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Green or brown: are article 8 & 9 fund portfolios different?

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ABSTRACT

This paper examines the extent to which the portfolios of green and conventional funds differ. We use non-metric multidimensional scaling to analyze the securities held by 6888 funds traded on European markets as of March 2023. This numerical methodology reduces the fund compositional matrix from thousands of dimensions to two dimensions, revealing patterns that can be studied graphically. We use the EU Sustainable Finance Disclosure Regulation's Articles 8 and 9 to classify green funds, and with few exceptions find that green fund portfolios are largely the same as conventional fund portfolios. A notable exception are energy sector funds, where there are distinct differences between the holdings of green and conventional funds. Our findings suggest that the EU's regulatory effort on sustainable finance has not yet delivered on anti-greenwashing objectives, and that green investing is doing little to shift investment allocations.

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1. Introduction

The stated purpose of 'green investment funds' (GIFs) is often put in terms of 'impact', achieved by aligning capital allocation with environmental or social objectives. A key issue debated is whether or not GIFs are, in fact, achieving stated objectives. The EU Sustainable Finance Disclosure Regulation (SFDR), which took effect in 2021, classifies funds under Articles 6, 8 and 9. A central objective of this regulation is to promote transparency on how financial market participants integrate impact and sustainability risks into investment decisions. It is hoped that this will help mitigate greenwashing, facilitate investor decision making, and support the EU's broader sustainability goals under the EU Green Deal.

It remains difficult to assess whether GIFs are in fact delivering on their impact purpose. One reason for this is the poor quality of the information used to assess investment impact, where Environmental, Social, and Governance (ESG) ratings and metrics have been a primary source of information. Despite many problems with ESG,[1] these measures continue to be widely used as a dependent variable in analyses designed to assess investment impact.[2] One reason for this is the lack of alternative methods to assess the environmental and social performance of investments.

The persistent problems with GIF assessments demand a new approach to assess the sustainability claims made by investors. This paper aims to assess whether GIFs achieve impact through their investment allocations. If GIFs are supposed to shift capital towards more sustainable activities, then one way GIFs should distinguish themselves from conventional funds is through the assets they hold. Comparing funds on the basis of their holdings would therefore offer a direct assessment of an important investment impact channel. If we find that GIF portfolios are indistinguishable from those of conventional funds, then it would provide partial but compelling evidence that GIFs may not be delivering on their impact claims. GIFs achieve impact through other mechanisms

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such as investor engagement but if there is little difference among fund portfolios, the onus would then fall on GIF managers to demonstrate the effectiveness of their engagement activities.[3]

A major challenge in the study of compositional differences of fund portfolios is the high dimensionality of the problem. The proportion of each individual security held in the portfolio represents a unique dimension along which fund holdings may vary. A single fund can hold hundreds of securities at any given time, which presents a challenge when comparing even a few funds, let alone the thousands of funds traded on the EU market. Accurately measuring compositional differences between fund portfolios therefore requires a method that can effectively keep track of the securities held, the relative within-fund weights of each security, correct for differences in the number of holdings, and allow for non-linear relations between co-varying dimensions. Yet, existing studies have not provided a convincing method to meet this challenge.

This paper fills this gap by adapting a computational method used by biologists and ecologists to capture the full dimensionality of fund holdings and respective holding weights for the portfolios of 6888 equity funds traded on European markets, and the 24,549 assets they hold. This allows us to evaluate the extent to which the allocations made by GIF managers are different from those made by the managers of funds without an impact objective. Non-metric multidimensional scaling (NMDS), as the method is called, is an ordination technique that allows us to both quantify and visualize differences in the composition of fund holdings. NMDS methods are particularly well-suited for this type of dimensional reduction challenge. They are well-established, featuring in literally thousands of published papers, but have not previously been applied to the study of fund portfolios.

As an analytical technique, NMDS aims to identify compositional trends in large multivariate datasets imposing few constraints on the shape of the input data. For EU equity funds, this means identifying patterns of divergence and similarity among funds that emerge as a result of examining the allocations made by funds at the level of the individual security. The input to the NMDS analysis is simply a fund compositional matrix consisting of 6888 rows (one for each fund) and 24,549 columns (one for each security). The NMDS output allows us to explore patterns of variation among fund portfolios by reducing the complexity of their relationships, based on the similarity of their holdings, into a two-dimensional visual representation. We then use *post-hoc* analyses of the NMDS results to further investigate the drivers of fund portfolio differences.

Our post-hoc analysis proceeds in two steps. In the first step we investigate the role of fund categories and benchmarks in determining fund portfolio allocations. Morningstar classifies funds into coarse categories based on the asset classes they invest in. These 'Fund Categories' should therefore explain a portion of observed patterns in the reduced-dimensional representation of EU fund portfolios. We expect funds of the same Morningstar category to cluster together. Likewise, benchmarks play an important role in determining the assets held by funds by defining the fund manager's preferred investment habitat (see Pavlova and Sikorskaya 2022). Fund managers have an incentive to hold stocks in the benchmark against which their performance is gauged. Benchmarking thereby plays an important role in shaping fund portfolios for both actively managed and passively managed funds (see Cremers and Petajisto 2009). We therefore expect funds to cluster around popular industry benchmarks. The Morningstar defined Fund Categories are coarse, with the largest Categories encompassing over 1500 funds with many benchmarks. We therefore use the NMDS method to define narrower fund peer groups and 'reveal' the benchmarks of funds with no benchmark information. This first step of the post-hoc analysis thus provides a reference point for the subsequent analysis of the similarity patterns of GIF portfolios.

In the second step we investigate the differences between the portfolios of GIFs and conventional funds. We use the fund classification system introduced by the EU's SFDR to define GIFs. SFDR sets requirements that classify all funds into one of three categories: funds with sustainable development as an explicit objective fall under Article 9; funds that promote sustainable development fall under Article 8; and all funds that do not have a sustainable development objective fall under Article 6. Given the SFDR objectives with GIFs, we should expect the NMDS based analysis to reveal systematic differences between Article 9, 8, and 6 fund portfolios. We examine the investment patterns of GIFs in aggregate, as well as within the coarse Morningstar Fund Categories and more narrowly define fund peer groups. Finally, we investigate carbon emissions and Morningstar's Fund Sustainability Rating to complement the analysis of SFDR Articles, and verify the extent to which these ESG metrics capture differences in fund portfolios.

The remainder of the paper is organized as follows: Section 2 reviews the literature on fund impact, Section 3 presents our methodology, and Section 4 introduces the data and key variables used in the analysis. Section 5 reports the results of the NMDS ordination as well as the results of the post-hoc analysis of Fund Categories and benchmarks. Section 6 compares GIFs and conventional fund portfolio allocations across the universe of EU equity funds. Section 7 performs a similar comparison within a selection of Fund Categories and Section 8 investigates fund portfolios, carbon emissions and Morningstar's Sustainability Rating. Section 9 concludes.

2. Barriers to assessing fund impact

As noted above, lack of reliable and credible information currently makes it challenging to assess the environmental and/or social performance of companies and funds (and thus assess their contribution to sustainable development). Much of the research on this topic has relied for the most part on ESG based metrics and ratings, which are problematic.

The first problem relates to the conceptual confusion over what ESG metrics are supposed to be measuring, often failing to distinguish between investing for financial *value*, and investing that is consistent with one's *values*, to use the terminology of Starks (2023). Many ESG ratings do not, and do not even claim to, align with sustainable development objectives, but are designed to capture primarily investment risk (see Chen, von Behren, and Mussalli 2021; Crona and Sundström 2023; Grewal and Serafeim 2020; Koenigsmarck and Geissdoerfer 2021; Wassénius, Crona, and Quahe 2024 and the review by Eccles, Lee, and Stroehle 2020).

Another problem is that ESG ratings are largely based on metrics reported by the corporations themselves using different reporting standards, resulting in biased and/or incorrect assessments. ESG reports have also been shown to selectively present favorable metrics (Kaplan and Ramanna 2021) and many corporations choose not to report certain ESG metrics at all, while others report a lot. Raghunandan and Rajgopal (2022) survey US corporations and find that actual corporate violations of environmental and social regulations correlate poorly with commercial ESG ratings. Inadequate verification of reported information and limited standardization has led to divergence between ESG ratings (Berg, Koelbel, and Rigobon 2022; Chatterji et al. 2016; Dimson, Marsh, and Staunton 2020).

Many studies of GIF performance suffer from flawed design. One flaw is that ESG ratings and metrics are often used as a dependent variable, while green fund managers often use ESG ratings to choose the securities. Comparing funds based on ESG ratings therefore makes for a circular or tautological design. Most papers conducting such comparisons therefore, unsurprisingly, find that GIFs have higher ESG ratings than conventional funds (see Curtis, Fisch, and Robertson 2021; Gibson Brandon et al. 2022; Joliet and Titova 2018; Kempf and Osthoff 2008; Nitsche and Schröder 2015; Pastor, Stambaugh, and Taylor 2023; Raghunandan and Rajgopal 2022). An exception is Kim and Yoon (2023), who find no evidence that funds that sign the United Nations Principles for Responsible Investment have higher ESG scores.

Another flaw is that many studies compare funds using fund-level weighted averages of ESG scores. This is problematic because many corporations do not report ESG metrics, as noted above. As a consequence, averaged metrics use various methods to adjust for holdings with missing data, or use imputed values (see e.g. Joliet and Titova 2018; McLean et al. 2022; Nitsche and Schröder 2015; Utz and Wimmer 2014). This introduces systematic biases, since companies that do not disclose ESG-relevant information (and thus do not have an ESG score) are likely to be among the worst performers.

Studies that examine differences in fund portfolios rely on various methods to simplify the problem. As noted earlier, comparing more than even a handful of fund portfolios is difficult due to the many dimensions involved. Various simplifications of this comparison problem have been employed in the literature. While not a flaw *per se*, these methods limit the extent of what can be examined. A simplification often employed is to focus only on a fund's top holdings (see Nitsche and Schröder 2015; Reiser, Tucker, and Beware 2020). Restricting the analysis to top holdings is problematic for several reasons. For one, this approach misses a significant and varying portion of the assets under management which could arguably have both positive and negative influence on a fund's sustainability achievement. It also ignores the fact that funds vary by the number of holdings in their portfolio. Moreover, it does not solve the problem of large dimension comparisons as keeping track of, and gleaning information from even the top holdings quickly becomes unmanageable for comparisons involving more than a handful of funds.

An approach that relates to the method we use is Active Share proposed by Cremers and Petajisto (2009), which measures the deviation of a fund's holdings from some reference point such as a benchmark. Active Share is also a way to simplify fund comparisons but relative to a given benchmark, and has been used in many studies assessing financial performance. It is, however, of limited use when examining differences between groups of fund, or for comparing funds relative to multiple benchmarks. We discuss Active Share and our method in the next section of the paper.

GIFs claim to deliver impact through their engagement activities, but it is a challenge to assess the extent to which GIF engagement changes corporate behavior. Heath et al. (2023) study the extent to which US GIFs improve US corporate environmental performance and workplace safety and conclude that GIFs are not following through on their promise of impact. Their analysis avoids commercially available ESG metrics and relies in part on official statistics gathered from the US Environmental Protection Agency and the US Department of Labor Occupational Safety and Health Administration.

These challenges require a new approach to help support the assessment of investment fund impact.

3. The NMDS method

This section introduces the method we use to analyze fund compositions, and motivates why the method is appropriate to study compositional differences of fund portfolios. NMDS is an unconstrained ordination technique that reduces the dimensions of a dataset, to two (and sometimes three) dimensions. For the study of funds, the NMDS axes are (a) non-linear re-combinations of all individual assets, weighted for their contribution in the main variation along those axes and (b) represent the main axes of compositional variation in the fund universe. The reduction to a manageable number of dimensions, and the fact that a dissimilarity index underpins how the analysis positions individual funds relative to each other while preserving to the extent possible the underlying data structure, makes visual representation and interpretation of the compositional differences in fund portfolios, even across many funds, both tractable and intuitive.

Differences in fund portfolio compositions are *not* likely to change gradually between different fund types. For example, certain groups of funds hold similar classes of assets (from a certain sector or country), whereas other groups of funds may hold entirely different classes of assets. This is a consequence, in part, of the fact that a key aim of asset management is to maximize risk adjusted returns, often against a defined benchmark, and to varying degrees, funds tend to track their benchmarks (see Cremers and Petajisto 2009).[4]

This means that Principal Components Analysis (PCA), which is an alternative method often used to study compositional differences in this type of data, is not appropriate for the study of compositional differences between funds. One problem is that PCA requires that each variable *must* relate linearly not only to the other variables but also to the principal components, and by definition uses only Euclidean distances as the similarity measure. PCA cannot therefore capture the compositional differences of funds holding entirely different assets, whereas NMDS methods can.

Another consideration is the handling of the large number of zero portfolio weights, which arise from the fact that the majority of assets from across the entire universe are absent in any given fund. While both PCA and NMDS can handle large numbers of zeros, NMDS is preferable since *(a)* it strives to preserve the rank-order of similarities in the reduced dataset as they were present in the full dataset and *(b)* zero-inflation renders the presence of non-linear relationships in the dataset far more likely.

We briefly describe the formal aspects of NMDS, but Legendre and Legendre (2012) provides a full treatment of the method. Let there be $(j, k) \in M$ funds with $i \in P$ holdings. The first step involves computing pairwise measures of fund portfolio dissimilarities for which the $M \times P$ matrix is the only input data. NMDS is then used to reduce the dimensions of the resulting symmetric $M \times M$ dissimilarity matrix.

3.1. Measuring dissimilarity

We apply the Bray-Curtis Dissimilarity measure:

$$d_{jk} = 1 - \frac{2 \sum_P \min(x_{ij}, x_{ik})}{\sum_P (x_{ij} + x_{ik})}, \tag{1}$$

where x_{ij} is the weight of holding i for fund j, and x_{ik} is the weight of holding i for fund k. We therefore have a Bray-Curtis Dissimilarity measure for each pair of funds, or $\frac{M(M-1)}{2}$ pairwise fund comparisons in a market with M funds, represented in a triangular $M \times M$ matrix.

This measure, developed by Bray and Curtis (1957) to study biological systems, is surprisingly similar to the Active Share measure developed by Cremers and Petajisto (2009) to study investment funds. Recall that the Active Share for a fund j with respect to its benchmark b is

$$S_{jb} = \frac{1}{2}\sum_{P}|x_{ij} - x_{ib}|, \tag{2}$$

Both Active Share and Bray-Curtis were developed to measure *dissimilarities*: Active Share is used to measure the degree to which a fund's asset allocation overlaps its benchmark index, and Bray-Curtis is a more general measure designed to compare the species overlap of two ecosystems. Where the reference fund is the benchmark ($k = b$) both Bray-Curtis and Active Share deliver essentially identical measures of distance. For example, both measures would be zero for a pure index fund, and unity for a fund that invests in none of the benchmark's assets.

The two measures differ in how long and short positions are considered. Active Share assumes that the weights of the two funds being compared each sum to 100%, hence the adjustment by the factor $\frac{1}{2}$. The Bray-Curtis denominator $\sum_P(x_{ij} + x_{ik})$ corrects for instances where a fund's holdings do not sum to 100%.[5]

An important difference between these two dissimilarity measures is that Bray-Curtis is used to measure the pairwise dissimilarity between all funds, and is therefore useful for comparing differences in holdings between individual funds that belong to different groups (e.g. do not share the same benchmark). Active Share, on the other hand, is more constrained to the study of how funds relate to their benchmarks. It requires that fund j's benchmark b is known, which may not always be the case.[6] Hence in a market of M funds tied to a single benchmark, there will be M Active Shares and $\frac{M(M-1)}{2}$ Bray-Curtis metrics.

Bray-Curtis Dissimilarities capture essential features of the fund market that Active Shares miss. GIFs may exclude certain assets from their portfolios entirely, i.e. negative screening. This is a popular GIF investment strategy that can involve avoiding certain 'sin' investments in e.g. fossil fuels, gambling and, up until recently, defense. Alternatively, GIFs may invest in the cleanest or most responsible corporations within a sector, i.e. best-in-class investing, or some GIFs could be called 'closet index funds', closely tracking an index. Bray-Curtis can capture these features, and perhaps others too, while Active Share can help identify closet index GIFs.

A systematic analysis of the differences between GIFs and conventional funds requires consideration of all *pairwise* dissimilarities between all funds in order to identify the systematic differences between fund holdings. The challenge is that a Bray-Curtis based analysis increases the dimensionality of the fund comparison problem to $\frac{M(M-1)}{2}$ pairwise dissimilarity measures. NMDS is then used to reduce the dimensionality of this problem.

3.2. Reducing the dimensions of the fund comparison problem

NMDS is an iterative optimization process aimed at finding a configuration of points in a reduced-dimensional space that preserves the rank order of the Bray-Curtis fund dissimilarities as closely as possible. This is achieved by fitting a monotonic function $f(d_{jk})$ that maps the symmetric $M \times M$ Bray-Curtis dissimilarities matrix to the ordination distances.

The specific monotonic function is determined iteratively during the NMDS optimization. The objective is to minimize Kruskal's Stress-1 function, which is:

$$y_1, y_2, \ldots$$

Care is needed when interpreting the plots in the ordination space. 'Distances' are non-metric (as the name of the method suggests). This means that pairs of funds may have different dissimilarities even if the ordination 'distance' between them is the same.

3.3. Fund categories, benchmarking, and active shares

Our analysis focuses on the extent to which EU SFDR Articles 6, 8 and 9 explain observed investment patterns across European equity funds. However, as a first step, our analysis investigates the extent to which other factors explain the observed investment patterns, namely Morningstar's Fund Categories, category benchmarks, and Active Share. We do this in part to verify the NMDS output with alternative measures of fund compositional differences, but also to provide a reference point for the insights revealed in the subsequent analysis of Article 6, 8, and 9 funds. The analysis of the NMDS output is done graphically, by simple visual inspection, and complemented by standard statistical tests.

Morningstar's Fund Categories provide a coarse classification of funds based on the assets they hold. Funds with similar assets belong to the same Fund Category. We should therefore expect the NMDS ordination to capture these Fund Categories. Practically, the NMDS ordination plot should show funds of the same Fund Category clustering together, and conversely funds of different Fund Categories separated from each other. Morningstar's Fund Categories are described in more detail in Section 4.

Fund benchmarks play an important role in determining the assets held by funds. Benchmarking defines the preferred investment habitat: fund managers have an incentive to hold stocks in the benchmark against which their performance is gauged, and benchmarks therefore play an important role in shaping fund portfolios for actively and *especially* passively managed funds (see Pavlova and Sikorskaya 2022). Benchmarks should therefore help explain similarities and differences between fund portfolios, and this should be evident by benchmarks featuring centrally in the output of the NMDS analysis. Funds with portfolios that closely track Fund Category benchmarks should appear as clusters around these benchmarks. Moreover, funds that cluster around the benchmarks should have a lower Active Share. However, an additional value of our ordination method is that it can reveal the benchmarks of funds that do not report a benchmark. The benchmark and Active Share data we use are described in more detail in Section 4.

3.4. GIF and conventional fund holdings

The EU's Sustainable Finance Disclosure Regulation (SFDR) became mandatory in March 2021, and specifies sustainability-related disclosures for the financial sector. SFDR requires financial market participants such as fund managers to collect ESG and other relevant data and align their reporting with the SFDR obligations. These reporting requirements apply to all investors, regardless of the environmental intentions of their investments.

The SFDR classifies funds into three levels by their contribution to sustainability, which we use in our analysis to distinguish the green intentions of funds:

Article 6 – Transparency of the integration of sustainability risks: Funds do not claim to have a sustainability scope but need to disclose how they have integrated sustainability-related risks into their investment decisions, and the potential impacts of these sustainability risks on financial returns.

Article 8 – Transparency of the promotion of environmental or social characteristics: Funds claim to *promote* environmental and social impact. Article 8 funds can make investments that meet certain ESG criteria, excluding investment in certain sectors (e.g. weapons and tobacco manufacturing) and/or invest in companies that have higher ESG scores.

Article 9 – Transparency of sustainable investments: Funds claim to have sustainable investment as their *primary objective* and shall specify alignment with the EU Platform on Sustainable Finance's Technical Advisory Body. Unlike Article 8, Article 9 funds need to disclose how the investment achieves its stated objectives; justification that the investment does no significant harm to some other social or environmental objective; and justification that the investment is in a company that follows good corporate governance practices.

The regulation aims to provide the financial industry with a common language (taxonomy) on what qualifies as a green investment and is part of an effort to keep greenwashing in check. We refer to EU's SFDR Article 8 and 9 funds collectively as GIFs.

Table 1. Fund categories defined by Morningstar and respective benchmarks selected for the analysis.

Fund Category	AUM	Number of Funds All	Art. 9	Art 8	Primary Category Benchmark
Global Equity Large Cap	1052.3	1560	133	782	MSCI ACWI
Europe Equity Large Cap	652.9	1545	64	813	MSCI Europe
Europe Equity Mid/Small Cap	114.2	555	12	304	MSCI Europe SMID
Global Emerging Equity	214.4	414	14	243	MSCI Emerging Markets
US Equity Large Cap Blend	392.0	350	7	173	Russell 1000
Technology Sector Equity	108.9	206	9	117	MSCI IT
Energy Sector Equity	30.4	72	14	29	MSCI Energy
Other	81.0	1986	101	851	NA
Total	2,718,527	6888	354	3312	

Note: Assets under management are expressed in billions of EUR.

4. Data and variables

We gather fund-holding data from Morningstar's Direct database for European equity funds for 2023-05-22. Of the 12 210 funds in the database with reported portfolio holdings, we exclude funds with non-equity holdings larger than 5%. We exclude all unidentifiable holdings (with no ISIN number), and shorted holdings (having a negative weight). To ensure that the funds in our sample have enough information for our analysis, we removed all the funds for which we can track less than 90% of the sum of holding weights. The resulting data set for the analysis includes 6940 unique funds and 24,569 holdings for the European market. 52 of these funds are outliers in terms of their holdings and are therefore also dropped from the analysis. The NMDS analysis covers 6888 funds and their holdings. The NMDS input data includes only the fund's name, the assets held by these funds, and the weight of each asset in the fund's portfolio.

In addition to fund holdings, our data includes an indicator for Article 8 and 9 GIFs, Morningstar defined Fund Category designations, fund benchmarks, tracking errors, Active Shares, carbon emission metrics, and Morningstar's Fund Sustainability Rating. These variables play a role in our post-hoc analysis of NMDS outputs.

4.1. *Fund categories*

Morningstar Fund Categories distinguish funds by the types of assets held over the last three years. Asset types are defined across sectors, geography, the size of the corporation, and other observed asset characteristics. This makes these categories useful for verifying how much the NMDS methodology captures the compositional variation in fund holdings between these categories. Therefore, we expect funds of the same category to cluster together in our NMDS ordination plots.

Morningstar also assigns a primary benchmark to each Fund Category. For example, the category for Global Equity Large Cap funds is benchmarked to the MSCI All Country World Index (ACWI) whereas the category for Energy Sector Equity funds is benchmarked to the MSCI World/Energy Index. Some Fund Categories are linked to more than one benchmark.

We focus our analysis on 7 of Morningstar's largest Fund Categories, and their respective benchmarks, which are listed in Table 1. There are several categories populated by fewer funds, which we aggregate under the category of 'Other'.

These Fund Categories provide a coarse overview of fund peers groups. However, we can use the benchmarking data to identify more granular sub-groups of fund peers. For example, Global Equity Large Cap includes 1560 funds, but we observe that most of these funds are not benchmarked to MSCI ACWI but to other more regional benchmarks such as EURO STOXX 50 or FTSE 100. The benchmarking data is useful for identifying more granular fund peer groups that will be useful for our analysis of fund holdings.

4.2. Article 6, 8 and 9 funds

Morningstar's data reports if a fund claims to comply with Article 8 or 9. We designate a fund as Article 6 if it makes no claim to comply with Article 8 or 9. Thus, Article 6 funds include funds that intend to become an Article 8 or 9 fund, but for various reasons had not yet done so as of the data access date.

The number of GIFs per fund category is reported in Table 1. Article 8 funds are the most common and Article 9 are the least common, with 3312 and 354 funds, respectively. 72% of the aggregate AUM of our fund sample falls under Article 6 Funds. Article 8 and 9 funds are on average relatively small.

5. EU equity funds and their holdings

In this section we introduce the NMDS ordination plot and use it to explore features of the fund market. We investigate investment patterns in terms of Morningstar's Fund Categories and benchmarking. We also use the NMDS ordination plot to define more granular fund categories and investigate funds that do not 'reveal' their benchmark.

The $M \times P$ matrix input to the Bray-Curtis dissimilarity calculation (Equation (1)) consists of 6888 rows (one for each fund M) and 24,569 columns (one for each security P). The resulting output is a symmetric matrix of $M \times (M - 1)$ pairwise dissimilarity measures, which are fed into the NMDS optimization process to minimize Kruskal's Stress-1 (Equation (3)). Note that the input data does not include information about the Fund Category, nor if it is an Article 6, 8, or 9 fund, which will enter only with the post-hoc analysis.

These computations reduce the 24,569 dimension European equity fund universe to three composite NMDS axes, with a final stress of 0.02. As a diagnostic, a stress value < 0.2 is generally considered to indicate an acceptable goodness of fit, values below 0.05 indicate a good fit. Our low stress of 0.02 suggests a goodness-of-fit between the original fund universe data structure and that of the reduced NMDS ordination space. In the discussions that follow we focus on the first two axes for clarity.

To familiarize ourselves with the interpretation of the NMDS ordination space, we first examine the full set of 6888 funds from the European fund universe Figure 1. Each dot represents a single fund. There are thus 6888 dots plotted in the figure.

The axes of the plot have no 'real' interpretation, but are an output of the NMDS ordination that is tasked with capturing the best two-dimensional fit for the relative dissimilarity between funds. The distance between the points in Figure 1 reflects the rank order of the dissimilarities between fund portfolios in the original 24,549-dimensional space. Hence, funds that are close to each other in the plot tend to have very similar holdings, whereas funds that lie far from each other have very different holdings. The position of each fund in the plot matters only in terms of the distance between them.

To illustrate, consider two pairs of funds identified with the blue and red dots. The blue pair of funds are located far from one another, at the top and bottom of the figure, and represent *Schroder UK Smaller Companies A Acc* and *SPDR S&P US Technology Select Sect ETF*, respectively. These two funds do not have any common holdings, and their Bray-Curtis Dissimilarity measure is 1.0.

The red pair of funds are located close to one another and have similar holdings that are also weighted similarly (see Appendix Table A1). This pair of funds is *State Street Switzerland Idx Eq P CHF* and *GKB Aktien Schweiz ESG I*. The Bray-Curtis Dissimilarity measure for these two funds is 0.148. This example illustrates how the NMDS ordination accounts for the multi-dimensionality of funds and provides a simple means to visually analyze fund portfolio (dis)similarity.

5.1. Fund categories

Figure 1 also exhibits a structure composed of various clusters. This suggests that funds vary in their degree of similarity. Some funds have holdings that are quite different from other funds, while other funds have holdings that are similar to other funds. We use the NMDS ordination plot to explore the factors that explain the clustering patterns we observe. As a first step of our post-hoc analysis we explore explanatory factors for observed

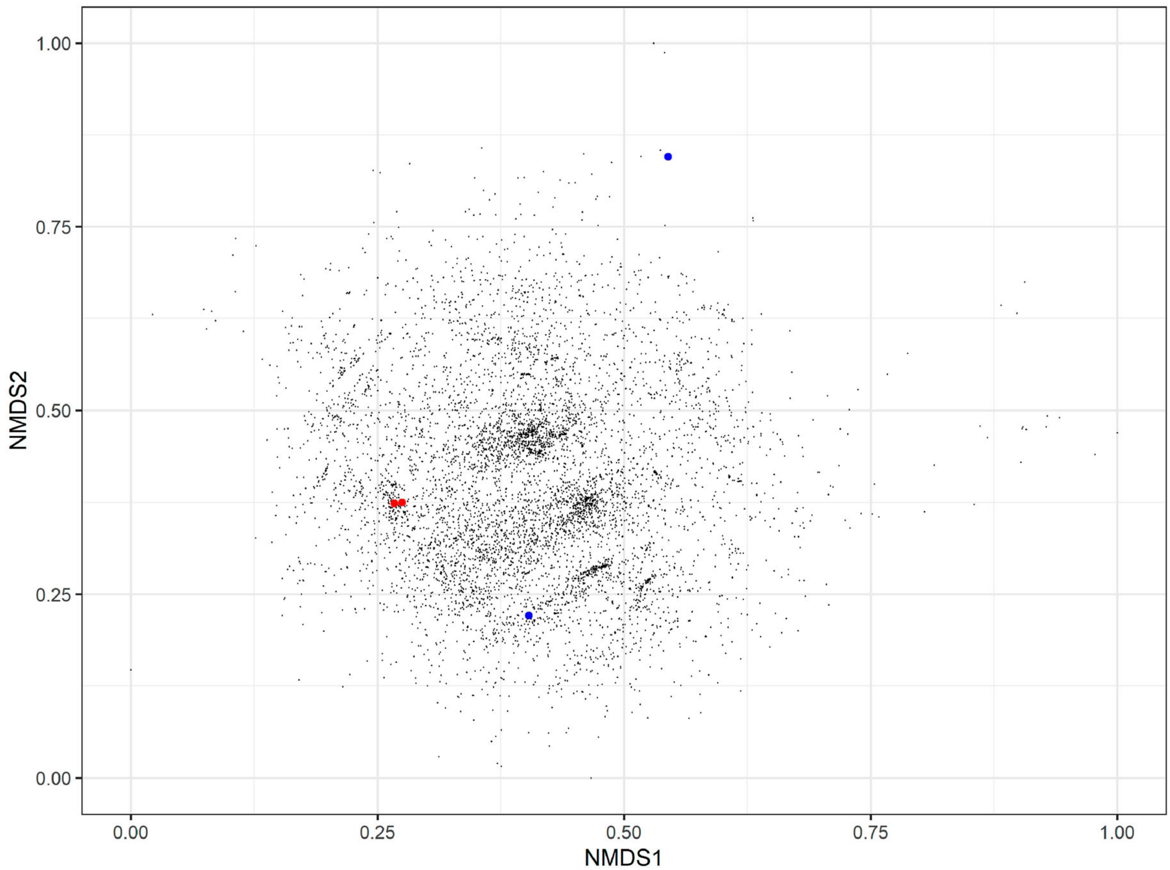


Figure 1. Bray-Curtis distance-based NMDS-analysis using a matrix of the relative abundances of 24,569 holdings in 6888 EU funds, with a fund pair with similar (in red) and dis-similar (in blue) holdings.

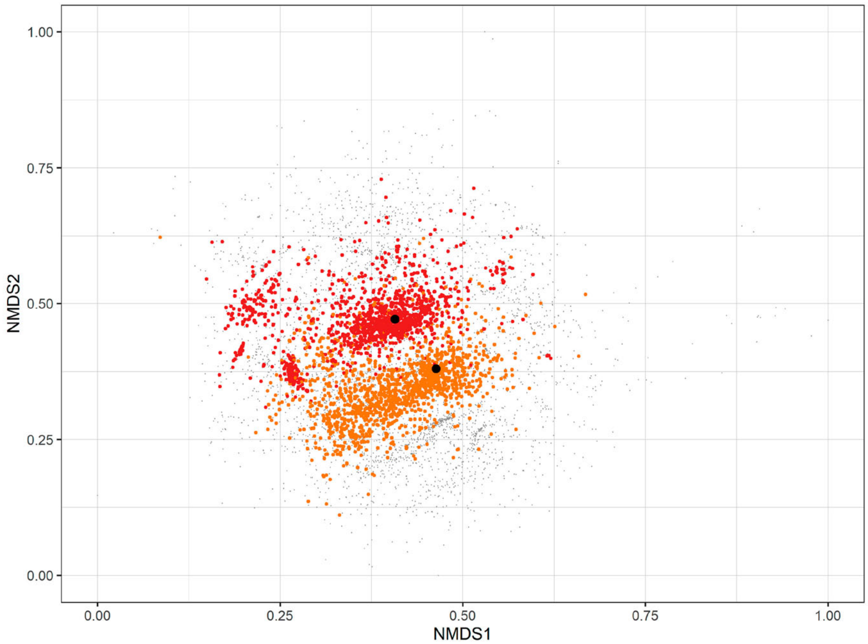
similarities and dis-similarities of fund portfolios with the help of Morningstar's Fund Categories, which are admittedly coarse but serve to illustrate the point.

Funds of the same Fund Category should theoretically cluster together, since each Category groups funds with similar holdings, as discussed in Section 4. We verify this by checking the degree to which funds from the same Fund Category cluster together, and the degree to which there is a positional separation of funds from different Fund Categories in the NMDS ordination space. For ease of interpretation, we plot sub-samples of Figure 1 and compare two pairs of Fund Categories.

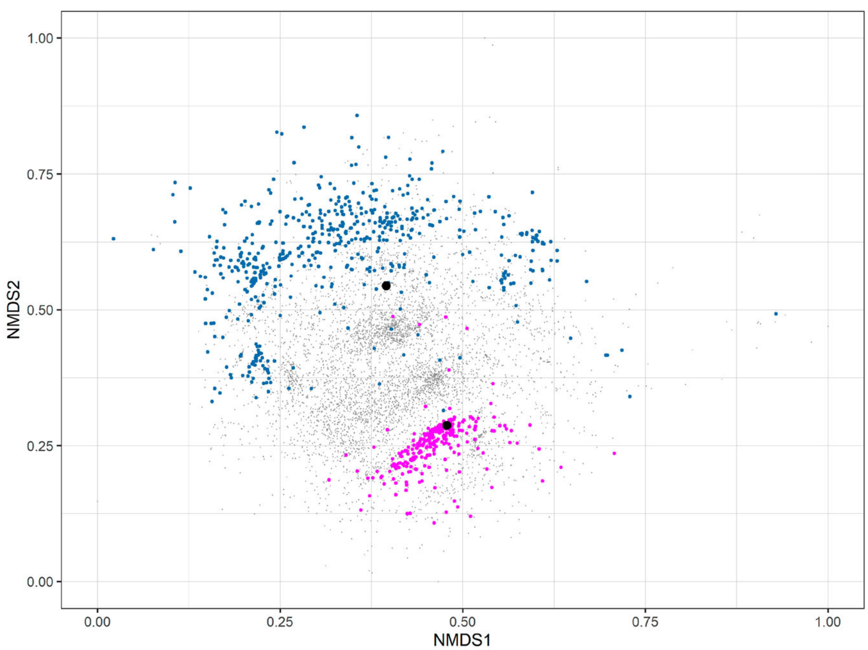
Figure 2(a) compares the two largest Fund Categories in our data set (by number of funds and AUM): Europe Equity Large Cap funds and Global Equity Large Cap Funds. By visual inspection of the figure, it is clear that the funds within each of these two Fund Categories cluster together, confirming our expectations.

Figure 2(b) compares the third and fourth largest pair of Fund categories: US Equity Large Cap Blend funds and Europe Equity Mid/Small Cap funds. Again, the funds clearly cluster along their respective Fund Categories. NMDS ordination plots making similar comparisons for Technology Sector Equity Funds, Global Emerging Equity Funds, and Energy Sector Equity funds are provided in Appendix Figure A1.

Fund Categories thus emerge as an important factor for explaining the patterns of fund holdings observed for the universe of European equity funds. As a first test it suggests the NMDS ordination does a good job of capturing known and expected differences between funds, helping to validate its use to compare fund portfolios.



(a) Europe Equity Large Cap funds (in red) and Global Equity Large Cap funds (in orange) clustered around their benchmarks, MSCI Europe and MSCI ACWI (in black), respectively.



(b) US Equity Large Cap Blend funds (in pink) and Europe Equity MidSmall Cap funds (in blue) clustered around their benchmarks, Russell 1000 and MSCI Europe SMID (in black), respectively.

Figure 2. NMDS ordination plot for pairs of fund categories. (a) Europe Equity Large Cap funds (in red) and Global Equity Large Cap funds (in orange) clustered around their benchmarks, MSCI Europe and MSCI ACWI (in black), respectively and (b) US Equity Large Cap Blend funds (in pink) and Europe Equity MidSmall Cap funds (in blue) clustered around their benchmarks, Russell 1000 and MSCI Europe SMID (in black), respectively.

5.2. Benchmarking and active shares

Benchmarking plays an important role in determining a fund manager's preferred investment habitat and should also help explain fund clustering patterns in the NMDS ordination plot. Passively managed funds should cluster around popular benchmarks, whereas actively managed funds plot on the periphery of these clusters.

Funds do cluster around popular Fund Category benchmarks, as expected. Recall that Morningstar designates a benchmark (see Table 1) to each Fund Category.[7] Figure 2(a) illustrates this clustering clearly: Europe Equity Large Cap funds and Global Equity Large Cap Funds cluster around the Category benchmarks, which are MSCI Europe and MSCI ACWI, respectively. In Figure 2(b), US Equity Large Cap Blend funds cluster closely around the Russel 1000. Interestingly, there is a relatively higher dispersion of Europe Equity MidSmall Cap funds around its category benchmark MSCI Europe SMID.[8]

The relatively tight cluster of US Equity Large Cap Blend funds in Figure 2(b) suggests these funds share similar holdings, and should have a higher share of passive management than the wider clustering of the Europe Equity MidSmall Cap funds. We verify this roughly by examining the number of passively managed funds (with 'ETF' or 'ishares' or 'index' in the fund name) and find that 7% of Europe Equity MidSmall Cap funds are ETFs, whereas 55% of the US Equity Large Cap Blend funds are ETFs. The tighter clustering of US Equity Large Cap Blend funds around the benchmark is most likely explained by the higher rate of ETFs in this category and is consistent with the way passive funds track popular benchmarks (Chinco and Sammon 2024 report on the prevalence of passive fund management). Morningstar provides an indicator for index funds, which yields the same insight as our rough check.

We also investigate Active Shares (where the data is available) for EU Equity Large Cap and EU Equity Mid/Small Cap Funds explicitly to see if they can explain the NMDS output. Figure 3 plots 2100 funds that belong to these two categories, and the Active Shares for each fund. There is a concentration of lower Active Share funds in the main central cluster of the figure, benchmarked to MSCI Europe Large Cap Index. Funds with a higher Active Share tend to be in the periphery. This is the pattern one would expect the NMDS ordination to capture. Funds with holdings that are dissimilar to the benchmark should be in the periphery and funds with holdings that are similar should cluster around the benchmark.

Many funds are, however, missing a benchmark and/or an Active Share. Of the 2100 funds plotted in Figure 3, Morningstar reports the benchmarks for 1795 funds, with 305 funds missing benchmarks. Active Shares are reported for 570 funds with 1530 missing. However, 192 funds have neither a Benchmark nor an Active Share. Missing Active Shares plot as gray dots in Figure 3, and appear not only within the main central cluster, but also in the periphery, and particularly in the south west quadrant of the plot.

Recall that Active Shares should correlate with the Bray-Curtis Dissimilarity measure between funds and their benchmarks (compare Equations (1) and (2)). Where Active Share is observed, the Spearman Correlation between the two is almost 88%, confirming the hypothesized similarity of the measures.[9]

5.3. 'Revealed' benchmarks

The NMDS ordination plot provides information that can 'reveal' the benchmark of a no-benchmark fund (shorthand for a fund with missing benchmark information). Funds with benchmarking information can help provide information on adjacent no-benchmark funds, as funds clustered together are likely to share a common benchmark. Index funds are particularly useful in this regard.

Figure 4(a) plots all 2100 EU funds. Index funds are highlighted and clustered based on holdings dissimilarity.[10] We designate each cluster by their geographic focus, which we can determine by examining the common holdings for each cluster: Pan Euro, Swiss/Danish, and Nordic. Funds in the Pan Euro clusters invest mostly in German, French and British assets.

We 'reveal' missing benchmarks with the help of these clusters of index funds. Cluster Swiss/Danish in Figure 4(b) is interesting because it contains a relatively tight cluster of 41 index funds, and 29 no-benchmark funds. The cluster also includes 145 non-index funds that report their respective benchmarks. Table 2 summarizes the many benchmarks for index and non-index funds in cluster Swiss/Danish, and the tracking errors for the funds with respect to the respective benchmarks.

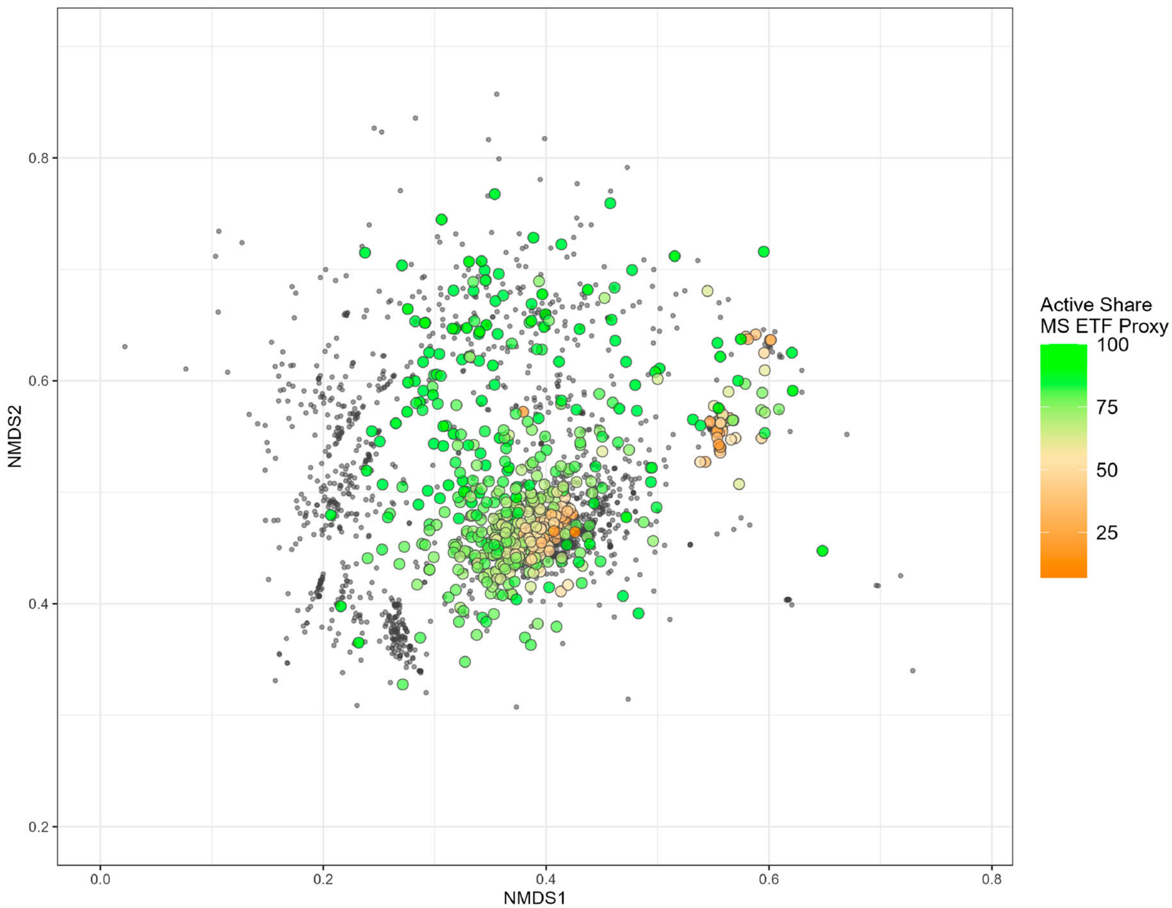


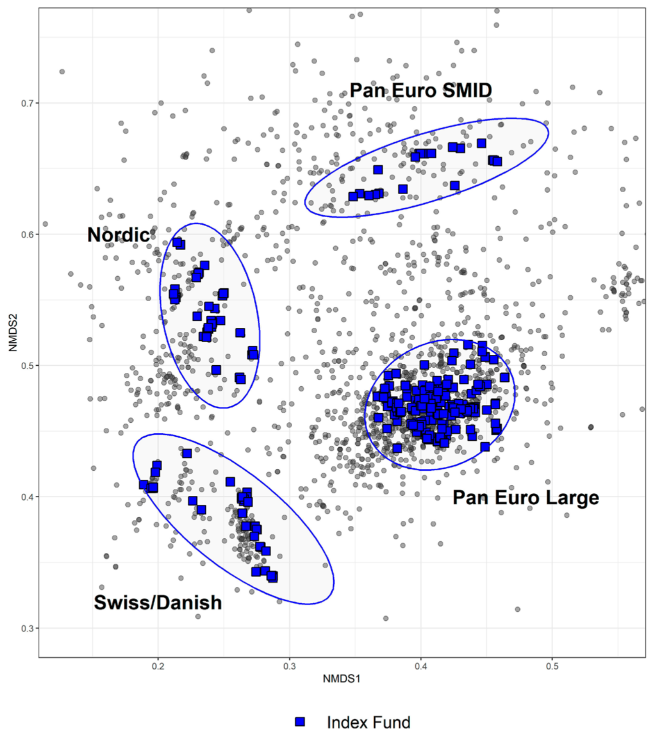
Figure 3. Active management of Europe equity large, mid, and small cap funds. Grey points indicate missing Active Share data.

Closer examination of Cluster Swiss/Danish (in Figure 4(b)) reveals that it is itself composed of three sub-clusters of funds that report their benchmark. The largest of the three by AUM includes funds benchmarked to SPI, which is a broad index for the overall Swiss equity market. The second cluster includes funds benchmarked to SPI EXTRA, which is an index of mid- and small-cap for the Swiss Equity Market. The third includes funds benchmarked to the NASDAQ OMX Cph index, for Copenhagen. Each of these three sub-clusters include funds that report their benchmarks, no-benchmark funds, and index funds.

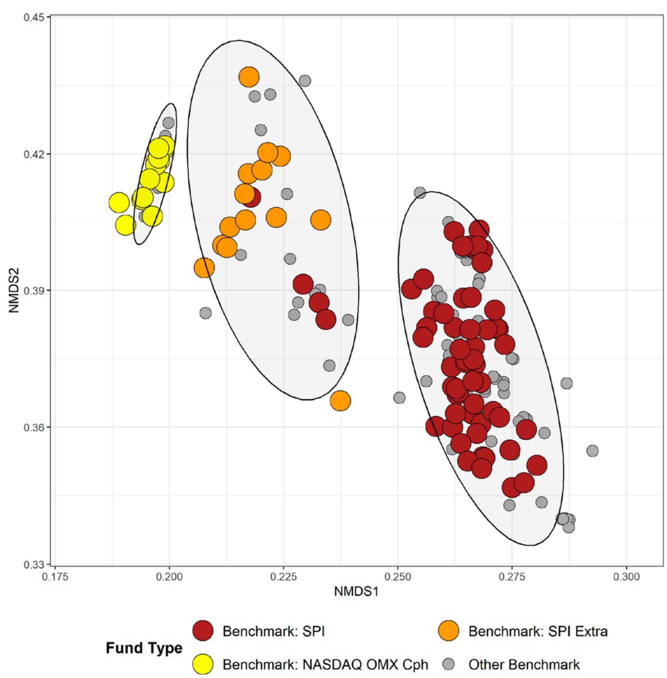
Figure 5(a) plots the same three sub-clusters as Figure 4(b) but indicates the no-benchmark in red and index funds in blue. The clustering of the no-benchmark funds together with the index funds provides information that can help reveal the benchmark of no-benchmark funds.

To verify that the NMDS ordination is conveying useful information, we formally test for differences in the Bray-Curtis dissimilarity measures to identify the best fit for the no-benchmark funds. This should be the clustering where Bray-Curtis dissimilarities between the no-benchmark funds and the index funds are the lowest. Figure 5(b) compares Bray-Curtis measures for no-benchmark funds in the SPI sub-cluster and index funds across the Cluster and sub-clusters of Swiss/Danish.

The left box-plot indicates the distribution of Bray-Curtis between no-benchmark funds and all index funds in Cluster Swiss/Danish. The mean dissimilarity is 0.52 with 0.40 and 1.00 for the 25th and 25th percentiles: each no-benchmark fund in the Cluster shares on average 48% of its holdings with each index fund and there is significant variation, some sharing much more and other sharing nothing.



(a) Clusters of index funds.



(b) The Swiss/Danish sub-clusters.

Figure 4. Clustering of EU Equity large cap, and eu equity small/mid cap funds. (a) Clusters of index funds and (b) The Swiss/Danish sub-clusters.

Table 2. Primary benchmarks for cluster Swiss/Danish funds.

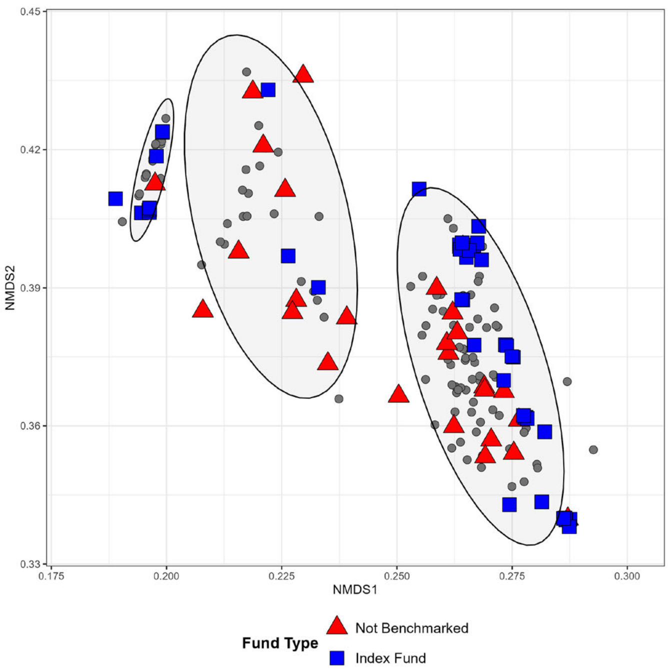
Benchmark	Count	Mean Tracking Error %	AUM
Index Funds			
SIX SMI TR CHF	4	1.73	6.91
SIX SPI TR CHF	4	1.40	5.62
SIX SLI Swiss Leaders TR CHF	3	3.19	1.65
MSCI Switzerland NR CHF	3	0.70	1.82
SIX SPI Select Dividend 20 TR CHF	2	1.94	2.58
SIX SMI Mid TR CHF	2	5.18	2.40
MSCI Switzerland 20/35 NR LCL	1	0.70	2.01
DJ Titans Switzerland 30 TR CHF	1	3.60	0.13
MSCI CH IMI HDY ESG Low C Sel NTR CHF	1	3.11	0.01
MSCI Switzerland IMI +5% Iss Cp NR CHF	1	3.67	0.81
MSCI Switzerland IMI Min Vol TR CHF	1	2.93	0.16
NASDAQ OMX Copenhagen Cap GR DKK	3	17.47	0.53
OMX Copenhagen 25 GI PR DKK	3	17.18	0.57
Other benchmarks	12	5.73	3.55
Total	41	–	31.87
Non-Index Funds			
SIX SPI TR CHF	36	2.94	14.63
SIX SPI Extra TR CHF	11	4.40	2.04
SPI TR	7	2.70	1.77
SPI EXTRA TR CHF	4	4.56	0.22
SIX SLI Swiss Leaders TR CHF	3	4.00	0.22
Swiss Performance Index CHF	3	2.58	0.85
SPI CHF	2	2.26	1.65
Swiss Performance Index (SPI) GD	2	3.03	0.22
SIX SLI Swiss Leaders PR CH	2	6.30	0.15
MSCI Switzerland 10/40 NR USD	1	2.16	0.03
MSCI Switzerland IMI Select ESG	1	1.42	0.13
MSCI Switzerland NR CHF	1	4.23	0.28
NASDAQ OMX Copenhagen Cap GR DKK	12	16.85	3.29
OMX Copenhagen Capped index NR	2	16.32	0.43
Not Benchmarked	29	5.05	3.79
Other benchmarks	29	3.00	3.37
Total	145	–	33.05

Notes: AUM is given in billions of Euro.
The reported mean tracking errors are calculated over the funds included in the 'Count' column.

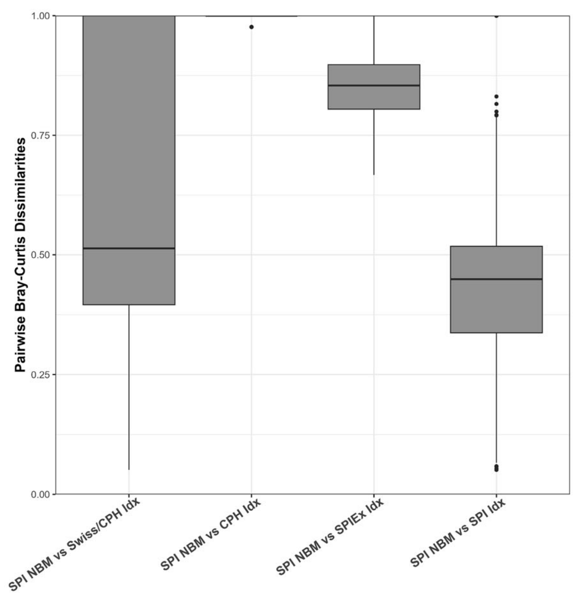
The second through fourth box-plots from the left compare Bray-Curtis between no-benchmark funds and the three respective sub-clusters index funds. The no-benchmark funds in the SIX SPI cluster have the lowest dissimilarity with the index funds in the SIX SPI cluster (with an average of 43%) indicating that the NMDS ordination is clustering funds as it should, and that the no-benchmark funds in the SPI sub-cluster are probably benchmarked to SIX SPI.

Revealing the missing benchmarks can be done manually without the help of the NMDS ordination by simply using the Bray-Curtis dissimilarities between funds and various benchmarks. One could simply identify fund and benchmark pairs with minimum dissimilarity measures and thereby identify the fund's benchmark, and also perhaps closet index funds. However, such a manual approach would provide less information about the funds than the NMDS method. While the manual approach can be used to reveal fund benchmarks, it would do little to identify systematic holding differences between different groups of funds, which is the main purpose of our paper. The NMDS method is particularly powerful for not only identifying fund peers but also for understanding how different peer groups relate to one another based on their composition of holdings. For example, an insight from Figure 5(b) is that no-benchmark funds in the SPI sub-cluster share more similar holdings with SPI Extra Index Funds, than with NASDAQ OMX Cph Index Funds.

The above elaborations and tests show that the patterns captured by the NMDS output are consistent with known features of the fund market. Specifically, Fund Categories, benchmarking and active management shares help explain the differences and similarities between fund portfolios and these features are captured by the



(a) Index Funds and NBM funds in the NASDAQ OMX Cph, SPI Extra, and SPI sub-clusters .



(b) Distributions of Bray-Curtis dissimilarities for NBM funds in the SPI cluster to index funds in the other benchmark sub-clusters. The boxes indicate the 25^{th} and 75^{th} percentiles and the whiskers $\pm 1.5 \times$ the inter-quartile range.

Figure 5. Index funds and no-benchmark (NBM) funds in Cluster Swiss/Danish. (a) Index Funds and NBM funds in the NASDAQ OMX Cph, SPI Extra, and SPI sub-clusters and (b) Distributions of Bray-Curtis dissimilarities for NBM funds in the SPI cluster to index funds in the other benchmark sub-clusters. The boxes indicate the 25th and 75th percentiles and the whiskers $\pm 1.5\times$ the inter-quartile range.

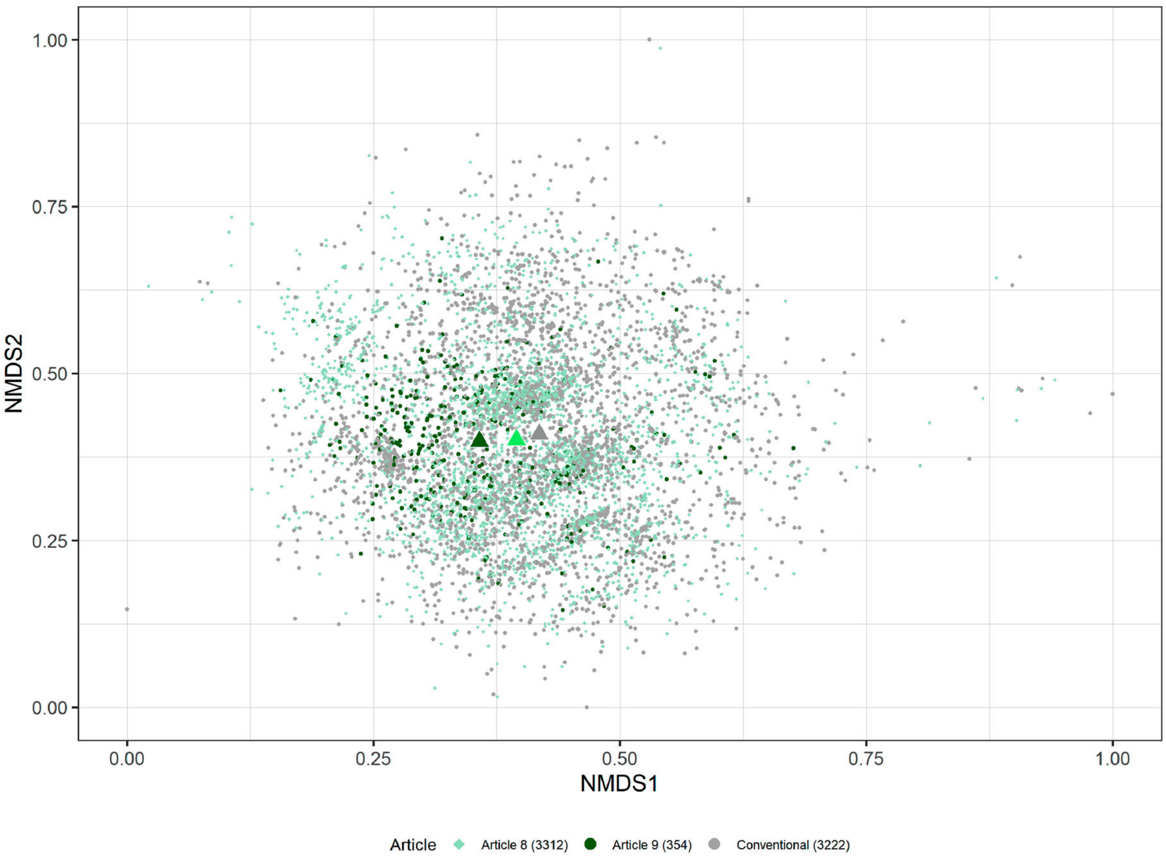


Figure 6. The universe of European funds with Article 6 (grey), Article 8 (light green), and Article 9 (dark green). The triangles indicate the centroid of each fund group.

NMDS ordination plot. Moreover, NMDS plots can be used to reveal the benchmark of no-benchmark funds, and help identify a fund's closest peer group. Confident in the usefulness and reliability of the Bray-Curtis Dissimilarity measure and NMDS methodology, we now use them to examine GIF holdings.

6. GIFs in the universe of European equity funds

Figure 6 plots the full set of 6888 funds in our data but distinguishes Article 6, 8, and 9 funds. The figure provides several insights.

One insight is that Article 9 funds appear as a subset cluster of Article 8 funds, which are themselves a subset of Article 6 funds. This nested pattern is consistent with the fact that a commonly used green investment strategy involves 'negative screening', which imposes constraints on a fund's investable universe.[11] The NMDS ordination suggests that there are certain assets that Article 8 and 9 funds do not invest in.

However, there is little evidence of the opposite outcome, where Article 8 and 9 funds invest in assets that Article 6 funds do not invest in. In fact, Figure 6 reveals that most Article 8 and 9 funds are surrounded by Article 6 funds, which means that for each Article 8 and 9 fund, one is likely to find an Article 6 fund with very similar holdings. The centroids of Articles 6, 8 and 9 funds are plotted in Figure 6.

In comparative terms, the differences between Article 6, 8 and 9 funds are an order of magnitude smaller than the differences between Fund Categories reported in Section 5.1.[12] To help the visualization, we plot the centroids of the Article 6, 8, and 9 fund clusters. This shows that Article 9 funds tend to cluster left of Article 8 funds, which themselves cluster to the left of the Article 6 funds.

We verify this in two ways. Firstly by calculating the correlation between Articles 6, 8 and 9 funds and the NMDS axes. The correlations align with the trend that GIFs cluster towards the left of the plot. The Spearman correlations are reported in Appendix Table A2.

Secondly by using ANOVA to test the degree to which Article 6, 8, and 9 funds cluster distinctly. The ANOVA test results confirm that funds cluster by SFDR Article mainly along the NMDS1 axis, but that the η^2 effect is smaller than that observed for Morningstar Categories, where the main effect is along the NMDS2 axis. These ANOVA test results are reported in Appendix Tables A3 and A4.

A claimed benefit of Article 8 and 9 funds is that they hold assets that Article 6 funds do not, and thereby provide opportunities for portfolio diversification. Our findings suggest that Article 8 and 9 funds generally invest in a subset of the assets that Article 6 invest in, which would speak against diversification benefits, although further analysis is required to assess this.

7. Are GIF portfolios different from their conventional fund peers?

The results presented above do not preclude the fact that Article 8 and 9 fund portfolios could be different relative to their peers. Differences in fund portfolios could emerge when restricting the comparison to a fund's peers; differences that could be hidden when these fund groups are compared in aggregate (for the full dataset). For example, Article 8 and 9 Energy Sector Equity funds might invest in assets that are deemed 'best-in-class', which would mean investing in assets that are 'cleaner' than other energy sector assets, but 'dirty' relative to non-energy sector assets, such as Technology-related assets. This would mean that differences between Article 6, 8, and 9 funds would appear as a separation of clusters on the NMDS ordination plot *within* a peer group. To test this, we begin with the peer groups defined by Morningstar's Fund Categories. While these are coarse definitions of fund peers, we complement the analysis with a granular fund peer group defined earlier in Subsection 5.2.

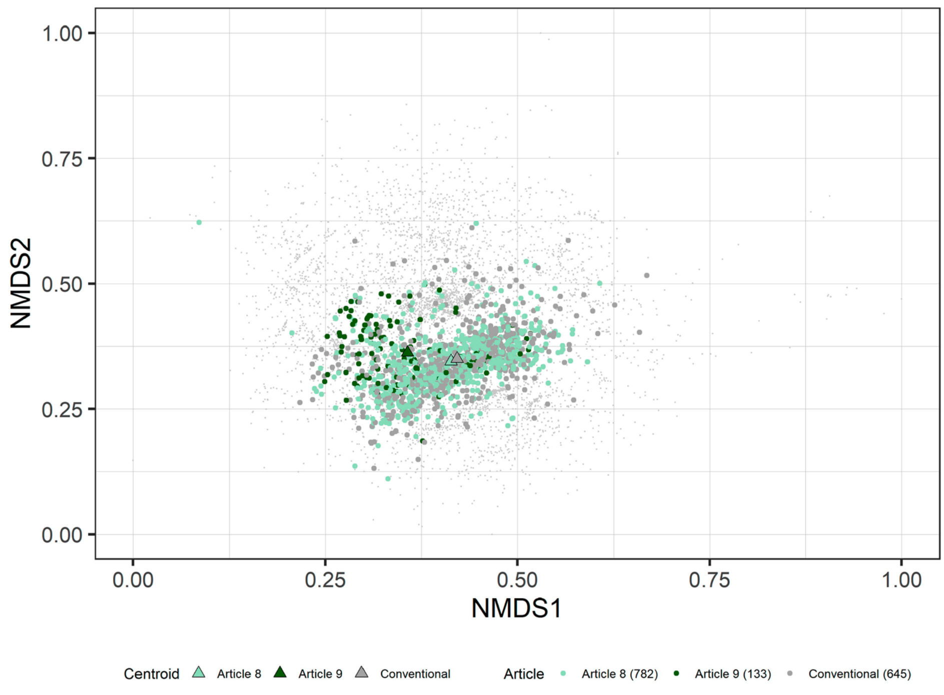
7.1. Broadly defined peer groups

We compare Article 6, 8, and 9 funds within four of the eight Fund Categories listed in Table 1, namely: Global Equity Large Cap Funds; Europe Equity Large Cap Funds; Europe Equity Midsmall Cap; and Energy Sector Equity. Figure 7 and 8 are the NMDS ordination plots for each of these four Categories. The comparisons for the other Fund Categories are reported in Appendix Figures A2 and A3. As before, Article 6, 8 and 9 funds are plotted with dark-green, light-green, and grey dots, respectively, and the centroids of these three fund types are indicated by triangles. Each plot also includes the full universe of funds (represented by smaller, light-grey dots) to help indicate the location and scale of each Fund Category cluster within the full universe.

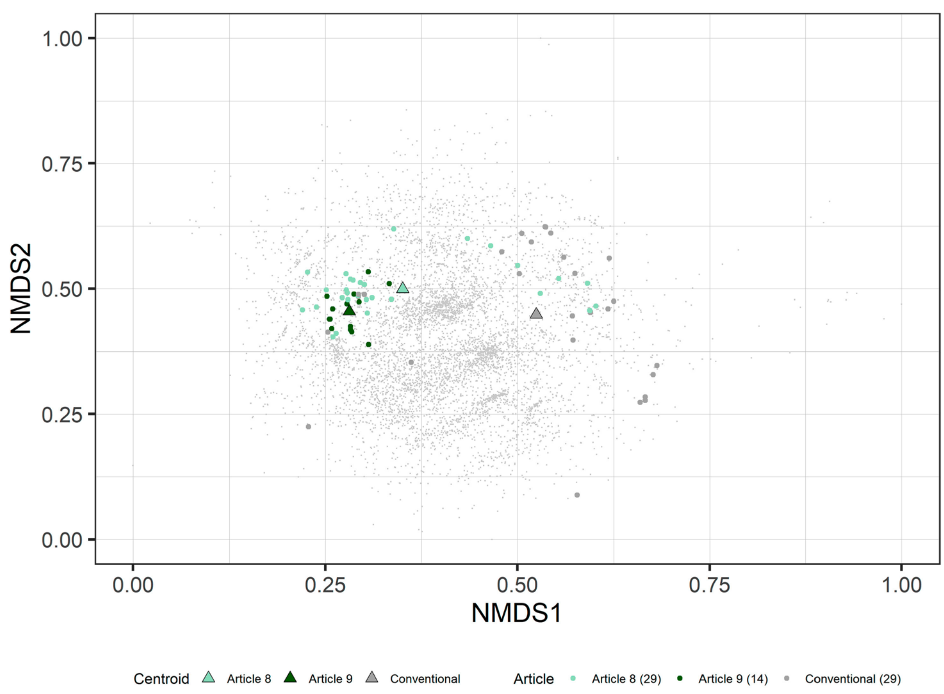
The patterns observed with the within-Fund Category comparison is largely consistent with the patterns observed for Articles 6, 8, and 9 within the full Universe of Funds reported above in Section 6. There is, however, some interesting variation between Fund Categories in terms of the degree to which Articles 6, 8, and 9 portfolios differ. We discuss each Fund Categories in turn.

Figure 7(a) covers Global Equity Large Cap funds, which has the most Article 8 and 9 funds of all the Fund Categories. For this fund category, Article 9 fund portfolios are a subset of the portfolios of the other funds and cluster towards the left of the other funds, suggesting there are some Article 9 funds that invest distinctly differently from their Fund Category peers. However, beyond the broad relative positions of Article 6, 8, and 9 centroids, there is significant overlap between these fund types. Several Article 9 funds lie within the main cluster of the other funds, indicating that the holdings of this group of Article 9 funds is very similar to a number of Article 6 and 8 funds. There is also little to indicate that Article 6 and 8 funds portfolios differentiate themselves from each other.

The Energy Sector Fund Category shown in Figure 7(b) is noteworthy as it represents the Fund Category with the most distinct separation between Article 6, 8, and 9 funds. The separation is not perfect, there are three Article 6 funds that appear in the the midst of the cluster of Article 8 and 9 funds in the left of the plot. Even so, the separation of these funds suggests that there are systematic differences in the portfolios of Article 6, 8 and 9 Energy Sector funds.

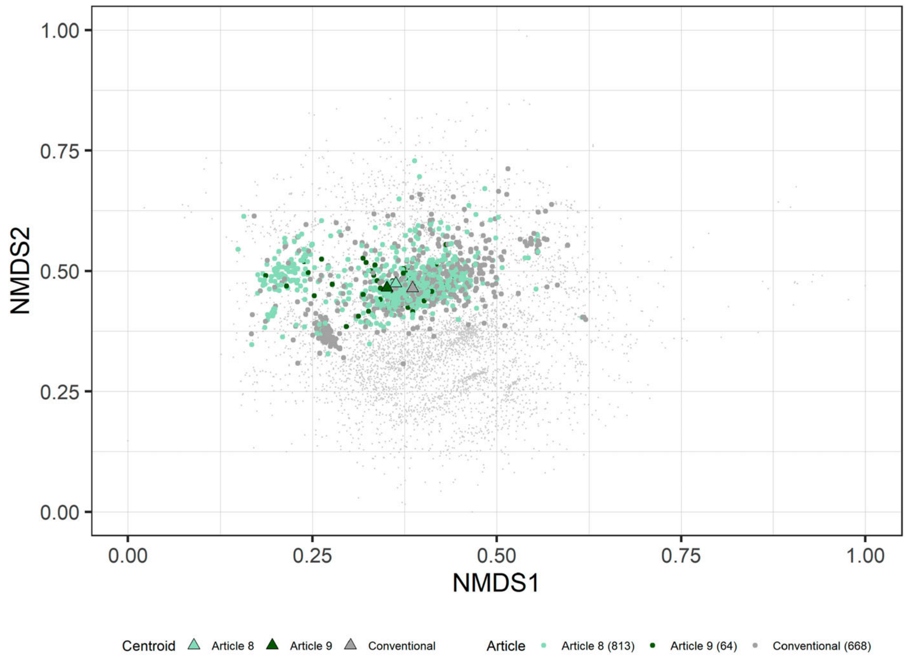


(a) Global Equity Large Cap

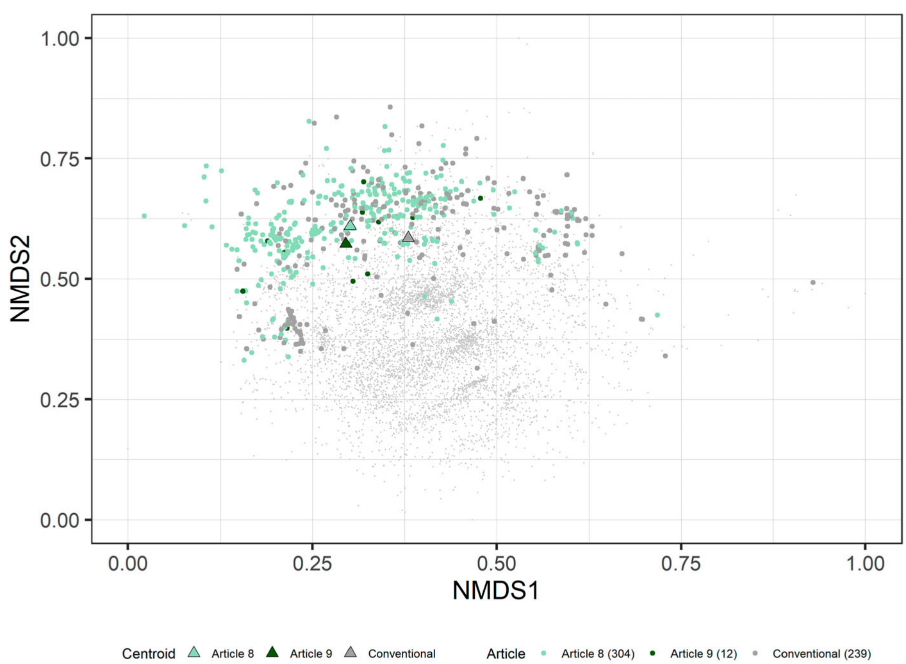


(b) Energy Sector Equity

Figure 7. Article 6, 8, and 9 funds as grey, light-green, and dark-green dots, and their and respective centroids (triangles) for Global Equity Large Cap and and Energy Sector Equity Fund Categories. (a) Global Equity Large Cap and (b) Energy Sector Equity.



(a)



(b)

Figure 8. Article 6, 8, and 9 funds as grey, light-green, and dark-green dots, and their and respective centroids (triangles) for Europe Equity Large and Mid/small Cap Fund Categories. (a) Europe Equity Large Cap and (b) Europe Equity Mid/Small Cap.

There are many factors that could contribute to the fund allocation patterns we observe in our sample of 6888 funds. While we refrain from confirming attribution of observed outcomes to specific factors, there are nonetheless some interesting patterns that deserve discussion.

The Energy Sector Equity Fund Category shows the clearest differences between the portfolios of Article 6, 8 and 9 funds. A potential explanation is that carbon accounting and related ESG metrics, as problematic as they are, have begun to capture information on greenhouse gas emissions that can guide fund managers in their portfolio allocation choices. Another factor is that clean energy technologies are a financially competitive alternative to 'brown' fossil based energy technologies, in part because of emerging climate policies that in one way or another price carbon. The EU's climate policy efforts are likely to have helped strengthen the financial performance of low carbon technologies versus fossil fuel based technologies. Combined, this means that it is more feasible for fund managers to identify climate friendly energy companies that they can invest in without sacrificing financial performance.

The reverse may explain why we do not see a clear separation between the portfolios of Article 6, 8 and 9 funds in the other Fund Categories. There may simply not be sufficient amounts of 'sustainable' companies that also satisfy the risk appetite of investors, forcing Article 8 and 9 funds to employ screening strategies, constraining their investment universe without significantly differentiating them from Article 6 funds that can hold any type of company, regardless of ESG ranking.

Figure 8(a) covers Europe Equity Large Cap funds. For this Fund Category the distinction between the portfolios of Article 6, 8, and 9 funds is weaker, with almost no systematic differences between the portfolios of these funds, as illustrated by the respective centroids. There are some Article 8 and 9 funds that cluster separately from the main cluster of Article 6 funds, which suggests that these fund portfolios are different from Article 6 portfolios. However, for many Article 8 funds (and a few Article 9 funds) there are Article 6 funds that have very similar portfolio composition.

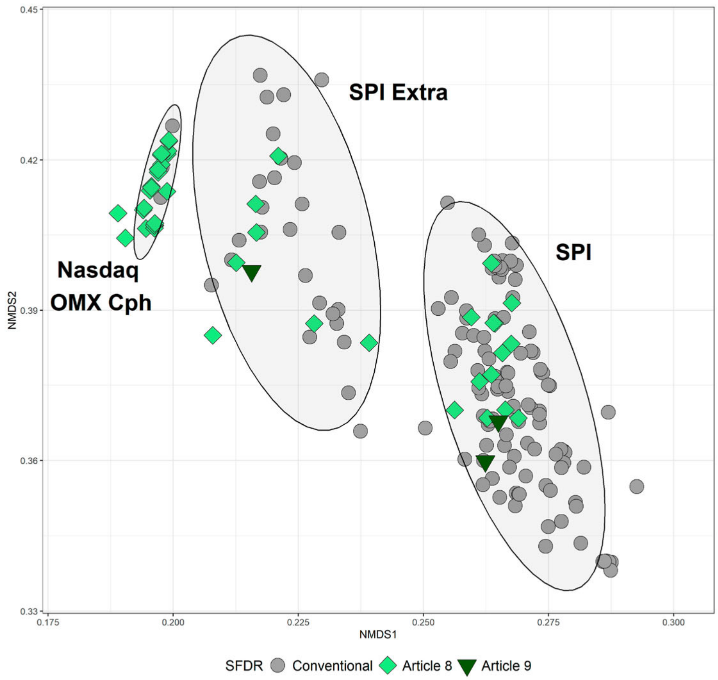
Figure 8(b) covers Europe Equity Mid/Small Cap funds. There is a number of notable Article 8 funds that appear towards the left side of the plot, suggesting that they are likely to be distinct from Article 6 portfolios. At the same time, there is a significant number of the remaining Article 8 funds that have portfolios that are very similar to Article 6 funds, in particular towards the right side of the plot. There are only 12 Article 9 funds included in this Fund Category and there is little distance between the Article 8 and 9 centroids, suggesting little differentiation.

We use the EU Large Cap and EU Mid/Small Cap Categories to compute the correlation coefficients (and associated standard error in parentheses) between the incidence of Article 8 and 9 funds and the NMDS axes. The correlations are summarized in Appendix Table A2 and confirm the observation that GIFs in Figure 8(a,b) cluster to the left of Article 6 funds. The reported correlations have the same sign as those reported for the full sample ($N = 6888$) but differ in magnitude somewhat.

We use ANOVA to test the clustering along Articles 6, 8, and 9 for all 8 Fund Categories listed in Table 1, along both NMDS axes. The results are reported in Appendix Table A3 and indicate that funds do cluster by Article within each Fund Category but that the η^2 effect is generally much weaker than that reported for Fund Categories in Appendix Table A4. Funds in Energy Sector Equity, Europe Mid/Small Cap, and 'Other Fund Cateogires' show the strongest effect. We also conduct pairwise t-tests for Article 8 vs. 6, Article 9 vs. 6, and Article 9 vs. 8. for both NMDS Axes. Overall, the t-tests confirm that the NMDS ordination is able to group the funds distinctly by Article, that the differences are most significant along NMDS1, and that there is little difference between Article 8 and 9 funds for funds in Europe Equity Large Cap, Europe Equity Mid/Small Cap, and Global Emerging Markets.

7.2. Narrowly defined peer groups

A challenge in determining if GIF portfolios are different from non-green funds is the identification of a suitable peer group. As noted above, funds within the Morningstar defined Fund Categories can differ substantially. The NMDS ordination helped defined fund peer groups more narrowly when we investigated 'revealed' benchmarks with the help of the sub-clusters in Figure 5(a). We use the same Swiss/Danish sub-clusters to assess the extent to which GIF holdings differ from their narrowly defined peers in Figure 9(a). We use these sub-clusters as



(a) GIFs in sub-clusters benchmarked to SIX SPI (Swiss Large Cap), SIX SPI Extra (Swiss Mid/Small Cap), and NASDAQ OMX Cph. (Danish Large Cap)

Figure 9. GIFs in the Cluster Swiss/Danish. (a) GIFs in sub-clusters benchmarked to SIX SPI (Swiss Large Cap), SIX SPI Extra (Swiss Mid/Small Cap), and NASDAQ OMX Cph. (Danish Large Cap).

an example of how one might examine the holdings of GIFs relative to their conventional fund counterparts, although similar results can be obtained for any sub-cluster of funds.

At the aggregate level and within coarse Fund Categories, we observe that for every GIF there are generally conventional funds with similar holdings. Verifying that this pattern holds for more narrowly defined peer groups would help verify the claim.

One way to determine the extent to which GIF holdings are different with respect to a more narrowly defined peer group is to examine the minimum Bray-Curtis dissimilarities between fund types within each sub-cluster. We are particularly interested in the *minimum* dissimilarities between Article 6, 8 and 9 funds within the sub-cluster. This would help verify our graphical observation that for every GIF there is a conventional fund with similar holdings.

The minimum dissimilarities between funds in each sub-cluster are reported in Table 3. The largest sub-cluster SPI includes 122 funds, of which 2 are Article 9 and 13 are Article 8. The minimum Bray-Curtis dissimilarity between Article 6 funds in this sub-cluster is 0.03.

The minimum Bray-Curtis dissimilarities for the SPI sub-cluster tell us that there are some Article 8 and 9 funds that have essentially the same portfolios as an Article 6 funds. We identify the funds by name and report them in Appendix Table A5.

The pair of Article 8 and 6 funds with the lowest Bray-Curtis of 0.03 are in fact both index funds that track the SPI ESG Weighted Benchmark (the fund pair is *UBS ETF – SPI ESG* and *Pictet CH I-Swiss Sust Eqs Tracker*). The second pair of similar Article 8 and 6 are two actively managed AXA funds with a Bray-Curtis of 0.04 (the fund pair is *AXAWF Switzerland Eq F Cap CHF* and *AXA (CH) SF Swiss Equity CHF S*). The pair of Article 9 and 6 funds with the lowest dissimilarity of 0.09 are both part of the same family of Swiss investors (the fund pair is

Table 3. Minimum Bray-Curtis dissimilarities between article 6,8, and 9 funds in sub-cluster SPI.

		Min Bray-Curtis		
SFDR Article	Observations	Min	Max	Mean
Sub-cluster SPI				
Article 6 to Article 6	107	0.01	1.00	0.22
Article 8 to Article 6	13	0.03	0.35	0.21
Article 9 to Article 6	2	0.09	0.44	0.26
Sub-cluster SPI Extra				
Article 6 to Article 6	25	0.01	1.00	0.34
Article 8 to Article 6	7	0.01	0.71	0.37
Article 9 to Article 6	1	0.93	0.93	0.93
Sub-cluster NASDQA OMX Cph				
Article 6 to Article 6	4	0.25	1.00	0.44
Article 8 to Article 6	23	0.01	0.34	0.20
Article 9 to Article 6	0	NA	NA	NA

Cadmos-Swiss Engagement B CHF Cap and *AS Swiss Equity Cadmos Engagement I*). Both are actively managed and claim to pursue ESG performance through investor engagement and negative screening of weapons, fossil fuels, etc. Apart from their SFDR designations both funds appear to be very similar. There are also GIFs in sub-cluster SPI with portfolios that are distinct from their 'nearest neighbor' Article 6 fund. The maximum of the minium Bray-Curtis metrics between an Article 8 and Article 6 fund is 0.35, and for the Article 9 fund it is 0.44.

The SPI sub-cluster is too small to be representative of the overall fund universe we investigate. Even so, it appears that the differences between Article 6, 8, and 9 funds reflect the patterns observed with the larger samples, namely: for each Article 8 or 9 fund there is an Article 6 fund with similar holdings; and Article 9 fund portfolios are more dissimilar to Article 6 fund than Article 8 fund portfolios.

8. Do ESG metrics capture differences in fund portfolios better than SFDR classifications?

ESG metrics may identify differences in fund holdings that are not captured by the SFDR Articles 6, 8 and 9. SFDR is after all a relatively new and evolving regulation. When we collected the holdings data, many investors may have still been interpreting the rules and had not yet adjusted their portfolios to fully align with the SFDR classifications. ESG metrics could also do a better job at capturing investor preferences. Examining funds with commercial provided ESG ratings might therefore capture distinctions in fund holdings that the SFDR Classification does not capture.

Our aim with the analysis of ESG metrics is: (i) to explore the extent to which funds cluster along these alternative non-financial measures of fund performance, and (ii) to compare the revealed ESG investment patterns with the revealed SFDR patterns. We investigate three fund-level ESG metrics: carbon emissions in tons, carbon emission intensity, and Morningstar's Sustainability Rating. Carbon emissions data are compiled from various corporate and public sources and aggregated to the fund level. Morningstar's Globe Rating, developed in partnership with Sustainalytics, transforms multiple environmental, social and governance indicators into a five-globe scale. Funds with a rating of five globes have the lowest ESG risk: the rating focuses on investing *value* as opposed to investor *values*.

These three metrics should presumably relate to a fund's SFDR classification. Funds with lower carbon emissions, and/or 5 Morningstar Globes should also be an Article 8 or 9 fund. If a fund's SFDR classification were perfectly predicted by these three ESG metrics, then we would expect the ESG and SFDR investment patterns to reflect each other. However, when we examine the full data set of 6888 funds we find a positive albeit noisy correlation between the SFDR Articles and these three ESG metrics. We therefore expect the analysis of these ESG metrics to reveal different fund investment patterns.

We examine carbon emissions first before turning to Morningstar's Globes. To help with the exposition, we focus on the same 2100 funds that invest in EU Equity Large Cap and EU Equity SMID CAP assets that were explored in Figure 4(a).

8.1. Climate transition risk

Growing evidence suggests that climate-related transition risks are having an impact on investment decisions. One strategy would be for funds to simply avoid risky transition assets, as with negative screening mentioned above. An alternative strategy would be for investors to require higher returns as compensation for holding these riskier assets. Bolton and Kacperczyk (2021) show that investors are considering transition risk, and that returns are adjusted upwards accordingly. They find that tons of carbon emitted, more so than carbon emission intensity, explains the transition risk premium. Cenedese, Han, and Kacperczyk (2023) report supporting evidence using a forward looking measure of transition risk. With this mechanism, investors would price carbon risk, and continue to hold high transition risk assets. One could therefore expect to see clusters of funds with high levels of carbon emissions (in terms of tons).

We plot the distribution of carbon emissions across the universe of funds Figure 10, to illustrate the distribution of Scope 1, 2, and 3 carbon emissions and fund AUM across the 2100 funds that invest in European assets. Both total carbon emissions and carbon intensity (expressed in terms of tons of carbon per million EUR of revenue) are plotted.

An advantage with carbon emissions data is that it does not suffer from missing data to the extent that other ESG metrics do. Appendix Figure A4 shows a summary of the coverage of various ESG metrics to confirm this, confirming high levels of missing data for variables such as water withdrawal or waste, while both total carbon emissions and carbon intensity have relatively good coverage at the company level.

In aggregate, visual inspection of Figure 10(a,b) indicate that low-carbon funds tend to cluster towards the bottom-left of the two plots, although this is clearer for carbon emission intensity. To check this we calculate the correlation between the NMDS axes and fund-level carbon emissions, which we summarize in Appendix Table A2. Indeed low carbon funds tend to cluster towards the left of the NMDS plot, which is where Article 9 (and to a lesser extent Article 8) also tend to cluster. This is consistent with results reported by Abouarab, Mishra, and Wolfe (2025). They find evidence that Article 9 funds are tilting their portfolios away from carbon intensive assets, more so than Article 8 funds.

Funds with significantly different climate profiles appear nearby one another (green coded funds appearing nearby red coded funds). This suggests that funds with similar holdings can have different emissions profiles if they exclude certain carbon heavy assets, and also that funds can continue to hold carbon heavy assets despite the associated transition risk. The η^2 effect by fund carbon emissions is similar to the effects reported for Article 6, 8, and 9, but weaker than for Morningstar Fund Categories (compare Appendix Tables A3 and A4).

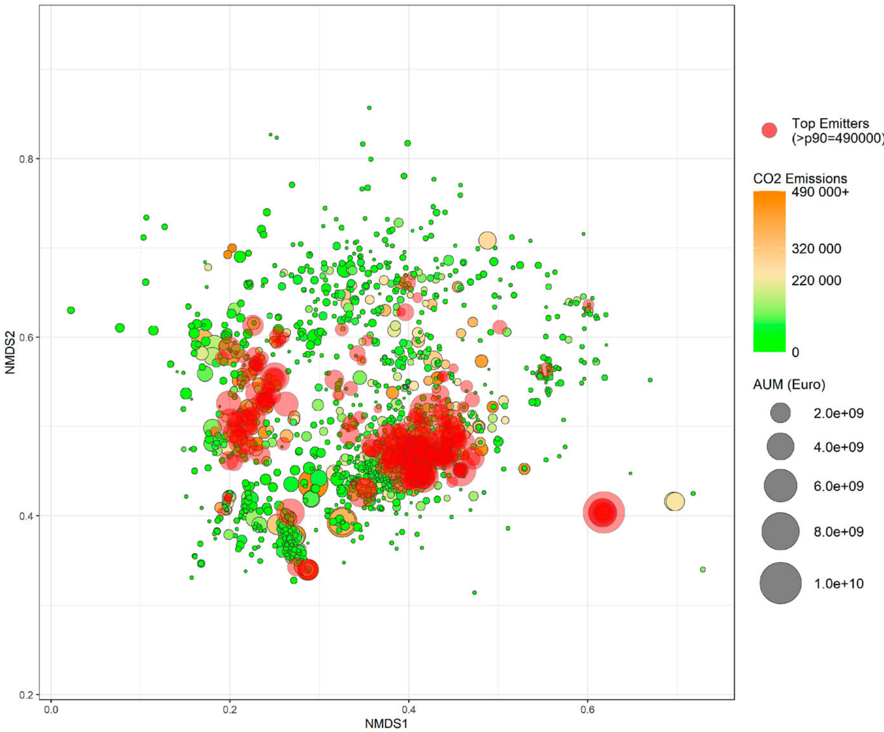
Another insight is that clusters of carbon heavy portfolios are in the Pan European Large and Nordic sub-clusters of Figure 4. This is most evident in Figure 10(a) although the pattern in Figure 10(b) is similar but less distinct. Moreover, the low carbon funds tend to be found to the left of these sub-clusters, which is further confirmation that identifying a fund's peers is essential for understanding how investors are responding to transition risks.

8.2. Morningstar sustainability rating

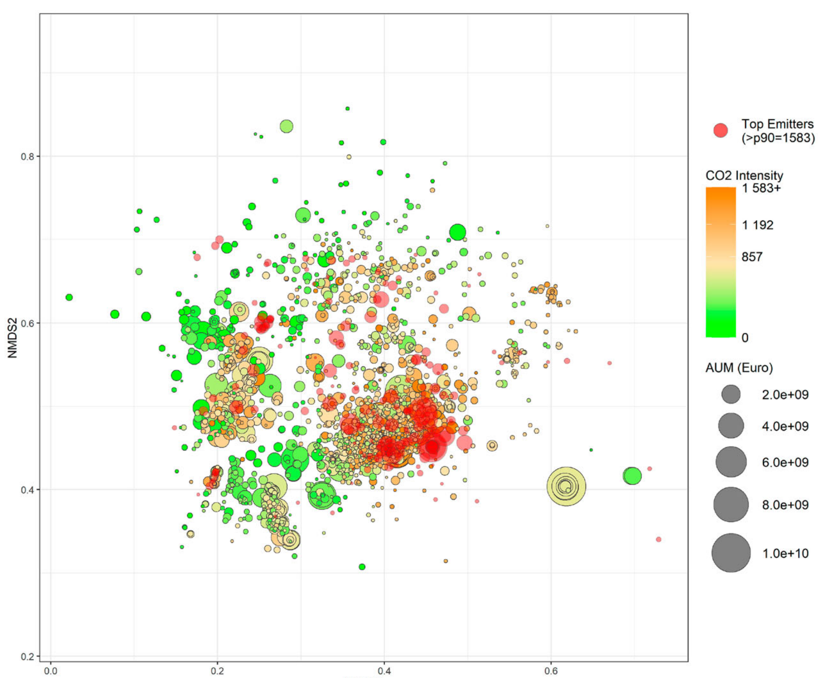
We investigate the Morningstar Globe rating for ESG risk for the same 2100 funds used to investigate carbon emissions. The correlation between the SFDR Articles, carbon emission intensity, and Morningstar's Globes suggests that there may be similar patterns. The Globes have been linked to higher investment inflows but not with better financial performance. Research by Hartsmark and Sussman (2019) reports that choose funds with more Globes in part because of non-pecuniary motivations, which is a contrast to the literature on carbon emissions and transition risk discussed earlier. As a measure of broader ESG risk, the Globe rating may reveal patterns of differences between funds that are not captured by carbon emissions alone.

Visual inspection of Figure 11 suggests that funds with similar holdings can have different ratings, with five Globe funds appearing close to one Globe funds, which means that relatively small adjustments to a fund's portfolio can affect a fund's Globe rating.

Funds with more Globes tend to locate towards the lower part of the plot (see Appendix Table A2). Moreover, ANOVA indicates that there is a significant clustering of funds by Globe, and that the η^2 effects of the Globes



(a) Tons of carbon emissions.



(b) Carbon emission intensity (tons/million EURof revenue).

Figure 10. The 2100 EU LC+SMID equity funds, AUM, and scope 1, 2, & 3 carbon emissions. (a) Tons of carbon emissions and (b) Carbon emission intensity (tons/million EURof revenue).

Figure 11. Europe equity large cap, Europe equity mid/small cap, and morningstar sustainability ratings.

are comparable to carbon emissions and SFDR Classifications (see Appendix Tables A3 and A6), although the main effect for the Globes is along NMDS2.

Overall, the clustering patterns of funds by their Morningstar Globes is similar to that observed for carbon emissions and SFDR Classifications. We do not observe a clearer clustering effect with the Morningstar Globes.

9. Concluding remarks

This study makes two novel contributions. One is the application of the Bray-Curtis dissimilarity measure and NMDS ordination methods to overcome the high dimensionality of the fund portfolio comparison problem. Comparing how funds invest, and specifically what they invest in, is a general problem that investors have faced, and not limited to assessments of green claims by funds.

The second is a novel analysis of European Equity funds that provides clear insights into the holding patterns of 6888 European equity funds (including over 3666 Article 8 and 9 funds). To our knowledge, this is the most comprehensive comparative analysis of fund-level portfolios yet conducted, overcoming the problems of ESG based assessments that much of the related literature suffers from.

Across the full universe of funds studied, the results suggest that there is little difference between Article 6, 8, and 9 portfolios. We find that for every Article 8 and 9 fund, investors are likely to find an Article 6 fund with the same (or a very similar) portfolio. We also find that Article 9 funds tend to invest in a subset of the assets other funds invest in. There are certain assets that Article 9 funds avoid, which is consistent with avoidance of 'sin' investments in tobacco, fossil fuel extraction, or similar (negative screening). However, there is little evidence that Article 8 or 9 funds invest in assets that Article 6 funds do not invest in. This suggests that presumed diversification benefits of Article 8 and 9 funds remain largely under-realized.

This pattern holds when comparisons are performed within Fund Categories, both the coarse categories defined by Morningstar and the narrower categories revealed by the NMDS ordination. A notable exception to this pattern are funds that focus on energy sector assets, where the interplay of technological factors, progress on carbon accounting and related standards, and climate policy, are likely to have played a role in shaping the observed differences between Article 6, 8, and 9 portfolios. We also examine portfolio differences for low-carbon and Morningstar's Sustainability Globe Rating. The patterns of investment that emerge are similar to those found with the SFDR classifications.

Our insights are also important for studies looking to examine GIF financial performance. Some are interested in GIFs for the potential financial *value*. Yet it is probably not surprising that the evidence on GIF financial performance is inconclusive given the similarity of portfolio composition between green and conventional funds.

In terms of investing to one's *values*, our results suggest that by and large, the EU's SFDR regulation has done little to harness investor preferences to shift the allocation of capital towards more 'better' corporations, as was the objective of the Green Deal. Investors should not assume that SFDR labels reflect significantly different portfolio compositions, and due diligence will need to involve a review of fund holdings rather than overt reliance on SFDR status. Article 8 and 9 funds with non-distinct portfolios will need to differentiate themselves in some other way, most likely through transparent accounts of their engagement with the corporations in their portfolios.

Notes

1. ESG metrics fail in several dimensions. The divergence of ESG ratings has been noted (Berg, Koelbel, and Rigobon 2022; Chatterji et al. 2016; Dimson, Marsh, and Staunton 2020), the reasons behind it made clear (Kotsantonis and Serafeim 2019). Moreover, there is confusion as to what ESG based assessment capture, for example focusing on corporate risk rather than impact (Crona and Sundström 2023). The challenges with ESG based assessments are discussed in more detail below.
2. See for example (Curtis, Fisch, and Robertson 2021; Joliet and Titova 2018; Kempf and Osthoff 2008; Nitsche and Schröder 2015; Raghunandan and Rajgopal 2022).
3. Broccardo, Hart, and Zingales (2022) study a theory of divestment (exit) and engagement (voice) and suggest that divestment is less effective than engagement in pushing firms to act in a socially responsible manner.
4. This is in fact what we will observe when we examine benchmarks and fund holdings across fund categories. The analysis will make use of Morningstar's Fund Categories, which we introduce in Section 4.
5. The Bray Curtis division by the sum of weights calculates the dissimilarity as a proportion of the total species abundance, reflecting the relative difference in species composition between the systems. This is useful also for capturing funds with weights that do not sum to 100%. The Bray-Curtis Dissimilarity measure for a pair of similar funds, described in Appendix Table A1 is 0.148. The corresponding Active Share is the same because both funds have weights that sum to 100%. Funds weights often do not sum to 100%. In Subsection 5.2 we report the correlation between Active Shares and Bray-Curtis metrics.
6. We investigate benchmarking in Section 5.
7. As we discuss below, there are many benchmarks, but Morningstar's Fund Category benchmarks are the more popular benchmark for a given fund category.
8. We do not observe benchmark holdings directly, but instead use index funds that track the benchmark closely. In this particular case the tracking error of the index funds we use is close to zero.
9. The corresponding Pearson Correlation is 90%.
10. The clustering of the index funds is determined with NMDS ordination coordinates and a Density-Based Spatial Clustering of Applications with Noise algorithm (DBSCAN). Of course, the clustering could very well be done visually with the NMDS ordination plot.
11. Negative screening means that certain 'bad' issuers are removed from a fund's investable universe, and can lead to exclusions of assets related to fossil fuels, weapons, tobacco, adult entertainment, gambling, animal testing, and so forth.
12. Care is needed when interpreting the distances on the NMDS ordination plot for reasons we discussed in Section 3.

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Data availability statement

The data that support the findings of this study are available from Morningstar Direct, which is available through commercial license.

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Appendix. Data tables and figures

Table A1. Comparison of two funds identified as sharing similar holdings (red dots in Figure 1) all shared holdings and respective weights in percent.

	State Street Switzerland Idx Eq P CHF	GKB Aktien Schweiz ESG I
Nestle SA	21.93	16.48
Novartis AG Registered Shares	13.73	13.52
Roche Holding AG	13.71	11.46
Compagnie Financiere Richemont SA	5.34	5.37
Zurich Insurance Group AG	4.52	5.39
UBS Group AG	4.21	5.35
ABB Ltd	3.52	4.97
Lonza Group Ltd	2.87	1.60
Sika AG	2.49	1.65
Holcim Ltd	2.27	4.23
Alcon Inc	2.25	1.43
Givaudan SA	2.02	0.99
Swiss Re AG	1.89	1.10
Partners Group Holding AG	1.36	0.94
Geberit AG	1.27	3.47
Swiss Life Holding AG	1.25	0.68
Swisscom AG	1.10	0.55
Straumann Holding AG	1.04	2.05
Sonova Holding AG	1.02	0.46
Logitech International SA	0.64	2.67
Swiss Prime Site AG	0.43	0.48
Other	11.14	15.16
Total	100.00	100.00

Table A2. Spearman correlation coeficients by SFDR Article and NMDS axis,standard errors are reported in parentheses.

	Correlation (SE)	
	NMDS1	NMDS2
Universe ($N = 6888$), Figure 6		
Article 6	0.13 (0.02)	0.03 (0.02)
Article 8	−0.08 (0.01)	0.02 (0.01)
Article 9	−0.12 (0.01)	−0.00 (0.01)
EU Large, Mid/Small Cap funds ($N = 2100$), Figure 8(a) and 8(b)		
Article 6	0.18 (0.02)	−0.10 (0.02)
Article 8	−0.16 (0.02)	0.09 (0.02)
Article 9	−0.06 (0.02)	−0.04 (0.02)
Universe ($N = 6888$)		
Emissions (tons)	0.14 (0.01)	0.11 (0.01)
Emissions (intensity)	0.25 (0.01)	0.18 (0.01)
Morningstar Globes	−0.07 (0.01)	−0.02 (0.01)
EU Large, Mid/Small Cap funds ($N = 2100$), Figure 10(a) and 10(b)		
Emissions (tons)	0.11 (0.02)	−0.04 (0.02)
Emissions (intensity)	0.37 (0.02)	−0.06 (0.02)
Morningstar Globes	0.02 (0.02)	−0.10 (0.02)

The coefficients are statistically significant to the 0.1% level.

Table A3. ANOVA and pairwise t-tests for SFDR articles 6, 8, and 9, by fund categories.

	ANOVA			p-values Pairwise t-test (by SFDR Article)		
	F Value	η^2	p-value	8 vs. 6	9 vs. 6	9 vs.8
Universe, ($K = 3$, $N = 6888$), Figure 6						
NMDS1	76.6	0.022	<0.001	<0.001	<0.001	<0.001
NMDS2	3.7	0.000	0.026	0.032	0.227	0.759
Global Equity Large Cap, ($K = 3$, $N = 1560$), Figure 7(a)						
NMDS1	49.5	0.064	<0.001	0.037	<0.001	<0.001
NMDS2	5.0	0.006	0.007	0.118	0.049	0.007
Europe Equity Large Cap, ($K = 3$, $N = 1545$), Figure 8(a)						
NMDS1	16.4	0.021	<0.001	<0.001	0.002	0.256
NMDS2	6.2	0.008	0.007	0.002	0.910	0.302
Europe Equity Mid/Small Cap, ($K = 3$, $N = 555$) Figure 8(b)						
NMDS1	26.4	0.096	<0.001	<0.001	0.037	0.880
NMDS2	4.7	0.017	0.009	0.010	0.670	0.290
Energy Sector Equity, ($K = 3$, $N = 72$), Figure 7(b)						
NMDS1	26.4	0.076	<0.001	<0.001	<0.001	0.071
NMDS2	2.4	0.070	0.026	0.120	0.840	0.220
Technology Sector, ($K = 3$, $N = 203$)						
NMDS1	0.2	0.001	0.842	0.933	0.890	0.891
NMDS2	8.8	0.053	<0.001	0.307	<0.001	<0.001
Global Emerging Markets, ($K = 3$, $N = 362$)						
NMDS1	4.9	0.027	0.008	0.008	0.153	0.686
NMDS2	3.1	0.017	0.048	0.045	0.742	0.731
Other Fund Categories,($K = 3$, $N = 1813$)						
NMDS1	12.5	0.047	<0.001	0.54	<0.001	<0.001
NMDS2	6.0	0.023	0.003	0.003	0.761	0.104

Note: Pairwise t-tests are BH-adjusted.

Table A4. ANOVA for various groupings of morningstar fund categories listed in Table 1.

	ANOVA		
	F Value	η^2	p-value
All Fund Categories, ($K = 8$, $N = 6888$)			
NMDS1	107.5	0.098	< 0.001
NMDS2	565.5	0.365	< 0.001
Global, EU and US Large Cap funds, ($K = 3$, $N = 3455$)			
NMDS1	263.1	0.132	< 0.001
NMDS2	2855.0	0.623	< 0.001
EU Mid/Small, Global Emerging, Tech, Energy, ($K = 4$, $N = 1247$)			
NMDS1	44.45	0.097	< 0.001
NMDS2	900.5	0.685	< 0.001
Other Categories (33 sub-categories), ($K = 33$, $N = 2186$)			
NMDS1	57.9	0.463	< 0.001
NMDS2	140.4	0.676	< 0.001

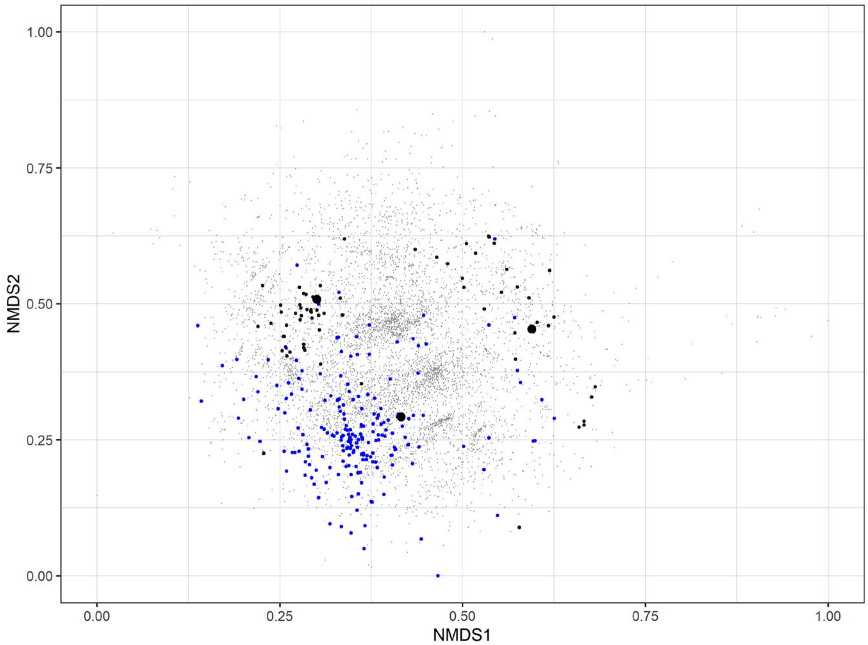
Table A5. Funds pairs with minimum Bray-Curtis dissimilarities to Article 6 funds for the 13 Article 8 funds and 2 Article 9 funds identified in sub-cluster SPI (see Table 3).

Article 8	Article 6	Bray-Curtis Dissimilarity
UBS ETF (CH) – SPI ESG (CHF) A-acc	Pictet CH I-Swiss Sust Eqs Trkr I dy CHF	0.03
AXAWF Switzerland Eq F Cap CHF	AXA (CH) SF Swiss Equity CHF S	0.04
Visionfund – Swiss Equity J CHF	LO Funds (CH) Swiss Leaders ID	0.15
UBAM Swiss Equity AC CHF	UBAM (CH) Swiss Equity I	0.15
Allianz Fonds Schweiz A EUR	ASAST Aktien Schweiz I	0.16
DWS Aktien Schweiz CHF LC	Willerequity Switzerland I Acc	0.17
DGC – Swiss Excellence B CHF	Aquila Intl Corby Swiss Equity P	0.23
Capital Swiss Dividend Fund A	Reichmuth Dividendenselektion Schweiz P	0.26
UBS(Lux)FS MSCI Swd IMI Scy Rp ACHF Acc	Migros Bank (Lux) Fonds SwissStock A	0.30
UBS ETF (CH) MSCI Swtzrld IMI SR(CHF)A d	Migros Bank (Lux) Fonds SwissStock A	0.30
LLB Aktien Schweiz ESG (CHF)	Swiss Strategic Leaders Fund Klasse 1	0.31
VP Bank Risk Optim ESG Eq Swiss CHF B	OLZ 1 – Equity Switzerland Optmz ESG IR	0.32
Fidelity Switzerland A-Dis-CHF	ZugerKB Aktien Schweiz CHF I	0.35
Article 9	Article 6	
Cadmos-Swiss Engagement B CHF Cap	AS Swiss Equity Cadmos Engagement I	0.08
Champion Ethical Equity Fund CH CHF	AS Swiss Equity Cadmos Engagement I	0.44

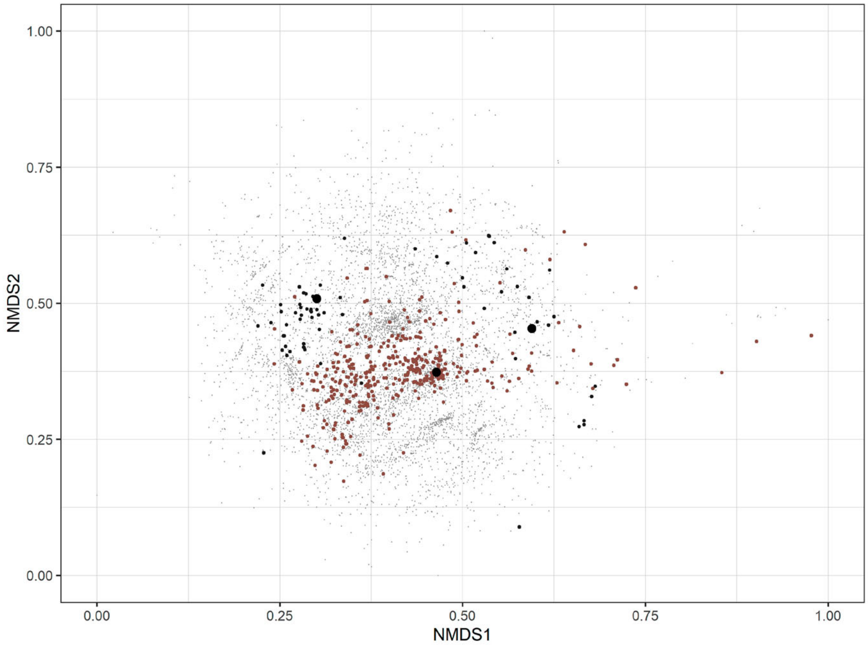
Table A6. ANOVA for EU large, mid/small cap funds by carbon emissions, intensity, and morningstar sustainability rating.

	ANOVA		
	F Value	η^2	p-value
EU Large and Mid/Small Cap			
Carbon emissions, by tercile, ($K = 3$, $N = 1961$), Figure 10(a)			
NMDS1	3.9	0.0039	0.021
NMDS2	12.4	0.0125	<0.001
Carbon intensity, by tercile, ($K = 3$, $N = 2092$), Figure 10(b)			
NMDS1	99.2	0.0876	<0.001
NMDS2	21.1	0.0196	<0.001
Morningstar Sustainability Rating, ($K = 5$, $N = 1993$), Figure 11			
NMDS1	5.4	0.0108	<0.001
NMDS2	9.1	0.0180	<0.001
EU Large Cap			
Carbon emissions, by tercile, ($K = 3$, $N = 1428$), Figure 10(a).			
NMDS1	3.1	0.0043	0.046
NMDS2	3.5	0.0048	0.031
Carbon intensity, by tercile, ($K = 3$, $N = 1538$), Figure 10(b)			
NMDS1	61.4	0.074	<0.001
NMDS2	18.7	0.024	<0.001
Morningstar Sustainability Rating, ($K = 5$, $N = 1467$), Figure 11			
NMDS1	2.2	0.008	0.071
NMDS2	20.6	0.053	<0.001

Note: Carbon emissions terciles are defined over the respective samples of N for each test.

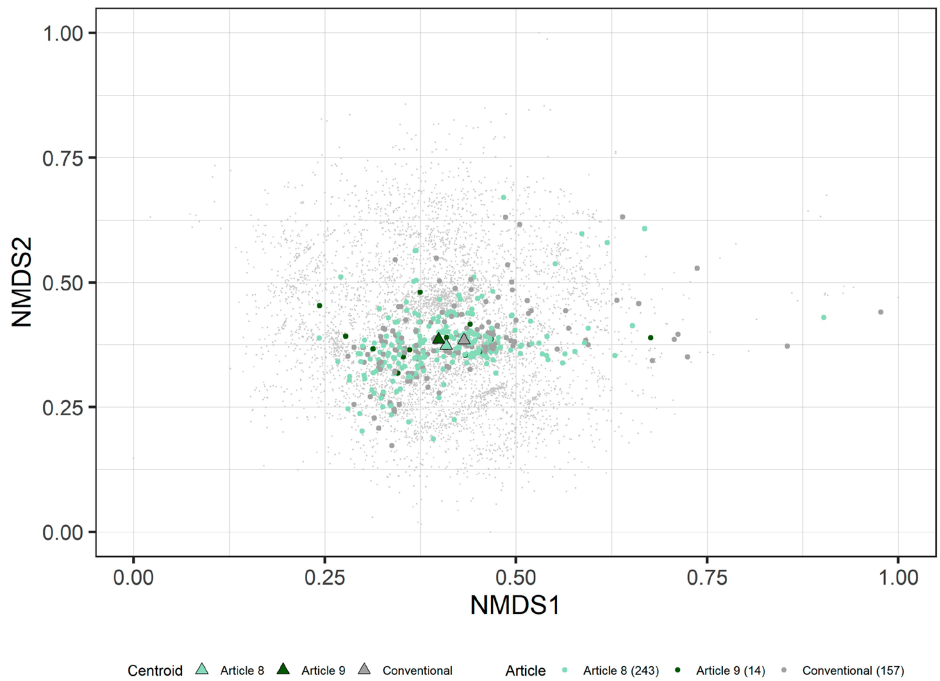


(a) Technology Sector Equity funds (in blue) and Energy Sector Equity funds (in dark grey) clustered around their benchmarks, MSCI IT, MSCI World Energy, and S&P Global Clean Energy (in black).

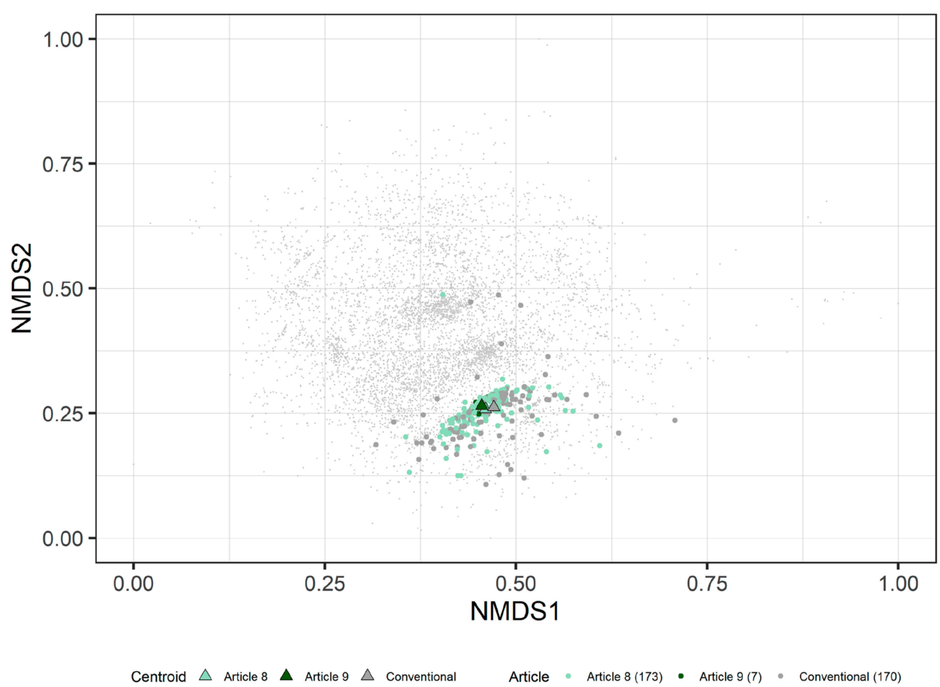


(b) Global Emerging Equity (in brown) and Energy Sector Equity funds (in dark grey) clustered around their benchmarks, MSCI Emerging Equity and MSCI World Energy, and S&P Global Clean Energy (in black).

Figure A1. NMDS ordination plot for pairs of fund categories. (a) Technology Sector Equity funds (in blue) and Energy Sector Equity funds (in dark grey) clustered around their benchmarks, MSCI IT, MSCI World Energy, and S&P Global Clean Energy (in black) and (b) Global Emerging Equity (in brown) and Energy Sector Equity funds (in dark grey) clustered around their benchmarks, MSCI Emerging Equity and MSCI World Energy, and S&P Global Clean Energy (in black).

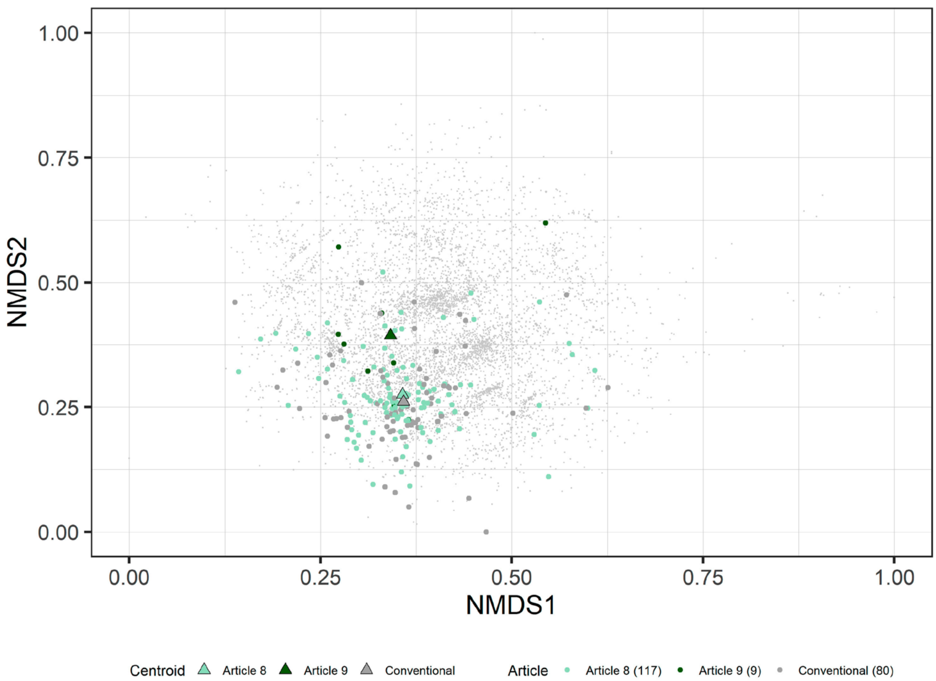


(a) Global Emerging Markets Equity

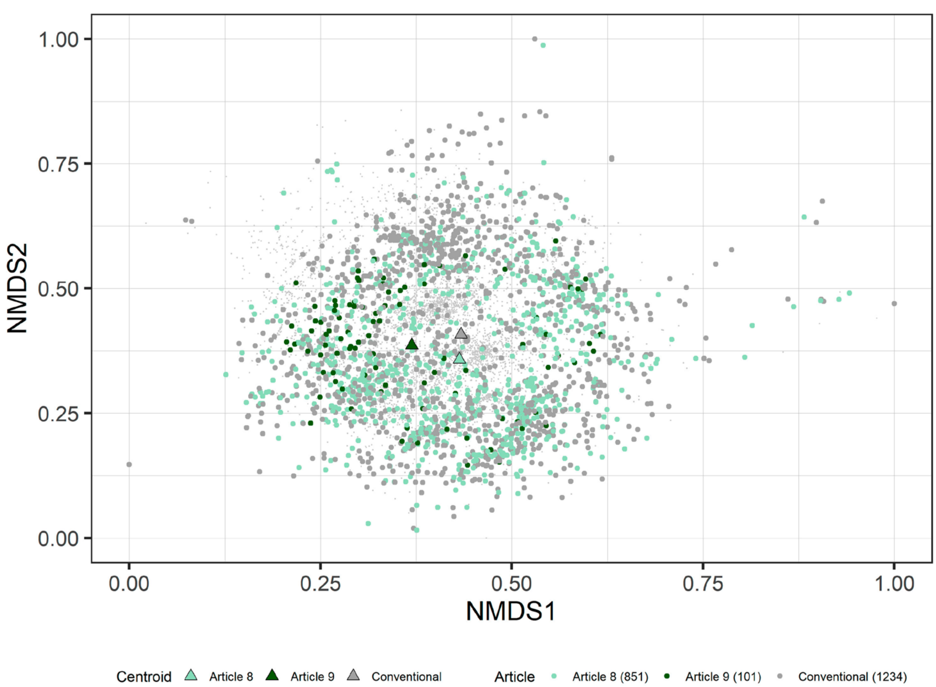


(b) US Equity Large Cap Blend

Figure A2. Article 6, 8, and 9 funds as grey, light-green, and dark-green dots, and their and respective centroids (triangles) for Global Emerging Markets Equity and US Equity Large Cap Blend Fund Categories. (a) Global Emerging Markets Equity and (b) US Equity Large Cap Blend.



(a) Technology Sector Equity



(b) Other

Figure A3. Article 6, 8, and 9 funds as grey, light-green, and dark-green dots, and their and respective centroids (triangles) for Technology Sector Equity and Other Fund Categories. (a) Technology Sector Equity and (b) Other.

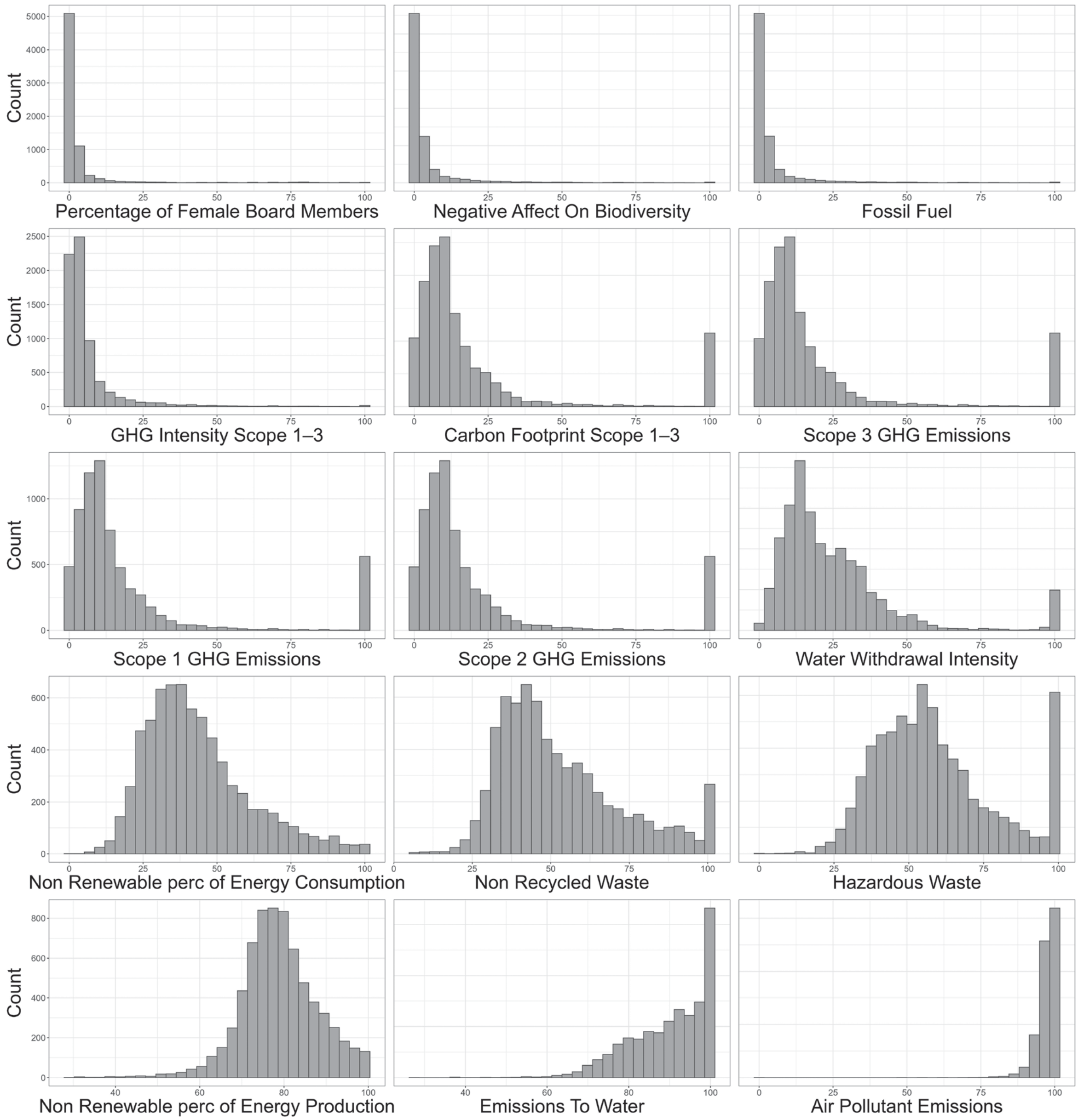


Figure A4. Histograms over percentage of missing ESG metrics for the 6888 EU equity fund universe under study.