A Scientific Beta Publication

ScientificBeta
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From ESG Confusion to Return Dispersion: Fund Selection Risk is a Material Issue for ESG Investors

February 2024

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We would like to thank Daniel Aguet and Vania Schleef for their helpful feedback and comments and Raphaël Dupont for his tireless support in building our ETF database. We thank Julien Scatena from Trackinsight for providing us with ETF data for validation checks.

Keywords: ESG Investing, sustainability, performance measurement, Exchange-Traded Funds, socially responsible investments, SRI

Printed in France, February 2024.
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Abstract

This paper shows that the well-known phenomenon of ESG confusion translates into substantial returns dispersion among sustainable investment strategies. Analysing a dataset of sustainable index funds investing in US equity markets, we identify annual return differentials of up to 18.5% across funds. Differences in CAPM alpha or in industry-adjusted returns are even more pronounced, reaching up to 25.3%. Contrary to the notion of a common sustainability factor driving ESG strategies, our results underscore the presence of significant fund-specific risks. Evaluation of performance persistence shows that selecting funds based on past performance or tracking error fails to generate performance. Overall, our findings reveal that fund selection risk is a material issue for ESG investors.

Executive Summary

Executive Summary

Investors increasingly incorporate Environmental, Social, and Governance (ESG) criteria – also known as sustainability criteria – into their investment strategies. However, defining sustainability and identifying material ESG issues remain contentious. The absence of clear standards has led to a large disparity of metrics, a phenomenon commonly referred to as ESG confusion.

Investors interested in sustainable investing strategies must assess whether such confusion has an impact on financial performance. We address this question by examining the performance dispersion in the cross-section of a set of ESG funds invested in the US stocks. Our findings reveal substantial performance disparities in the cross-section of these ESG funds. Over a six-year period, the difference in annualised returns between the best and worst ESG funds is 6.5% when adjusting for differences in market exposure. When removing effects due to differences in industry exposure, the difference remains high with 4.9%. Over single years, the dispersion can be even more dramatic, reaching a maximum of 22.5% in terms of returns adjusted for market exposures, and 25.3% in terms of industry-adjusted returns. This large dispersion shows that fund returns are not mainly driven by a common sustainability factor. Instead, fund returns largely depend on fund specific choices of how to integrate ESG information. This suggests that ESG investors face substantial fund selection risk. Importantly, traditional fund selection strategies like relying on past performance or tracking error are inadequate for predicting future ESG fund performance.

In conclusion, our evidence emphasises that inconsistencies in ESG approaches contribute to significant cross-sectional dispersion in the performance of ESG investment products. Investors need to be aware that fund selection risk is a material issue for sustainable investment strategies.

1. Introduction

1. Introduction

Over the past years investors have been showing an increasing interest for integrating non-financial considerations, such as environmental, social, and governance (ESG) criteria, in their financial decisions[1]. The growth of the exchange-trade-fund (ETF) market has fostered the adoption of such investment practices. Today ESG-motivated investors, or ESG investors, can choose from a number of ETFs that tilt towards sustainability and which employ systematic and transparent approaches. The appeal of these Sustainable ETFs is that they offer a cost-effective way to accommodate investors' interest or preference for sustainability.

In a related paper, Bruno and Goltz (2023), we show that over the past decade the market of Sustainable ETFs achieved overall a performance that was statistically indistinguishable from the one of its reference benchmark. While a zero outperformance may not be enticing from a financial point of view, the prospect of avoiding at least significant losses may attract those investors that are interested in sustainability to satisfy non-financial motives. But should investors expect to achieve a similar performance with any Sustainable ETF?

One might be tempted to assume that a common sustainability factor drives most of the performance of all the Sustainable ETFs. The reason for this would be that the Sustainable ETFs all tilt towards sustainability and they are all passive strategies, so there is no room for management skill to affect their performance. As they all tilt towards the same theme in a passive way, cross-sectional dispersion in Sustainable ETFs' performance should be minimal. ESG investors may then be justified in expecting to obtain a similar performance regardless of the specific Sustainable ETF they choose. Would this expectation be accurate? Is there truly just a small cross-sectional variation in the performance of the Sustainable ETFs?

A large cross-sectional variation would pose a risk to those investors seeking to increase the sustainability of their portfolio employing only a specific ETF[2]. For these investors the risk would be to end up with a performance that strongly deviates from the one of the overall Sustainable ETFs' market. However, even if there was a substantial cross-sectional dispersion in performance, one could argue that ESG investors would not truly face a risk if they could easily distinguish the best Sustainable ETFs from the worst ones. But is such a distinction possible?

These are the questions that form the basis of our inquiry, and we summarise them all in a single general question: Do ESG investors face fund selection risk? To answer this question, we use a novel dataset of ETFs investing in the US equity universe that integrate sustainability criteria in a systematic and transparent way – in short, the Sustainable ETFs. We quantify the fund selection risk of the sustainable investors computing the dispersion in performance in the cross-section of the Sustainable ETFs. In addition, we analyse whether investors can use observable ETFs' characteristics, such as past performance and tracking error, to identify Sustainable ETFs that perform consistently better than others and so reduce their fund selection risk[3].

1 - The 2022 USSIF report on sustainable investing trends (USSIF, 2022) reports that the total amount of assets professionally managed in the US in 2022 was USD66.6 trillion, of which USD8.4 trillion (or 12%) was invested following some sort of sustainability practice.
2 - An ESG investor may prefer to invest in a single ETF because it is more convenient and easier to manage than investing in a portfolio of Sustainable ETFs, but also because the ESG approach implemented by a specific ETF may be more aligned with their type of preferences for sustainability.
3 - Notice that in this work we are purely concerned with the cross-sectional dimension of the risk within the universe of Sustainable ETFs. We do not analyse the performance of the average Sustainable ETF. For this the interested reader can find an extensive analysis in our previous work, Bruno and Goltz (2023).

1. Introduction

To obtain our cross-section of Sustainable ETFs, we put much effort into going through the official documentation of dozens of ETFs. We did this to ensure that we included only those ETFs that
1) limited their investment universe to US equities;
2) that actually incorporated ESG information passively into their construction process; and
3) that did not explicitly tilt towards possible alternative performance drivers such as factors and sectors.

This selection enables us to attribute the cross-sectional variation in the performance of sustainable ETFs to differences in their approaches to integrating sustainability, thereby eliminating confounding effects on performance such as geographic bias, management skill, or non-ESG tilts.

Because we want to analyse differences in performance that we can attribute to the ESG component, we evaluate the performance of each ETF adjusted for market and industry exposures. To do this, we follow the advice of Berk and van Binsbergen (2017) and use comparable benchmarks that we construct using ETFs that invest in the same universe as our selection of Sustainable ETFs.

We find a large and economically meaningful variation in performance within our selection of Sustainable ETFs. Over the whole sample, the difference in performance between the best and the worst performing Sustainable ETFs (dispersion) is 6.5% per year if we adjust performance only for market exposure, and 4.9% per year if we account for industry contributions too. Over shorter time-samples (full calendar years), the dispersion can reach 22.5% if we adjust performance for market exposure alone, and 25.3% when we also adjust for industry exposures[4].

We also find that observable fund characteristics, typically used in the mutual fund literature, do not help to distinguish the best Sustainable ETFs from the worst ones. In fact, we find no evidence of performance persistence, meaning that Sustainable ETFs that were the best performers in the past do not continue to be the best in the future. Only a minority of the Sustainable ETFs in the top quintile of past performance are also in the top quintile of future performance. Moreover, the difference in the performance (performance spread) between the Sustainable ETFs in the top and the bottom quintile portfolios based on past performance is statistically indistinguishable from zero. Using tracking error and the interaction of tracking error with past performance we obtain similar results; we are not able to distinguish the best from the worst Sustainable performing ETFs in the future. Overall, our findings suggest that ESG investors face considerable fund selection risk, and that they cannot reduce this risk using information from observable funds characteristics.

We also contribute to the sprouting literature on ESG. Several papers have studied the relationship between ESG and risk-adjusted performance, and, as highlighted by three recent literature reviews (Gerard 2019, Matos 2020, and Liang and Renneboog 2021), there is no consensus so far on the matter. One of the problems is that there is no consensus on the definition of sustainability or ESG, and different definitions of sustainability can give rise to very different stock classifications as shown in Avramov et al. (2022), Berg, Kölbel, and Rigobon (2022), and Amenc, Goltz, and Naly (2023).

4 - We focus on the difference in performance over the full cross-sectional range (best vs worst) as this describes the maximum fund selection risk taken by ESG investors, but we show that the differences in performance are also large when we look at less extreme quintiles of the cross-sectional distribution. For example, we find that the difference in CAPM alpha between the 80th and 20th percentiles of the distribution is 1.7% over the full sample and can be as high as 7.1% over a single year.

1. Introduction

The result of this inconsistency in ESG definitions is that they can lead to a large dispersion in the performance achieved by different ESG strategies. For instance, Edmans (2011) finds that companies with high employees' satisfaction, which are generally associated with high sustainability, achieve positive risk-adjusted returns. Meanwhile, Hong and Kacperczyk (2009) find that companies that operate in 'sinful' industries[5], which are generally classified as low sustainability, also achieve positive risk-adjusted returns.

We show that the dispersion in the ESG-performance relationship is also reflected in real-world products (i.e., our Sustainable ETFs). Other papers have shown evidence of cross-sectional variation in performance of funds that have sustainability objectives, notably Lean, Ang, and Smyth (2015), and Capelle-Blancard and Monjon (2014). However, these two studies analyse a cross-section of mutual funds, whose performance can be affected by management skill. Instead, by using only passive ETFs, we ensure that our performance dispersion arises from the differences in the systematic ESG approaches adopted by the different Sustainable ETFs and not from differences in management skill.

The link between the dispersion in performance and the ESG-definition confusion allows us to highlight another important implication of our results. ESG investors should be on the alert for the risk of data mining when presented with positive results from a particular Sustainable ETF. Given that different definitions of sustainability can generate very different performances, the existence of many ETFs that use different definitions of sustainability will increase the likelihood of finding at least some Sustainable ETFs that outperformed in-sample. This may give the impression that there are at least some ESG approaches that can consistently outperform. However, this outperformance will not likely repeat out-of-sample, as our results on the lack of persistence in performance show. We stress this point as recent evidence from the literature shows that this may be a salient risk for investors. Specifically, Ben-David et al. (2023) show that ETFs that have recently outperformed tend to generate high attention and high demand among investors[6], especially ETFs that follow specialised themes such as ESG. This suggests that investors can easily fall into the trap of giving too much attention to recent performance and, because of the ESG-definition confusion, this is particularly dangerous for ESG investors. In fact, given the quantity of different ESG approaches that one can use to create Sustainable ETFs, it will always be possible to point out to some Sustainable ETFs that have recently generated enough positive performance to attract attention. This is another aspect of the fund selection risk that ESG investors have to face and which they should carefully take into account.

The rest of the paper is organised as follows. Section 2 presents our data; we describe our selection of ETFs and report the cross-sectional distribution of the characteristics of our Sustainable ETFs. In Section 3 we describe how we measure performance of the Sustainable ETFs. Section 4 reports the analysis of the cross-sectional variation in the performance of the Sustainable ETFs. Section 5 reports the analysis of the persistence in performance. In Section 6 we analyse the relationship between tracking error and the performance of the Sustainable ETFs. Section 7 presents our conclusions.

5 - Tobacco, Alcohol, and Gambling.
6 - Estimated from funds' flows.

2. Data

2. Data

Our primary source of data is Refinitiv Eikon Datastream, from which we obtain total returns, market values, and total expense ratio at a daily frequency for all the ETFs in our analyses. These include the sustainable ETFs and those that we use as benchmarks. For all the ETFs, we obtain data for their entire life up until the end of our sample, which is 31 December 2022. In the rest of the section, we describe the list of the sustainable ETFs and their benchmarks.

2.1 The sustainable ETFs

We obtain our initial list of Sustainable ETFs from Bloomberg[7], selecting all the equity ETFs that are categorised[8] as either "Socially Responsible" or "ESG". We focus on ETFs tracking US equities because it is the largest equity market[9]. Limiting our analysis to the ETFs that invest in a well-defined geographic region also enables us to avoid the contamination of any geographical bias linked to ESG ratings. We ensure that the funds' investment focus is limited to the US equity universe by checking official documents linked to the ETFs[10].

Amongst the remaining ETFs, we impose three requirements for inclusion in our Sustainable Investing Portfolio.

1) The first and main requirement is that the construction of the ETF portfolio should reflect a sustainable investing approach, thus we require a self-declared ESG objective. We manually check the description of the ETFs and retain only the funds that mention explicitly the integration of ESG information in their portfolio construction process[11]. We do this because focusing on funds that use transparent and systematically replicable methodologies to tilt towards sustainability allows us to avoid the confounding effect on performance of managers' skills.

2) As a second requirement, we want the sustainable ETFs not to be polluted by explicit tilts unrelated to ESG. Thus, we exclude the ETFs with explicit smart beta or industry tilts[12].

3) Finally, we require ETFs to have a minimum of 148.2 weeks of return history (95% of three years of observations) because we need sufficient observations to estimate factor exposure at the fund level. This brings our list of sustainable ETFs to a total of 34 ETFs.

Table 1 shows the cross-sectional distribution of some characteristics of the sustainable ETFs at the end of our sample. We report the distribution of the market value (in USD millions) at the end of our sample (31 December 2022), the distribution of the total expense ratio[13] (also at the end of our sample), the distribution of fund age, and the distribution of the annualised tracking error[14] relative

7 - We use Bloomberg's Fund Screening function to extract the initial list of sustainable ETFs. We make our extraction as of June 2022.

8 - Bloomberg uses documents provided by the fund company (prospectus, fact sheet, annual/semi-annual reports) to classify the funds (see Bloomberg, 2013).

9 - In Bruno and Goltz (2023) we provide details on the evolution of the total AUM of the market of the Sustainable ETFs in our list over a period of 10 years. We show that this market has experienced a remarkable growth in popularity among investors over the last ten years. we report details on the Starting at about USD350 million in 2012, the market value of sustainable ETFs has grown to almost USD 100 billion at the end of 2022.

10 - For each ETF, we conduct our checks looking at fact sheets, the prospectus or the website of the ETF provider or the provider of the index tracked by the ETF.

11 - We only check whether the ETFs integrate ESG criteria in the construction process of their portfolios, we do not attempt to distinguish between 'true' ESG practices and 'greenwashing'. For a discussion on 'greenwashing' in the funds' industry, see Gibson Brandon et al. (2022).

12 - This means that we exclude funds that claim their objective is to gain exposure to a single industry (e.g., utilities or technology) which implies 100% exposure to this industry.

13 - Total Expense Ratio (after waivers/reimbursements are subtracted, but before expense offsets/brokerage service arrangements are subtracted) as reported in the financial highlights in the annual report.

14 - For each sustainable ETF in our list, we compute the tracking error relative to the SPDR 500 ETF. To account for non-synchronicity in returns we use a SPDR 500 ETF traded in North America for the sustainable ETFs traded in North America and a SPDR ETF traded in Europe for the sustainable ETFs traded in Europe. In practice, for each ETF we compute the tracking error as $TE^i = \sqrt{\frac{\Sigma\left(R_t^i - R_t^{B,i}\right)^2}{T-1}}$ in which R_t^i is the return of the ETF '*i*', $R_t^{B,i}$ is the return of the SPDR 500 ETF used as benchmark for the sustainable ETF 'i', and '*T*' is the number of weeks for which the ETF '*i*' is available. We then annualise the tracking error multiplying by the square root of 52 because we use weekly returns.

2. Data

to the US equity market index. From Table 1, we can already see that, although our cross section is quite narrow, we have a large dispersion in terms of characteristics. This means that our selection of Sustainable ETFs should provide a good representation of the sustainable investing approaches available to investors in practice.

Table 1: Descriptive statistics sustainable ETFs invested in US equity

	Market Value (USD millions)	Total Expense Ratio (per year)	Age since Inception (years)	Tracking Error (annualised)
Min	23	0.05%	2.95	1.02%
20th Percentile	165	0.09%	3.55	2.56%
50th Percentile	715	0.19%	4.28	3.47%
80th Percentile	3,628	0.25%	6.47	5.10%
Max	19,581	0.75%	17.93	13.99%

The table shows descriptive statistics of the 34 Sustainable ETFs in our list. We report the distribution (minimum, 20th percentile, 50th percentile, 80th percentile, and maximum) of the market value of the ETFs in USD millions (as of 31 December 2022), of the total expense ratio (as of 31 December 2022), of the age (from inception to 31 December 2022) expressed in years, and of the annualised tracking error of each ETF relative to the proxy of the US equity market, which we compute using weekly returns over the entire period for which the returns of the ETF are available.

2.2 Benchmark ETFs

To adjust the performance of our sustainable ETFs, we need to use the appropriate benchmarks. For our main set of analyses, we use as market and industry benchmarks a collection of SPDR ETFs managed by State Street Global Advisors (SSGA). We use ETFs as benchmarks to remain consistent with our aim to analyse real-world performances. This is preferable to using academic benchmarks that may be difficult to replicate and do not include fees and transaction costs. As market benchmark we use the SPDR ETFs that replicate the performance of the S&P 500, and as industry benchmarks we use a set of SPDR ETFs that replicate the performance of nine industry portfolios: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Financials, Health Care, Technology, and Utilities.

Because we estimate exposures at ETF level, to account for the non-synchronicity of the returns due to the difference in trading hours between North America and Europe, we obtain two different sets of benchmarks ETFs. The first set includes only ETFs traded in North America and the second includes only ETFs traded in Europe[15].

15 - The history of the nine industry ETFs traded in Europe starts in July 2015. To extend the time-series of these ETFs to the beginning of our sample (July 2012) we create a proxy for each of them using the returns of the corresponding industry ETF traded in North America, and we check that this does not have a material impact on our results. For details, see appendix of Bruno and Goltz (2023).

3. Measuring Performance of the Sustainable ETFs

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Our objective is to conduct an analysis on the cross-section of the performance of the Sustainable ETFs. In this section we explain how we define and compute performance.

We want to analyse the added value that the Sustainable ETFs provide relative to standard benchmarks that do not attempt to tilt towards sustainability. Therefore, we compute performance in excess of the performance of a set of benchmarks. Specifically, we compute three different measures of performance that we obtain as the difference between the returns of the Sustainable ETFs and the returns of three different benchmark portfolios. For each Sustainable ETF we construct the benchmark portfolios using SPDR ETFs traded in the same region[16]. The first benchmark portfolio is simply the SPDR ETF representing the US equity market. We then obtain for each Sustainable ETF 'j' the first measure of performance, the Relative Returns, as the difference between the returns of the Sustainable ETF 'j' and the returns of market benchmark.

Note that the first measure does not account for any source of risk exposure. This means that the performance of a Sustainable ETF may be higher simply because it is taking more risk. With the second measure of performance, CAPM Alpha, we control contributions to performance due to risk exposure to the market. We compute CAPM Alpha as shown in Equation 1 below, as the difference between the returns of the sustainable ETF (R_t^j) and the returns that are explained by its CAPM exposure:

Equation 1

$$\alpha_t^{CA,j} = R_t^j - (R_t^f + \beta_j R_t^{e,M})$$

In which, R_t^f is the return of the risk-free asset, $R_t^{e,M}$ is the excess return[17] of the SPDR ETF used as market benchmark, and β_j is the market exposure, that we estimate for each ETF using OLS regressions with weekly returns over the entire sample. In other words, we assume the market exposure to be constant.

Finally, the third measure of performance is the Industry Adjusted Returns. This measure allows us to control for differences in performance due to differences in exposure to the market factor and to nine industry factors. Adjusting for industry exposure is useful to understand whether we can replicate the performance of the Sustainable ETFs without using ESG information. As such, this adjustment enables us to assess the value of using ESG information in addition to what can be obtained with a simpler industry tilt[18]. For each Sustainable ETF, we compute Industry Adjusted Returns as shown in Equation 2 below, as the difference between the returns of the sustainable ETF and the returns that are explained by its exposures to the market plus nine industry factors:

Equation 2

$$\alpha_t^{IA,j} = R_t^j - (R_t^f + \beta_j R_t^{e,M} + \sum_k \gamma_{j,k} IF_t^k)$$

in which IF_t^k is the excess return of the industry factor 'k' that we obtain as the return of a portfolio that is long the SPDR ETF representing the industry 'k' and short the SPDR ETF used as market benchmark. As for the previous factor model, we compute the exposures to the market factor β_j, and to the industry factors $\gamma_{j,k}$ using OLS regressions with weekly returns over the entire sample.

16 - Either North America or Europe.
17 -Return minus return of the risk-free asset.
18 - An alternative or complementary approach would be to adjust for equity factor exposures. However, as we do not have comparable ETFs on the set of equity factors that make up the standard equity factor models with a long enough history, we would have to use returns from 'paper' portfolios. This would not allow us to make a 'real world' comparison, which is one of the benefits of our methodology.

3. Measuring Performance of the Sustainable ETFs

In the next sections we use these three measures to analyse the cross-section of the performance of the Sustainable ETFs.

4. Performance Dispersion

4. Performance Dispersion

In this section we analyse we analyse the cross-sectional dispersion in the distribution of the Sustainable ETFs' performance. This is important because some investors who care about sustainability (sustainable investors) may decide to tilt towards sustainable themes using a single Sustainable ETF. This can expose them to a substantial fund selection risk when the dispersion in performance of the Sustainable ETFs is large. Analysing the dispersion in the performance enables us to quantify the fund selection risk to which sustainable investors are exposed.

Table 2 shows that there is indeed a substantial fund selection risk over the period that we analyse. We report the cross-sectional distribution of our three performance measures over seven time periods. For each time period the cross-sectional distribution is composed of only the Sustainable ETFs that are available for the entirety of that period. To obtain a meaningful analysis of the dispersion of the performance we need a minimum number of ETFs available. We thus start our analysis in 2017 because it is the first full calendar year for which we have at least 10 ETFs.

We first look at the performance dispersion over the longest period that available, which goes from 1 of January 2017 to 31 December 2022. We find that the difference in performance between the best and worst performing Sustainable ETF, reported in the last column of Table 2, is large and economically meaningful. For instance, the CAPM Alpha dispersion is 6.5% on an annual basis, and even looking at the difference between the 20th and 80th percentile the difference is non-negligible, 1.7% on an annual basis[19].

Accounting for industry-factor exposures reduces the total cross-sectional dispersion between the best and wort performing ETF, but it is still large (4.9% on an annual basis). This means that at least some of the difference between the performance of the ETFs at the extremes of the distribution is imputable to differences in industry exposures that can have a strong impact on short periods of analyses like the one that we are considering. However, most of the dispersion is still there even when we account for industry exposures. Indeed, the difference between the 80th and 20th percentile is even larger than the one observed for the CAPM Alpha – 1.9% on an annual basis. This means that most of the fund selection risk is not due to differences in industry exposures.

It is also worth noticing that the median Relative Returns and CAPM alpha are close to zero, and accounting for industry factor exposures the median performance is even mildly negative (-0.6%). This is in line with our earlier study, Bruno and Goltz (2023), in which we find that on average the performance of the market of Sustainable ETFs over the last decade was close to zero, and even slightly negative when adjusted for industry-factors exposures.

We also look at the dispersion over each calendar year in our sample. We find that the dispersion can be quite dramatic during these shorter time periods. For instance, CAPM Alpha's dispersion ranges from a minimum of 4.1% in 2018 to a maximum of 22.5% in 2021. Adjusting for factors exposures we find similar levels of dispersion – from 3.8% in 2018 to 25.3% in 2022. This suggests again that the differences in performance that we find are not imputable to differences in industry

19 - To provide a term of comparison for these numbers, we calculated the cross-sectional dispersion for a set of 13 Value ETFs that we identified using a similar approach to the one that we used to obtain our selection of sustainable ETFs. We found that the dispersion (max – min) in terms of relative returns over the full period for the Value ETFs is 2.5%, which is much lower than the dispersion in relative returns found for our selection of sustainable ETFs over the same period (6.3%).

4. Performance Dispersion

exposures. We observe a large dispersion even in periods characterised by a generally positive performance of ESG. Specifically, in 2020 the distribution of the performance of the Sustainable ETFs tends to be above zero; indeed it is the only year for which the 20th percentile of both CAPM Alpha and Relative Returns is positive (while it remains negative in terms of Industry Adjusted Returns), and it has the largest median for all measures of performance. This is also in line with the results that we report in Bruno and Goltz (2023) in which we show that in 2020 the average performance of the market of the Sustainable ETFs was strongly positive, although an outlier. Here we highlight that even in a good year like 2020, investors could have underperformed by investing in certain Sustainable ETFs. Indeed, the worst performing ETF has a CAPM Alpha of -1%, and when factors' contribution are removed, the performance is even more negative – -3.7% in terms of Industry Adjusted Returns.

These results suggest that although the ETFs in our list all tilt towards sustainability, the approach that they use can lead to a strong divergence in performance. This seems somewhat puzzling; if the performance of these ETFs was mainly driven by a common sustainability factor, investors could expect to get a similar performance irrespective of the specific ETF that they choose. The strong divergence that we find seems instead to suggest that there is very limited commonality across these ETFs. Because we are looking at a set of passive ETFs, we can exclude that this dispersion is imputable to differences in management skills[20]. Any difference in performance that we find must therefore be due to the differences in the systematic approaches used by the Sustainable ETFs.

A possible explanation for this is the divergence existing between different ESG ratings, a phenomenon known as ESG rating disagreement or confusion, which has been discussed in several papers such as Avramov et al. (2022), or Berg, Kölbel, and Rigobon (2022). Indeed, in our list of Sustainable ETFs include ETFs that use quite different ESG ratings; these range from very general ESG ratings that leverage on several ESG dimensions to very specialised ones such as gender equality scores. The literature has already shown that this phenomenon can lead to large differences in performance of stylised equity strategies[21].

Here we highlight that ESG rating disagreement may be at the origin of the large dispersion in Sustainable ETFs performance and translate in fund selection risk for the investors that care about sustainability. In any case, we do not attempt to properly explain the origin of the dispersion in performance as it is outside the scope of this work. Our objective here is simply to stress the point that there is a large divergence in performance within the universe of Sustainable ETFs and that this represents a risk for the sustainable investors.

In the next sections we test whether there are sensible approaches that investors can take to mitigate this fund selection risk.

20 - By contrast, differences in management skills may explain the dispersion in performance in ESG mutual funds found by Lean, Ang, Smyth (2015) and Cremers, Fulkerson and Riley (2022).
21 - This can also explain the lack of consensus in the academic literature on the relationship between ESG and financial performance, as highlighted in Gerard (2019).

4. Performance Dispersion

Table 2: Cross-sectional distribution of Sustainable ETFs' performance.

Time Period	Min	20th Pctl.	50th Pctl.	80th Pctl.	Max	80th-20th	Dispersion (Max-Min)
Panel A: Relative Return							
2017-2022	-3.9%	-0.3%	-0.1%	0.8%	2.4%	1.1%	6.3%
2017	-2.2%	-0.9%	0.7%	1.4%	2.4%	2.3%	4.6%
2018	-1.1%	-0.5%	0.7%	1.2%	2.8%	1.7%	3.9%
2019	-7.6%	-1.2%	-0.1%	1.0%	3.4%	2.2%	11.0%
2020	-0.9%	0.8%	4.2%	7.5%	15.7%	6.7%	16.6%
2021	-13.6%	-2.6%	0.1%	2.7%	4.9%	5.3%	18.5%
2022	-8.7%	-3.9%	-2.2%	-0.3%	0.5%	3.7%	9.2%
Panel B: CAPM Alpha							
2017-2022	-4.1%	-0.8%	0.0%	0.9%	2.4%	1.7%	6.5%
2017	-2.7%	-1.0%	-0.1%	1.6%	1.9%	2.6%	4.5%
2018	-1.3%	0.0%	0.6%	1.4%	2.8%	1.4%	4.1%
2019	-8.3%	-1.7%	0.0%	1.2%	2.4%	2.9%	10.7%
2020	-1.0%	0.9%	3.9%	8.0%	16.2%	7.1%	17.2%
2021	-14.3%	-2.8%	0.7%	2.8%	8.2%	5.5%	22.5%
2022	-6.8%	-4.0%	-2.1%	-0.3%	0.5%	3.7%	7.3%
Panel C: Industry Adjusted Returns							
2017-2022	-3.3%	-1.2%	-0.6%	0.7%	1.6%	1.9%	4.9%
2017	-2.9%	-2.2%	-0.9%	0.6%	3.5%	2.8%	6.4%
2018	-1.6%	-0.5%	0.1%	1.6%	2.2%	2.1%	3.8%
2019	-5.9%	-1.6%	-0.4%	0.9%	2.8%	2.6%	8.7%
2020	-3.7%	-0.9%	2.4%	4.0%	12.5%	4.9%	16.2%
2021	-13.6%	-2.9%	0.8%	2.8%	11.8%	5.8%	25.3%
2022	-5.5%	-2.8%	-1.1%	0.4%	1.3%	3.3%	6.8%

The table shows the cross-sectional distribution of the performance of the Sustainable ETFs for seven different time periods. To represent the distribution we report the minimum, the max, the 20th, the 50th, and the 80th percentile. In the last two columns we report the difference between the 80th and the 20th percentile of the distribution and the Dispersion, the difference between the min and the max value in the cross-section. In each of the time periods we only consider the Sustainable ETFs that were live for the whole period. As measures of performance, we report the annualised Relative Return (Panel A), the annualised CAPM Alpha (Panel B), and the annualised Industry Adjusted Return (Panel C).

5. Persistence in Performance

5. Persistence in performance

The previous section shows that there is sizeable fund selection risk within the market of Sustainable ETFs. However, such a risk could be reduced if investors were able to separate the best performing funds from the worst ones. A popular approach in the mutual funds literature to identify the funds that can potentially outperform in the future is to look at the past year's performance. As argued in Grinblatt and Titman (1992), the most skilled funds' managers should be able to persistently outperform[22]. Although the evidence on performance persistence is mixed, previous studies on funds' flows show that investors consider past performance as salient information. For instance, Sirri and Tufano (1998) show that there is a strong positive relationship between fund flows and past performance. In addition, this performance-chasing behaviour is not limited to mutual funds. Clifford, Fulkerson, and Jordan (2014) find strong evidence of performance chasing also in the universe of ETFs, and more recently Ben-David et al. (2023) show that the performance-chasing behaviour is stronger for specialised ETFs that invest in specific sectors or themes like sustainability. Of course, here we need to make a distinction between the mutual fund literature. Performance persistence in the mutual funds literature is interpreted as evidence that some managers have skills that enable them to consistently outperform; thus, past performance is supposed to provide information on the skills of the funds' managers. Our Sustainable ETFs are passive strategies whose performance does not depend on the managers' skills but rather on the systematic approaches used to integrate sustainability in the portfolio construction. Therefore, in our context, looking at persistence in performance is a way to analyse whether some of these systematic approaches are consistently better than others at capturing financial performance. This is interesting, because in this case, investors could exploit information in past performance to identify the best Sustainable ETFs and reduce their funds selection risk. We analyse whether there is indeed performance persistence within the Sustainable ETFs in two ways:

First, we look at the probability that a top outperforming ETF in one year will still be a top performer the following year. For each pair of years (t, t+1) we compute this probability as the percentage of Sustainable ETFs that are in the top quintile based on year 't' Relative Return that are also in the top quintile of performance in year 't+1'. We identify the Sustainable ETFs in the top quintile in year 't' only based on Relative Returns[23], but we identify three types of top future performers, one for each of the three measures of performance. We compute these probabilities for each couple of years in our sample and then take the time-series average. We report the results in Panel A of Table 3. We find that on average only a minority of the top past performing Sustainable ETFs are still top performing the following year. For instance, on average only 20.7% of the Sustainable ETFs that were in the top performance quintile in year 't' are also in the top quintile of Relative Return and CAPM Alpha in year 't+1', and only 23.6% are in the top Industry Adjusted Returns quintile in year 't+1'. As a term of comparison, in Panel B of Table 3, we report the percentage of the wort performing Sustainable ETFs in year 't' (bottom Relative Returns quintile) that ended up in the top performance quintile on the following year. On average we find that the results are quite similar to the ones reported in Panel A. Actually, relative to the previous results, we find that a larger percentage of the worst performing ETFs in year 't' end up in the year 't+1' top quintile based on CAPM Alpha and Industry Adjusted Returns, however it is still a minority (lower than 50%).

22 - Evidence of persistence in performance in the mutual funds literature are mixed. For instance, Grinblatt and Titman (1992) and Hendricks, Patel, and Zeckhauser (1993) find that there is indeed some evidence of persistence in performance, but Carhart (1997) argues that this is not evidence of managers' skills, but it is rather due to momentum exposure.

23 - To select the past top performing Sustainable ETFs, we only use Relative Returns because this approach does not require any future information at the moment of selection formation. In contrast, the other two measures of performance would require using future returns' information for the estimation of the exposures, because we estimate exposure statically using the entire sample available for each ETF. This makes our selection process perfectly replicable for investors. We use the same logic for selecting the bottom performing Sustainable ETFs. However, we show in the Appendix that selecting the top and the bottom ETFs using either of the alternative performance measures would not affect our results.

5. Persistence in performance

Table 3: Performance persistence – probability of being a future top outperformer based on the previous year's performance

Panel A: From top Relative Return quintile in year (t) to top quintile performer in year (t+1)			
Period	Relative Return	CAPM Alpha	Industry Adjusted Return
From 2017 to 2018	50.0%	50.0%	50.0%
From 2018 to 2019	0.0%	0.0%	0.0%
From 2019 to 2020	25.0%	25.0%	25.0%
From 2020 to 2021	0.0%	0.0%	14.3%
From 2021 to 2022	28.6%	28.6%	28.6%
Average	**20.7%**	**20.7%**	**23.6%**
Panel B: From bottom Relative Return quintile in year (t) to top quintile performer in year (t+1)			
Period	Relative Return	CAPM Alpha	Industry Adjusted Return
From 2017 to 2018	0.0%	0.0%	0.0%
From 2018 to 2019	0.0%	100.0%	50.0%
From 2019 to 2020	25.0%	25.0%	25.0%
From 2020 to 2021	42.9%	42.9%	42.9%
From 2021 to 2022	14.3%	0.0%	14.3%
Average	**16.4%**	**33.6%**	**26.4%**

The table shows the probability of the Sustainable ETFs being future top performers based on the previous year's performance. We define as top (bottom) past performing Sustainable ETFs the Sustainable ETFs that are in the top (bottom) quintile of the year 't' Relative Return. We define three types of top future performers. The first type is based on the Sustainable ETFs that are in the top quintile based on year 't+1' Relative Return, the second type is based on year 't+1' CAPM Alpha, and the third type is based on year 't+1' Industry Adjusted Return. For each pair of years (t, t+1) we compute the percentage of top and bottom past performing Sustainable ETFs that are top future performing Sustainable ETFs, and then we compute the time-series average of the percentages. We report the percentages and their averages for the top past performing Sustainable ETFs in Panel A, and for the bottom past performing Sustainable ETFs in Panel B. Time periods are indicated in the first row. Future performance type is indicated in the columns' headers.

Our second approach to test whether there is persistence in performance is to look at the performance spread between the best and worst performing Sustainable ETFs. At the end of each calendar year 't' we sort the Sustainable ETFs based on their year 't' Relative Returns and form two equally weighted portfolios, one composed of the Sustainable ETFs in the top quintile and one with those in the bottom quintile[24]. We hold the position in the two quintile portfolios for the full following calendar year 't+1' and compute the performance spreads as the difference between the performance of the two portfolios. In Table 4 we report the average annualised performance spreads[25] between the top and the bottom Relative Returns quintile portfolio for all three our measures of performance for the entire out of sample period[26]. If the performance of the Sustainable ETFs was persistent the performance spreads should be positive and statistically significant. As it appears clear from the results reported in Table 4, we do not find evidence of persistence; the spread in Relative Returns and CAPM Alpha are both small and statistically insignificant and adjusting for industry factor contributions the spread becomes even marginally negative.

24 - Note that we use only Relative Returns as a measure of performance when selecting the Sustainable ETFs in the two quintile portfolios because it does not require any future information at the moment of portfolio formation. By contrast, the other two measures of performance would require using future returns' information for the estimation of the exposures, because we estimate exposure statically using the entire sample available for each ETF. This makes our portfolio construction perfectly replicable from investors.
25 - For instance, the Relative Return spread is the Relative Return of the top quintile portfolio.
26 - Because we use the first year to select the ETFs, we lose one year, so the out of sample period goes from 1 January 2018 to 31 December 2022.

5. Persistence in performance

Table 4: Performance persistence – performance spread between top and bottom quintile portfolios of Sustainable ETFs based on past year's Relative Returns

Performance Spreads		
Relative Return	CAPM Alpha	Industry Adjusted Returns
0.83	0.44	-0.11
(0.88)	(0.47)	(-0.16)

The table shows the performance spreads between the top and the bottom quintile portfolios of Sustainable ETFs that we form using the previous year Relative Returns. On 31 December of each year 't' we sort Sustainable ETFs based on their year 't' Relative Returns and form two equally weighted portfolios, one with the top quintile ETFs and one with the bottom quintile ETFs and keep the positions for the entire following year. We compute the performance of the top and bottom quintile portfolios as Relative Return, CAPM Alpha, and Industry Adjusted Returns on a monthly frequency. We then compute the performance spreads on a monthly frequency as the difference between the monthly Relative Returns, CAPM Alpha, and Industry Adjusted Returns of the top and bottom quintile portfolios (spread is performance of top quintile minus performance of the bottom quintile portfolio). We show the average of the three performance spreads, which we annualise multiplying them by 12. Between the brackets we report the t-stat of the spreads obtained using standard errors adjusted for heteroskedasticity and serial correlation. We form the top and bottom quintile portfolios for the first time on 31 December 2017 and compute monthly returns until 31 December 2022.

Overall, the results in this section indicate the there is no evidence of performance persistence. The main implication is that the past year's performance does not provide useful information on future performance, hence investors cannot use this information to reduce fund selection risk. In the next section we test whether investors can rely on an alternative source of information, tracking error, to identify the Sustainable ETFs that are more likely to consistently outperform.

6. Relation between Performance and Tracking Error

6. Relation between Performance and Tracking Error

The previous section shows that ESG investors cannot rely on past performance alone to select the best sustainable ETFs. However, there may be other characteristics that are useful in predicting the performance of sustainable ETFs. Again, drawing on the mutual fund literature, we look at the degree of tracking error of ETFs, which is one way to measure the deviation of the ETF's portfolio from the reference market index. The mutual fund literature has examined the relationship between various measures of divergence from the reference index and future performance[27]. The argument for using divergence as a predictor of performance is that funds with information advantages that allow them to outperform the market tend to concentrate their portfolio positions in the part of the market where the information advantage is strongest[28]. If the funds really do have an informational advantage, concentrating the portfolio in the part of the market where the informational advantage is strongest will have two effects: first, these funds will outperform the benchmark reference market and, second, the composition of their portfolios will diverge significantly from that of the market. This leads to a link between divergence and performance, which we call the divergence-performance hypothesis.

As with the previous section, we note that we have a different perspective from the mutual fund literature. In the mutual fund literature, the informational advantage that leads to divergence and outperformance comes from the skills of the fund managers. Therefore, looking at divergence is a way of identifying management skill. Our perspective is different; we are not trying to identify management skill because we have a selection of passive ETFs. Rather, we analyse whether divergence can help identify sustainable ETFs that use approaches to integrate sustainability into portfolio construction that are systematically superior to others. The idea is that if ESG ratings (or scores) contain useful information about future performance, the sustainable ETFs that benefit most from this information will be those that make the most use of it. To exploit this hypothetical ESG information advantage, sustainable ETFs will have to concentrate their allocations on the stocks for which the ESG signal is strongest (the EGS leaders)[29]. This concentration will lead to divergence from the market benchmark and, if the ESG-related information advantage exists, this concentration will also lead to outperformance. We test the divergence-performance hypothesis in our selection of sustainable ETFs using tracking error as a measure of divergence[30].

We start with an analysis of the cross-sectional dispersion in tracking error[31] for different time-samples[32]. Table 5 shows that there is indeed considerable dispersion in annualised tracking error over all the time-samples that we consider. Over the full time sample the dispersion in annualised tracking error is 5.7%. However, because we want to use the past year tracking errors to identify the Sustainable ETFs that have the potential to outperform, it is more interesting to analyse the distribution in tracking error over the single full calendar years. We find that also within single calendar years the dispersion

27 - See for instance Israelsen and Cogswell (2007), Cremers and Petajisto (2009), or Doshi, Elkamhi, and Simutin (2015).
28 - Kacperczyk, Sialm, and Zheng (2005) provide empirical evidence supporting this hypothesis and Van Nieuwerburgh and Veldkamp (2005) argue that it is optimal to under-diversify because of increasing returns to scale in learning.
29 - From this point of view the relation between divergence and performance could also be linked back to the debate on whether it is better for performance to adopt a positive or negative screening ESG-approach (see for instance Derwall, Koedijk, and Ter Horst, 2011). Indeed, positive screening consists in concentrating the portfolio in the stocks that have the highest ESG-ratings, while negative screening consists just in removing certain companies that are defined as controversial (e.g., companies in the Tobacco industry). Therefore, the two approaches can lead to different levels of divergence, and some papers, like Dumitrescu, Järvinen, and Zakriya (2023), argue that it is the ETFs that adopt positive screening that tend to outperform.
30 - While Israelsen and Cogswell (2007) show that there is some evidence of a positive relationship between tracking error and future funds' returns, over the years the literature has developed alternative measures of divergence based on funds' holdings that seem to provide superior information relative to tracking error, such as Active Share in Cremers and Petajisto (2009). Unfortunately, to test these most sophisticated measures we need data on the holdings of the Sustainable ETFs which we do not have. However, the literature has also shown that there is a strong cross-sectional correlation between tracking error and these alternative measures of divergence based on funds' holdings. Therefore, we believe that using tracking error can still provide a reasonably good approximation of divergence.
31 - Tracking error is relative to the benchmark representing the US equity market.
32 - As for the analysis of the dispersion of the performance, to form the cross-sectional distribution for each time-sample we only consider the Sustainable ETFs that are available for the full time-sample in consideration.

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in tracking error is indeed economically meaningful, ranging from a minimum of 3.3% in 2019 to a maximum of 13.4% in 2017 with an average of 8% across the six years. This level of dispersion should provide enough cross-sectional variation to test the divergence-performance hypothesis.

Table 5: Cross-sectional distribution of Sustainable ETFs' tracking error

Time Period	Min	20th Pctl.	50th Pctl.	80th Pctl.	Max	80th-20th	Dispersion (Max-Min)
Tracking Error							
2017-2022	1.2%	2.4%	3.9%	5.2%	6.9%	2.9%	5.7%
2017	0.9%	1.8%	2.2%	3.9%	14.3%	2.1%	13.4%
2018	0.9%	2.2%	2.6%	4.9%	8.7%	2.7%	7.8%
2019	0.4%	1.4%	1.9%	2.8%	3.8%	1.4%	3.3%
2020	0.8%	2.5%	3.9%	5.7%	10.0%	3.2%	9.2%
2021	0.5%	1.6%	2.5%	4.8%	6.4%	3.2%	5.9%
2022	0.9%	1.9%	3.3%	5.6%	9.5%	3.8%	8.7%

The table shows the cross-sectional distribution of the annualised tracking error of the Sustainable ETFs for seven different time periods. To represent the distribution we report the minimum, the max, the 20th, the 50th, and the 80th percentile. In the last two columns we report the difference between the 80th and the 20th percentile of the distribution and the Dispersion, the difference between the min and the max value in the cross-section. In each of the time periods we only consider the Sustainable ETFs that were live for the whole period. We consider tracking errors relative to the ETF representing the market benchmark for each ETF and we compute it using weekly returns over the entire period reported in the first column.

We now move to analyse whether the cross-section of tracking error contains useful information to predict future performance. We start by analysing the probability that the Sustainable ETFs in top quintile based on the tracking error of year 't' are also in the top in the top quintile of performance in year 't+1'. As for the previous section, we consider our three measures of performance in year 't+1' separately. We report the results in Table 6. We find that tracking error is not able to identify the best performing Sustainable ETFs in a consistent way. There is only a small chance that an ETF that is part of the top quintile of tracking error in year 't' is also in the top quintile of performance in year 't+1'. At best we find that the average probability of identifying the top performing ETFs in terms of Industry Adjusted Returns is 23%.

As for the analysis of persistence, we also provide a more formal test of the divergence-performance hypothesis testing the performance spreads between the top and the bottom quintile portfolios of Sustainable ETFs based on the distribution of the past year tracking error[33]. If high tracking error is indeed associated to high performance the performance spreads should be positive. Table 7 shows the average annualised performance spreads for our three measures of ETFs' performance. Results are statistically insignificant and relatively small in magnitude. In addition, all the results performance spreads are negative, thus in the opposite direction relative to what we would expect under the divergence-performance hypothesis.

33 - At the end of year 't' we form the top and the bottom tracking error portfolios of Sustainable ETFs sorting on year 't' tracking error, and we keep the positions until the end of year 't+1'. We compute the performance (Relative Return, CAPM Alpha, and Industry Adjusted Return) of the top and bottom tracking error quintile portfolios on a monthly frequency and compote monthly performance spreads as the performance of the top quintile portfolio minus the performance of the bottom quintile portfolio.

6. Relation between Performance and Tracking Error

Table 6: Probability of being a future top outperformer based on previous year's tracking error

From top tracking error quintile in year (t) to top quintile performer in year (t+1)			
Period	Relative Return	CAPM Alpha	Industry Adjusted Returns
From 2017 to 2018	0.0%	0.0%	0.0%
From 2018 to 2019	50.0%	50.0%	100.0%
From 2019 to 2020	0.0%	0.0%	0.0%
From 2020 to 2021	0.0%	0.0%	0.0%
From 2021 to 2022	14.3%	0.0%	14.3%
Average	**12.9%**	**10.0%**	**22.9%**

The table shows the probability of the Sustainable ETFs being future top performers based on the previous year's tracking error. We define as top past tracking error Sustainable ETFs those that are in the top quintile of the year 't' tracking error. We consider tracking errors relative to the ETF representing the market benchmark for each Sustainable ETF, and we compute it using weekly returns. We define three types of top future performers. The first type is based on the Sustainable ETFs that are in the top quintile based on year 't+1' Relative Return, the second type is based on year 't+1' CAPM Alpha, and the third type is based on year 't+1' Industry Adjusted Return. For each couple of years (t, t+1) we compute the percentage of top past tracking error Sustainable ETFs that are top future performers, and then we compute the time-series average of the percentages. We report the percentages and their averages. Time periods are indicated in the first row. Future performance type is indicated in the column headers.

Table 7: Performance spread between Sustainable top and bottom quintile portfolios based on past year's tracking error

Performance Spreads		
Relative Return	CAPM Alpha	Industry Adjusted Return
-0.84	-1.17	-0.7
(-0.82)	(-1.21)	(-0.72)

The table shows the performance spreads between the top and the bottom quintile portfolios of Sustainable ETFs formed using the previous year tracking error. On 31 December of each year 't' we sort Sustainable ETFs based on their year 't' tracking error and form two equally weighted portfolios, one with the top quintile ETFs and one with the bottom quintile ETFs and keep the positions for the entire following year. We consider tracking errors relative to the ETF representing the market benchmark for each Sustainable ETF, and we compute it using weekly returns. We compute the performance of the top and bottom quintile portfolios as Relative Return, CAPM Alpha, and Industry Adjusted Returns on a monthly frequency. We then compute the performance spreads on a monthly frequency as the difference between the monthly Relative Returns, CAPM Alpha, and Industry Adjusted Returns of the top and bottom quintile portfolios (spread is performance of top quintile minus performance of the bottom quintile portfolio). We report the average of the three performance spreads, which we annualise multiplying them by 12. Between the brackets we report the t-stat of the spreads obtained using standard errors adjusted for heteroskedasticity and serial correlation. We form the top and bottom quintile portfolios for the first time on 31 December 2017 and compute monthly returns until 31 December 2022.

Finally, investors may still think that past performance and tracking error can provide useful information on future performance if they are used in concert. In other words, investors may think that amongst the ESG approaches that generate the greatest tracking error, only those that have shown to perform better than the others in the past are consistently better at capturing financial performance. This means that to identify the best Sustainable ETFs, investors should consider those that had both high tracking error and high performance. We call this the interaction hypothesis, which we test by constructing two portfolios:

• In the first (second) portfolio we have a selection of the top (bottom) Sustainable ETFs in terms of both past year performance (Relative Return) and divergence (tracking error). Specifically, at the end of each year 't' we sort the Sustainable ETFs into two independent distributions, the first based on the year 't' Relative Returns and the second on the year 't' tracking errors.

• In the top (bottom) interaction portfolio we put the Sustainable ETFs whose year 't' Relative Returns are above (below) or equal the 60th (40th) percentile of the distributions of the year 't' Relative

6. Relation between Performance and Tracking Error

Returns and at the same time their year 't' tracking errors are above (below) or equal the 60th (40th) percentile of the distributions of the year 't' tracking errors.

The difference between the top and the bottom interaction portfolios gives us the performance spreads[34]. If the interaction between past divergence and performance is useful to predict future performance of the Sustainable ETFs, the performance spreads should be positive and statistically significant. We find that the performance spreads between the top and the bottom interaction portfolios is instead negative and statistically insignificant for all three of our measures of performance (Table 8). This means that the interaction hypothesis does not hold. In other words, neither tracking error nor past performance provide useful information on future performance, not even when they are used together.

Table 8: Interaction between pest Relative Return and tracking error – performance spread between Sustainable top and bottom quintile portfolios based on past year's Relative Returns and tracking error

Performance Spreads		
Relative Return	CAPM Alpha	Industry Adjusted Return
-1.24	-1.68	-1.62
(-0.85)	(-1.14)	(-1.19)

The table shows the performance spreads between the top and the bottom Sustainable ETFs based on the interaction of the past year's Relative Return and tracking error. On 31 December of each year 't' we form two independent cross-sectional distributions, the first based on their year 't' Relative Return and the second on their year 't' tracking error; we put in the top (bottom) interaction portfolio the Sustainable ETFs that are above (below) or equal to the 60th (40th) percentile in both the distributions. Both the top and the bottom interaction portfolios are equally-weighted. We keep the positions in the top and bottom interaction portfolios for the entire following year. We consider tracking errors relative to the ETF representing the market benchmark for each Sustainable ETF, and we compute it using weekly returns. We compute the performance of the top and bottom interaction portfolios as Relative Return, CAPM Alpha, and Industry Adjusted Returns on a monthly frequency. We then compute the performance spreads on a monthly frequency as the difference between the monthly Relative Returns, CAPM Alpha, and Industry Adjusted Returns of the top and bottom interaction portfolios (spread is performance of top minus performance of the bottom interaction portfolio). We report the average of the three performance spreads, which we annualise multiplying them by 12. Between the brackets we report the t-stat of the spreads obtained using standard errors adjusted for heteroskedasticity and serial correlation. We form the top and bottom interaction portfolios for the first time on 31 December 2017 and compute monthly returns until 31 December 2022.

All the evidence in this section points in the same direction. Tracking error does not provide useful information for predicting future performance, so the divergence-performance hypothesis does not hold. Tracking error does not help identify the best sustainable ETFs, even when it is used together with past performance. Therefore, ESG investors cannot hope to use information about tracking error to reduce fund selection risk.

34 - Which we compute on a monthly frequency.

7. Conclusions

7. Conclusions

Sustainable ETFs offer an opportunity to investors to implement their preferences for sustainability at relatively low cost. Because they all follow a common theme, investors may think that the choice of a specific Sustainable ETF over another will only have a marginal impact on performance. However, it is well known that there are substantial inconsistencies across different ESG-ratings or scores. In this paper, we show that there is also significant dispersion in performance in the space of the ESG strategies. This means that ESG investors face fund selection risk. The contribution of this paper is to document and quantify this risk.

To conduct our analyses, we construct a dataset of Sustainable ETFs – passive ETFs that have explicit ESG objectives. To construct this dataset, we started with readily available classification of funds but also analysed the documentation of each fund to make sure that we include only those funds that use ESG information in a systematic and transparent manner. Focusing our analysis on funds tracking systematic ESG indices allows us to eliminate the confounding effects of manager skills. This enables us to impute any dispersion in performance that we find to differences in the ESG integration approach rather than to differences in discretionary choices of the funds' managers.

Overall, our results indicate that ESG investors face a large fund selection risk. Over the full sample dispersion is 6.5% (4.9%) in terms of annualised CAPM Alpha (Industry Adjusted Returns), and it can reach 22.5% (25.3%) over single calendar years. We also show that past performance and tracking error do not contain useful information on future performance.

An important aspect of fund selection risk is that the large dispersion in performance also creates the possibility of data mining. Indeed, dispersion in performance allows ETF providers to always present investors some strategy that has recently outperformed. The evidence from the literature on funds' flows suggests that investors are particularly sensitive to recent performance. This issue is aggravated by the fact that there is no consensus on the definition of ESG, which gives ETF providers a license to come up with new products that replicate ESG approaches that have recently outperformed.

It remains to be seen whether the industry will move towards harmonisation of ESG definitions and practices, a shift that would reduce divergence and ultimately returns dispersion. Our empirical results suggest that the current confusion of ESG practices translates into to return dispersion that in turn creates risk for those investors who select among different ESG investing products. In other words, fund selection risk is a material ESG issue.

Appendix

Appendix

In Section 5 we show that the top performing sustainable ETFs based on the previous year have a low probability of being top performers also in the following year. To obtain the results reported in Table 3 and 4, we select the top and the bottom performing sustainable ETFs based on their Relative Returns in the previous year. We use Relative Returns because they are fully observable at the time of the selection, making the selection implementable for the investors. Using CAPM Alpha and Industry Adjusted Returns would not be fully implementable because we estimate the factor exposures using the full sample. This means that a selection based on CAPM Alpha and Industry Adjusted Returns would be subject to hindsight bias. However, it's worth asking whether using these two alternative performance measures would have an impact on the results reported in Section 5. We make sure that changing the selection measure does not affect our conclusions by selecting the top and bottom sustainable ETFs using CAPM Alpha and Industry Adjusted Returns instead of Relative Returns. We report the results in Tables A.1 and A.2. Our results are very similar to the ones reported in Section 5. The probability of selecting a future top performer is still low and the performance spreads between the top and the bottom sustainable ETFs are low and statistically insignificant. Therefore, changing the measure of performance has no relevant impact on our conclusions.

Table A.1: Performance persistence - probability of being future top outperformers based on the previous year's performance

Panel A: From top CAPM Alpha quintile in year (t) to top quintile performer in year (t+1)			
Period	Relative Return	CAPM Alpha	Industry Adjusted Returns
From 2017 to 2018	50.0%	50.0%	50.0%
From 2018 to 2019	0.0%	0.0%	0.0%
From 2019 to 2020	25.0%	25.0%	75.0%
From 2020 to 2021	0.0%	0.0%	14.3%
From 2021 to 2022	0.0%	0.0%	0.0%
Average	**15.0%**	**15.0%**	**27.9%**
Panel B: From top Industry Adjusted Returns quintile in year (t) to top quintile performer in year (t+1)			
Period	Relative Return	CAPM Alpha	Industry Adjusted Returns
From 2017 to 2018	0.0%	0.0%	50.0%
From 2018 to 2019	0.0%	0.0%	0.0%
From 2019 to 2020	50.0%	50.0%	75.0%
From 2020 to 2021	0.0%	14.3%	14.3%
From 2021 to 2022	0.0%	0.0%	0.0%
Average	**10.0%**	**12.9%**	**27.9%**

The table shows the probability of the Sustainable ETFs being future top performers based on the previous year's performance. In Panel A (Panel B) we define as top (bottom) past performing Sustainable ETFs the Sustainable ETFs that are in the top (bottom) quintile of the year 't' CAPM Alpha (Industry Adjusted Returns). We define three types of top future performers. The first type is based on the Sustainable ETFs that are in top quintile based on year 't+1' Relative Return, the second type is based on year 't+1' CAPM Alpha, and the third type is based on year 't+1' Industry Adjusted Return. For each pair years (t, t+1) we compute the percentage of top and bottom past performing Sustainable ETFs that are top future performing Sustainable ETFs, and then we compute the time-series average of the percentages. We report the percentages and their averages for the top past performing Sustainable ETFs. Time periods are indicated in the first row. Future performance type is indicated in the columns' headers.

Appendix

Table A.2: Performance persistence – performance spread between top and bottom quintile portfolios of Sustainable ETFs based on past year CAPM Alpha and Industry Adjusted Returns

Performance Spread		
Panel A: Selection of top and bottom performer ETFs based on CAPM Alpha		
Relative Return	CAPM Alpha	Industry Adjusted Returns
0.35	0.04	-0.14
(0.49)	(0.05)	(-0.2)
Panel B: Selection of top and bottom performer ETFs based on Industry Adjusted Returns		
Relative Return	CAPM Alpha	Industry Adjusted Returns
-0.36	-0.14	0.21
(-0.38)	(-0.15)	(0.21)

The table reports the performance spreads between the top and the bottom quintile portfolios of Sustainable ETFs that we form using the previous year's performance. To identify performance, we use CAPM Alpha (Industry Adjusted Returns) in Panel A (Panel B). On 31 December of each year 't' we sort Sustainable ETFs based on their year 't' performance and form two equally weighted portfolios, one with the top quintile ETFs and one with the bottom quintile ETFs and keep the positions for the entire following year. We compute the performance of the top and bottom quintile portfolios as Relative Return, CAPM Alpha, and Industry Adjusted Returns on a monthly frequency. We then compute the performance spreads on a monthly frequency as the difference between the monthly Relative Returns, CAPM Alpha, and Industry Adjusted Returns of the top and bottom quintile portfolios (spread is performance of top quintile minus performance of the bottom quintile portfolio). We report the average of the three performance spreads, which we annualise multiplying them by 12. Between the brackets we report the t-stat of the spreads obtained using standard errors adjusted for heteroskedasticity and serial correlation. We form the top and bottom quintile portfolios for the first time on 31 December 2017 and compute monthly returns until 31 December 2022.

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About Scientific Beta

About Scientific Beta

Scientific Beta's aim is to encourage the entire investment industry to adopt the latest advances in smart factor and ESG/climate index design and implementation. Our institution was established in December 2012 by EDHEC-Risk Institute, one of the top academic institutions in the field of fundamental and applied research for the investment industry, as part of its mission to transfer academic know-how to the financial industry. Scientific Beta brings the same concern for scientific rigour and veracity to all the services that it provides to investors and asset managers. We offer the smart factor and ESG/Climate solutions that are most proven scientifically, with full transparency of both methods and associated risks.

On 31 January 2020, Singapore Exchange (SGX) acquired a majority stake in Scientific Beta. SGX continues to support our strong collaboration with EDHEC Business School, and the principles of independent, empirical-based academic research that have benefited our development to date.

Scientific Beta has developed two types of expertise over the years, responding to two of the major challenges that investors face:
- Smart Beta and, more particularly, factor investing.
- ESG, in particular climate investing.

To date, Scientific Beta has made offerings with two major types of climate objective available to investors:

Since 2015, we have offered products with financial objectives that respect ESG and carbon constraints. These correspond to the application of exclusion filters, the design of which allows the financial characteristics of the index to be conserved. This involves reconciling financial objectives and compliance with ESG norms and climate obligations. As such, our Core ESG, Extended ESG and Low Carbon filters can be integrated into smart beta or cap-weighted offerings in line with the financial objectives targeted by the investor.

Since 2021, Scientific Beta has also offered indices with pure climate objectives (Climate Impact Consistent Indices) that enable climate exclusions and weightings to be combined in order to translate companies' climate alignment engagement into portfolio decisions.

Since it was acquired by SGX in January 2020, Scientific Beta has accelerated its investments in the area of Climate Investing as part of the SGX Sustainable Exchange strategy, which is mobilising an investment of SGD20 million. In addition, EDHEC and Scientific Beta have set up a EUR1 million/year ESG Research Chair at EDHEC Business School.

With the aim of providing worldwide client servicing, Scientific Beta has a presence in Boston, London, Nice, Singapore and Tokyo. Scientific Beta has a dedicated team of 40 people who cover not only client support from Nice, Singapore and Boston, but also the development, production and promotion of our index offering. Scientific Beta signed the United Nations-supported Principles for Responsible Investment on 27 September 2016. We became an associate member of the Institutional Investor Group on Climate Change on 9 April 2021.

About Scientific Beta

Today, Scientific Beta devotes more than 40% of its R&D investment to climate investing and more than 45% of its assets under replication refer to indices with an ESG or climate focus. As a complement to its own research, Scientific Beta supports an important research initiative developed by EDHEC on ESG and climate investing and cooperates with Moody's ESG and ISS ESG for the construction of its ESG and climate indices.

On 27 November 2018, Scientific Beta was presented with the Risk Award for Indexing Firm of the Year 2019 by the prestigious professional publication Risk Magazine. On 31 October 2019, Scientific Beta received the Professional Pensions Investment Award for "Equity Factor Index Provider of the Year 2019." On 2 February 2022, Scientific Beta was named "Best Specialist ESG Index Provider" at the ESG Investing Awards 2022.

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