratio that comes with ETFs. Kostovetsky et al (2003) among many others confirm that for active mutual funds the expense ratio can be up to 2% which is much higher than for index funds, whose expense ratio is usually below 0.5%, which are generally also higher than those of ETFs, who offer the lowest expense ratio. A potential explanation for these low expense ratios is given by Gastineua (2001), who suggests that the elimination of 'shareholder accounting' can save ETFs anywhere from 5 to 35 basis points in expense costs. Shareholder accounting in this context refers to maintaining and managing records of individual accounts, tax reporting and more. Carhart (1997) & Sivanmalaiappan (2013) both touch upon the low management as an intrinsic benefit of ETFs relative to mutual funds. The authors argue that active funds have higher expenses because of additional costs required to maintain research houses, trading costs during the frequent churning of portfolio, which results in higher expense ratio for active funds. Lower expense ratios however do not necessarily mean there are always low costs associated with ETFs. In contrast to mutual funds, ETFs are sold like stocks as mentioned before on the secondary market, meaning actively buying and selling ETFs will lead to commission costs just as with stocks. Dellva et al (2001), confirm this and further believe that as the size of the investment increases, transaction costs will increase for ETFs due to per-share bid/ask spread, which creates a significant cost advantage for mutual funds such as the Vanguard index 500 who have zero transaction costs. Kostovetsky et al (2003) also touch upon the cost advantage when it comes to commission when comparing no-load index funds with ETFs. Large institutional investors on the other hand can obtain many ETF shares without affecting the price in the secondary market or being affected by these commission costs by acting in the market as participants in the creation and redemption mechanism mentioned earlier (Blackrock, 2024) (Kostovetsky et al. 2003). Our focus for this paper will not be on ETF characteristics, however it is important to note with some academic background why these instruments appeal to the investors. What we will focus on in this paper is the tracking error and performance of ETFs, for which the theoretical framework can be seen on the next page.

2.2 ETFs and Tracking Error

Almost all articles that measure or compare the performance of ETFs mention a form of tracking error as a performance measure. Going back to early works of Markowitz (1952) we learn that an efficient portfolio is a portfolio that maximizes the expected return for a given level of risk. In the ETF framework this measure of risk is often directly related to tracking error, which is an active risk measure that reflects a portfolio manager's decision to deviate from weights of benchmark positions to achieve returns more than the benchmark (Maxwell et al. 2018). Roll et al. (1992) argue that the main problem of a portfolio manager is the minimization of tracking error in respect of a specific level of expected tracking error. Hassine et al. (2013) moreover suggests that the objective of an exchange traded fund (ETF) is precisely to offer an investment vehicle that presents a very low tracking error compared to its benchmark. With this said, tracking error in isolation should not be used solely as a performance measure but is best used in combination with other performance evaluators such as the information ratio and Value at Risk (Maxwell, 2018). Thomas et al. (2013) for example find it undesirable to deviate away from the index touching upon the fact that higher TEs may indeed translate into higher returns, however, more often lead to diminishing outcomes. Thomas et al. (2013) argues that the excess returns that come from high tracking errors on aggregate, ignore the research that validates the positive relationship between risk and tracking error. Rompotis et al. (2006) also show in their work that tracking error is positively associated with management fees and risk, two undesirable traits for investors and managers. Thomas et al. (2013) outline several causes of TE and say the principal objective of past research has aimed to solve the following optimization: maximizing excess returns while maintaining a prescribed tracking error. The authors further go on to say that tracking error does not provide a directional metric since it only measures excess return volatility, thus it provides no information about the direction of the return differences (i.e. whether they are positive or negative). When it comes to the direction of the performance often Beta and Alpha coefficients are used among tracking errors. As mentioned earlier many papers use tracking error as their comparative performance measure of which I will give examples. Narend et al. (2014) empirically compares the performance of ETFs and index funds in terms of three parameters: tracking error, active returns and Jensen's alpha, with a similar approach as us instead this paper uses two measures. Farinella et al. (2018) also conduct a similar study comparing 61 ETFs and 61 mutual funds using tracking error to find that ETFs have lower tracking errors, higher returns and lower annual fees hinting towards serious benefits of ETFs relative to mutual funds. Earlier articles at times find negative sides to having a close tracking error but also always mention it as a risk factor. Two mere examples of these articles are from Israelsen et al. (2007) who found that low tracking error exhibits lower alpha, higher beta, and lower average performance compared to funds with high tracking error, which complemented the work of Gupta et al. (1999) who found that alpha generation of top-quartile managers (within their peer groups) is positively related to tracking error, however mentions as stated earlier that there are positive signs when the tracking errors are minimal. Besides the past literature mentioning the importance of tracking error let's get into some of the results when it comes to this measure in the scope of this paper, with many finding the persistence of tracking error when it comes to Exchange-Traded-Funds. Shin et al. (2010) who do a very similar study to this paper, focussed on general equity ETFs and measured the tracking error using 3 forms of tracking error, two of which are used in this paper. They find that for the 26 ETFs tracking errors are persistent and different from 0. Rompotis et al. (2011) also find from a regression analysis that ETFs have a persistent short term tracking error using 50 iShares in their sample. Chen et al. (2017) conduct an analysis on the determinants of tracking error as well as tracking performance using the exact same measures and find that there are significant differences between the ETF and its underlying index. Many more articles find this TE persistency using different forms of tracking error as well as the measures we will go on to use.

2.3 'Green' ETFs

Socially Responsible Investing (SRI) is a central topic in finance dating back to 1954 with the publication of Bowen named "the Social Responsibilities of a Businessman." Since then, the concept has been further developed and leaves incentives for companies to adopt ethical practices that are bigger than just the positive social aspects aligned with adapting. This paper will focus on ETFs that incorporate sustainability which are referred to as 'green' equity ETFs. These types of ETFs track an index just like a normal equity ETF, only these indices only include companies with pre specified sustainable practises that must be followed. Any type of active ETF is neglected in this paper. 'Green' ETFs have increased in popularity among with general ETFs and sustainable investing meaning a lot research is being done. Purely from a financial aspect, Sabbaghi et al. (2011) constructed an equally weighted portfolio of green ETFs and compared its return performance to that of the S&P 500 equity index. They found the equally weighted green portfolio outperforms the S&P 500 prior to the financial market collapse of 2008 and due to highly volatility of the green instruments they subsequently underperform the S&P 500 in the years following the financial market crash. Using the Capital Asset Pricing Model (CAPM), Fama–French (F & F) three-factor model and Carhart four-factor model, Yue et al. (2020) compared samples of 30 sustainable and 30 traditional funds. The evidence couldn't support any benefit when it comes to returns for the green ETFs, however evidence supported them being less risky than traditional funds with the Fama-French three factor model being the most suitable model. Rompotis et al. (2022) similarly used the CAPM, F & F four and five factor model and found no significant alpha by ESG ETFs in the UK as well as no significant differences in relevant ratios researched (Sharpe ratio & Treynor ratio). The authors did however find some empirical evidence indicated that ESG ETFs outperform the FTSE 100 index, which stands as a proxy for the UK stock market. Miralles-Quirós et al. (2019) also highlight the positive side of ethical ETFs, showing that it is possible for investors to obtain benefits from investing in ETFs, which track companies focused on contributing to the SDGs, especially those focused on decent work and economic growth. Many similar articles discuss green ETFs in times of crisis. Ennajar et al. (2022) for example find no difference between 'green' ETFs and traditional funds post or pre Covid-19 crises. Folger-Larode et al. (2022) find that higher levels of sustainability performance of ETFs do not safeguard investments from financial losses during severe market turndown. Weston et al. (2023), similarly find no evidence of ethical ETFs outperforming conventional ones. The authors do however highlight that firms who follow the PRI guidelines (similarly to almost all firms included in our sample) tend to outperform those who don't. Pavlova et al. (2022) employ a five-factor model accompanied by post expense returns before and after the pandemic. The results reflected that lower-rated sustainable ETFs tended to outperform the market and high-rated sustainable ETFs before the crash period. During the pandemic, the alpha of the models is found to be negative and insignificant. The overall conclusion by the author was that higher rated sustainability ratings of ESG ETFs did not protect the losses during a downturn besides not performing worse than the market. All in all, sustainable ETFs and their characteristics have been well research with varying outcomes.

2.4 Europe and American Regulations affecting 'Green' ETFs

Even though the shift to an environmentally driven economy is global, there are deadlines and regulations affecting the European and the American markets differently on separate timelines. This part of the literature review wishes to take you through different regulations in our two different geographical samples that affect the outcomes and conclusions of this work. Before this however, there have already been papers that indicate influence's geographical locations could have on ETF returns. Shin et al. (2010) find using a panel regression analysis of tracking error and tracking performance that Asian markets (compared to US and Europe) display greater tracking error persistence and are less efficient in disseminating information. Tsalikis et al. (2019) investigate 15 European and 15 American ETFs and finds that American ETFs are better at tracking their index with fund size and expense ratios as influential factors. Zawadski et al. (2020) also aims to investigate the performance of ETFs using similar tracking error measures as will be done in this paper and they focus on the differences in emerging and developed markets. They find that developed markets can track their index more accurately relative to emerging ones. These papers among others not mentioned thus suggest that the more developed and efficient the market is, the better the ETF will be at performing its tracking task.

2.4.1 European regulations

EU taxonomy: The first difference between European markets when it comes to sustainable investing is the recent publication of a EU taxonomy report published on the 22nd of June 2020. Dusìk et al. (2022) clarify the use of taxonomies for the stipulation of what can be deemed as 'sustainable investments' or 'sustainable economic activity' and further claims "they have the potential to radically change the environmental outcomes of decision making, based on a ‘significant contribution’ and ‘do no significant harm’ approach to critical environmental components.” The European Commission defines their taxonomy as a transparency tool based on a classification system translating the EU’s climate and environmental objectives into criteria for specific economic activities for private investment purposes (European Commission, 2022). It therefore does not serve to make certain investments mandatory. Ingre et al. (2020), investigated the impact of the taxonomy proposal thinking it would be ineffective in Sweden with a similar set up in place. With respect to six aspects: environmental, social, governance, general, ethical and design the authors saw great change and concluded that the new classification system has a substantial potential of being effective among actively managed sustainable funds in the Swedish markets. Pacces et al. (2021) are in favor of the mandatory disclosure requirements in the EU taxonomy and argue they could tackle greenwashing issues and align the interests of institutional investors with their beneficiaries, driving more investments into sustainable activities as investors seek to meet the growing demand for environmentally responsible investment options. Schütze et al. (2024) commented repeatedly on the potential importance of the EU taxonomy and labelled it as the first comprehensive science-based classification system designed to help understand whether an economic activity is sustainable. With they already outline some detailed improvements moving forward. All in all, the EU taxonomy has taken a step towards aligning impact and legislation and it is impacting European companies and will continue to impact them as deadlines come closer.

SFDR: Additionally, to the EU taxonomy, in March 2021 the European Commission put into force the Sustainable Finance Disclosure SFDR, a tool aimed at increasing transparency of green investments to make a difference. The Sustainable Finance Disclosure Regulation (SFDR) imposes mandatory ESG disclosure obligations for asset managers and other financial markets participants with substantive provisions of the regulation (KPMG, 2022). JP Morgan AM UK (2023) claims the EU SFDR is designed to reorient capital towards sustainable growth and help clients make better sustainable investing choices with one of the main goals being the creation of common standards for reporting and disclosing information related to sustainable considerations. Becker et al. (2022) already showed in his work that mutual funds and investors were impacted after SFDRs introduction, as ESG scores raised after the announcement and high ESG fund flows raised significantly relative to low ESG funds. Besides this little thorough research has been done on SFDR, due to its recency and room for improvement. With this being said, the European Commission and many big asset managers believe it will play a crucial role in the proper disclosure of sustainable information contributing to one of the EU’s big political objectives: “attracting private funding to help Europe make the shift to a net-zero economy (European Commission, 2024).” If the SFDR does help with transparency of information we will likely see an increase in consumer confidence as well as stability in the sustainability markets following the negative relationship between information asymmetry and the two factors mentioned earlier following the theory and empirical evidence of the famously cited papers of (Graham et al. 2009), (Botosan et al. 1997), (Healy et al. 2001) and many more.

EU Deadlines: Europe has a strategy to be climate neutral by 2050, which is a legally binding target thanks to the European Climate Law (ECL) (European Commision, 2024). This multilayered plan covers many areas all reflected in the European Green Deal (EGD). Europe has a 2030 climate target to reduce greenhouse gas emissions by 55% compared to 1990 levels. They also make this target legally binding through ECL with a comprehensive set of policies clarified in the 'fit for 55' package included in the EGD, which also still has room for improvement but already paves a way for the road Europe must take in order to achieve goals. Europe also has a Renewable Energy Directive setting an overall binding renewable energy target of 42.5% by 2030, aiming for it to be 45% (European Commision, 2024). In 2020 the European commission also adopted the new circular economy action plan (CEAP). Friant el al. (2021), describes the Circular Economy Action Plan as a mechanism to enhance the competitiveness of the EU economy by promoting sustainable economic growth and creating new job opportunities. This transformation aims to make the EU economy more resilient to resource scarcity and environmental challenges. All in all, just by these mere examples we can see that Europe is as a collective entity when it comes to setting deadlines and mandating its execution.

2.4.2 American regulations

When it comes to sustainability concerns in the United States, there is less of a general taxonomy relative to Europe. For example, 'America is Beautiful' is an initiative by the Biden administration to guide conservation aiming to conserve 30% of US lands and waters by 2030. This is comparable to the 2030 EU Biodiversity Strategy however, it is not legally binding, whereas the European inventive is. Moreover, when it comes to a 'circular economy' or 'waste management' the US programs vary greatly by state also making it harder to have clear objectives. In California for example, there is a law that goes by "SB 1383", which aims to reduce waste, have resource recovery, food distribution and offer economic opportunities which is binding mandates and laws, however as mentioned it is only state specific. The same can be said of the US Net Zero targets by 2050, which are present but with less legislation and enforcement relative to Europe. Awortwi et al. (2016) correctly reflects that the US approach to sustainability often relies on state-level initiatives and voluntary measures rather than federally mandated, legally binding targets. The authors go on to say that the decentralized nature of US governance allows for flexibility but may result in inconsistent implementation and less stringent enforcement compared to the EU's legally binding frameworks. This is supported by Mojska et al. (2023) who reflect upon the directive approach of the EU having a strong regulatory stance on sustainability compared to the more voluntary and decentralized approach of the US. All in all, I could go on to mention every state specific government regulation put in place in America, however it would lead to the same conclusion and that is that the US has a less structured and legally binding approach. This allows for interesting outcomes for this paper as the two geographical samples should have clear differences in the field of sustainable finance

2.5 Hypothesis

Considering the theoretical framework above this paper wishes to make a prediction on what it expects the outcome of the paper to be. The implications of this hypothesis will be touched upon if validated in the conclusion of the paper.

Hypothesis 1: 'Green' equity ETFs have a persistent tracking error.

Considering all the research in the theoretical frameworks, this paper expects to see statistically significant tracking errors for both American and European ETFs. This would be reflected in a number that is non-zero for both tracking error measures in the first part of the analysis. This would also be seen in the timeseries regression in the second part of the regression if the dependent variable is statistically significant and different from one, but more on how we will conduct this research will be seen below in the data section.

Hypothesis 2: 'Green' equity ETFs in the US perform better and track their index closer relative to similar ETFs in the Europe.

This paper predicts that the American ETFs will perform better than the European ETFs for our sample in the used timeline. The main reason for this is due to the flexibility of American companies when it comes to sustainability. For an American company to be considered sustainable they require less bindings actions allowing for ETF providers to create ETFs with less constraints allowing for better passive management strategies. Secondly, the American market is highly developed, mature and greater in volume. To put it into perspective, the Average Daily Value Traded (ADVT) in 2023 in the US was 4.4x higher than in Europe (Euronext, 2024). These factors make it so that it is assumed the US sample will perform better.

3. Data

This paper is a quantitative study that regresses 14 'Green' ETFs, 7 being from Europe and the remaining representing American ETFs. Daily return data of all ETFs and their index were gathered from the Refinitiv Eikon database for a period from 14/11/2019 up until 28/03/2024. Bid/ask spread, volume, turnover and which index is being tracked by which ETF were also gathered from Refinitiv Eikon. The risk-free rate used in the paper is the 3-month US treasury bill also gathered from the Refinitiv Eikon database. Because an American risk-free rate is used all ETF data is converted to the US dollar using the Refinitiv Eikon database currency converter. All expense ratios and the sustainability ratings were gathered from Morningstar and are constant throughout our research. An overview of the ETFs where we can see their sustainability rating can be seen in Appendix B. For all statistical models 'stata MP' is used. Moreover, all indexes and ETFs must have return data on the exact same day to calculate tracking error or excess returns. Due to missing data, we also used 'stata MP' to match the returns to the date for the ETF and the index and we also used 'stata MP' to match the risk-free rate to the date.

3.1 Methodology

3.1.1 Tracking error

In the first part of the analysis, we will calculate the yearly tracking errors for both ETFs using daily return data to compare the European and American ETFs for every year in the sample. This part of the analysis will use two commonly used forms of tracking error as suggested by Frino et al (2001). The first form of tracking error measures tracking error using the absolute difference as seen below:

$$(1)\ TE_1 = \frac{\sum_{t=1}^{n} |(\Delta R_{ETF} - \Delta R_{IND})|}{n}$$

In the equation above 'Δ' stands for difference in monthly returns of the ETF and its respective index ($\Delta R_{ETF} - \Delta R_{IND}$). Moreover, 'n' stands for the number of months in the respective year. As the data gathered is daily data, this paper takes a step in between to get $R_t ETF - R_t ETF$ in terms of monthly returns. To convert our daily data to monthly data we use the equations below:

$$\text{(2) Monthly Return ETF: } \frac{\Sigma(Daily\ returns\ ETF)}{Number\ of\ days\ in\ the\ month}$$

$$\text{(3) Monthly Return Index: } \frac{\Sigma(Daily\ returns\ INDEX)}{Number\ of\ days\ in\ the\ month}$$

After these calculations we have all variables to calculate the first form of tracking error. It is important to note that for the years 2019 and 2024 we don't have a full year of data and thus 'n' will be 2 and 3 respectively.

The second form of tracking error will use the standard deviation to get month-to-month variability of tracking error as done by Shin et al (2010), Rampotis et al (2006) and many more. The equation of this form of tracking error can be seen below:

$$(4)\ \text{TE}_2 = \sqrt{\frac{1}{n-1}\Sigma\,(\Delta R_{ETF} - \Delta R_{IND}) - (\overline{\Delta R_{ETF} - \Delta R_{IND}})^{2}}$$

In the equation above, ‘’ stands for difference in monthly returns of the ETF and its respective index. The average of the differences between the ETF and its respective index in captured by ‘$\overline{(\Delta R_{ETF} - \Delta R_{IND})}$’. Also, for this form of tracking error we convert our daily data into monthly data as seen in equation 2 and 3.

When we have calculated the tracking error for both measures, we will conduct a comparative analysis for the regions US and Europe to see if there are evident differences. This comparative analysis will be a two-sample t-test using the platform Stata. This t-test will utilise the average of the yearly tracking errors for every ETF, meaning every fund has one observation for years 2019-2024 for both forms of tracking error.

3.1.2 Time series regression using CAPM model

The second part of our analysis will be a time series regression made up of three parts represented by the equations seen below. First, we simply compare the abnormal returns of the ETF relative to the Index. Secondly, we include controlled variables that have proven to impact tracking error and performance as proven by past literature. Lastly, we will include lagged variables to correct for potential autocorrelation. The CAPM model used for the tracking performance of our ETFs is like that done by Chen et al (2017). Every model in the regression uses robust standard errors to ensure robustness and to deal with potential weaknesses in the model helping for example heteroskedasticity or the general applicability of the model. For a timeseries regression to work effectively, stata must set the time variable for every ETF. This is done using the ‘tsset’ command. The timeline of the data is mostly complete with some minor gaps in the date variable.

$$(5)\ (R_tETF - R_tf) = \alpha + \beta(R_tIND - R_tf) + \varepsilon_t$$

$$(6)\ (R_tETF - R_tf) = \alpha + \beta1(R_tIND - R_tf) + \beta2\ln(Volume) + \beta3\ln(Turnover) + \beta4\,(Bid - Ask\ Spread\ \%) + \varepsilon_t$$

$$(7)\ (R_tETF - R_tf) = \alpha + \beta(R_tIND - R_tf) + control\ variables + \beta5L.(R_tETF - R_tf) + \beta6L.(R_tIND - R_tf)\varepsilon_t$$

In the equations above R_tETF stands for the daily % change in returns of the ETF relative to the previous day. R_tIND stands for the daily % change in returns of the applicable index relative to the previous day. R_tf stands for the 3-month US Treasury bill rate.
Dependent Variable: The dependent variable in this equation will be the daily excess returns of the ETF relative to the risk-free rate. It is calculated by taking the daily excess returns of the ETF and subtracting the applicable risk-free rate from that day.

Independent variable: The independent variable in this equation in the daily excess returns of the respective Index relative to the risk-free rate. It is calculated by taking the daily excess returns of the Index and subtracting the applicable risk-free rate from that day. The β coefficient therefore reflects the % change in excess returns of the IND as the excess returns of the ETF increase by 1%. Moreover, the α coefficient reflects the average excess returns of the ETF if both the excess returns of the index and the controlled variables are 0. Both these variables are thus useful to see the quality of tracking performance of these instruments.

Control Variables: There are many factors that can influence tracking errors of the ETFs and therefore additional variables will be added to the time series model to solidify the model and to portray the full picture.

Bid-ask spread: The bid-ask spread is the difference between the highest price a buyer is willing to pay for an asset and the lowest price that a seller is willing to accept (Plerou, 2005). In practise, bis-ask spread is often used as a measure of liquidity. The impact of liquidity on factors such as trading volume, price and **tracking error** are well researched and therefore adding a measure of liquidity into our regression will isolate the impact of our primary independent variable on our outcome variable allowing for more representative results. The bid-ask spread in our paper is a percentage and is calculated as followed:

$$(8)\ Bid - Ask\ Spread\ \% = \frac{Ask - Bid}{Bid}$$

Volume: Trading volume of ETFs will also be included in the regression as a control variable. Higher trading volumes often result in higher market efficiencies, lower spreads, higher liquidity and more favourable bid-ask spreads. Including the volume of our ETFs will again play a crucial role in isolating the impact of our predictor on our outcome. Originally this paper also included turnover as a controlled variable due to its proven impact on the performance on ETFs. We tested for collinearity using the Variance Inflation Factor (VIF) and found that including both variables leads to high multicollinearity issues, negatively impacting the results. As a result of this turnover was removed as a variable. In the regression the natural logarithm of volume is used rather than just volume for three main reasons. Firstly, the relationship between the excess returns of the ETF and volume might not be a linear relationship which is linearized by taking the logarithm. Secondly, including the logarithm helps with skewness by having more of a natural distribution and lastly as a logarithm, the results can be interpreted easily as elasticities or in other words a percentage change.

The summary statistics seen in Appendix A give an overview of all ETFs in the sample. What becomes evident is that on average American firms tend to be bigger when looking at the volume figures. The biggest European ETF in our sample by far is EDM4, which has a volume of 99113, almost 5 times as much as the second biggest European ETF XZEU at around 21000 in volume. When it comes to the American sample the average is 135 210 in volume, relative to 19 520 for the European sample across the 7 ETFs with 5 of the 7 American ETFs being substantially greater than the EDM4. When looking at the bid/ask spread (our liquidity measure), American firms show more desirable figures with very low bid/ask spreads relative to the European sample. The mean returns of the index and the ETF tend to be extremely similar for all in the sample, however many already show differences when looking at the 4th decimal place, showing reasonable but imperfect tracking error by just looking at the summary statistics.

4. Results

The first part of our research was aimed at finding the yearly tracking errors for all our ETFs using two different calculations as seen by equation (1) and (4), which will be referred to at TE1 and TE2 respectively. Table 1 on the next page shows the tracking error calculations for the European part of the sample and table 2 on the next page will show these tracking error for the American sample. What can be seen is that tracking error is persistent for every ETF using both measures, even if this figure is very small for ETFs such as ESGU or IESE when looking at TE1, who have a tracking error of 0.00001 and 0.00003 for this measure respectively. TE1 shows extreme similarities when comparing European and American ETFs with a 0.00001 difference in the averages of tracking error for the first measure. Moreover, in 2020, a year of uncertainty with the COVID-19 pandemic we see little affect in the sample when looking at the first measure of tracking error. Many show to have more volatile returns relative to their index in 2019 rather than 2020 for TE1, which is an interesting observation and can be said for both the European and the American sample for this tracking error measure. Another noteworthy observation is that almost all ETFs show signs of decreasing TE1 when comparing the early years to 2023 and 2024. As these tracking errors decrease, the quality of ETFs will continue to increase. When conducting a two sample t-test to compare TE1 for the American and European sample there was no significant difference in the scorees of Europe (M=0.00008, SD=0.00012) and America (M=0.00007, SD=0.00006) conditions; t(82)= 0.4698, p=0.6398.

With TE2, tracking error is also persistent. European ETFs such as IQEE, CMUD, XZEU and XEUM all have a tracking error of 0.00030 or more, whilst the average of the American sample is around 0.00017. Two American ETFs, NULG and USSG do however show relatively similar figures for TE2 relative to the European sample. On average the tracking error for the American ETFs in the sample is lower by 0.00010. This follows our second hypothesis, but it is important to note that some European funds portray fantastic tracking errors measures such as EECN and IESE, who outperform certain American funds in the sample. When it comes to the COVID-19 pandemic and specifically the transition from 2019 to 2020 we see more obvious results when looking at the second measure of tracking error. For the European sample 5 out of the 7 funds in the sample see an increase in tracking error with XEUM seeing the greatest increase from 0.00009 in 2019 to 0.00102 in 2020. IESE, IQEE, ECN and XZEU also see big increases in tracking error when comparing theses two years. For the American sample the only noteworthy increase in tracking error when looking at the introduction of the pandemic is for SUSL, which increased from 0.00009 to 0.00021. The rest of the American sample did not seem to be very affected when it comes to tracking error measures, hinting towards great management. When conducting a two sample t-test to compare TE2 for the American and European sample there was a significant difference in the scores of Europe (M=0.00027, SD=0.00003) and America (M=0.00017, SD=0.00002) conditions; t(82)= 2.6715, p=0.0091.

EU	IESE			XEUM		EDM4		CMUD		ECN		XZEU		IQEE		Average	
	Year	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2
	2019	0,00004	0,00004	0,00074	0,00009	0,00010	0,00033	0,00000	0,00024	0,00006	0,00006	0,00014	0,00036	0,00012	0,00012		
	2020	0,00000	0,00021	0,00030	0,00102	0,00002	0,00030	0,00008	0,00022	0,00002	0,00017	0,00011	0,00063	0,00013	0,00053		
	2021	0,00002	0,00015	0,00008	0,00036	0,00001	0,00030	0,00007	0,00036	0,00001	0,00009	0,00001	0,00030	0,00005	0,00029		
	2022	0,00002	0,00012	0,00002	0,00014	0,00009	0,00027	0,00004	0,00044	0,00002	0,00011	0,00001	0,00048	0,00001	0,00039		
	2023	0,00004	0,00014	0,00005	0,00010	0,00007	0,00017	0,00011	0,00055	0,00003	0,00009	0,00007	0,00026	0,00031	0,00085		
	2024	0,00003	0,00011	0,00001	0,00008	0,00003	0,00014	0,00009	0,00054	0,00001	0,00008	0,00026	0,00009	0,00007	0,00021		
	AVG	0,00003	0,00013	0,00020	0,00030	0,00005	0,00025	0,00006	0,00039	0,00003	0,00010	0,00010	0,00035	0,00011	0,00040	0.00008	0.00027

Table 1: Table 1 shows the yearly TE results of European ETFs. TE 1 is the tracking as done in equation (1) and TE 2 is the tracking error as done in equation (4).

US	SUSA			ESGU		NULG		SUSL		USSG		DSI		SPYX		Average	
	Year	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2	TE1	TE2
	2019	0,00014	0,00012	0,00003	0,00026	0,00032	0,00034	0,00020	0,00009	0,00009	0,00041	0,00012	0,00019	0,00013	0,00017		
	2020	0,00007	0,00014	0,00001	0,00013	0,00015	0,00037	0,00009	0,00021	0,00013	0,00051	0,00007	0,00014	0,00007	0,00017		
	2021	0,00005	0,00005	0,00001	0,00007	0,00020	0,00064	0,00005	0,00008	0,00003	0,00018	0,00005	0,00004	0,00005	0,00015		
	2022	0,00005	0,00008	0,00002	0,00007	0,00004	0,00006	0,00003	0,00007	0,00004	0,00025	0,00006	0,00005	0,00000	0,00012		
	2023	0,00006	0,00010	0,00000	0,00010	0,00003	0,00006	0,00006	0,00010	0,00004	0,00037	0,00006	0,00009	0,00009	0,00013		
	2024	0,00008	0,00009	0,00002	0,00007	0,00004	0,00003	0,00010	0,00016	0,00008	0,00045	0,00008	0,00008	0,00003	0,00011		
	AVG	0,00008	0,00010	0,00001	0,00012	0,00013	0,00025	0,00009	0,00012	0,00007	0,00036	0,00007	0,00010	0,00006	0,00014	0.00007	0.00017

Table 2: Table 2 shows the yearly TE results of American ETFs. TE 1 is the tracking as done in equation (1) and TE 2 is the tracking error as done in equation

EUR (1)	R_IND	_cons	N	R^2
IESE	**1.0030*** (.0020)**	**.0001 (.0001)**	**1082**	**0.9958**
XEUM	**1.0052*** (.0034)**	**.0001 (.0001)**	**1078**	**0.9895**
EDM4	**.9897*** (.0038)**	**-.0002 (.0001)**	**1075**	**0.9842**
CMUD	**1.0002*** (.0001)**	**.0001 (.0001)**	**1067**	**0.9999**
ECN	**.9978*** (.0021)**	**-.0001 (.0001)**	**1083**	**0.9956**
XZEU	**.9962*** (.0030)**	**-.0000 (.0001)**	**1070**	**0.9924**
IQEE	**.9881*** (.0068)**	**-.0002 (.0002)**	**1059**	**0.9644**

Table 3: *The table above shows the results of a timeseries regression for equation (5) for the European sample. The dependent variable is the daily abnormal returns of the ETF relative to the risk-free rate. The independent variable is the daily abnormal returns of the respective Index relative to the risk-free rate. Within brackets are robust standard errors.* *t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

What is seen above are the results of the European sample for the second part of our analysis. The best ETF statistically in this sample is 'CMUD,' who has a significant coefficient at a 99% significance level of 1.0002. This can be interpreted in the following way: a 1% increase in the returns of the index CMUD tracks would lead to a 1.0002% increase in the returns of CMUD, the same could be said for the inverse if the index loses returns. Moreover, CMUD has a R^2 of 0.999, which means the regression here shows the full picture when it comes to variation of returns of the ETF relative to its index. In theory this R^2 should be high if not 1 by just including the dependent and the independent variable in the regression. ETFs should technically perfectly track their index meaning the variation of returns of the ETF should be fully explained by the variations of returns of the index resulting in a high if not perfect R^2 with ust the two variables mentioned. Any ETF that does not have a high figure for R^2 in this part of the investigations therefore does not carry out its task. The R^2 of CMUD thus highlights the strength of correlation between the ETF and its index for CMUD. Generally, when looking at table 3, the instruments are relatively good at tracking their index with most showing significant figures close to 1 as well as good R^2 numbers. None of the constants are significant meaning no variation is explained by external factors.

US (1)	R_IND	_cons	N	R^2
SUSA	**.9968***(.0015)**	**-.0001***(.0000)**	**1092**	**0.9990**
ESGU	**1.0005*** (.0034)**	**.0000(.0000)**	**1092**	**0.9989**
NULG	**.9886***(.0038)**	**-.0003(.0001)**	**1085**	**0.9933**
SUSL	**.9856***(.0071)**	**-.0004**(.0002)**	**1092**	**0.9914**
USSG	**.9347***(.0387)**	**-.0014(.0010)**	**1091**	**0.8421**
DSI	**.9978***(.0010)**	**-.0001***(.0010)**	**1092**	**0.9992**
SPYX	**.9963***(.0018)**	**-.0001***(.0006)**	**1092**	**0.9980**

Table 4: *The table above shows the results of a timeseries regression for equation (5) for the American sample. The dependent variable is the daily abnormal returns of the ETF relative to the risk-free rate. The independent variable is the daily abnormal returns of the respective Index relative to the risk-free rate. Within brackets are robust standard errors. t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$

Above in table 4 we see the results of equation 5 for the American sample. The results are very similar to the European sample with all coefficients for our independent variable being statistically significant at a 99% level with a coefficient close to 1. The best ETF in this sample is ESGU with a highly significant coefficient of 1.0005 as well as a very high R^2 value of 0.9989. Some constants in table 4 are significant, however have no real implication as they are very low figures. The worst ETF in the sample given the regression we are running is USSG who show a figure of 0.9347, which is a significant difference from 1 and this certain regression has the lowest R^2 in the sample at 0.8421.

EUR (2)	R_IND	Bid-ask spread %	ln_Volume	_cons	N	R^2
IESE	**1.0036*** (.0029)**	**.0013 (.0019)**	**.0000 (.0000)**	**-.0001 (.0004)**	**1074**	**0.9958**
XEUM	**1.0044*** (.0036)**	**.0043 (.0039)**	**-.0001 (.0000)**	**.0005** (.0002)**	**1015**	**0.9894**
EDM4	**.9875*** (.0046)**	**.1398 (.1002)**	**-.0000 (.0001)**	**-.0001 (.0009)**	**1030**	**0.9845**
CMUD	**1.0002*** (.0001)**	**-.0003 (.0053)**	**-.0001 (.0001)**	**.0003 (.0004)**	**408**	**0.9999**
ECN	**.9986*** (.0025)**	**.0071 (.0077)**	**-.0000 (.0000)**	**.0001 (.0003)**	**1082**	**0.9957**
XZEU	**.9948*** (.0036)**	**.0695 (.0837)**	**-.0000 (.0001)**	**.0000 (.0005)**	**1057**	**0.9925**
IQEE	**.9964*** (.0123)**	**-.0392 (.0608)**	**.0000 (.0001)**	**-.0003 (.0009)**	**473**	**0.9592**

Table 6: *The table above shows the results of a timeseries regression with controlled variables for equation (6) for the American sample. The dependent variable is the daily abnormal returns of the ETF relative to the risk-free rate. The independent variable is the daily abnormal returns of the respective Index relative to the risk-free rate. The control variables are the natural logarithm of volume and bid ask spread as a percentage. Within brackets are robust standard errors. t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 above shows the outcomes for regression (6) for the European sample. Adding the control variables always adds or keeps the R^2 constant, whilst not affecting the coefficient or significance of the independent variable too much. CMUD is still the best performing ETF in the sample with the same exact coefficient of 1.0002. When it comes to the significance of the controlled variables, however, none are significant and thus non hold significant statistical relevance. Adding the controlled variables moreover removed a lot of the observations for some of the funds that did not have full information such as CMUD and IQEE, who had a significant amount of blank data when it came to bid ask figures as well as volume. The overall conclusion when looking at this table remains that there is a very close correlation between the ETFs and respective indexes shown by the coefficients being very close to 1.

US (2)	R_IND	Bid-ask spread %	ln_Volume	_cons	N	R^2
SUSA	**.9964***(.0017)**	**.1046(.1924)**	**.0000(.0000)**	**-.0003 (.0004)**	**1092**	**0.9990**
ESGU	**1.0006***(.0016)**	**.0013(.2193)**	**.0000(.0000)**	**-.0001 (.0006)**	**1092**	**0.9989**
NULG	**.9868***(.0036)**	**.4729*(.2623)**	**.0001(.0001)**	**.0011(.0011)**	**1085**	**0.9936**
SUSL	**.9852***(.0068)**	**.0755(.3649)**	**.0000(.0000)**	**-.0005 (.0005)**	**1092**	**0.9914**
USSG	**.9257***(.0365)**	**-3.344** (1.1970)**	**.0001 (.0002)**	**.0028(.0024)**	**1091**	**0.8600**
DSI	**.9968***(.0128)**	**.3335*(.2375)**	**.0001(.0000)**	**-.0005 (.0005)**	**1092**	**0.9992**
SPYX	**.9964***(.0018)**	**.0611(.1222)**	**.0000(.0001)**	**.0003 (.0007)**	**1092**	**0.9981**

Table 6: *The table above shows the results of a timeseries regression with controlled variables for equation (6) for the American sample. The dependent variable is the daily abnormal returns of the ETF relative to the risk-free rate. The independent variable is the daily abnormal returns of the respective Index relative to the risk-free rate. The control variables are the natural logarithm of volume and bid ask spread as a percentage. Within brackets are robust standard errors. t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 above shows the outcomes for regression (6) for the American sample. We see the same trend as in table 4, which is that the R^2 figures of the regression improve slightly when including these controlled variables, without greatly changing the magnitude, direction or significance of the results. All American ETFs perform well with a coefficient respectively close to 1 apart from USSG, which remains the weakest ETF and the weakest model, when looking at the coefficient and the R^2. USSG is also one of the 3 funds in this sample that have a significant bid/ask spread that influences the abnormal returns of the ETF relative to the risk-free rate. The other two are NULG and DSI who unlike USSG have a bid/ask spread influences our outcome variable positively, in relation to USSG whose impact is also significant yet negative as seen in table 6 above. None of the coefficient for the volume variable are significant and the constant also proves to be insignificant. The all-round conclusion when looking at table 6 is that tracking error is indeed persistent for the sample and this part of the regression and when comparatively looking, we see little difference in quality of 'green' ETFs when comparing the coefficients and other factors seen in tables 5 and 6.

EUR (3)	R_IND	Bid-ask spread %	ln_Volume	L.R_ETF	L.R_IND	_cons	N	R^2
IESE	**1.0022****	**-.0013**	**.0001**	**-.4083****	**.4040*****	**-.0004**	**839**	**0.9972**
	(.0050)	**(.0017)**	**(.0000)**	**(.0576)**	**(.0594)**	**(.0004)**		
XEUM	**1.0003*****	**.0041**	**-.0001***	**-.1183****	**.1278****	**.0007****	**784**	**0.9909**
	(.0092)	**(.0037)**	**(.0001)**	**(.0585)**	**(.0592)**	**(.0003)**		
EDM4	**1.0013*****	**.1364**	**.0000**	**-.4349*****	**.4254*****	**-.0005**	**801**	**0.9867**
	(.0079)	**(.0985)**	**(.0001)**	**(.0408)**	**(.0391)**	**(.0009)**		
CMUD	**1.0005*****	**-.0021**	**.0000**	**-.5819*****	**.5816*****	**-.0002**	**292**	**0.9999**
	(.0001)	**(.0024)**	**(.0001)**	**(.1390)**	**(.1390)**	**(.0004)**		
ECN	**.9984*****	**.0003**	**.0000**	**-.3268*****	**.3244*****	**-.0002**	**844**	**0.9965**
	(.0044)	**(.0070)**	**(.0000)**	**(.0757)**	**(.0752)**	**(.0004)**		
XZEU	**.9999*****	**.0726**	**-.0000**	**-.1618*****	**.1553*****	**.0001**	**821**	**0.9936**
	(.0071)	**(.0919)**	**(.0000)**	**(.0382)**	**(.0385)**	**(.0005)**		
IQEE	**.9984*****	**-.0982***	**.0001**	**-.4637*****	**.4140*****	**-.0005**	**366**	**0.9731**
	(.0044)	**(.0070)**	**(.0001)**	**(.0757)**	**(.0520)**	**(.0008)**		

Table 7: *The table above shows the results of a timeseries regression with controlled and lagged variables for equation (7) for the European sample. The dependent variable is the daily abnormal returns of the ETF relative to the risk-free rate. The independent variable is the daily abnormal returns of the respective Index relative to the risk-free rate. The control variables are the natural logarithm of volume and bid ask spread as a percentage. Within brackets are robust standard errors.* t statistics in parentheses, * $p <$ 0.05, ** $p < 0.01$, *** $p < 0.001$

Above in table 7 the results of equation (7) are shown for the European sample. What can be seen is that by adding the lagged variables we increase the R^2 values, meaning these lagged variables contribute to the overall fit of the model. In other words, previous time periods for returns have an influence on the present abnormal returns and including them in the model increases the influence of our independent variable has on our outcome. Both the lagged variable of the returns of the index as well as the ETF are significant and are thus useful to include in the model also considering they help with potential autocorrelation issues. The other two controlled variables stay insignificant for most of the European sample apart from IQEE who has a significant and negative coefficient for bid/ask spread, however the lack of sample size for this specific ETF might influence these results. XEUM has a negative and significant coefficient for lnVolume, however this coefficient is so low it can be neglected. Generally, Table 7 shows improvements when it comes to the coefficient of our independent variable for 5 out of the 7 ETFs with all coefficients going closer to 1 when including the full model. The only two ETFs that did not move closer to a coefficient of 1 is CMUD and ECN, which were two ETFs who already had very good figures. All in all, the European sample clearly shows that tracking error is persistent as the coefficients deviate from 1, however it also shows that European ETFs can be efficient in tracking their index with XZEU portraying a coefficient of 0.999 at a 99% significance level when including the controlled variables as well as the lagged variables.

US (3)	R_IND	Bid-ask spread %	ln_Volume	L.R_ETF	L.R_IND	_cons	N	R^2
SUSA	**.9956*** **	**-.1332**	**.0000**	**-.4082*** **	**.4142*** **	**.0007** **	**853**	**0.9992**
	(.0028)	**(.1241)**	**(.0000)**	**(.0653)**	**(.0644)**	**(.0003)**		
ESGU	**1.0022*** **	**.1278**	**.0000**	**-.2887*** **	**.2865*** **	**.0000**	**853**	**0.9990**
	(.0034)	**(.2254)**	**(.0000)**	**(.0783)**	**(.0772)**	**(.0005)**		
NULG	**.9842*** **	**-.4395**	**-.0002**	**-.2525* **	**.2674* **	**.0020**	**847**	**0.9931**
	(.0060)	**(.6266)**	**(.0001)**	**(.1470)**	**(.1492)**	**(.0015)**		
SUSL	**.9826*** **	**-.4364**	**.0000**	**-.4851*** **	**.5060*** **	**.0002**	**853**	**0.9944**
	(.0073)	**(.5001)**	**(.0000)**	**(.1906)**	**(.1918)**	**(.0007)**		
USSG	**.9275*** **	**-1.2925**	**.0000**	**-.3673**	**.5060**	**.0001**	**847**	**0.8790**
	(.0753)	**(2.5848)**	**(.0002)**	**(.2508)**	**(.2584)**	**(.0021)**		
DSI	**.9943*** **	**.3459** **	**.0000**	**-.3149*** **	**.3191*** **	**-.0006**	**853**	**0.9994**
	(.0034)	**(.1983)**	**(.0000)**	**(.0560)**	**(.0559)**	**(.0005)**		
SPYX	**.9938*** **	**.0180** **	**.0000**	**-.3628*** **	**.3672*** **	**-.0005**	**853**	**0.9986**
	(.0040)	**(.1315)**	**(.0000)**	**(.0644)**	**(.0640)**	**(.0007)**		

Table 8: *The table above shows the results of a timeseries regression with controlled and lagged variables for equation (7) for the American sample. The dependent variable is the daily abnormal returns of the ETF relative to the risk-free rate. The independent variable is the daily abnormal returns of the respective Index relative to the risk-free rate. The control variables are the natural logarithm of volume and bid ask spread as a percentage. Within brackets are robust standard errors. t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 shows the results of equation 7 for the American sample. Similarly to the European sample, adding the lagged variables into the model slightly increases the R^2 values found. Moreover, besides USSG all lagged variables are significant with 5 out of the 7 being significant at a 99% significance level. Adding these variables also only slightly altered the coefficients of the studied variables in paper. The results of table 7 continue showing the trend of the paper, which is that the returns of the index are highly correlated to the abnormal returns of the ETF with a coefficient close but not exactly 1. No controlled variables are significant besides bid ask spread for SPYX and DSI. For DSI the results show that bid/ask spread does influence the dependent variable substantially looking at the significance and the magnitude of the coefficient. What is also noteworthy is that the coefficient for the constant of SUSA is significant and positive meaning if all else is 0 the ETF still outperforms the Index slightly.

4.1 How results relate back to past literature

The result above on 'green' ETFs supports the work of Chen et al (2017), Rompotis et al (2011), Thomas et al (2013) and many more mentioned in the theoretical framework as well as in other academic papers who found a persistency in tracking error for their ETF sample. These findings support the fact that there are certain risks when it comes to buying ETFs as they tend to deviate away from their underlying index. Secondly when it comes to the location and regulations impacting ETF performance, we see little differences between Europe and the US in the first measure of tracking error as well as our timeseries regression. This can be related back to the findings of Zawadski (2020), who compare developed markets to emerging ones and shows that developed markets act more in line with each other and have better tracking error performance than emerging ones. For the first part of the investigation and our second measure of TE (TE2), we find that American ETFs show less tracking error, which relates back to Tsalikis (2019) who finds that American ETFs tend to perform better due to liquidity and size, which is also very true for our sample as the American ETFs are more liquid and are bigger. When it comes to sustainable ETFs in times of distress, we see slight spikes in tracking error for European ETFs siding with Folger-Larode et al (2022), Ennajar et al (2022) and Pavlova et al (2022) who suggest ethical ETFs do not perform well in adverse market conditions. This is especially the case for funds: IQEE, ECN, XEUM and IESE, who all expereince an exponential increase in their TE2 measure when comparing years 2019 to 2020. The American sample on the other hand found similar if not better measures of tracking error during the pandemic for both TE2 and TE1. These results thus go against much of the previous literature and could hint towards ETFs as reliable tools even through economic downturn. With all this being said we can relate this back to the two main hypothesis of the paper:

Hypothesis 1: My first hypothesis stated: "'Green' equity ETFs have a persistent tracking error." Looking at the results we can validate this hypothesis for both parts of the study. Firstly table 1 and 2 show all figures are not 0, meaning for the two calculations there were no years in which the ETFs perfectly tracked their index. Secondly, looking at the time series regression tables we can also see that the independent variables are strongly significant and not 1, meaning that even though the returns of the index and the ETF are highly correlated they do not have the same movement and thus have tracking error.

Hypothesis 2: My second hypothesis stated: "'Green' equity ETFs in the US perform better and track their index closer relative to similar ETFs in Europe." This hypothesis is less obvious to validate using the results found in this paper. For the first part of the analysis, we can see that on average for the second tracking error measure that Americans have lower tracking error on average in line with the hypothesis. It is important to mention however that this is very ETF dependant with some European ETFs showing low TE figures relatively to American ones. When it comes to the second part of the analysis, we cannot conclude that this hypothesis is correct as the European and American ETFs perform with little obvious differences. Reasons for this could again relate to the work if Zawadski (2020), who say developed markets, which the US and Europe both have, help perform consistent and desirable tracking errors, allowing for the two samples to be similar in this case.

5. Conclusion

All in all, this paper aimed to contribute to earlier research on the quality of ETFs by analyzing how effectively they track their index. More specifically, the focus of the paper was solely on equity ETFs who track sustainable indices and how the quality of these funds differ in two regions with different sustainability frameworks. It is of extreme importance to research this field as ETFs are rapidly increasing in popularity and will thus inevitably play a crucial role in the shift towards Net Zero, a goal in which both Europe and the United States will have to play a big role. The scope of this paper will thus remain important up until at least 2050, as we close in on sustainability deadlines. ETF providers will have to adapt certain techniques to adhere to sustainable practices in line with goals and laws set. If green ETFs can maintain high tracking ability this will be a great way for investors to experience sustainability incentives, diversification and return goals through these financial instruments.

We studied the quality of ETFs using two analyses. The first part of the paper calculated two measures of tracking errors commonly used by researchers in this field. When these tracking errors were calculated a comparative analysis was done using a two sample t-test in order to statistically determine if there is a difference in the quality of green equity ETFs in the two regions in question. The second part of the analysis was a time series regression in which we used the abnormal daily returns of the ETF relative to the risk free rate as the dependent variable and the abnormal daily returns of the index relative to the risk free rate as the independent variable with volume and bid ask spread as controlled variables. Both these analyses should give different and good views on how well the ETFs track their index and if there are apparent differences in Europe and America.

Firstly, what was found was a persistence of tracking errors for ‘green’ ETFs in our sample as shown by the first and the second analysis. When tracking error is found, it can be said that these tools do not flawlessly carry out their task of tracking their index. For every ETF it is thus important for all types of investors to consider the quality of tracking rather than just assuming the fund will coincide perfectly with its underlying index. This view on tracking error will allow for investors to have a better risk perception when it comes to these tools. For some of the ETFs in our sample we do see clear signs of the minimization of tracking error for both the calculated tracking error measure in the first part as well as a coefficient very close to 1 in the second analysis. As these minimization techniques for tracking error get better, ‘green’ ETFs get more transparent, favoring all investors. For ‘green’ ETFs specifically, transparency is key in moving forwards towards a green economy. Fully transparent ETFs can play a big role in consumer confidence when it comes to aligning their sustainability views with their investments. The more efficiently the ETF functions relative to their index, the more capital will stream towards these ethical investments allowing for plans to become actions as we near specific sustainability deadlines. Secondly, this thesis was written in a comparative scope for two different markets, Europe and America. The differences between American and European ETFs in our sample were minimal, slightly favoring the American sample, who on aggregate have lower tracking error statistically backed by the two sample t-test for the second measure of tracking error. The small advantage of the American sample could be down to the added liquidity and the bigger volumes of these funds; however, little can be attributed to the differences in sustainable policies, which is a limitation of our research. Bigger differences can be expected in the future as more legal mandates attributed to European firms will reach its implementation date. This will undoubtedly lead to adjustments being made in European Indices and ETFs, causing volatility. This is another reason why we potentially see better tracking error figures for the American sample, who have now had more flexibility around sustainability. In the further future however, it will most likely be that the European markets will have fully adapted to the laws and their market will have stabilized. On the contrary the American market could at this point see more uncertainty due to the changes in flexibility of sustainable practices.

5.1 Improvements for further research

To have had more influential results this paper needed to change some aspects. Firstly, the expense ratios of the ETFs were not included as a controlled variable in the regression as every ETF was regressed separately with a constant expense ratio meaning it was dropped due to collinearity issues. With expense ratios differing for ETFs, not including this negatively impacted the applicability of the results as many past articles have found this expense ratio to be an influential factor of tracking error. In the scope of sustainable investing this paper also failed to include sustainability rating as a binary variable, due to every ETF being regressed separately with a constant number for this Morningstar figure seen in Appendix B. If we had more ETFs, we could have run a panel regression with the sustainability rating as a controlled variable, showing a perspective of how the better 'green' funds have different tracking errors in different years. Another potential improvement would be finding a way to include both volume and turnover into the regression by using a combined measure or any other method. Another weakness to our research was that for some ETFs in the sample, such as CMUD and IQEE in the European sample did not have full information when it comes to the data for the controlled variables. This meant that observations dropped when adding these into the regression analysis and the number of observations for table 7 was too slim for these two funds, negatively affecting the reliability for the results for this part of the study. Two examples of ETFs that has this issue were CMUD and IQEE. Lastly, to help me with the second hypothesis and to clarify the differences in performance of 'green' ETFs in different regions it would have been very beneficial to add an equal amount of non-sustainable ETFs for both the American and European sample. In this way we could have clarified if the differences in tracking error in these regions was due to the characteristics associated with the different markets such as volume and liquidity of these funds or rather if the differences in qualities came from sustainability policies. Comparing the differences in quality of green and non-green ETFs for both regions would thus also show us how different these markets react to sustainable investments which would have further proven or disproven the second hypothesis more clearly.

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Appendix A: Summary statistics.

The following appendix shows the mean, standard deviations as well as the minimum and maximum for all variables in the data gathered from Refinitiv Eikon. The '% Chg ETF' stands for the average difference of daily returns for the ETF. The '% Chg IND' stands for the average difference of daily returns for the respective index. Bid-ask spread is calculated as shown in equation 8. Volume is unchanged from the Eikon Refinitiv data.

IESE	mean	sd	min	max
%Chg ETF	0.0004	0.0131	-0.1087	0.0861
%Chg IND	0.0004	0.0128	-0.1151	0.0866
Volume	5979.7823	12533.0657	1.0000	158689.0000
Bid/ask spread %	0.0152	0.0284	0.0002	0.1521
Observations	1114			

XEUM	mean	sd	min	max
%Chg ETF	0.0004	0.0134	-0.1261	0.0895
%Chg IND	0.0004	0.0129	-0.1184	0.0890
Volume	703.9152	1680.3475	1.0000	20568.0000
Bid/ask spread %	0.0058	0.0129	0.0002	0.3890
Observations	1117			

EDM4	mean	sd	min	max
%Chg ETF	0.0004	0.0145	-0.1321	0.0926
%Chg IND	0.0004	0.0146	-0.1375	0.0891
Volume	99113.1545	190830.0130	1.0000	3143341.0000
Bid/ask spread %	0.0022	0.0018	0.0001	0.0301
Observations	1117			

CMUD	mean	sd	min	max
%Chg ETF	0.0003	0.0146	-0.1307	0.0945
%Chg IND	0.0003	0.0138	-0.1282	0.0906
Volume	433.5520	1321.3819	1.0000	11900.0000
Bid/ask spread %	0.0141	0.0870	0.0014	1.0000
Observations	1122			

ECN	mean	sd	min	max
%Chg ETF	0.0003	0.0129	-0.1162	0.0786
%Chg IND	0.0003	0.0129	-0.1167	0.0837
Volume	5224.1404	22540.8121	18.0000	541608.0000
Bid/ask spread %	0.0030	0.0052	0.0001	0.1200
Observations	1083			

XZEU	mean	sd	min	max
%Chg ETF	0.0003	0.0132	-0.1109	0.0870
%Chg IND	0.0003	0.0131	-0.1200	0.0886
Volume	21542.9584	64937.4543	1.0000	1275851.0000
Bid/ask spread %	0.0023	0.0017	0.0002	0.0207
Observations	1076			

IQEE	mean	sd	min	max
%Chg ETF	0.0003	0.0140	-0.1259	0.0911
%Chg IND	0.0003	0.0135	-0.1290	0.0961
Volume	3645.2536	6069.6805	1.0000	41708.0000
Bid/ask spread %	0.0057	0.0056	-0.0030	0.0370
Observations	1077			

SUSA	mean	sd	min	max
%Chg ETF	0.0006	0.0140	-0.1034	0.1050
%Chg IND	0.0006	0.0142	-0.1098	0.1023
Volume	219211.9964	587976.6579	20116.0000	10450324.0000
Bid/ask spread %	0.0005	0.0004	0.0001	0.0073
Observations	1099			

ESGU	mean	sd	min	max
%Chg ETF	0.0006	0.0142	-0.1200	0.0968
%Chg IND	0.0006	0.0141	-0.1169	0.0960
Volume	150319.7898	130270.4949	902.0000	1393693.0000
Bid/ask spread %	0.0005	0.0006	0.0001	0.0090
Observations	1099			

NULG	mean	sd	min	max
%Chg ETF	0.0007	0.0160	-0.1035	0.1054
%Chg IND	0.0008	0.0163	-0.1247	0.1040
Volume	73676.0618	86853.1423	6129.0000	1470936.0000
Bid/ask spread %	0.0010	0.0010	0.0001	0.0296
Observations	1085			

SUSL	mean	sd	min	max
%Chg ETF	0.0006	0.0137	-0.0923	0.0968
%Chg IND	0.0007	0.0142	-0.1212	0.0992
Volume	107951.3185	888177.7929	849.0000	28474194.0000
Bid/ask spread %	0.0008	0.0006	0.0001	0.0119
Observations	1099			

USSG	mean	sd	min	max
%Chg ETF	0.0007	0.0160	-0.1035	0.1054
%Chg IND	0.0008	0.0163	-0.1247	0.1040
Volume	73676.0618	86853.1423	6129.0000	1470936.0000
Bid/ask spread %	0.0010	0.0010	0.0001	0.0296
Observations	1085			

DSI	mean	sd	min	max
%Chg ETF	0.0006	0.0144	-0.1205	0.1002
%Chg IND	0.0007	0.0145	-0.1225	0.0983
Volume	187249.3412	147222.3726	43616.0000	2626278.0000
Bid/ask spread %	0.0005	0.0003	0.0000	0.0063
Observations	1099			

SPYX	mean	sd	min	max
%Chg ETF	0.0006	0.0139	-0.1144	0.0915
%Chg IND	0.0006	0.0140	-0.1195	0.0936
Volume	134383.7375	179189.3970	11307.0113	2124815.0000
Bid/ask spread %	0.0008	0.0010	0.0001	0.0180
Observations	1099			

Appendix B: General overview of sample

This Appendix shows every ETF used in the sample, their label as well as their respective index. On top of this the table shows the constant expense ratio for every ETF gathered from Morningstar as well as their Morningstar sustainability rating. This sustainability rating helps investors measure portfolio-level risk from ESG factors, for which Morningstar uses Sustainalytics to measure this material ESG risk. Moreover what can be seen in this appendix is whether the ETF is European or American.

ETF	Label	Index	Expense Ratio	Sustainability Rating	EU or US
Ishares MSCI Europe SRI UCITS ETF	IESE	MSCI Europe SRI Select Reduced Fossil Fuel Index.	0.2%	5	EU
Xtrackers MSCI Europe ESG UCITS ETF 1C	XEUM	MSCI Europe Select ESG Screened Index.	0.12%	3	EU
Ishares MSCI EMU ESG Enhanced UCITS ETF EUR	EDM4	MSCI EMU ESG ENhanced Focus CTB index.	0.12%	4	EU
Amundi MSCI EMU ESG Leaders Select UCITS ETF DR EUR	CMUD	MSCI EMU ESG LEADERS SELECT 5% Issuer Capped Index.	0.25%	5	EU
BNPP Easy low carbon 100 Europe	ECN	Low Carbon 100 Europe PAB.	0.59%	5	EU
Xtrackers MSCI Europe ESG	XZEU	MSCI Europe Low Carbon Leaders Net Index.	0.2%	4	EU
IndexQ Factors Sustainability Europe Equity	IQEE	Solactive Candriam Factors Sustainable Europe Equity Index.	0.25%	3	EU
Ishares MSCI USA SRI ESG Select ETF	SUSA	MSCI USA Extended ESG Select Index	0.25%	5	US
iShares ESG Aware MSCI USA ETF	ESGU	MSCI Usa Extended ESG focus index	0.15%	4	US
Nuveen ESG Large-Cap Growth ETF	NULG	MSCI TIAA ESG USA Large Cap Growth Gross Index	0.26%	5	US
iShares MSCI USA SRI ETF	SUSL	MSCI USA Extended ESGLeaders Index	2019: 0.15% 2020-2024: 0.1%	5	US
Xtrackers MSCI USA ESG Leaders Equity ETF	USSG	Low Carbon 100 Europe PAB.	0.1%	5	US
iShares MSCI KLD 400 Social ETF	DSI	MSCI KLD 400 Social Index	0.25%	5	US
SPDR S&P 500 Fossil Fuel Reserves Free ETF	SPYX	S&P 500 Fossil Fuel Free Index	0.2%	3	US

Appendix C: ETF market figure

This appendix gives a visual presentation of the ETF market from a Blackrock article released in 2023. What can be seen is the distinction between the primary and the secondary market and how APs trade underlying securties and ETF shares on the primary market so that investors can buy these ETF shares on the secondary market.

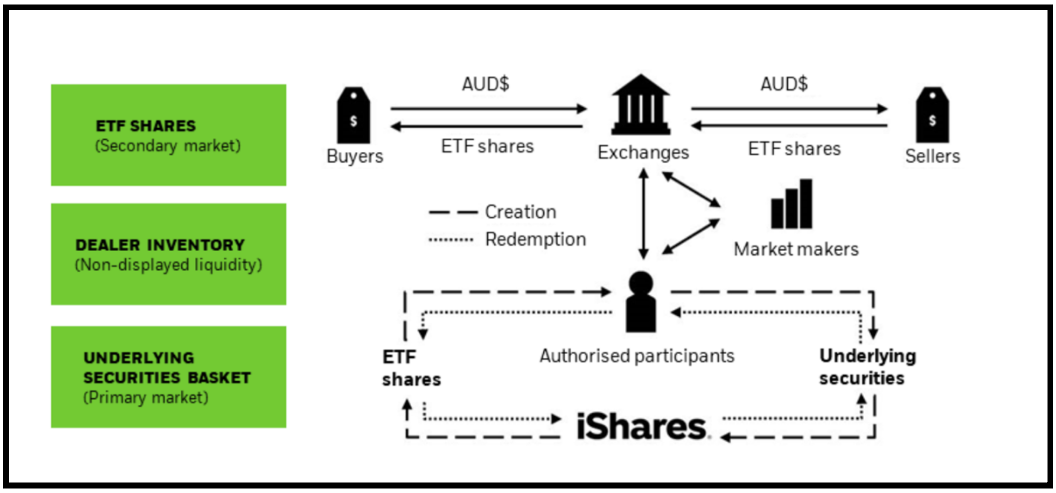

Figure: Blackrock (2023)