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Measuring the emissions profile of green exchange-traded funds – initial finding and lessons for official statistics[1]

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[1] This presentation was prepared for the conference. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the event.

Measuring the Emission Profile of Self-Proclaimed Sustainable Exchange-Traded Funds

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Abstract

The number of exchange-traded funds (ETFs) that proclaim themselves as sustainable has proliferated in the past years and attracted substantial investor interest. Until new regulations enforce standardized and comparable classification criteria, it remains difficult to understand how self-proclaimed sustainable ETFs differ in terms of sustainability strategy and metrics. We investigate the construction of self-proclaimed sustainable ETFs and assess their environmental footprint thorough scope 1 greenhouse gas (GHG) emission intensities. We combine public information about fund assets from fund issuers' websites and ETF databases, fund-level textual information extracted from fund disclosure documents, and proprietary firm-level emission data. Our analyses rely on 178 self-proclaimed sustainable ETFs, covering the largest global issuers, and 38 reference ETFs, i.e., the non-sustainable conventional ETFs that issuers state as the benchmark reference.

We find that self-proclaimed sustainable ETFs have lower average emission intensities than their reference ETFs. Part of this reduction is driven by divesting from emission-intensive sectors. We find little evidence of best-in-class selection effects, i.e., of funds selecting firms that spearhead emission reductions in their sector. Our results suggest that investors may reduce the carbon footprint of their investments by investing in self-proclaimed sustainable ETFs, when compared to reference ETFs. However, investors looking to cover a broad market while rewarding the lowest emitters within a sector cannot generally do so by investing in self-proclaimed sustainable ETFs.

Keywords: Green finance, exchange-traded funds, sustainable finance, carbon emissions, GHG emissions, ESG investing, sustainable investing

JEL classification: F18, G00, G10, Q56

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1. Motivation

In the past years, the volume of investment into passive exchange-traded funds (ETFs) has increased considerably, especially among private investors. In 2021, global ETFs assets hit $9 trillion invested, with record net inflows (Wursthorn, 2021). Compared to individual stocks, ETFs are attractive in that they enable investors to cover a broad, diversified market with low transaction costs, high liquidity, intra-day trading, and high tax efficiency (Antoniou et al., 2022; Hasbrouck, 2003).

Similarly, the past years have witnessed a steady increase in investor interest in sustainable investment. As a result, the number of ETFs that are marketed as "sustainable" or focused on environmental, social, and governance (ESG) aspects is rapidly rising (Aramonte and Zabai, 2021). Sustainable investment is usually referred to as ESG investment, underlining the multi-faceted nature of the issue.

However, measuring these multiple dimensions of sustainability for investment products remains difficult. Aiming to close this gap, the European Union (EU) Regulation 2020/852 introduces a taxonomy for sustainable activities and provides a framework for classifying investments as "sustainable". In addition, the Sustainable Finance Disclosure Regulation (SFDR)[1] requires issuers to classify funds in three progressively stricter categories: Article 6, Article 8, and Article 9. Article 6 covers funds that do not consider sustainability aspects. Article 8 requires funds to "promote" either environmental or social aspects, or both. In a further step, Article 9 requires funds to have sustainable investment as their objective.

Issuers can generally construct self-proclaimed sustainable ETFs in three ways or a mixture of them: negative, positive, and best-in-class selection (BaFin, 2021). In a "negative selection", issuers may start from an established market index and remove stocks based on thresholds (e.g., for greenhouse gas (GHG) emissions) or other exclusion criteria (e.g., no firearms, alcohol, or tobacco) globally applied to all sectors. Alternatively, issuers can also include stocks from the ground up, passively, or actively based on pre-defined criteria, constituting a "positive selection". Finally, issuers may apply sector-specific criteria or thresholds to account for different sector characteristics and dynamics, which represents a "best-in-class" selection.

Consequently, it is difficult for investors to glimpse through the different metrics and strategies involved in the composition of self-proclaimed sustainable ETFs, which compromises their ability to make informed decisions. Furthermore, anecdotal evidence suggests that self-proclaimed sustainable ETFs may still be "stuffed full of polluters and sin stocks", invest in firms "not aligned with the goals of the Paris agreement", and do not substantially differ from "traditional" funds (Barclays Research, 2020; The Economist, 2021; Time, 2021).

While new regulations are welcoming steps towards increasing transparency in sustainable investments, there is still surprisingly little research on how self-proclaimed sustainable ETFs differentiate themselves in terms of investment strategy and resulting sustainability performance. Shedding light into this topic is important for several stakeholders.

For investors, this information can support informed decisions and enable them to measure the suitability footprint of their investments. For firms, it can inform their future decisions towards sustainable initiatives and business models, as the composition strategy of self-proclaimed sustainable ETFs affects their cost of capital and incentives. Finally, for policymakers, it can help them to assess the impact of recent regulations and inform future policy decisions.

We contribute to closing this gap by investigating the composition of self-proclaimed sustainable ETFs and comparing them with their respective reference ETFs, i.e., the conventional ETFs that issuers state as the

[1] Regulation (EU) 2019/2088

benchmark reference. We assess their sustainability metrics and analyse whether differences are related to a particular composition strategy – i.e., positive, negative, or best-in-class selection. Because of the current data gaps in measuring societal and governance impact, we focus our analyses on their environmental impact and measure differences in scope 1 greenhouse gas (GHG) emission intensities. Scope 1 refers to the GHG emissions that result directly from the production process of the company instead of e.g., its electricity consumption (scope 2) or activities along the value chain (scope 3). We measure GHG emission intensity in tons of CO_2-equivalent per million € of revenue.

We combine public information about fund assets from fund issuers' websites and ETF databases, fund-level textual information extracted from fund disclosure documents, and proprietary firm-level emission data. We match the equity assets and emissions data using the International Securities Identification Number (ISIN) as a common identifier and by performing a string-matching-based record linkage. Our analyses rely on 178 self-proclaimed sustainable ETFs and their respective 38 reference ETFs, covering the largest global issuers.

Issuers classify most of the self-proclaimed sustainable ETFs in our sample as Article 8 under SFDR. Our analyses point to a large variance in emission intensities within self-proclaimed sustainable ETFs and between them and their reference ETFs. Furthermore, out of 101 self-proclaimed sustainable ETFs that have a reference ETF, five have higher average emission intensity (AEI) than their reference ETFs. The differences are statistically significant at a confidence level of 99%.

Our results suggest that self-proclaimed sustainable ETFs shift away from the two most emission-intensive sectors (energy and mining and quarrying) towards the two least emission-intensive sectors (finance and information technology). Therefore, differences in sector composition explain part of the difference in emission intensities between self-proclaimed sustainable ETFs and their reference ETFs. Within emission-intensive sectors, we find little evidence for a "best-in-class" selection strategy.

Our paper provides important insights into the composition of self-proclaimed sustainable ETFs and uncovers avenues for future research. The rest of this paper is structured as follows. In section 2, we briefly discuss related literature. Following in section 3, we describe the data used for this paper before proceeding with the empirical analysis in section 4. We discuss findings in section 5 and conclude in section 6.

2. Literature

Several studies in the marketing-finance interface literature highlight the interplay between sustainability and marketing claims. For instance, Luo and Bhattacharya (2009) find that the effect of sustainable engagement on firms' financial market performance is more pronounced under higher advertising levels. In addition, Martin and Moser (2016) find in an experimental setting that investor reactions to firms' efforts towards reducing carbon emissions are not solely based on the expected effect of these efforts on firms' future cash flows. Instead, their reactions also depend on how firms frame these activities in their disclosures.

Consequently, firms have an incentive to maintain a veneer of sustainable engagement (Torres et al., 2012) and may overly emphasize it for marketing purposes, a phenomenon known as "greenwashing" (Laufer, 2003). Previous studies find evidence of firms and financial products exhibiting greenwashing behaviour while publicly claiming adherence to sustainability standards (Liang et al., 2021; Tucker, 2021).

Responding to the record inflows to self-proclaimed sustainable financial products (Kerber and Jessop, 2021), an emerging literature stream in finance investigates whether investors can "do well by doing good". Most recent studies focus on understanding whether self-proclaimed sustainable financial products differ in terms of return and risk, and on the possible drivers and moderators of this relationship, with somewhat inconclusive evidence. As Gillan et al. (2021) summarize it, there are still many conflicting hypotheses and results.

When looking at ETFs, multiple studies find no statistically significant difference between the risk-weighted performance of self-proclaimed sustainable and conventional ETFs (Lobato et al., 2021; Weston and Nnadi, 2021). Other studies examine this potential performance difference during economic downturns and find conflicting results (Folger-Laronde et al., 2022; Omura et al., 2021; Pavlova and de Boyrie, 2022)

Clements (2021) underscores that given the rapid increase in the number of self-proclaiming sustainable ETFs and the currently high effort involved in acquiring and standardizing information, it is not realistic for investors or even professional advisors to compare and distinguish them. The U.S. Securities Exchange Commission (SEC) has also recognized this problem and issued a series of recommendations for investors, issuers, and policymakers (SEC, 2020).

Understanding the degree of product differentiation within self-proclaimed sustainable ETFs and between them and conventional ETFs is crucial for informed investment decisions. Furthermore, obtaining reliable information on the environmental, social, and governance footprint of different sustainability investment strategies is equally relevant for investors and for policymakers. Anecdotal evidence in the popular press suggests that self-proclaimed sustainable ETFs continue to invest in emission-intensive industries and firms, whilst maintaining a substantial overlap with conventional ETFs (e.g., Mohr, 2022; The Economist, 2021; Time, 2021).

However, most of the existing literature focuses on the "doing well" part, that is, on differences in risk and return. Despite the topic's relevance, there is surprisingly little research on how self-proclaimed sustainable ETFs differentiate themselves in terms of investment strategy and resulting sustainability performance, in comparison to conventional ETFs. Our study aims to contribute towards closing this research gap.

Closest to our study is the work of Reiser and Tucker (2019), who analyse hand-collected data of 31 actively and passively managed self-proclaimed sustainable ETFs and 7 conventional ETFs. The authors note that "*the underlying variation across funds is largely opaque to consumers, who rely on the ESG acronym at their peril*".

3. Data

The lack of unified metrics and standardised reporting framework presents the first challenge for our study. Fund- and fund asset-level information is generally public, but dispersed across many sources and partly in unstructured, textual documents. Emissions data on firm-level mostly originates from public sustainability reports, but in practice, these data are restricted in usability due to their unstructured nature, dispersion across multiple sources, as well as non-standardised definitions and reporting frameworks.

Therefore, our study relies on data from multiple sources. We start by collecting decentralised public information about ETF assets provided by fund issuers. We scrape this information automatically from the websites of five fund issuers' and one public ETF database. Our data encompass the largest issuers worldwide, based on issuers' total assets under management (AUM).

We collect a list of ETFs per issuer, including the assets for each fund, their weights, and respective ISINs (for equity assets). For the sample of self-proclaimed sustainable ETFs, we retain all ETFs that our data sources classify as "ESG", "SRI", or "sustainable". In the cases in which the data source provided no such automatic filtering or labels, we search for a list of terms in the ETF titles that typically refer to sustainability: clean, sustainable, green, wind, solar, renewable, climate, water, decarbonization, environment, cleantech, low carbon, planet, and forestry. Furthermore, we only consider equity ETFs for our analyses. Fund assets typically include equity (firms' stocks) and cash. Only few occurrences of forwards, futures, swaps, and contracts for difference in our sample of equity funds.

To compare the emission intensity between self-proclaimed sustainable ETFs and their respective non-sustainable reference ETFs, we create two groups of ETFs. The first is the self-proclaimed sustainable ETFs' group, which contains ETFs screened for sustainability considerations. For each of these ETFs, we also retrieve similar data for their "non-sustainable" reference version, whenever one exists. We identify reference indices as they are provided in the self-proclaimed sustainable ETF's fund documents. We retrieve ETF data in March 2022 with updates in June 2022. The combined data set contains 178 self-proclaimed sustainable ETFs and 38 reference ETFs. Out of the self-proclaimed sustainable ETFs, 101 ETFs have a matching (non-sustainable) reference ETF.

An example of a self-proclaimed sustainable ETF with a reference index would be one based on the "MSCI World", e.g., a hypothetical "MSCI World SRI". In such cases, issuers typically create the self-proclaimed sustainable ETFs funds starting from the conventional index ("MSCI World" in this example) and then excluding assets by applying global or sector-based thresholds based on various ESG criteria. Multiple self-proclaimed sustainable ETFs can have the same reference index – in this example, many self-proclaimed sustainable ETFs may be based on "MSCI World". Self-proclaimed sustainable ETFs without a reference ETF are typically topic-based, e.g., a hypothetical "Global Clean Water Index". In such a case, there is typically no conventional non-sustainable reference ETF to match it.

Then, we complement these data with information provided by fund issuers in the ETFs' prospects in textual form. This source provides information on the investment goal and fund strategy stated by the issuers, as well as on the stated classification according to the SFDR, whenever applicable. We manually categorize this textual information into structured data for further analyses.

Exemplary and simplified data structure

Table 1

Information is available on fund-level and asset-level.

ETF	Inception date	Self-proclaimed sustainable	Assets	Weight	Emission intensity (CO2-eq/revenue)
A	2020-01-01	1	Firm 1	60%	0.5
A	2020-01-01	1	Firm 2	40%	0.4
B	2017-01-01	0	Firm 1	33%	0.5
B	2017-01-01	0	Firm 2	33%	0.4
B	2017-01-01	0	Firm 3	34%	0.8

Note: This table is simplified and made-up for illustrative purposes containing no real-world data.

Finally, we combine the asset-level information from equity assets with proprietary emissions data on firm-level greenhouse gas emissions. This information is based on firms' non-financial reports and third-party estimations and are attributed to a single ISIN. We obtain scope 1 GHG emission intensity and the NACE sector of the firms from ISS ESG, a proprietary data provider.

The information available from issuers' websites contains different sets of variables and are presented in different formats. We standardize their formats and measuring units. Furthermore, we use a string-matching record linkage procedure for issuers that provide only non-unique asset names but no ISINs. We rely on observations from other issuers for which we have both the asset names and ISINs to fill the missing ISINs in all cases where we have an exact name match, after standardizing the asset names.

Ultimately, we obtain a cross-sectional dataset with 216 ETFs after joining the combined data sets with fund- and asset-level variables with the data set containing emission intensities and the NACE sector classification at the asset level. Fund-level variables include the fund's inception date, the number of assets, and assets under management. Asset-level variables include firms' names and identifiers, asset weights, firms' economic sectors, and scope 1 and 2 GHG emission intensities. Table 1 provides an example of our data structure.Within our sample of 216 ETFs, we compare 101 self-proclaimed sustainable ETFs with 38 reference ETFs. The 101 self-proclaimed sustainable ETFs contain 38,876 assets with 6,474 unique firms. The 38 reference ETFs contain 20,227 assets that represent 6,977 unique firms. Furthermore, in our sample, we have 77 self-proclaimed sustainable ETFs without a reference index, which cover a total of 20,959 assets and 8,185 unique firms. In our sample 97.5% of all assets are equity. We exclude all non-equity assets from our sample. Table 2 presents selected summary statistics.

Summary Statistics — Table 2

For n = 216 ETFs in our sample, out of which 178 self-proclaimed sustainable and 38 reference

Indicator	Fund age in days			Number of assets			Average Scope 1 GHG* Emission intensity			Average Scope 2 GHG Emission intensity		
	all	sps**	ref**	all	sps	ref	all	sps	ref	all	sps	ref
Minimum	150	150	444	12	16	12	1.8	1.8	3.4	3.7	3.7	7.4
1st Quartile	443	398.2	2341	62.8	63.5	61.3	35.9	35.2	62.6	24.4	24.1	28.8
Median	905.5	774.5	3448	163.5	163.5	178	83.5	77.3	154.2	32.8	31.9	36.6
Mean	1728	1356.5	3471	364.1	329.7	525.1	132.5	123.7	174.0	41.8	41.2	44.7
3rd Quartile	2304.5	1468.2	4758	380	355	600.3	152.4	130.2	198.0	53.1	53.2	52.2
Maximum	7657	6398	7657	5205	5205	3460	966.2	966.2	773.3	203.6	192.3	203.6
Number of Missing Values	0	0	0	0	0	0	9982	7645	2337	9982	7645	2337

* Greenhouse gas.

** sps: self-proclaimed sustainable ETFs, ref: reference ETFs

Our data suggests that the number of assets held per fund is smaller in self-proclaimed sustainable ETFs than in reference ETFs – self-proclaimed sustainable ETFs have an average of 330 assets, compared to 525 assets in reference funds. We also observe that average weighted scope GHG emission intensities are smaller for self-proclaimed sustainable ETFS than for their reference ETFs (123.7 vs. 174.0 tCo2eq/rev). Considering average weighted scope 2 emission intensities, the difference almost disappears (41.2 vs. 44.7 tCo2eq/rev).

The average age of self-proclaimed sustainable ETFs is 3.7 years, whereas reference ETFs are on average 9.5 years old. Figure 1 shows the inception dates of self-proclaimed sustainable ETFs and their reference

ETFs. In line with previous studies, we also observe a steady increase in the inception of self-proclaimed sustainable ETFs in recent years.

Using the textual information from the fund documents, we analyse the stated funds' strategy, ESG criteria considered, and reported data sources for ESG information. From 178 self-proclaimed sustainable ETFs in our sample, 163 are managed passively and 15 ETFs are managed actively. All those passively managed track a sustainable index. Hence, when talking about an ETF's impact in designing a sustainable investment opportunity, in practice this choice is closely reflects the index provider's asset choices.

By far, MSCI is the most often cited index provider in our sample (or provider of sustainability-related information). It appears in fund documents with 101 occurrences, followed by S&P (21), and Deutsche Boerse AG (10). We note that these mentions can add up to more than the number of self-proclaimed sustainable ETFs, because some funds report multiple data sources for ESG information. 122 ETFs in our sample consider investments in a broad range of sectors, whereas 56 funds target one or few specific industry sectors, such as the hypothetical "Global Clean Water Index" in our previous example.

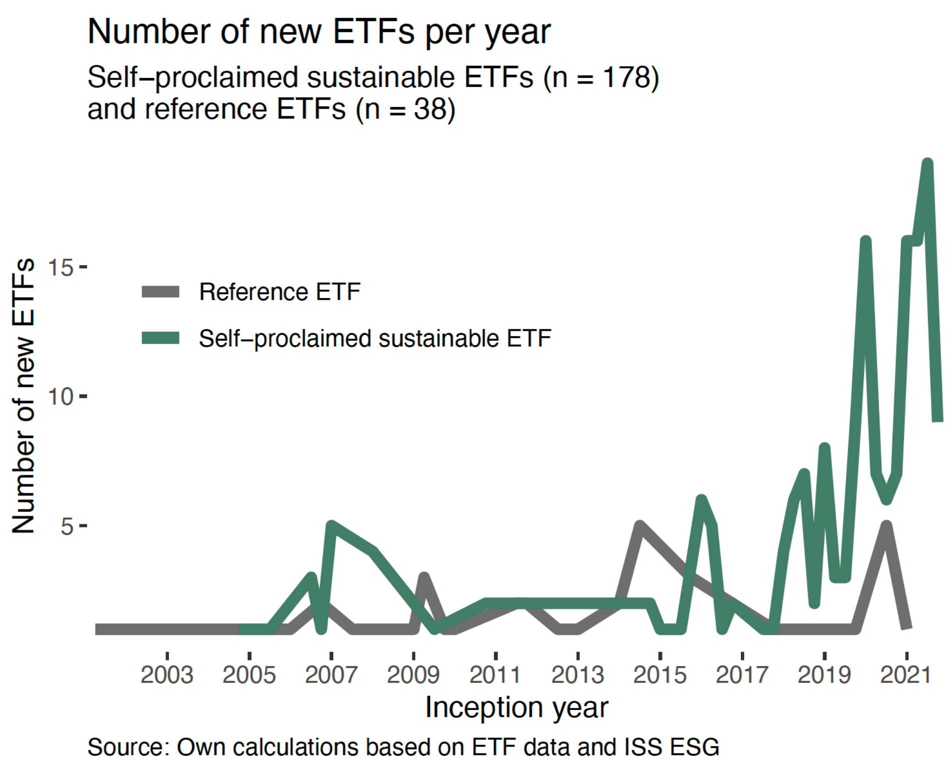

Figure 1: The inception of self-proclaimed sustainable ETFs and reference ETFs in our sample over time

The self-proclaimed sustainable ETFs or the indices they are based on often report following a negative-selection approach with 117 mentions, followed by a positive (33), best-in-class (21), and active selection (14). Only one ETF in our sample states that it is based on an index that explicitly does not exclude firms, but reweights the assets based on ESG information. Similarly, we note that these mentions can add up to more than the number of self-proclaimed sustainable ETFs, because some funds report a combination of selection methods. In particular, 9 self-proclaimed sustainable ETFs report a combination of global thresholds (negative selection) and sector-specific thresholds (best-in-class).

As self-proclaimed sustainable ETFs can target a combination of ESG aspects or can incorporate only one or two aspects, we regard their stated sustainability criteria. We see that 169 mention the general "ESG" goal as a criterion in their composition. In addition, 34 mention low carbon emission as a criterion, and 5 mention "social" aspects. Mentions can add up to more than the number of self-proclaimed sustainable ETFs, because some report a combination of criteria. Specifically, 29 self-proclaimed sustainable ETFs report a general combination of ESG aspects and low-carbon emissions criteria.

Where this information is available, 81 self-proclaimed sustainable ETFs report themselves as adhering to SFDR Article 8 and 14 to Article 9. This information is missing for a considerable fraction of our sample, as it is typically only available for European targeted ETFs.

The summary statistics indicate that, on average, self-proclaimed sustainable ETFs have smaller emission intensities than their conventional counterparts. In our empirical analysis, we investigate how this reduction in emission-intensities may relate to different possible asset selection strategies.

4. Empirical Analysis

In a first step of analysis, our intention is to discover patterns in our dataset, whether investors could differentiate between self-proclaimed sustainable ETFs and reference ETFs, short of reading the fund documents. Therefore, we try to mimic investor decisions based on available information by classifying ETFs using k-Means clustering. This can be seen as a continuation of Reiser and Tucker (2019), who noted that investors have to rely on the ESG label of the ETF. We are interested in how this holds up following legislative changes to standardise definitions and disclosures in the meantime.

We prepare a dataset without any labels about self-proclaimed sustainable ETFs and reference ETFs and let the algorithm classify them into two different groups. We choose the Hartigan-Wong k-Means clustering algorithm (Hartigan and Wong, 1979), which is a popular unsupervised machine learning method. The algorithm requires the pre-defined number of clusters and assigns each data point to a cluster. We choose the number of clusters as two. As this is an unsupervised method, the clusters are not automatically assigned to a specific group. After finding the highest performance model, our aim is to identify and explore which variables are the most informative and which variables should we take a deeper look at our following analysis.

We base this analysis on available sector and emission information, as well as fund-level data. In order to classify funds, we consider the following available fund-level variables: fee, age of the fund, total assets under management and number of assets.

As features providing information on funds' emissions, we consider the average GHG emission intensities (scope 1 and scope 2) for each fund. We compute these by aggregating the weighted average of the scope 1 (scope 2) GHG emission intensity at the asset-level for a given ETF. We do so by calculating the weighted sum over all N equity assets in an ETF for which we have emission intensity information available:

$$AEI_{ETF} = \sum_{i=1}^{N} \frac{E_i}{R_i} w_{iETF} \quad , i \in 1, \ldots, N$$

Where AEI_{ETF} represents the weighted average emission intensity (AEI) of a given ETF, E_i asset i's total scope 1 GHG emission, R_i asset i's (firm) revenue, and w_{iETF} the asset i's weight in the ETF composition. AEI's unit is:

$$\frac{Total\, Scope 1\; emissions\; in\, Tons\, of\; CO_2\; equivalents}{Revenue\; in\; million\; EURO}$$

Furthermore, we consider the maximum emission intensity of a fund's asset: $\max_i(EI_{ETF}) = \frac{E_i}{R_i}$.

As proxies for the sector composition of the fund we compute the sector weights (SW), i.e. the % of a funds holding for each sector j, where j is the NACE2 sector on level 1 ("letter level").

$$SW_{jETF} = \sum_{j=1}^{S} \sum_{i=1}^{N} I_{w_i}(j) w_i \quad , i \in 1, \ldots , N, \ , j \in 1, \ldots , S$$

Where I is the indicator function, 1 if asset I belongs to sector j, 0 if not, S is the number of NACE2 sectors (on the highest level 1, 21 NACE2 sectors exist). Furthermore, we compute the number of a fund's asset in each sector j, which is similar to SW, without considering the weights w.

As a proxy, for "best-in-classness" BC, we compute the average differences in emission intensity between all assets of a given ETF in a given sector as opposed to the sector average emission intensities:

$$BC_{jETF} = \sum_{j=1}^{S} \sum_{i=1}^{N} I_{w_i}(j) \left(\frac{E_i}{R_i} - avg(EI)_{(j)} \right) , i \in 1, \ldots , N, \ , j \in 1, \ldots , S$$

As we obtain a relatively large numbers of features for the sector-based variables, we also compute principal components in order to reduce the dimensions.

In this way, we have the features required for our model. To find the model gives us the highest predictive power, we try these features in a variety of combinations.

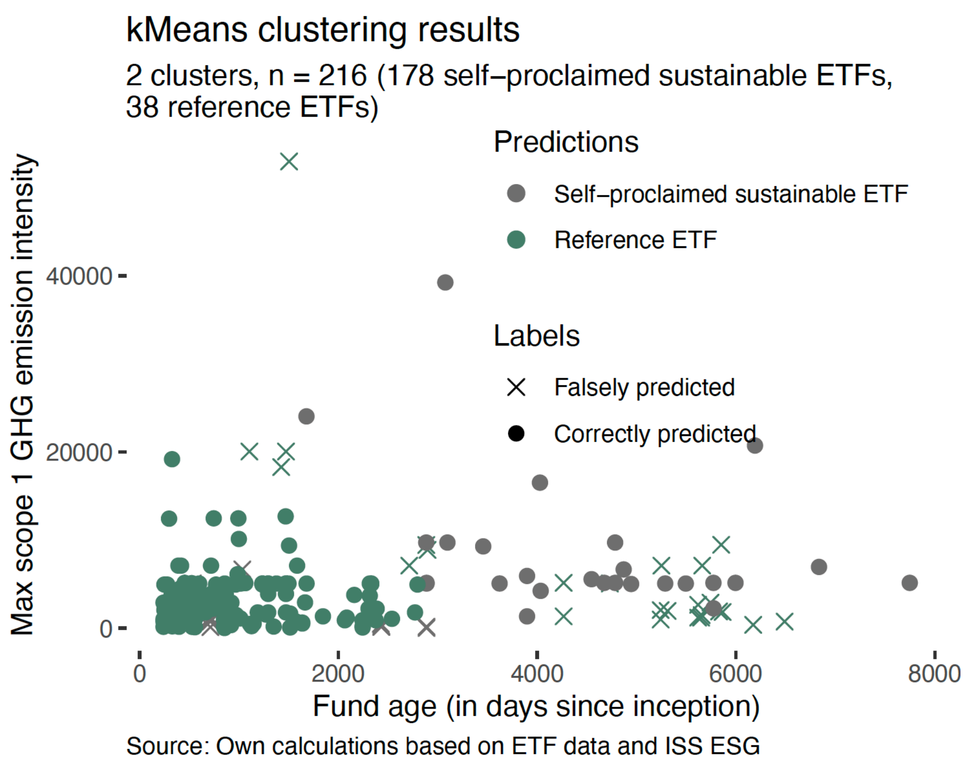

Figure 2: Resulting clusters of self-proclaimed sustainable and reference ETFs using kMeans.
Note: In the lower left corner, the green dots and grey x's form one cluster, the grey dots and green x's form the other cluster.

The results somewhat surprisingly show that the most informative variables are the maximum scope 1 GHG emission intensities (not weighted) and the ETFs' age. This means that the best predictive power is obtained using the highest emitter's emission intensity in any given ETF and not the average emission intensity. Contrary to expectations, sector composition does not seem to add much predictive value (nor do its principal components). Neither do emission intensities compared to sector average emission intensities play a significant role.

Figure 2 displays the ETF's distribution across the two most informative variables "maximum scope 1 GHG emission intensity in fund" and "fund age". It shows how the 216 ETFs are assigned to two separate categories, which we later label as sustainable and non-sustainable, based on the majority of the true available labels. Based on these labels, we assess whether the algorithm classified each ETF in the correct category. We see two clusters roughly emerging. The first one consists of green dots and grey x's in the lower left corner, and the second cluster consists of grey dots and green x's. The green and grey dots ("x" marks) represent the correctly (incorrectly) predicted self-proclaimed sustainable ETF and reference ETF, respectively.

Confusion Matrix — Table 3

Predictions of the clustering algorithm vs. self-descriptions of ETFs

	Self-proclaimed sustainable ETF	Reference ETF
Predicted sustainable ETF	153	12
Predicted reference ETF	25	26

Source: Own calculations based on ETF data and ISS ESG

To measure the performance of the algorithm, we use a confusion matrix. Table 3 shows that, out of 178 self-proclaimed sustainable ETF, 153 are predicted correctly and 25 are predicted incorrectly. From the confusion matrix, we can also calculate the model's precision and recall. In our analysis, precision is the share of self-proclaimed sustainable ETF that are correctly classified out of all self-proclaimed sustainable ETFs. Our model classifies 86% of self-proclaimed ETFs correctly. On the other hand, the recall of 93% provides a measure how our model's ability to identify self-proclaimed ETFs. As we have highly imbalanced classes, a combination of these two metrics, the F1-score, provides a better assessment of our model performance. A F1-score of 89% indicates the harmonic mean of the precision and recall.

The cluster classification performs relatively well; even though it has some limitations, such as the sensitivity of clusters on the initial seed, an overrepresented majority class issue, and the lack of additional sustainability variables on asset-level and firm characteristics that could improve future analyses. Following this clustering from an investor's perspective, we proceed to analyze the environmental footprint.

We compare the AEI of the self-proclaimed sustainable ETFs with their non-sustainable reference ETFs and calculate the respective differences in emission intensity for each pair:

$$AEI_{difference} = AEI_{\substack{self-proclaimed \\ sustainable\ ETF}} - AEI_{reference\ ETF}$$

Out of the 101 self-proclaimed sustainable ETFs that have a reference ETF, we identify 5 ETFs that have higher average emission intensity than their respective reference ETFs. For the remaining 96 self-proclaimed sustainable ETFs, we find their AEI to be lower than their reference ETFs. We test our results with a paired t-test and the differences in AEI are statistically significant ($p < .01$). However, we should interpret these results with care, as groups in our setting are not independent and reference group observations repeat themselves, because many self-proclaimed sustainable ETFs have the same reference ETFs. Consequently, degrees of freedom are not obvious to compute, and we cannot rule out the presence of heteroscedasticity. Nevertheless, we note that other test settings lead to the same substantive conclusions. Figure 3 shows the distribution of AEI for self-proclaimed ETFs and the reference ETFs, as well as the paired differences.

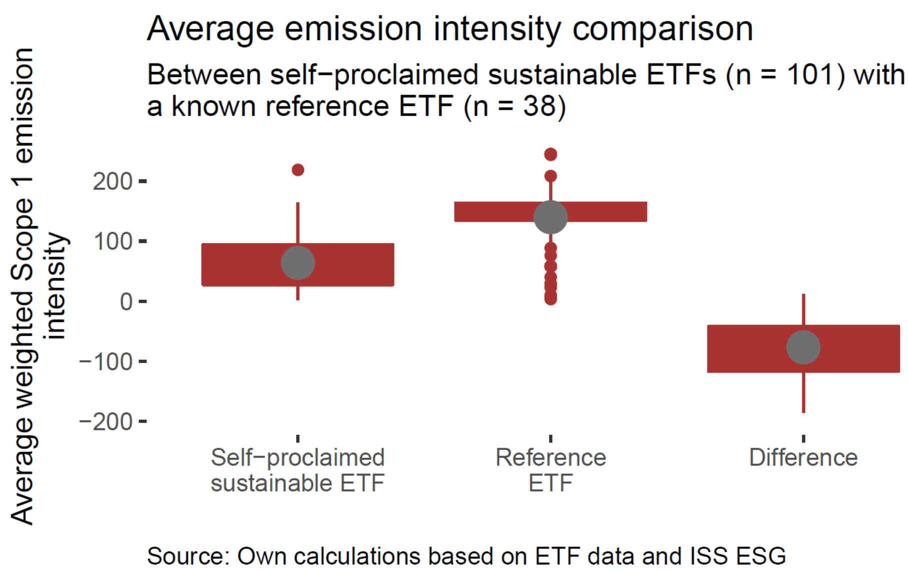

Figure 3: Boxplot of average emission intensities for self-proclaimed sustainable, reference ETFs and paired differences

To shed light into the drivers of these differences, we examine further the sector composition across the pairs. In particular, we are interested in understanding the reductions in AEI – do they originate from a best-in-class selection strategy or from simply delisting emission-intensive sectors?

If a best-in-class selection takes place, we would expect the sector composition to remain relatively stable in a self-proclaimed sustainable ETF when compared to its reference ETF. Under this scenario, self-proclaimed sustainable ETFs would feature assets of firms with lower greenhouse gas emission intensities within emission-intensive sectors in a comparison against peers in their own industry, even if their absolute emission intensities remain high compared to other sectors. Instead, if negative selection criteria are more predominant, we would expect funds to remove assets of firms in emission-intensive sectors, as they would tend to remove those beyond a certain ESG threshold in a comparison against everyone. Under this approach, funds would tend to end up with higher weights in less emission-intensive sectors.

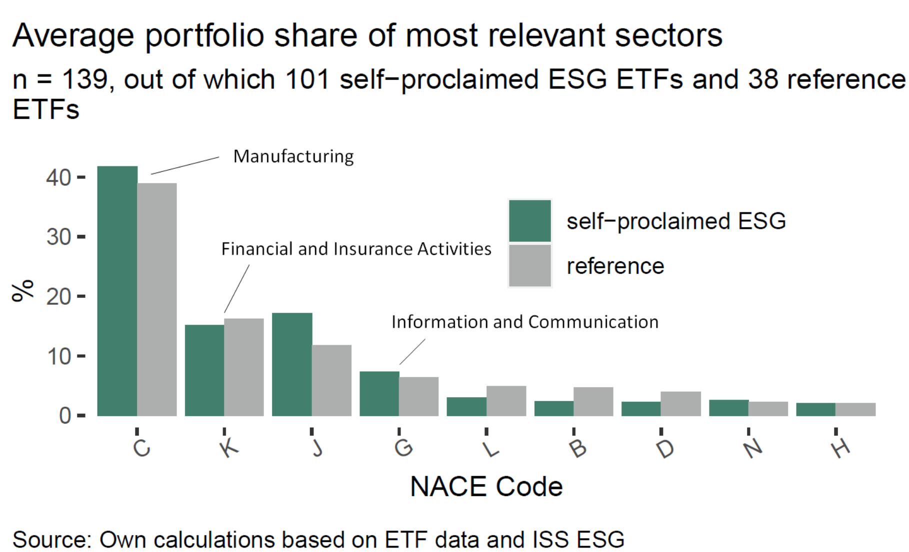

Figure 4: Dominating sectors in self-proclaimed and reference ETFs based on NACE2 level 1 codes

For this analysis, we examine the pairs of 101 self-proclaimed sustainable ETFs and their respective 38 reference ETFs using the NACE classification system. The NACE Level 1 Codes includes 21 sectors identified by the letters A to U. We compute the sector shares in each ETF based on the sum of weights of the firms that belong to the respective sector. Figure 4 shows that the most dominant sector in our sample is manufacturing (NACE C), followed by financial and insurance activities (NACE K), and information and communication (NACE J). Even though the rank of most dominant sectors is the same for both self-proclaimed sustainable ETFs and reference ETFs, self-proclaimed sustainable ETFs contain substantially more assets in the sector information and communication (NACE J).

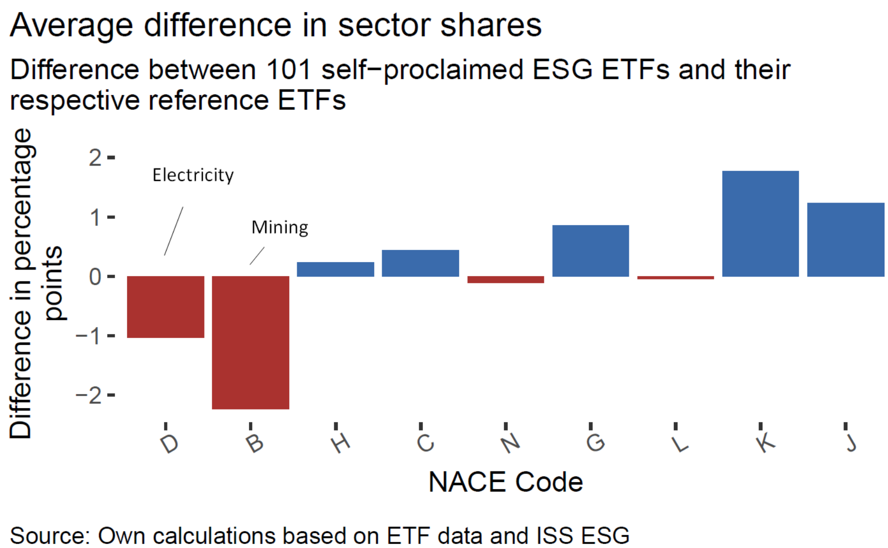

Figure 5: Average differences in sector shares between self-proclaimed sustainable ETFs

Then, we further compare the percentage differences in sector composition with their original starting point in the reference ETFs. The results in Figure 5 suggest that self-proclaimed sustainable ETFs shift away from the two most emission-intensive sectors, electricity (NACE D) and mining and quarrying (NACE B), towards investing more into financial and insurance activities (NACE K) and information and communication (NACE J), which are among the least scope 1 GHG emission-intensive sectors. Even though the reductions in percentage points seem small – e.g., 2 percentage points less in mining and quarrying – these amount to a substantial proportion of the original sector shares in the reference ETFs. Overall, we find that differences in sector composition partly explain the differences in scope 1 GHG emission intensity between self-proclaimed sustainable ETFs and their reference ETFs.

To further shed light into the sources of the observed differences in emission intensities, we proceed to assessing whether assets in the self-proclaimed sustainable ETFs have substantially lower emission intensities than other assets in their respective sectors. Our aim is to assess whether there is any evidence for a "best-in-class" asset selection between self-proclaimed sustainable ETFs and reference ETFs.

To do so, we first take the universe of assets in the ISS data, which are based on emissions of 29,264 firms and calculate the average emission intensity for each sector, weighted by the firm's revenue. Figure 6 shows that the most emission intensive sectors are electricity (NACE D) and mining and quarrying (NACE B). In comparison to these sectors, manufacturing (NACE C) has a moderate average emission intensity, whereas finance and information technology (NACE K) and information and communication (NACE J) have a substantially lower average emission intensity.

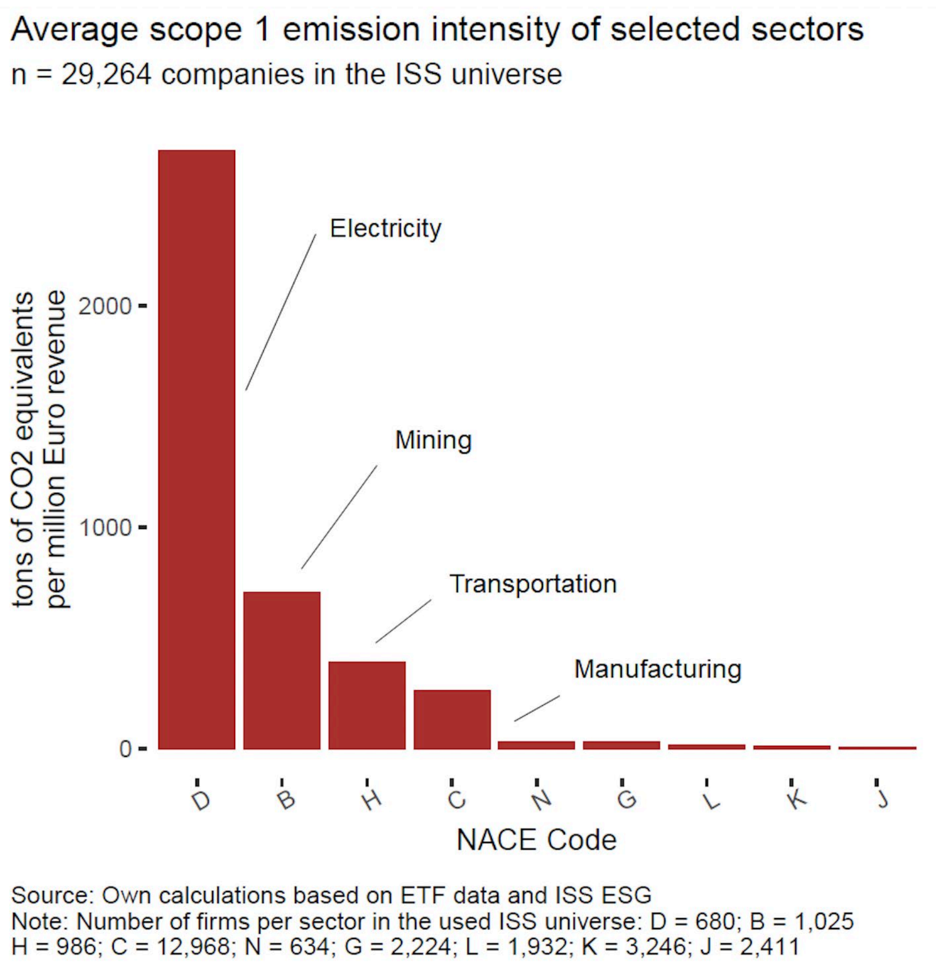

Figure 6: Global average scope 1 greenhouse gas emission intensities per sector, based on NACE2 level 1 codes
Note: Calculation based on all available observations in ISS ESG using greenhouse gas emission intensity.

Then, for each asset in an ETF, we calculate the difference between its emission intensity and the average emission intensity in its respective sector, as calculated from the ISS universe. Then, we aggregate these differences at the ETF level by weighting them using the asset weights in each ETF's composition. If self-proclaimed sustainable ETFs predominantly followed a best-in-class asset selection strategy, then we would expect their aggregated differences from sector averages to be predominantly negative, as the assets they select would systematically have lower scope 1 GHG emission intensities than their sector peers.

The results in Figure 7 indicate that even though the deviations from sector averages in self-proclaimed sustainable ETFs are predominantly negative, their distribution has a substantial overlap with the distribution for their respective reference ETFs. Their selected assets do not seem to be substantially better than their peers in the corresponding sectors, compared to the assets present in the reference ETFs. Furthermore, for a few self-proclaimed sustainable ETFs, we find positive deviations from sector averages, which suggests that they are investing in assets of firms that are, on average, more emission-intensive than their sector peers. Taken together, these results provide little evidence corroborating a "best-in-class" asset selection in the self-proclaimed sustainable ETFs in our sample. We replicate these analyses considering scope 2 emission intensities and combined scope 1 and scope 2 GHG emission intensities and find similar substantive results. In the next section, we discuss these results' main insights and implications.

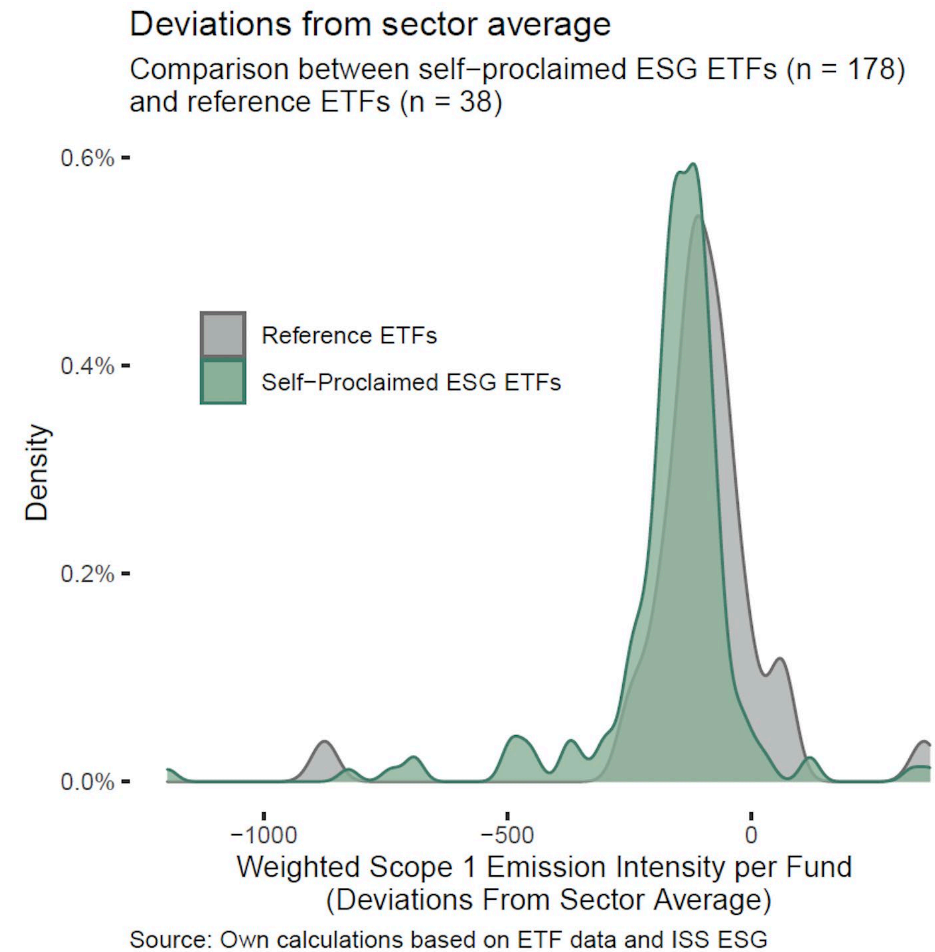

Figure 7: Distribution of weighted scope 1 emission intensities per ETF, deviations from sector averages

5. Discussion

When simulating the typical information set available to investors to differentiate between self-proclaimed sustainable ETFs and their respective non-sustainable reference ETFs using k-Means clustering, we find that the most informative variables are the maximum (non-weighted) scope 1 GHG emission intensities and the ETF's age. Interestingly, neither the sector compositions, nor their differences or average emission intensities have much value in distinguishing self-proclaimed sustainable ETFs from non-sustainable reference ETFs. These results suggest that many self-proclaimed sustainable ETFs follow a global approach with a negative asset selection – i.e., removing the most emission-intensive assets. This finding substantiates claims in self-proclaimed sustainable ETFs' prospects, which predominantly report following a negative-selection approach, with a total of 117 mentions.

Out of the 101 self-proclaimed sustainable ETFs that have a non-sustainable reference ETF, 96 have lower average emission intensities than their reference ETFs. These differences are statistically significant ($p<.01$). Out of the 5 identified ETFs that have a higher average emission intensity (AEI) than their reference ETF, none focuses specifically on carbon reductions based on their fund documents. Indeed, in the textual analyses of the ETFs' prospects, we find that most of them mention general "ESG goals" as their composition criterion. Maybe noteworthy could be that three out of these five are focused on specific sectors (energy, communication, and consumer goods respectively).

Manufacturing (NACE C) is the most dominant sector in the ETFs represented in our paired sample of self-proclaimed sustainable ETFs and their reference ETFs, followed by finance (NACE K), and information technology (NACE J). The most scope 1 GHG emission-intensive sectors are energy (NACE D) and mining and quarrying (NACE B). Manufacturing has moderate scope 1 GHG emission intensity, while finance and information technology produce very little scope 1 GHG emissions. Our results suggest that self-proclaimed sustainable ETFs shift away from the two most emission-intensive sectors towards the two least emission-intensive sectors.

We further analyze the deviations between the emission intensity of each asset in an ETF and the average emission intensity in its respective sector, as calculated from the ISS universe, and aggregate them for each ETF using the assets' weights. Our results provide little evidence that self-proclaimed sustainable ETFs follow a "best-in-class" asset selection. This finding only partly substantiates the information reported by fund issuers in their fund prospects, as the textual data indicates that 21 self-proclaimed sustainable ETFs claim to follow a "best-in-class" approach, whereas nine report a combination of global thresholds (negative selection) and sector-specific thresholds (best-in-class).

Our findings corroborate the initial results provided by Reiser and Tucker (2019) – they also find that investment strategies vary widely among self-proclaimed sustainable ETFs. Furthermore, they also find that self-proclaimed sustainable ETFs' assets substantially overlap with those of "conventional" ETFs. Because the degree of a firm's sustainable activities depends on the sector in which it operates (Banerjee, Iyer, and Kashyap, 2003), self-proclaimed sustainable ETFs should exhibit different sustainability performance, depending on their sector composition. Indeed, our results suggest that differences in sector composition explain a great proportion of the differences in emission intensities.

Interestingly, Folqué et al. (2021) find that funds that only apply negative selection obtain worse ESG risk scores and worse carbon risk on average. The prevalence in negative selection in our study, which is stated in the fund documents and substantiated by our empirical analyses, opens interesting further roads for future studies.

6. Conclusion

In the past years, investor interest in sustainable investments has increased substantially. As a result, the number of ETFs that are marketed as "sustainable" also rose to record levels. However, despite recent regulatory steps to increase the transparency in this market, there is no coherent set of international regulations as to what defines a sustainable financial product. It is therefore challenging for multiple stakeholders to discern from the different metrics and strategies involved in the composition of self-proclaimed sustainable ETFs, which compromises their ability to make informed decisions.

We contribute to closing the research gap in this area by investigating the composition of 101 self-proclaimed sustainable ETFs and outlining the differences in comparison to their respective 38 reference ETFs. We further investigate whether differences arise from a particular composition strategy – e.g., positive, negative, or best-in-class selection – and assess whether the extent to which they lead to reductions in scope 1 GHG emission intensities.

We find that self-proclaimed sustainable ETFs generally have lower average emission intensities than their reference ETFs, but there is a high variance in the measured differences. We find them to be statistically significant at the confidence level of 99%. Part of this reduction is driven by divesting from emission-intensive sectors, in particular, from energy and mining and quarrying. Self-proclaimed sustainable ETFs shift their assets to least emission-intensive sectors, such as finance and information technology.

We find little evidence of a best-in-class approach within emission-intensive sectors. Only 21 self-proclaimed sustainable ETFs explicitly mention this strategy in their as stated in their fund disclosure documents. Nevertheless, our data shows that little signs of a best-in-class selection effect on average for a sample. For future work, it seems valuable to investigate the differences in sector composition specifically in those ETFs that mention best-in-class as their selection criteria.

Our results indicate that investors may, on average, reduce GHG exposure by investing in self-proclaimed sustainable ETFs. However, investors looking to cover a broad market while rewarding the lowest emitters within a sector cannot generally do so by investing in self-proclaimed sustainable ETFs. If investors wish to incentivize the least emission intensive firms per sector (best-in-class) they currently do not have an easy way to identify such funds.

Investors who wish to support the transition to a less carbon-intensive economy through a specific strategy could make a deep analysis of the fund disclosure documents. They could assess whether self-proclaimed sustainable funds aspire to be ecological-, social-, or governance-oriented (or any combination of these) and assess their adherence to the claimed strategy with hard data.

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Measuring Emissions Profiles of Self-Proclaimed ESG ETFs

Initial findings and lessons for official statistics

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The authors would like to thank colleagues in the RDSC for their valuable suggestions and feedback.
All views expressed in this report are personal views of the authors and do not necessarily reflect the views of Deutsche Bundesbank or the Eurosystem.

Understanding the investment strategy of self-proclaimed ESG[1] ETFs[2] is important for informed investing

1

Motivation

IMPORTANCE

- Increasing interest in **ESG** investing
- Self-proclaimed "ESG" investments reached a market capitalization of **$1.7 trillion** in 2020 and continue to grow[1]

ISSUE

- **Increasing number** of self-proclaimed "ESG" ETFs
- Difficult to measure how they differ in terms of **sustainability strategy and metrics**
- Lack of transparency, **limited and scattered** information available

IMPACT

- **Critical information** for informed investment decisions and for policy-making

[1] ESG: Environmental, Social, Governance
[2] ETF: Exchange Traded Fund
[3] Jessop and Howcroft (2021)

Current evidence suggests incentives for ETFs to self-classify as “ESG”

2

Literature

For **marketing purposes**, funds have an incentive to maintain a veneer of ESG engagement[1]

Anecdotal evidence suggests that self-proclaimed ESG ETFs may still:

- be *“stuffed full of polluters and sin stocks”*[2]
- invest in companies *“not aligned with the goals of the Paris agreement”*[3], and
- not substantially differ from “traditional” funds[4]

Findings in literature suggest that hedge funds exhibit **greenwashing behavior** while publically endorsing adherence to ESG standards[5, 6]

Investors may not be able to adequately **estimate the expected impact** of ESG investments[7]

RESEARCH QUESTION

- How do self-proclaimed “ESG” ETFs carry out their **investment strategy**?
- I.e. do they choose “*best-in class*” assets per sector or do they divest from emission-intensive sectors?
- Does their strategy lead to a **consistently lower emission-intensity** in their holdings?

[1] Torres et. al (2012)
[2] The Economist (2021)
[3] Time (2021)
[4] Barclays Research (2020)
[5] Liang, Sun, and Teo (2021)
[6] Tucker, K. P. (2021)
[7] Martin and Moser (2016)

Data for this study comes from ETF issuers and proprietary emission data

MATCH EXAMPLE

MSCI World Index

*"iShares MSCI World **SRI** UCITS ETF"*	*"iShares Core MSCI World UCITS ETF"*
Top 3 Holdings	**Top 3 Holdings**
Microsoft (4.5%)	Apple (4.4%)
Tesla (4.4%)	Microsoft (3.5%)
NVIDIA (4%)	Amazon (1.2%)

CHALLENGES

- No **central public data source** for self-proclaimed ESG ETFs (webscraping from each fund issuer)
- Available information **heterogeneous** and in **different formats**

FINAL SAMPLE

216 ETFs

Self-proclaimed ESG ETFs

Match

101 ETFs
38,876 holdings
6,474 unique companies

Non match

77 ETFs
20,959 holdings
8,185 unique companies

Reference ETFs

38 ETFs[2]
20,227 holdings
6,977 unique companies

EXAMPLE

"Global X Clean Water ETF"

↓

ETFs constructed "ground up" with no reference index

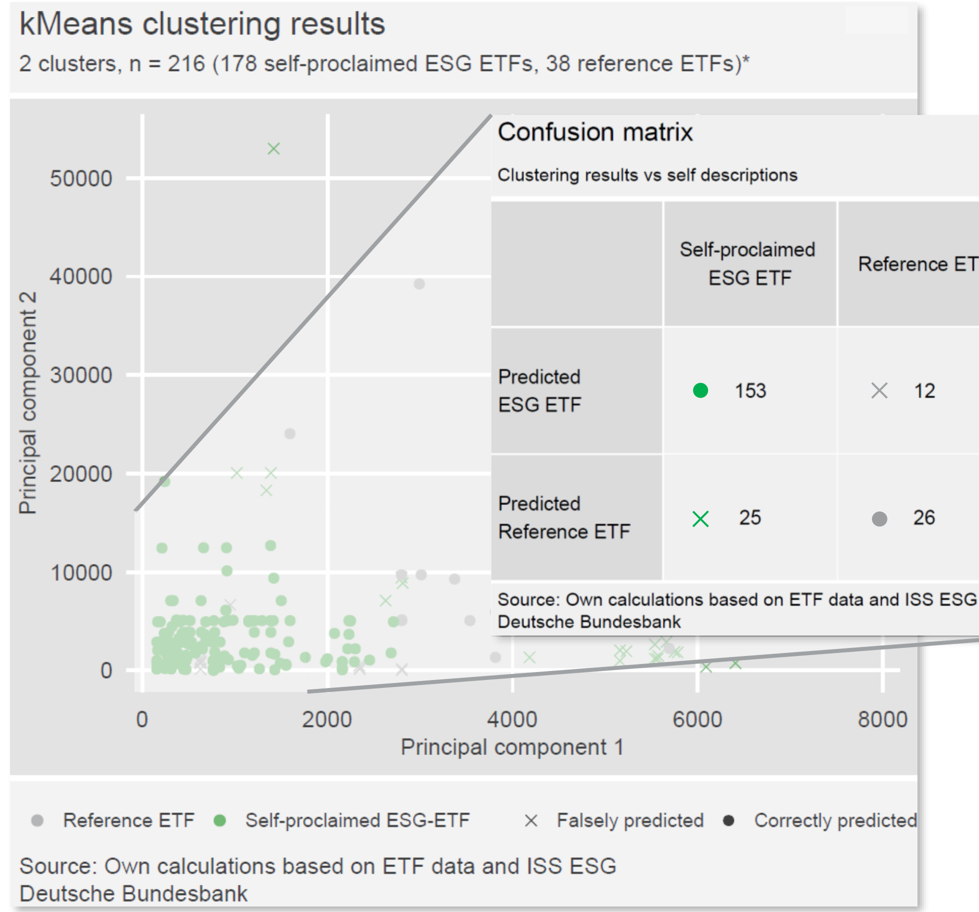
[1] Institutional Shareholder Services (ISS) ESG climate core package, data as of March 2022

[2] The 38 reference ETFs serve as a benchmark for 101 self-proclaimed ESG ETFs. Reference ETFs can be identified whenever ESG ETFs are based on a large reference index (e.g., "MSCI Europe ESG Screened" is based on "MSCI Europe"). For the remainder of 77 self-proclaimed ESG ETFs, we cannot map a reference index, usually because these ETFs are constructed "ground up" and do not have a regular reference index.

To mimic investor information, we cluster ETFs based on sectors and emissions

RESULTS

- We cluster using k-Means and a range of **features based on emissions, sectors,** best-in-class proxies, and fund-level variables
- Most informative features are **maximum scope 1 emission intensities** (not weighted) and the **ETF's age**
- **Sector composition doesn't seem to add much predictive value** (neither single nor aggregated using PCA**)
- Cluster classification is decent, however findings have some limitations***



	Self-proclaimed ESG ETF	Reference ETF
Predicted ESG ETF	153	12
Predicted Reference ETF	25	26

- Included variables in this graphic are "maximum holding's scope 1 emission intensity in fund" and "fund age". We try a wide range of predicted features and feature combinations including sector weights, average emission differences in fund holdings compared to sector averages, and others (details in Annex)
  ** PCA: Principal Component Analysis
  *** Limitations in the analysis include the variance of clusters depending on initial seed, an overrepresented majority class issue and more potential ESG variables on company-level to be considered

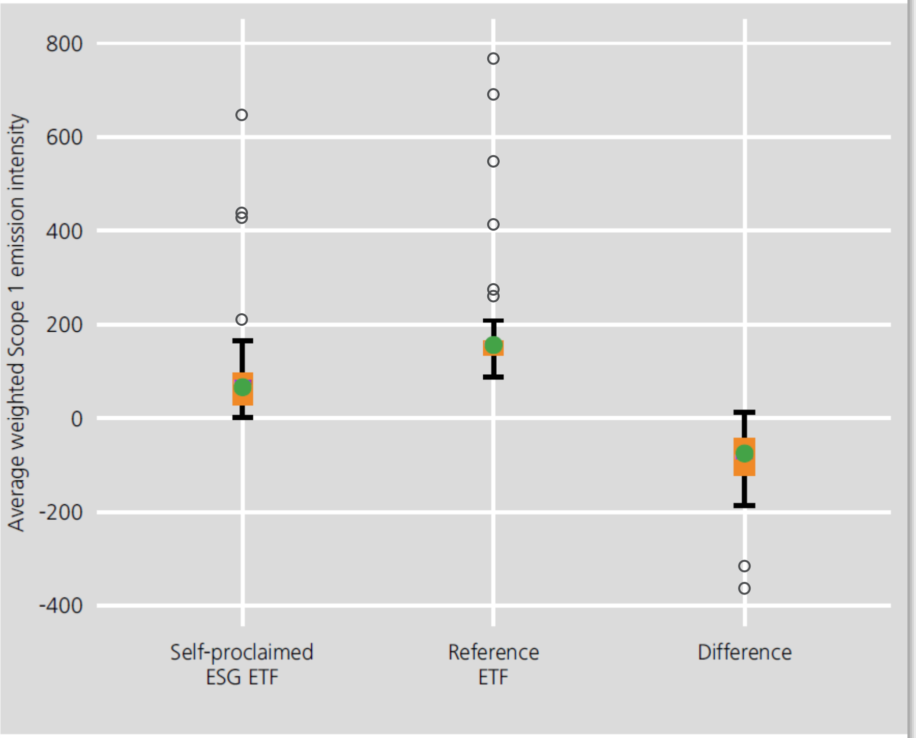
We compare emission intensities to further explore the drivers of incorrect cluster classifications

RESULTS

- Out of 101 self-proclaimed ESG ETFs that have a reference ETF, we identify **5** ETFs that have **higher average emission intensity** (AEI)* than their non-ESG reference ETFs
- For the remainder of **96 self-proclaimed ESG ETFs, we find their AEI to be lower** than their reference ETFs
- **Differences in AEI are significant** between self-proclaimed ESG ETFs and reference ETFs (p-value<.01)**

Average emission intensity comparison

Between self-proclaimed ESG ETFs (n = 101) with a known reference ETF (n = 38)



Source: Own calculations based on ETF data and ISS ESG
Deutsche Bundesbank

* Average emission intensity is the weighted sum of emission intensities of all holdings in a fund. Emission intensities are scope 1 CO_2 emissions as a fraction of company revenue
** Challenges for a t-test in our setting are that groups are not independent, reference group observations repeat themselves, degrees of freedom are thus not obvious to compute, and there is heteroscedasticity present. We consider a paired t-test, however other test settings similarly let us reject the null hypothesis that AEI between groups follows the same distribution

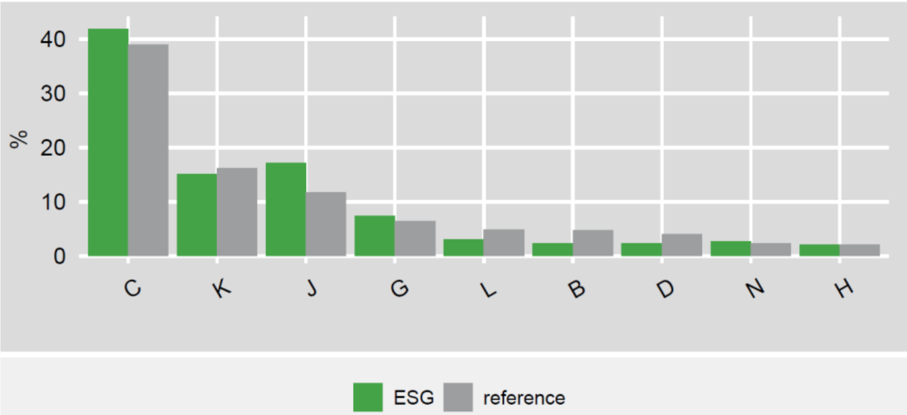
An analysis of sector composition suggests that funds reduce emissions by relocating capital across sectors

SECTOR COMPOSITION

- The most **dominant sector** in our sample is **manufacturing** (NACE C), followed by finance (NACE K) and information technology (NACE J)
- The **most emission intensive sectors** are **energy** (NACE D) and mining and quarrying (NACE B)
- Manufacturing has moderate emission intensity, while finance and information technology produce very little scope 1 emissions

Average share of most important sectors

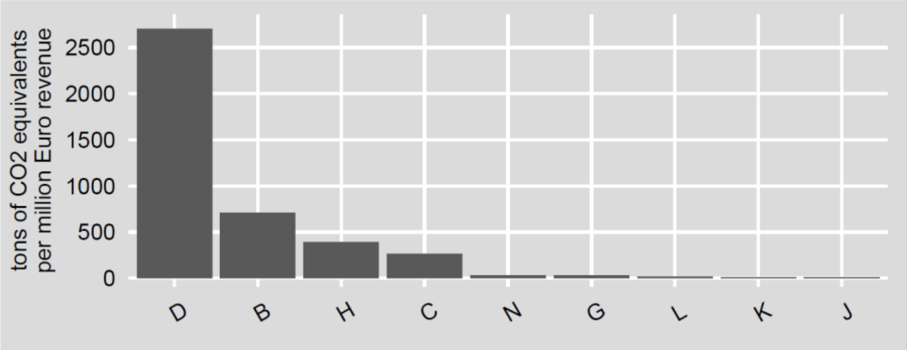
n = 139, out of which 101 self-proclaimed ESG ETFs and 38 reference ETFs



Source: Own calculations based on ETF data and ISS ESG
Deutsche Bundesbank

Average emission intensity of most important sectors

n = 29,264 companies in the ISS universe



Source: Own calculations based on ETF data and ISS ESG
Deutsche Bundesbank

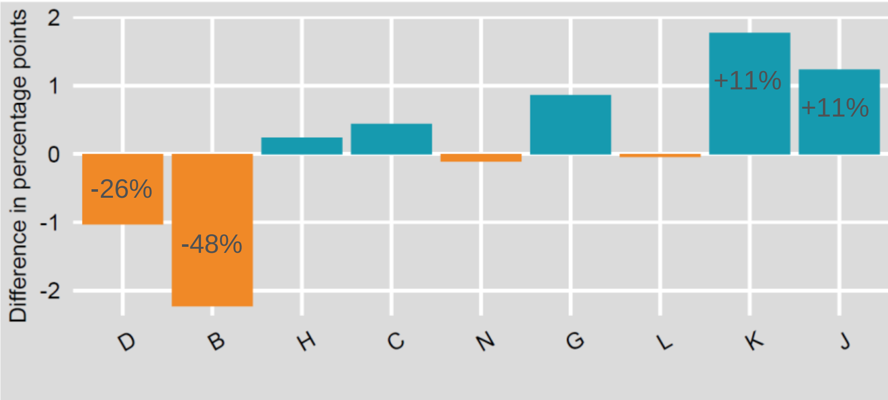
ESG ETFs seem to reduce investments in emission-intensive sectors

SECTOR COMPOSITION

- Self-proclaimed ESG ETFs seem to **shift away from the two most emission-intensive sectors** towards the two least emission-intensive sectors
- Therefore, part of the **emission intensity difference** between self-proclaimed ESG-ETFs and their reference ETFs can be **explained by differences in sector composition**
- Within emission-intensive sectors, there is **little evidence for a "best-in-class" asset selection**

Average difference in sector shares

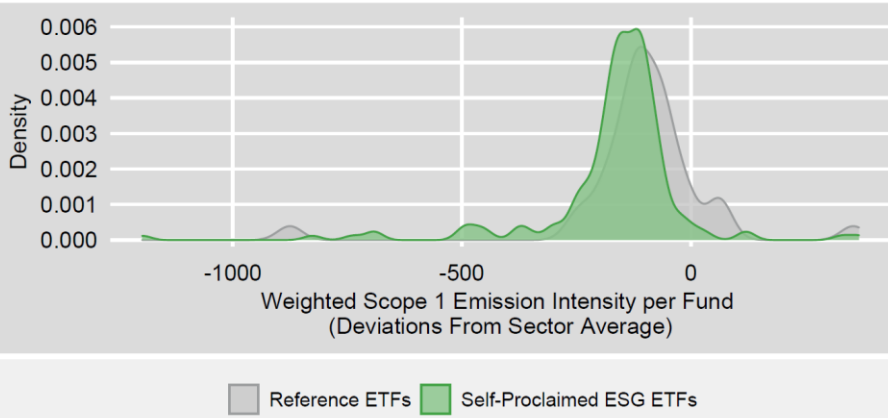
Difference between 101 self-proclaimed ESG ETFs and their respective reference ETFs



Source: Own calculations based on ETF data and ISS ESG
Deutsche Bundesbank

Deviations from sector average

Comparison between self-proclaimed ESG ETFs (n=178) and reference ETFs (n = 38)



Source: Own calculations based on ETF data and ISS ESG
Deutsche Bundesbank

Our results suggest that self-proclaimed "ESG" ETFs reduce emissions through a "sustainable sectors strategy"

1

CARBON FOOTPRINTS

- Self-proclaimed ESG ETFs seem to have **lower average emission intensities** than their reference ETFs
- Part of this reduction is driven by **divesting from emission-intensive sectors**
- We find **little evidence of a best-in-class** (positive selection) approach

2

TAKE AWAYS

- **Investors** on average reduce carbon exposure by investing in self-proclaimed ESG ETFs
- **Investors** looking to cover a **broad market**, while rewarding **lowest emitters within a sector**, cannot generally do so by investing in self-proclaimed ESG ETFs
- **Policymakers** need to ensure better data availability and transparency

3

ROAD FORWARD

- **Standardization** of sustainability criteria, enhanced transparency and data availability **is underway on company-level**.* Standardization on fund-level is yet to come
- Further analyses may focus on how positive and negative selection in self-proclaimed ESG ETFs **affects companies' cost of capital and incentives**

* e.g "EU taxonomy" (Regulation (EU) 2019/2088), Corporate Sustainability Reporting Directive (CSRD), Procedure (EU) 2021/0104/COD

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