How green are SRI labelled funds?
Insights from a Machine Learning based clustering approach

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March 25, 2022

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Abstract

With the advent of Sustainable Finance Disclosure Regulation (SFDR), the question of the obsolescence of Socially Responsible Investment (SRI) labels in the fight against greenwashing has arisen in Europe. To address this question, this paper examines the portfolios of European funds, which hold the French SRI label at a stock level, in order to study their greenness.

Our study relies on a clustering approach based on a set of widely used environmental performance metrics to differentiate European SRI labeled funds in terms of greenness.

We document a decarbonization trend for SRI labeled funds that has accelerated since 2019. We also explain that the difference between dark and light green clusters of funds depends on their investment strategies. *Dark green* funds invest in a restricted number of equities while *light green* funds invest in a broader set of equities.

Finally, we report significant discrepancies between SFDR categories and their expected degree of greenness, implying serious greenwashing concerns. Therefore, dividing the French SRI label into four grades fully compatible with the three EU's SFDR categories allows to better capture the green heterogeneity of SRI labeled funds.

KEYWORDS: Socially Responsible Investment (SRI), label, greenness, clustering, k-means, fuzzy c-means

JEL CLASSIFICATION: G11, G18, G23, C38, Q56

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The project has received funding from Clermont Auvergne University (CleRMa) for which we are thankful. An earlier version of the paper has been presented at the finance seminars of CleRMa and Lyon University (Magellan). The authors thank Jean-François Gajewski, Mathieu Gomes, Pierre-Olivier Klein, Sylvain Marsat, Pascal N'Guyen, Cao Wang and seminar participants for their comments and suggestions. They also thank Novethic for supplying the data used in this paper. Any remaining errors or omissions are solely the responsibility of the authors.

1. Introduction

A recent Carbon Disclosure Project (CDP)'s investigation on the portfolios of 16,500 investment funds highlights that only 158 of them have a temperature pathway in line with the Paris agreement based on Scope 1 and 2 carbon emissions (CDP, 2021). A handful of studies has also documented that funds' exposures to carbon-intensive sectors such as fossil fuels, utilities, cement remain substantial (e.g., Battiston et al., 2017; ECB 2021). Remarkably, these studies have emerged during a period of strong growth for SRI funds, especially in Europe.

According to PwC estimates, EU-domiciled sustainable funds hold 3.3 trillion EUR of Assets under Management (AuM) in 2021, representing 32% of the EU-domiciled total of assets (PwC, 2021). SRI fund labels are an important driver of those fund flows (IMF, 2021), which is consistent with the idea that investors value sustainability (Hartzmark and Sussman, 2019). Labels are a convenient way to summarize a fund's investment strategy and its approach to engagement and stewardship within a range of fund characteristics (e.g., carbon intensity,…) (IMF, 2021). Yet, IMF forewarns that proper regulatory oversight must be in place in order to prevent "greenwashing" and to ensure that labels fairly represent funds' investment objectives.

One major effort to move in this direction is the EU's Sustainable Finance Disclosure Regulation (SFDR hereafter), which went into effect in March 2021. As explained by Morningstar (2021), all European funds must be classified into three SFDR categories: For the brown category they will be labeled *Article 6;* for the light green, *Article 8;* and ~~to~~ for the dark green: *Article 9*. When studying a panel of 567 European sustainable funds that may be classified as green, Novethic reports that 31% of the funds (*resp.* 33%) are Article 8 (*resp.* Article 9) funds while 36% are not yet classified (Novethic, 2021a). With the advent of SFDR regulation, the question of the obsolescence of SRI labels in the fight against greenwashing, however, cannot be ignored (Novethic 2021a; Becker et al., 2022). Novethic (2021a) reports that European fund managers have used SFDR classification rather freely as a declarative process, leading them to self-assess the degree of sustainability of their funds. For Becker et al. (2022), the fact that Article 9 funds experience higher net fund flows four months after SFDR introduction suggests that it is not the true greenness that matters but the SFDR categories for investors. Michèle Pappalardo, President of the French SRI Label Committee, considers that funds may view Article 9 as a green label.[2] All of these comments beg the following question: How does one differentiate between SRI labels from SFDR categories and how will they remain relevant tools to distinguish green strategies of SRI funds?

[2] Her interview is available at: http://www.revue-banque.fr/article/michele-pappalardo-madame-plus

The goal of this paper is to address this question, which is of key importance during a period where the European Commission (EC hereafter) is developing an EU Ecolabel for green funds, which aims to connect the SFDR and the EU Taxonomy disclosures by setting clearer thresholds (EC, 2020). In fact, if investors are better informed about the sustainability and greenness of funds, this creates an incentive for funds to invest in more sustainable ways (Hartzmark and Sussmann, 2019). For that purpose, our paper is the first, to the best of our knowledge, to analyze the portfolios of mutual funds that hold the French SRI label at a stock level and study their green trajectories over a six-year period (2015-2020).

We are focusing on the French SRI label for four reasons. Firstly, it has been leading the race of SRI labels in Europe with 833 labeled funds representing 635 billion ~~of~~ AuM as of September 30, 2021 (Novethic, 2021b). Secondly, the French label is appealing to researchers because it favors the use of positive ESG screenings with no sectoral exclusion, implying that "best-in-class" strategies are dominant (Leite and Cortez, 2015).[3] Thirdly, SRI funds must select their portfolio companies based on environmental criteria with specific attention paid to their "carbon footprint" in order to obtain the label. Our fourth and final reason, is the fact that in a recent report made for the Ministry of Economy and Finance, which manages the French SRI label, emphasizes the necessity to divide it in grades to promote funds, which then delivers the best environmental and/or social performances (IGF, 2020). Such an approach would make it possible to show investors the financial compensation associated with the fund's extra financial ambition (e.g., a higher level of risk or fees). Also, the French chapter of Eurosif, Forum pour l'Investissement Responsible (FIR) recommends to divide the labels in four grades in order to distinguish funds that meet Articles 8 or 9 of SFDR requirements and to grant funds offering a sustainability or green impact the best grading of the label (FIR, 2021).

In response to these recommendations, our paper proposes to examine the possibility of classifying French SRI labeled funds in clusters (or grades) in terms of their greenness degree.

Our methodological framework presents two immediate advantages. First, we rely on a set of variables to assess their environmental performance, which includes the most popular metrics used by fund managers, namely the level of carbon emissions, the carbon and energy footprints, the carbon and energy intensities (Popescu et al., 2021; Novethic, 2021a) as well as environmental and ESG controversies score (DasGupta, 2021; Novethic, 2021a). Second, we run two simple and widely used clustering algorithms: the k-means; and the fuzzy c-means algorithms, on the aforementioned variables to group funds according to their degree of

[3] To qualify for the French SRI label certification, a fund must exclude 20% of its initial universe based on ESG criteria, or the average ESG rating of a portfolio must be higher than the rating of its benchmark index.

greenness. If such an unsupervised learning approach is quite common in detecting hedge fund managers' investment styles (e.g., Brown and Goetzmann, 1997; Béreau et al., 2020), our paper is the first, to the best of our knowledge, to deal with the case of SRI funds.

Given this framework, we build on the insights of three strands of literature on SRI. First, our paper refers to the literature that studies the impact of SRI labels. For Bilbao-Terol et al. (2017), mutual funds increased their market valuation after obtaining the French SRI Label. According to Huang et al. (2020), funds linked to a performance label enjoy larger inflows due to greater reputation, but this relation depends on how fund managers promote their labels. For Allevi et al. (2021), labeling funds as "green" or "sustainable" helps investors identifying them as that to address environmental issues. However, Kaustia and Yu (2021) show that a self-designated SRI label helps funds attract more investors' flows than their non-SRI peers with similar traits, which may signal greenwashing motivations. Rzeźnik et al. (2021) confirm that investors care more about the label itself than the degree of ESG integration of funds.

Second, our paper is related to emerging research which assesses the efforts of funds and investors to decarbonize their portfolios. Boermans and Galema (2019) documented that those Dutch pension funds actively decarbonize their equity portfolios between 2009 and 2017. Humphrey and Li (2021) show that fund managers decided to "green" their fund families after having signed the United Nations-supported Principles for Responsible Investment (PRI) because "greener" portfolios attract investors. Benz et al. (2020) provide evidence that institutional investors engage in decarbonization herding since they tend to follow their own or other investors' buys (*resp*. sales) in green (*resp*. brown) stocks. Bolton and Kacperczyk (2020) find that institutional investors divest more from foreign carbon-intensive firms than from domestic ones. Boermans and Galema's findings (2021) complement those of Bolton and Kacperczyk (2020) by showing that the domestic (*resp*. foreign) part of the European investors' portfolio is more carbon intense since they are home biased when investing in carbon intensive stocks within Europe, because most carbon regulations come from this region.

Finally, our study speaks to the literature on SRI determinants and strategies. Due to the growing popularity of ratings and labels among investors, Dorfleitner et al. (2021) explain that SRI funds pursue clear and consistent investment policies in the short and long-term. This result is important for investors who are not likely to actively rebalance their investments. Leite and Cortez (2015) show that French SRI labeled funds exhibit lower stock-picking abilities during stable periods. They also find that SRI funds with positive (*resp*. negative) screenings i.e., adopting best-in class investment (*resp*. sector exclusion) strategies, offer similar (*resp*. lower) performance compared to conventional funds in those periods.

Our paper contributes to the above-mentioned literature in several respects. First, we provide evidence that is consistent with Benz et al. (2020) that finds managers of SRI labeled funds have engaged in decarbonization herding, which has accelerated since 2019. Second, our results indicate that the combination of six environmental performance variables: the level of net energy use; carbon emissions; the energy footprints; and carbon footprints; the energy intensities; and carbon intensities are able to differentiate (cluster) funds in a consistent manner. Moreover, the clusters are found to be stable over the period in question (2015-2020) due to the absence of fund transfers from one cluster to another. These clusters are also specific since membership grades of fuzzy c-means are significantly high (Klir and Yuan, 1995) regardless of the number of clusters tested (3 or 4). Third, we detect the existence of carbon home bias among SRI labeled fund managers (Boermans and Galema, 2021). In fact, we document that SRI labeled funds with a European investment focus are significantly less green in proportion when compared to those with a world perspective or with an out-of-Europe focus. This result implies that funds tend to be biased to carbon and energy intensive (*resp*. green) stocks within (*resp*. outside) Europe since they perceive lower uncertainty on both current and future carbon regulations, provided that most of those regulations only affect Europe. Fourth and quite importantly, our results highlight that the three SFDR categories, Articles 6, 8, and 9, cannot give a clear picture on the differences between funds in terms of environmental performance. To avoid such attempts, we show that four grades of label distinctiveness, which are fully compatible with the three SFDR categories, better capture the green trajectories of SRI French labeled funds. The *dark green* cluster of funds corresponding to Article 9 funds is homogenous to the extent that it invests in a limited number of equities and sectors consistent with thematic investment and/or ESG integration approaches (Morningstar, 2021). By contrast, the *light green* cluster of funds corresponding to Article 8 funds appears to be heterogeneous (Morningstar, 2021) owing to the predominance of best-in-class investment strategies that focus on a broad scope of companies and sectors. In this way, this light green cluster should be further broken down into two distinct grades to better capture such a heterogeneity. Finally, the *brown* cluster of funds may be considered as representative of Article 6 funds.

The rest of the paper is organized as follows. Section 2 describes the data and the methodology used to differentiate funds according to their greenness. Section 3 discusses our main empirical results. In Section 4, we present robustness tests. Section 5 is the conclusion.

2. Data and methodology

2.1. Data

2.1.1. SRI labeled mutual funds data

We obtained information on 462 equity funds from the list available on the dedicated website of the French SRI label as of July 2021. We collected for each fund the ISIN code, geographical focus, the launch date, the investment vehicle and the names of fund managers.

We extracted an initial sample of 462 equity funds after removing balanced, bond, money market, convertible funds and funds of funds from the initial list. We excluded ETFs, ETNs, and funds whose names contain the word 'index', 'MSCI', 'ETF', and 'iShares', as we aimed to study investment decisions made by active fund managers as in Humphey and Li (2018).

We also removed equity funds which have been fully reinvested in another existing fund to avoid overlapping. Finally, we excluded insufficient~~ly~~ funds, with a number of equity positions lower than five and those that only focus on private companies, to avoid outliers. By applying those filters, our final sample contains 380 SRI equity funds. For those selected funds, we collected the following information over the period of 2015 to 2020 from Refinitiv Eikon: (1) A detailed list of stock holdings and net assets invested at the end of each year; (2) For each stock holding, the Refinitiv Identifier Code (RIC), which is unique to the corresponding portfolio company, the number of shares in this company and the respective weight; (3) For each portfolio company, the amount of Scope 1 and 2 emissions, the level of Energy use (*Total Energy Use – Renewable energy produced*), the annual revenues (or turnover sales), the environmental pillar score, the ESG controversies score and the market capitalization.

Our study period starts in 2015 to account for the implications of the Paris summit on Climate Change (COP 21) on the investment decisions of SRI funds just before the launch of the French SRI label. Over the period between 2015-2020, our security-by-security analysis of stock holdings consists of 9,200 equities and 79,650 observations of funds' stock positions.

2.1.2. SFDR data classification

We used a proprietary database from Novethic, which reports the Article of SFDR (6,8,9) assigned to 1600 SRI funds that hold at least one European SRI label, including the French SRI label. Because SFDR has been voted in March 2021, some fund managers have not yet self-declared the SFDR article chosen for their SRI labeled funds. In this respect, Novethic tracks any new self-declaration contained in the latest publicly available fund prospectus or reportings in order to update its database on a weekly basis (Novethic, 2021b). The current study is based on the latest available update of the Novethic database as of December 31, 2021, to report the SFDR article pertaining to all our sampled SRI labeled funds.

2.2. Two clustering approaches: k-means and fuzzy c-means

One critical aspect of the methodology lies in the identification of green vs. non-green labeled funds through the use of a clustering technique. Hartigan (1975) showed that clustering techniques helped in summarizing, predicting and explaining information on data based on the characteristics of clusters. Contrary to the regression approach, they do not impose any linearity restrictions or theoretical structure between the endogenous and exogenous variables.

Newer research (e.g., Parnphumeesup and Kerr, 2011; Di Lascio et al., 2018; Affes and Hentati-Kaffel, 2019; Béreau et al., 2020; Mercadier et al., 2021; Vilas et al., 2022) has applied clustering techniques for grouping observations according to economic or financial variables' similarities. Among others, Vilas et al. (2022) has run five types of clustering algorithms, notably the k-means, to assess whether inclusion and exclusion processes of sustainability indices differ from those of conventional indices. Béreau et al. (2020) proposed a new procedure based on adaptative & non-adaptative k-means for measuring the impact of strategy distinctiveness among European equity mutual funds in terms of financial performance. Mercadier et al. (2021) proposed a dynamic decision support tool, which allows to cluster listed banks depending on their riskiness using an adjusted version of the k-means.

The main point of commonality of those papers is that they use a partitioning approach of clustering. This approach is particularly appropriate~~d~~ for our study, as we aim at gathering funds in terms of greenness based on a set of environmental variables (see above). Although partitional clustering requires better knowledge of the dataset regarding the parameters' tuning (Di Lascio et al., 2018), it is also, by construction, faster (Hartigan, 1975), and generally considered as more reliable, stable, and less sensitive to errors than hierarchical clustering. Based on this argument~~ation~~, we used two partitional clustering approaches to segment SRI labeled funds in green vs. brown (or less green) categories: the k-means, and the fuzzy c-means algorithms. The two approaches are complementary (Shin and Sohn, 2004). While the k-means splits funds into distinct clusters, implying that they only belong to one cluster, the fuzzy c-means removes this constraint by allowing them to belong to several clusters (Bezdek, 1981). We also used the fuzzy c-means for robustness purposes (Mingoti and Lima, 2006) and as a way to assess the specificity (or uncertainty) of our clusters (Klir and Yuan, 1995).[4]

[4] Mingoti and Lima (2006) show that FCM performs better than KM due to its capacity to remain stable in the presence of outliers and overlapping data.

2.2.1. K-means clustering

K-means (KM hereafter) is one of the most influential and widely used clustering techniques (Jain, 2010). KM exhibits many favorable properties and is well accepted for its simplicity and fast convergence in practice (Hartigan, 1975). On the empirical side, Aker and Aghaei (2019) used KM to cluster MENA countries based on economic diversification and performance. Parnphumeesup and Kerr (2011) employed it to segment a sample of Certified Emissions Reductions (CDM) (i.e., carbon credit) buyers in two clusters which varied with respect to their involvement in the Gold Standard (GS) label. The KM algorithm was run with five independent variables with the aim to assess buyers' involvement in the GS label.

To effectively partition the N sample funds (observations) into K clusters based on M clustering variables, we made three adjustments. We first standardized those M variables by applying the well-known z-score methodology particularly adapted to global standardization (Milligan and Cooper, 1988). Second, we set K =3 and K= 4 clusters. As seen in Figure 1, the inertia method commonly used to measure the compactness of each cluster (Nanda et al. 2010; Mercadier et al., 2021) leads us to select 4 clusters. We also chose K=3 clusters to be consistent with the number of SFDR categories (Articles 6, 8, and 9 respectively).

[INSERT FIGURE 1]

Finally, we applied the method developed by Arthur and Vassilvitskii (2007) to choose the initial centroids called the k-means++. Given these adjustments, we ran the KM algorithm in two steps as in Parnphumeesup and Kerr (2011):

Step 1: Each observation (SRI labeled fund) $\boldsymbol{x}_i \in \mathbb{R}^M$ is assigned to its closest centroid $\boldsymbol{c}_j \in \mathbb{R}^M$ out of K possible clusters, as expressed with the following loss function.

$$f(\boldsymbol{c}_j) := \sum_{i=1}^{N} \underset{1\le j\le k}{\operatorname{argmin}}\, d(\boldsymbol{x}_i, \boldsymbol{c}_j) \tag{1}$$

Where $d(\boldsymbol{x}_i, \boldsymbol{c}_j)$ is computed using the Euclidean distance. The (fund) observation assigned to a given centroid $\boldsymbol{c}_j$ make up the set S_j.

Step 2: For each cluster, a new centroid is computed as the mean of all observations of the set corresponding to the jth cluster, as follows:

$$\boldsymbol{c}_j = \frac{\sum_{x_i \in S_j} \boldsymbol{x}_i}{Card(S_j)} \tag{2}$$

The algorithm stops running as soon as the centroids remain the same or when the maximum number of iterations is achieved.

2.2.2. *Fuzzy c-means clustering*

The fuzzy c-means algorithm (FCM hereafter) is a variation of the KM algorithm, in which a degree of membership of clusters is incorporated for each fund (Bezdek, 1981). Barès et al. (2001) relied on FCM to assess the level of commitment of hedge fund managers to a specific strategy over time. Shin and Sohn (2004) used the FCM to group stock traders into three categories based on their traded amount and found that FCM provided more stable results than KM. By contrast, Nanda et al. (2010) obtained less specific clusters by applying FCM to classify returns of stocks traded in the Bombay Stock Exchange when compared to KM.

FCM decomposes the sample of labeled funds into K clusters given M clustering variables, by simultaneously estimating their cluster membership and the centroid of the cluster. The cluster membership of x_i in the cluster $\boldsymbol{c}_j$, which is denoted $u_{i,j}$ is defined as follows:

$$f(\boldsymbol{c}_j) := \underset{1 \leq j \leq k}{\mathbf{arg}\min} \sum_{i=1}^{N} \sum_{j=1}^{k} u_{ij}^{m} d(\boldsymbol{x}_i, \boldsymbol{c}_j) \tag{3}$$

$$\text{With} \quad u_{ij} = \left(\sum_{j=1}^{k} \frac{\|x_i - c_z\|^{2/m-1}}{\|x_i - c_j\|^{2/m-1}} \right)^{-1}, \text{ and } \quad \boldsymbol{c}_z = \frac{\sum_{i=1}^{N} u_{iz}^{m} x_i}{\sum_{i=1}^{N} u_{iz}^{m}} \; and \; 1 \leq z \leq k \tag{4}$$

We determined the degree of fuzziness $m = 2$ by using the optimization method of Ozer (2005).

The membership grade is the distance between each fund observation and all clusters, which is expressed in values ranging from 0 to 1. The closer the value is to 1 (*resp*. 0), the higher (*resp*. lower) the likelihood that the fund is a member of the cluster. Put simply, the closer the value is to 1 (*resp*. 0), the more the cluster is specific (*resp*. uncertain). In fact, Klir and Yuan (1995) showed that the membership grades ~~as~~ a cluster's measure of uncertainty (or non-specificity).[5]

2.3. *Clustering variables*

Most existing studies use scope 1 and scope 2 direct emissions to capture the level of carbon emissions as in Bolton and Kacperczyk (2021). Indeed, Scope 3 indirect emissions estimates are not sufficiently consistent across data providers due to the difficulty of their estimation and because companies rarely report those emissions data (Pospescu et al., 2021).[6]

For those reasons, we first extracted from each portfolio company of SRI funds their scope 1 & 2 emissions and their net energy use ~~net~~ of renewable energy produced at the end of the year using Refinitiv.[7] Second, we calculated the fund level of carbon emissions (*resp*.

[5] Klir and Yuan (1995) provide a detailed presentation on uncertainty or non-specificity measures related to FCM.
[6] Scope 1 emissions are direct carbon emissions from the company's operations e.g., chemical processes, combustions, vehicles. Scope 2 emissions are indirect emissions from the company using purchased electricity.
[7] The Refinitiv database (previously Thomson ASSET 4 database) provides yearly Scope 1 and 2 carbon emission levels. Refinitiv uses company reports to obtain data on carbon emissions in line with the Greenhouse Gas Protocol,

energy use) by calculating the weighted average of the carbon emissions (*resp*. energy use) of portfolio companies by considering the weight that they represent in the fund in terms of invested amount. Third, we took the log of **weighted** (portfolio) **carbon emissions** as in Humphrey and Li (2021) or in Azar et al. (2020) but also the log of **weighted** (portfolio) **Energy use** for consistency purposes. In the following paragraphs, we denote the Weighted Energy use (*resp*. Carbon emissions), **WE** (*resp*. **WC**).

We also circumvented the need for apportioning ownership of carbon, revenue or environmental impacts to individual holdings. Portfolios with larger assets under management will have a higher amount of total apportioned resources/pollutants than smaller portfolios because of their size. It is essential to normalize these absolute quantities to allow for fair comparison year on year against other portfolios or benchmarks. For that purpose, we used the metrics developed by S&P Trucost widely used by fund managers in their reporting (Novethic, 2021b; Rohleder et al., 2022) to assess the environmental performance of their portfolio companies (or stock holdings) i.e., Carbon to Value Invested, Carbon to Revenue.

Taking the relevance of those above-mentioned metrics into account, we computed the following clustering variables for each fund of the sample:

Weighted Energy use (*resp.* Carbon) footprint is the weighted Energy use (*resp*. Carbon) to Revenue. For each company, we obtained the Energy use (*resp*. Carbon) footprint by dividing the level of Energy use (*resp*. Carbon emissions) by their amount of USD revenues year by year. Then, summing up the product of all holding's weights corresponding to each portfolio company with its own Energy use (*resp*. Carbon) footprint, we obtained the Weighted Energy use (*resp*. Carbon) footprint. These metrics measure the environmental (or) carbon performance with respect to output (as revenues are closely linked to productivity). In the following paragraphs, we denote the Weighted Energy use (*resp*. Carbon) footprint, **WEF** (*resp*. **WCF**).

Weighted Energy use (*resp.* Carbon) intensity is the weighted Energy use (*resp*. Carbon) to Value Invested. For each portfolio company, we first computed the ratio Energy use (*resp*. Carbon emissions) divided by the amount in USD invested in this company by the fund, year by year. Then, summing up the product of each holding's weight in the portfolio with the company level carbon/environmental revenue intensity, we obtained the Weighted Energy use (*resp*. Carbon) intensity. These two metrics provide an indication of carbon or environmental efficiency with respect to shareholder value creation. In the following paragraphs, we denote

Kyoto Protocol or EU ETS, even if the reported Greenhouse Gas Protocol score is the preferred measure. If a firm does not report carbon emissions, Refinitiv estimates them using their Carbon Data & Estimate Model.

the Weighted Energy use (*resp*. Carbon) intensity, **WEI** (*resp*. **WCI**). In particular, the WACI is widely used to construct low-carbon indices, and many funds disclose it (TCFD, 2020)

In a similar fashion, we computed two other weighted measures: **Weighted Environmental Pillar (WEP)** score and **Weighted ESG Controversies (WESGC)** score for each fund.

Like Gibson et al. (2021), we used the Environmental score as measured by Refinitiv for each company, which depends on three aspects[8]: i) *Emissions*: carbon emissions, waste, biodiversity, environmental management systems; ii) *Innovation*: product innovation, green revenues, R&D & capital expenditures; iii) *Resource use*: water, energy, sustainable packaging, and environmental supply chain. The score ranges between 0 and 100%. 0% (*resp.* 100%) indicating poor (*resp*. excellent) environmental performance and insufficient (*resp*. high) degree of transparency in reporting material environmental data publicly.

Consistent with Dorfleitner et al. (2021) and DasGupta (2021), we also used the ESG Controversies score[9]. This score is based on 23 ESG controversy topics and is calculated by Refinitiv for each company. ESG controversies are public news stories about questionable ESG conducts of firms, collected from diverse media sources including major English-speaking news outlets, and NGOs. Environmental controversies notably include biodiversity matters, spills, and pollution (DasGupta, 2021). Companies with no controversies get a score of 100.

In order to calculate funds' **WEP** and **WESGC**, we matched the stock-level (i.e., portfolio company) information to mutual fund holdings as previously made for **WE, WC**, and **WEF, WCF** or **WEF, WCF** which is consistent with Rohleder et al. (2021).

3. Empirical results

3.1. Descriptive statistics

3.1.1. Presentation of the two samples used

Table 1 describes the sample of SRI labeled equity funds selected as well as the restricted sample of those funds that have yet disclosed their SFDR categories (i.e, Articles). Our full sample of equity funds is comparable in size to that used by Novethic (2021a) for its study on European green funds. On average, funds have 1.21 labels (including the French SRI label) meaning that 21% of funds hold another SRI label. About two third of SRI labeled funds have a geographic investment exposure to Europe. The rest of the funds mainly undertake either a global approach or invest in Asia and emerging countries to a lower extent.

[8] The respective weights applied to Emissions, Innovation and Resource Use is 34%, 34% and 32%.

[9] Refinitiv controls for the market capitalization bias that may significantly affect the differences of ESG Controversies score given large-cap companies attract more media attention than smaller-cap companies.

The full sample shows an average number of funds per manager that is slightly higher than the sample of SFDR categorized funds. However, our two samples are comparable in terms of duration and of invested amount that guarantees the relevance of carbon/energy intensities.

[INSERT TABLE 1]

3.1.2. Environmental performance of the two samples used

Descriptive statistics of the clustering variables are presented in Table 2. Over the six-year period (2015-2020), we observed that SRI labeled funds have increased by more than 66% with an average of 45 equity per fund. This confirms that the market is growing rapidly and becoming industrialized (Novethic, 2021a). They also revealed that SRI funds have decarbonized their portfolios over the past few years consistent with Humphrey and Li (2018) and Benz et al. (2020). Moreover, we noted that the environmental pillar (*resp*. controversies) score tends to increase (*resp*. decrease) over the six-year period (2015-2020) for both samples. Interestingly, we noticed that SFDR categorized funds have slightly better environmental and controversies scores on average. This observation is in line with that of Morningstar (2021).

[INSERT TABLE 2]

We constructed Figs. 2, 3, and 4 based on KM run with a minimum weight (w) = 50% and for K=3 or K=4 clusters respectively. All of these graphs are based on the average of weighted environmental metrics seen in § 2.3 over the six-year period (2015-2020).

Fig. 2 plots the level of weighted energy use (**WE**) and of carbon emissions (**WC**) for each cluster. As one might expect, it shows that those variables expressed in a logarithmic scale are highly and positively related for all of three or four clusters. Also, we find that the less (*resp*. more) green the cluster is, the higher (*resp*. lower) its levels of energy use and carbon emissions is for K=3 or K= 4 clusters, which is consistent with Humphrey and Li (2021). Taken together, these two observations confirm the relevance of those variables to assess environmental performance at a stock and fund level (Bolton and Kasperczyk, 2020; Novethic, 2021).

[INSERT FIGURE 2 HERE]

Fig. 3 shows that the weighted energy footprint (**WEF**) and the weighted carbon footprint (**WCF**) are highly and positively correlated as expected. We observe that the less (*resp*. more) green the cluster is, the higher (*resp*. lower) its carbon and energy footprints is for either 3 or 4 clusters consistent with Rohleder et al. (2022). It confirms the relevance of those two variables to assess environmental performance at a fund level (TCFD, 2020; Novethic, 2021).

[INSERT FIGURE 3 HERE]

Fig. 4 plots the weighted energy intensity (**WEI**) and carbon intensity (**WCI**), which are highly and positively related, as one might expect. In parallel to the observations made in Figs 1 and 2, we notice that the less (*resp*. more) green the cluster is, the higher (*resp*. lower) their carbon and energy intensities are for both 3 and 4 clusters consistent with Rohleder et al. (2022). These two results also highlight the relevance of those two variables to assess environmental performance at a fund level (TCFD, 2020; Novethic, 2021b; Rohleder et al. 2022).

[INSERT FIGURE 4 HERE]

3.2. Clustering results with K=3 clusters

In this subsection, we summarized the main results regarding K=3 clusters, a number that is consistent with this of SFDR categories. The Article 6 category may be viewed as the "*brown*" category since it does not rely on any sustainability objectives i.e., all managed funds. The Article 8 category is a catch-all category, including funds that promote environmental or social characteristics that Morningstar (2021) call "*light green*". It covers a wider range of funds, which mainly follow best-in-class or positive screening approaches. In contrast, the Article 9 category may be considered "*dark green*" for Morningstar (2021) in the sense that a majority of Article 9 funds have a green thematic and/or impact focus aligned with UN Sustainable Development Goals (SDG). Said differently, Article 9 funds often follow thematic and/or ESG integrated approaches to focus mainly on greener equities.

Table 3 presents the number of funds belonging to each cluster and the percentage that they represent year by year over the six-year period. Panel A results, which refer to the full sample, indicate that on average 34.2% of funds belong to the greenest cluster 1 related to Article 9, while almost 50% belong to cluster 2 related to Article 8 if we consider w=50%. For w=60%, ~~the~~ 31.6% figure for ~~the~~ cluster 1 as well as the 48.6% figure for cluster 2 are slightly lower. Panel B results, which are related to the restricted sample of labeled funds that have reported their SFDR classifications, are close to those obtained in Panel A in terms of distributions among the three clusters for both w=50% and w=60%.

Another important result observed in both Panels is the proportion of cluster 1 funds that has increased twofold between 2015 and 2020. More especially, 2019 is a turning point in the decarbonization trend of funds' portfolios with a significantly higher (*resp*. lower) percentage for the cluster 1 (*resp*. cluster 3) of funds. This result provides evidence that managers of funds, which have held the French SRI label especially from this year (important in number), engage in decarbonization herding detected by Benz et al. (2020) on the market of US mutual funds.

Overall, Panels A and B results show that cluster 1 is suitable to account for the *dark green* Article 9 category because their percentages are similar, whatever the KM scenario. Furthermore, the percentages of cluster 2 are lower than these of the *light green* Article 8 category while the percentages of cluster 3 are significantly higher than these of the *brown* Article 6 category. We can interpret this latest result as evidence of greenwashing incentives provided that fund managers can self-declare about 20% of their funds in Article 8 funds while they are likely to belong to the *brown* Article 6 category according to our estimations.

[INSERT TABLE 3]

Table 4 displays the number of funds that belong to the three clusters and the proportion that they represent for two subsamples: one subsample is composed of funds with a domestic or a European focus and another is composed of funds with out of Europe focus (Asia, Emerging Markets, North America) or a world focus.

We can see from Panels A (corresponding to weight w=50%) and B (corresponding to w=60%) that the *dark green* cluster of funds is significantly larger for funds with an out of Europe or wold focus. By contrast, the *brown* cluster of funds is significantly larger for funds with a domestic or a European focus. These two results clearly indicate the prevalence of a carbon and energy home bias among French SRI labeled fund managers who invest for their main clientele of European investors (Boermans and Galema, 2021).

[INSERT TABLE 4]

Panels A and B of Table 5 report the average number of equities held by labeled funds cluster by cluster for the whole sample and the restricted sample respectively. On average, this number is 30% lower for the greener cluster 1 as compared to the cluster 2.

Considering the case of w= 50% (*resp*. 60%) and the whole sample of labeled funds, we can also calculate that 45.7% (*resp*. 43.9%) of total equities studied are invested by the greenest cluster 1 of funds, while 60.6% (*resp*. 59.8%) of them are held by the cluster 2 of funds.

Those two results indicate that the cluster 1 related to the Article 9 category invests in a smaller and relative homogenous panel of equities, leaving funds with lower stock-picking possibilities (Leite and Cortez, 2015) whereas the cluster 2 related to the Article 8 category invests in a larger panel of equities that are more carbon intensive consistent with Morningstar (2021).[10] Moreover, we obtain that 33.5% (*resp*. 32.6%) of total equities held are invested in

[10] Morningstar (2021) estimates that approximately 40% (*resp*. 17%) of Article 9 (*resp*. Article 8) funds have at least 10% exposure to companies with carbon solutions.

common by the clusters 1 and 2 funds for w=50% (*resp*. 60%), which is close to the estimates of Morningstar (2021) that detects a 29% overlap of equities held by Article 8 and 9 funds.

Regarding the *brown* cluster 3 of funds, it invests in larger and more diversified portfolios with an average number of equities, which is about twice (*resp*. 60%) higher than this of cluster 1 (*resp*. cluster 1) funds on average. If we consider w=50% (*resp*. 60%), we find that cluster 3 invests in 79.8% (*resp*. 79.1%) of total equities on average, suggesting that cluster 3 funds tend to follow a well-diversified and passive investment strategy.

Remarkably, the average number of equities held by each cluster remains relatively stable over the period of 2015-2020, suggesting that SRI labeled funds pursue clear and consistent investment policies in the long term, which confirms the findings of Dorfleitner et al. (2021).

[INSERT TABLE 5]

Table 3 provides preliminary insights into the constitution of our clusters when applying the KM approach. We then describe the stability and the uncertainty of the three clusters by computing two specific measures related to the KM and FCM algorithms.

Cluster stability depicts the similarity percentage of associated SRI labeled funds in two consecutive periods. Table 6 displays the probabilities that those funds change (or not) their cluster membership based on KM tests run for Table 3. Those probabilities assess the cluster instability (*resp*. stability) because they represent the average % change (*resp*. % similarity) provided that funds move (*resp*. do not move) from one cluster at the start (2015 or after if they are created after) to another cluster at the end of the period (2020 or before if they were closed).

The probabilities that clusters 1 and 2 stay in the same clusters range from 81.8% and 85.3% depending on the sample and the weights (w=50% and w=60%) used. As for t~~he~~ cluster 3, the probabilities are slightly lower ranging from 70.4% and 76.8%. Notwithstanding this slight difference, this first set of result signals an important cluster stability which is indicative of consistent investment policies followed by mutual funds in the long term, as previously seen in Table 4, in line with the findings of Dorfleitner et al. (2021). Quite importantly, it also underscores the relevance of our KM tests and of the six environmental (clustering) variables.

In addition to the above, the percentages of change are only significant for probabilities that are related to the closest clusters. About 20% of cluster 2 (*resp*. cluster 3) funds move to cluster 1 (*resp*. cluster 2) so they become greener, which confirms the decarbonization trend of SRI labeled funds observed in Table 3 over the period between 2015-2020.

[INSERT TABLE 6]

We thus obtained a measure of cluster uncertainty after having run FCM tests on the full and restricted samples given the two previously tested scenarios w=50% and w=60%.

The FCM algorithm estimates membership grades of funds for belonging to the three clusters. If the membership grade for a cluster is 1 and for each of the other clusters is zero then its cluster association is totally specific. However, if the membership grades are distributed over several clusters, it leads to a higher uncertainty in the association. In our case, the more uniformly the membership grades are distributed over the three clusters, the more nonspecific or uncertain the cluster assignment of the fund is. The total uncertainty for a cluster depends on the uncertainties contributed by the two other cluster alternatives (Klir and Yuan, 1995).[11]

Panels A and B of Table 7 report the average membership grades for the three FCM clusters over the full sample of funds, and the restricted sample with only SFDR categorized funds, respectively. The average membership grades are computed as the membership grades averaged over the six-year period under scrutiny (2015-2020).

Overall, the membership grades between the same clusters are close to 70% for clusters 1 and 2, signaling that those clusters can be considered as specific or certain. Regarding the *brown* cluster 3, the membership grades for the same cluster are close to 67%. However, their standard deviations from the mean membership grade are twice as high than those of clusters 1 and 2. The cluster 3 may be therefore viewed as less specific and stable to a slight extent.

Further investigation on the lower stability and specificity of the *brown* cluster 3 will be made in the following paragraphs through FCM tests with 4 variables.

[INSERT TABLE 7]

Table 8 shows the number of funds, which belong to each cluster by considering their membership grades split by an interval of 10% distance. Only the funds that have disclosed their SFDR categories in their prospectus are considered.

The highest confidence intervals [90%-100%] [80-90%], [70-80%] are concentrated between 53% and 62% of funds belonging to greener clusters 1 and 2. By comparison, those intervals represent 52% of funds belonging the cluster 3, whatever the weight. This slight difference reinforces the idea of lower specificity of cluster 3 formulated from Table 6 results.

Table 8 also reports for each confidence interval of membership grades the number of funds with a cluster consistent with its SFDR category self-declared by their fund managers.

[11] Klir and Yuan (1995) provide a detailed presentation on uncertainty (non-specificity) measures related to FCM.

When considering the highest confidence interval [90%-100%], the percentage of adequacy between cluster 1 and Article 9 is 93% while the percentage of adequacy between cluster 2 and Article 8 is slightly lower (83% for w=50% and 88% for w=60%). ~~Then,~~ this percentage of adequacy then decreases as the confidence interval is descending but remains higher than 45% for the confidence interval [50%-60%]. As for cluster 3, the percentage of adequacy is significantly lower, between 0% and 25% whatever the confidence intervals. This result is not surprising given that the percentages associated to cluster 3 membership obtained in Panel B of Table 3 is five times as high as those of Article 6 funds at least.

[INSERT TABLE 8]

3.3. Clustering results with K=4 clusters

In this subsection, we summarize the main results regarding K=4 clusters, which is found to be the optimal number of clusters according to Figure 1.

Table 9 displays the number of funds belonging to each cluster and the portions that they represent year by year over the period 2015-2020.

Panel A results refer to the full sample of labeled funds. From Panel A, we can see that 18% of funds belong to the greenest cluster 1 on average, while 33% (*resp*. 39%) belong to cluster 2 (*resp*. cluster 3) on average. Interestingly, the share of funds belonging to cluster 1 increased more than twofold between 2015 and 2020 when the percentage of funds belonging to cluster 2 (*resp*. cluster 2) increased (*resp*. decreased) by 76% (*resp*. 70%) if we consider w=50%. Similar trends are obtained for w=60%. Regarding cluster 3, the percentages appear to be more stable ranging from 11% and 16% for both w=50% and 60%.

Panel B results relate to the restricted sample of labeled funds that have already reported their SFDR classifications. Those results are close to those obtained in Panel A in terms of distributions among the four clusters for both w=50% and w=60%.

Another important result previously observed is that 2019 marked a turning point in the decarbonization trend of funds' portfolios, with a significantly higher (*resp*. lower) percentage for clusters 1 and 2 (*resp*. cluster 3 and 4) of funds for both Panels. In particular, the aggregate share of clusters 1 and 2 increased by a quarter from 2018 to 2019. These results confirm this in Table 3 since managers of funds, which hold the French SRI label, engage in decarbonization herding, which has accelerated from 2019, consistent with Benz et al. (2020).

Taken together, Table 9 results indicate that the *dark green* cluster 1, referring to Article 9 category, may be less represented compared to those seen in Table 3. We can interpret this result as evidence that some fund managers may be inclined to greenwashing attempts leading to market *light green* funds in Article 9 funds. In turn, the aggregate share of clusters 2 and 3, which refer to the *light green* Article 8 category are much closer to the percentage related to cluster 1 in Table 3. In this respect, the clusters 2 and 3 are likely to represent the heterogeneous Article 8 category, while cluster 1 accounts for the homogeneous Article 9 category. These considerations are supported by the percentages of cluster 4, which are closer to these of Article 6 category seen in Table 3. This latest result leads us to believe that greenwashing incentives are less significant than anticipated from the Table 3 results obtained with 3 clusters.

[INSERT TABLE 9]

Table 10 presents the number of funds that belong to the four clusters and the share that they represent for two subsamples. One is composed of funds with a domestic or a European focus, and the other is composed of funds with out of Europe focus (Asia, Emerging Markets, North America) or a world focus.

We can see from Panels A (which corresponds to w=50%) and B (which corresponds to w=60%) that the *dark green* cluster of funds is significantly more important for funds with a domestic or a European focus. By contrast, the brown cluster of funds is significantly larger for those with a domestic or a European focus. Taken together, these two results suggest the existence of a carbon and energy home bias among French SRI labeled fund managers who invest for their main clientele of European investors (Boermans and Galema, 2021).

[INSERT TABLE 10]

Panels A and B of Table 11 displays the average number of equities held by labeled funds, cluster by cluster, for the whole sample and the restricted sample respectively. On average, this number is 40% higher for the light green cluster 2 as compared to the greenest cluster 1. The difference between the clusters 2 and 3 is less significant, on average 35%. Considering w= 50% (*resp*. 60%) and the full sample of labeled funds, we find that 43.3% (*resp*. 42.8%) of total equities studied are invested by the greenest cluster 1, while 55.5% (*resp*. 54.9%) of them are held by cluster 2 and 62.5% (*resp*. 61.8%) of them are invested by cluster 3.

The above results are consistent with Table 5 results. They confirm that cluster 1 related to the Article 9 category invests in a smaller and relative homogenous panel of equities, limiting the stock-picking possibilities of funds (Leite and Cortez, 2015) whereas clusters 2 and 3 related to the Article 8 category invest in a larger panel of equities, which explain that their portfolio are more carbon intensive consistent with Morningstar (2021).[12] Interestingly, we obtain that 34% (*resp*. 33.8%) of total equities held are commonly invested by ~~the~~ clusters 1, 2 and 3 funds for w=50% (*resp*. 60%), in line with the estimates of Morningstar (2021) that finds a 29% overlap of equities held by Article 8 and 9 funds.

The *brown* cluster 4 is found to have more diversified portfolios as compared to the previous *brown* cluster 3 seen in Table 4 with an average number of equities, which is about 2.5 times higher than the *dark green* cluster 1. If we consider w=50% (*resp*. 60%), cluster 4 invests in 81.8% (*resp*. 80.9%) of total equities on average, indicating that clustered 4 funds are likely to follow a highly diversified and passive investment strategy.

As seen previously in Table 5, the number of equities held by each cluster remains stable over the six-year period (2015-2020), which confirm that SRI labeled funds pursue consistent investment policies in the long term, consistent with the findings of Dorfleitner et al. (2021).

[INSERT TABLE 11]

Table 12 outlines the probabilities that funds change their cluster membership based on KM tests run for Table 8. The probabilities that clusters 1, 2, and 3 do not move to other clusters from 71% to 83.6%. As for *brown* cluster 4, the probabilities are between 70.4% and 72.2%, which are greater than the probabilities observed for *brown* cluster 3 related to KM tests that were run with 3 clusters (see Table 5). This latest result suggests that 4 categories in the French SRI label allows better cluster stability, especially for the *brown* cluster.

Furthermore, the percentage of changes are only significant for probabilities that are calculated between the closest clusters. Between 20.8% and 24.4% of cluster 3 funds move to cluster 2 so they become greener, while only between 11.1% and 12.8% of cluster 2 funds drop down to cluster 3 so they become browner. This result is important for two reasons. First, it confirms the existence of a decarbonization trend among SRI labeled funds detected previously over the period between 2015-2020. Second, it emphasizes the importance of four grades in the French SRI label to allow the greenest cluster 1 funds to differentiate from cluster 2 funds among the Article 8 category and to stimulate decarbonization efforts of those cluster 3 funds that do not necessarily have a clear environmental or sustainability objective.

Taken together, Table 12 results point to a higher cluster stability for the four KM clusters scenario provided that it allows 3 changes, as compared to 2 changes, for three clusters. Such a stability is associated with consistent investment strategies followed by mutual funds in the

[12] Morningstar (2021) estimates that approximately 40% (*resp*. 17%) of Article 9 (*resp*. Article 8) funds have at least 10% exposure to companies with carbon solutions.

long term (Dorfleitner et al., 2021). Also, Table 12 results stress the relevance of our KM tests run with four clusters and the six environmental clustering variables selected.

[INSERT TABLE 12]

Table 13 displays the values of average membership grades for the four FCM clusters for the two samples of funds studied. As in Table 7, the average membership grades are computed as the membership grades averaged over the six-year period (2015-2020).

Overall, the membership grades between the same clusters are higher than 62% for clusters 1, 2, and 3, i.e., slightly lower than those obtained for the three FCM clusters (about 70% on average). Note that the average membership may decrease by 33.3% with four FCM clusters as compared to three FCM clusters. In this respect, ~~the~~ clusters 1, 2, and 3 can be considered as specific or certain no matter the sample (Panels) considered. Whereas the uncertainty exists for brown cluster 3 given 3 FCM tests (see Table 6), the membership grades between the same cluster for the equivalent *brown* cluster 4 are comparatively higher and closer to those found for clusters 1, 2, and 3. This result signals that the specificity of the *brown* cluster 4 is comparable to clusters 1, 2 and 3. Therefore, this *brown* FCM cluster 4 is significantly less uncertain than the previous brown FCM cluster 2 (FCM run with 3 clusters).

[INSERT TABLE 13]

4. Robustness tests

In our main analysis, we clustered SRI labeled funds given a limited set of six environmental variables, which are the most widely used by academics and practitioners. However, our variables are only dependent on two environmental metrics i.e., energy consumption, and Scope 1 and 2 carbon emissions. Therefore, this section proposes the inclusion of two alternative variables and presents further robustness checks.

A first alternative variable is the environmental pillar score provided by Refinitiv. In addition to energy use and carbon emissions, this score includes additional metrics related to innovation efforts (e.g., green revenues, R&D & capital expenditures), which account for a third of the score (Gibson et al., 2021) and that have been ignored until now on.

A second alternative variable is the ESG controversies score. According to Morningstar (2021), Article 8 and 9 funds are less exposed to severe controversies than Article 6 funds. Its recent report published several months after SFDR introduction states that 81% (*resp*. 55%) of Article 9 (*resp*. Article 8) funds' strategies exhibit zero exposure to severe controversies.

Figs. 5, 6, 7 and 8 are based on KM run with a minimum weight (w) = 50%, and 8 variables ~~i.e.,~~ (the six variables previously used: **WE, WC**, **WEF, WCF**, **WEF, WCF** and the two above-mentioned variables i.e., **WEP** and **WESGC.)**

Figs. 2, 3, and 4 point out a positive relation between level of energy and carbon emissions as well as between energy and carbon footprints or intensities assuming either 3 or 4 clusters. Similar findings can be made after observing Figs 5, 6 and 7 respectively. Also, we can verify that the less (*resp*. more) green the cluster ~~is~~, the higher (*resp*. lower) its levels of energy/carbon, energy/carbon footprints and energy/carbon intensities, ~~is~~ whatever the number of clusters.

[INSERT FIGURE 5]

[INSERT FIGURE 6]

[INSERT FIGURE 7]

Moreover, Fig. 8 plots the weighted environmental score (WEP) and ESG controversies (WESGC), which are negatively related as one might expect. We also noticed that the less (*resp*. more) green the cluster is, the more (*resp*. less) it is subjected to ESG controversies assuming either 3 and 4 clusters (Das Gupta, 2021; Dorfleitner et al., 2021) Those results confirm the relevance of the two variables to grasp environmental performance more exhaustively.

[INSERT FIGURE 8]

Based on KM tests run with 3 clusters and the 8 variables, Table 14 presents the number of funds belonging to each KM cluster and the percentage that they represent year by year. The conclusions made from Table 3 apply to both Panels of Table 13. From Panel B, ~~the~~ cluster 1 appears to be suitable to account for the *dark green* Article 9 category in a sense that their percentages are similar. We note, however, that the percentages attached to cluster 2 are slightly lower as compared to those of Table 3. Furthermore, if the percentages of cluster 2 are lower than these of the *light green* Article 8 category, we find that the percentages of cluster 3 are significantly higher than these of the *brown* Article 6 category. Taken together, these findings highlight the existence of greenwashing attempts. In particular, fund managers self-declare almost 20% of their funds in Article 8 funds while they are more likely to belong to the *brown* Article 6 category according to our estimations.

[INSERT TABLE 14]

Table A1 (see Appendix) displays the probabilities that those funds may or may not change their cluster membership based on KM tests run for Table 14. Previous findings related to the three clusters' stability apply. If greener clusters 1 and 2 continue to be stable, the *brown* cluster 3 is significantly more unstable, as seen previously.

[INSERT TABLE A1]

Table A2 (see Appendix) presents the average membership grades for the three FCM clusters based on FCM run with 8 variables. Greener clusters 1 and 2 are found to be specific while the *brown* cluster 3 is significantly more uncertain confirming our initial findings.

[INSERT TABLE A2]

Based on 4 KM clusters, Table 15 shows the number of funds belonging to each cluster and the portions that they represent over the period 2015-2020.

Overall, we can see that about 25% of funds belong to the greenest cluster 1 in 2020 no matter the sample and the weight considered. If this percentage is lower than this displayed in Table 8, the percentage of funds belonging to cluster 1 increased twofold between 2015 and 2020 as in Table 8. Moreover, we find that the *light green* clusters 2 and 3 achieve 60% on aggregate, which is consistent with the percentage of Article 8 category.

We can also confirm that 2019 is a tipping point in the decarbonization trend of funds' portfolios with a significant higher (*resp*. lower) percentage for ~~the~~ clusters 1 and 2 (*resp*. cluster 3 and 4) of funds for both Panels A and B. Notably, the percentage of cluster 1 has increased by 25 % from 2018 to 2019 on average. This corroborates our previous findings about the existence of a decarbonization herding (Benz et al., 2020) given that managers of funds, which have held the French SRI label, engage in greening their portfolio especially from 2019.

[INSERT TABLE 15]

Table B1 (see Appendix) outlines the probabilities that funds may or may not change their cluster membership based on KM run for Table 15. Similar conclusions on stability may be made. Clusters 1, 1 and 3 are always stable while the *brown* cluster 4 is slightly less stable.

[INSERT TABLE B1]

Table B2 (see Appendix) presents the average membership grades for the four clusters obtained from FCM run with the 8 variables. As seen, all clusters appear to be specific but to a lower extent probably due to the influence of the ESG controversies.[13]

[INSERT TABLE B2]

Taken together, our results suggest that the *dark green* cluster 1 may be slightly less represented in proportion, as one might expect given the number of Article 9 reported by fund managers. Also, ~~the~~ two clusters 2 and 3 appear to better capture the heterogeneity of Article 8 rather than only one cluster. Accordingly, the committee of the French SRI label, which currently considers reshaping its organization, may decide to implement a first grade (or level) for the label in line with Article 9's objectives. However, this grade may be more demanding in terms of energy or low carbon performance and related disclosures than SFDR in order to reduce greenwashing motivations. A second grade and ~~a~~ third grade may be helpful since the Article 8 category is too heterogeneous to compare the green performance of funds (Novethic, 2021b; Becker et al., 2022). In this way, some SRI labeled funds, which are not specifically designed to be green, may be rewarded for their efforts in terms of decarbonization by progressing from the third grade (i.e., cluster 3) to the second grade (i.e, cluster 2). A fourth grade with objectives consistent with Article 6 may be implemented. For this grade, a particular attention to controversies in addition to environmental performance would be relevant and desirable. Quite importantly, these four grades (or levels) should be frequently revised in order to ensure the integrity of the label and its own capacity to differentiate green strategies of funds.

[13] We also run KM and FCM with 7 variables excluding the controversies score (**WESGC**) in an identical manner. The results that we obtain are closer to those found in our main analysis. Available upon request.

5. Conclusion

Extensive research has been done on the influence of SRI labels on mutual funds in terms of market valuation (e.g., Bilbao et al., 2015), inflows (e.g., Huang et al., 2020) and performance (e.g., Leite and Cortez, 2015). However, little is known as to the green features of SRI labeled funds and the style of their investment strategies. Our paper fills this gap.

Motivated by the potential confusion between SRI labels and SFDR regulations (Becker et al., 2022), we explored how those labels can still differentiate green strategies of European mutual funds. For that purpose, our paper develops a novel approach to distinguish equity funds, which hold the French SRI label, in clusters. Specifically, we used two complementary unsupervised learning approaches: the KM and the FCM clustering algorithms.

By diving into the portfolio composition of French SRI labeled funds through the use of the two above clustering algorithms, our study contributes to the current existing literature in several respects. First, our results indicate that managers of SRI labeled funds engage in decarbonization herding especially from 2019 consistent with Benz et al. (2020). Second, from a methodological perspective, our results suggest that the combination of six environmental performance variables, namely the level of net energy use/carbon, energy and carbon footprints or energy and carbon intensities, are able to differentiate mutual funds in a consistent manner. We then find that clusters are stable due to the absence of changes of SRI labeled funds from one cluster to another over the period under scrutiny (2015-2020). Third, we provided evidence of carbon home bias among fund managers (Boermans and Galema, 2021). SRI labeled funds with a European investment focus are significantly less environmentally friendly (or less green) in proportion to those with a world perspective or with an out of Europe focus. This important result implies that funds are biased to carbon and energy intensive (*resp*. green) stocks within (*resp*. outside) Europe since they perceive lower uncertainty on carbon regulations in Europe given that most of those regulations only relate to the European area. Fourth, we showed that the 3 SFDR categories i.e., Articles 6, 8, 9, cannot reflect the differences between funds in terms of greenness. Notably, fund managers tend to exaggerate the environmental performance of funds that they self-declare as Article 8 and 9 funds, consistent with greenwashing motivations (Kaustia and Yu, 2021). To avoid such attempts, our results point out the necessity of having four grades of distinctiveness (or levels) for the French SRI label that are fully compatible with the three SFDR categories to better capture green trajectories of funds. The first grade, i.e., the *dark green* cluster of funds related to SFDR Article 9 category appears to be homogenous because it invests in a limited number of equities and sectors in line with thematic investment and/or ESG integration approaches. However, the *light green* clusters of funds related to Article 8 category is found to be heterogeneous and should be decomposed in two specific clusters. Such ~~a~~ heterogeneity is notably due to the domination of best-in-class investment strategies, which focus on a broad scope of sectors and companies. Therefore, a second grade and a third grade combined together are able to better capture the heterogeneity of the Article 8 funds (Morningstar, 2021; Becker et al., 2022). Finally, the *brown* cluster of funds as the fourth grade may be considered as representative of Article 6 funds.

At a time when the European Commission is developing an EU Ecolabel for funds, likely linking to the SFDR and label disclosures by setting clearer thresholds, our findings are useful for investors, fund managers and regulators. For investors, we show that the SRI label remains essential to differentiate environmental (or green) performance of mutual funds, especially if they are structured in grades. In either case, fund managers who develop costly thematic or ESG integration approaches to make their portfolio green in the long term may gain greater visibility (Rzeźnik et al. 2021) and may be compensated as a result (Dorfleitner et al., 2021).

From the perspective of regulators, the fact that SFDR categories and SRI label grades may be compatible is essential to better detect potential greenwashing attempts of mutual funds. Besides, knowing the existence of a carbon and energy home bias among fund managers and investors is important for two reasons. First, it is a barrier to the international diversification of their carbon risks. Second, those mostly at carbon risk are those with a higher home bias. They are not inclined to reduce these risks, especially if they earn a carbon premium on their carbon- and energy- intensive European investments (Boermans and Galema, 2021).

Two avenues for further research may be identified. A possible extension of this work would be to study the social performance of SRI funds to have a more complete view on their sustainability. Another direction would be to compare the degree of greenness of labels, which require sector exclusions with those that promote positive screenings, like the French SRI label.

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List of Tables and Figures

Figure 1. Elbow method for determining the number of clusters

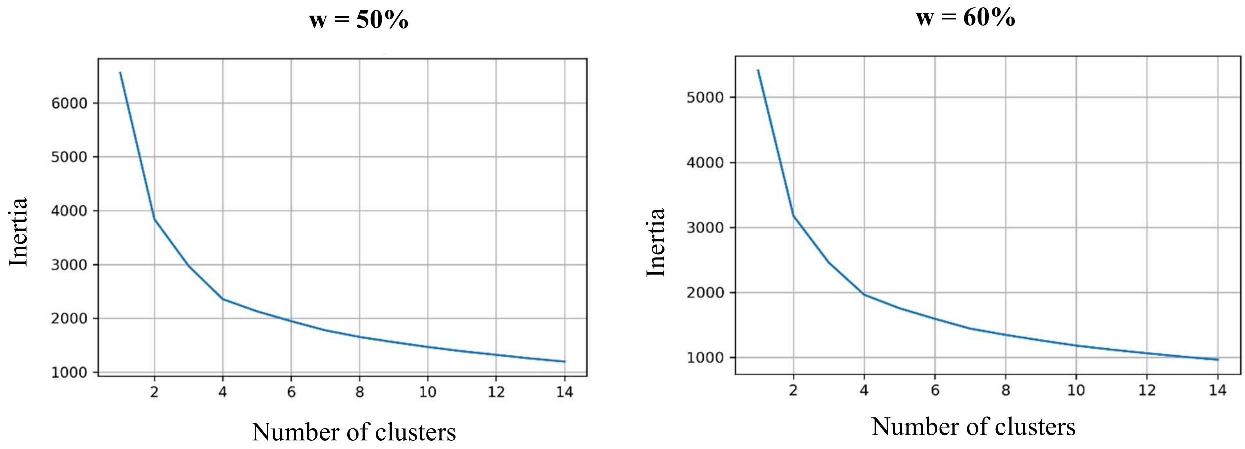
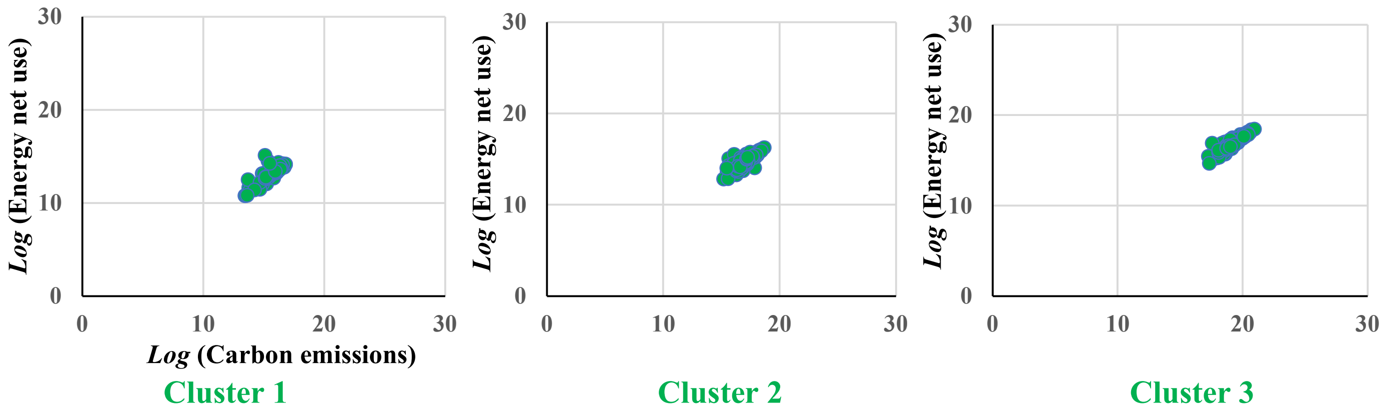
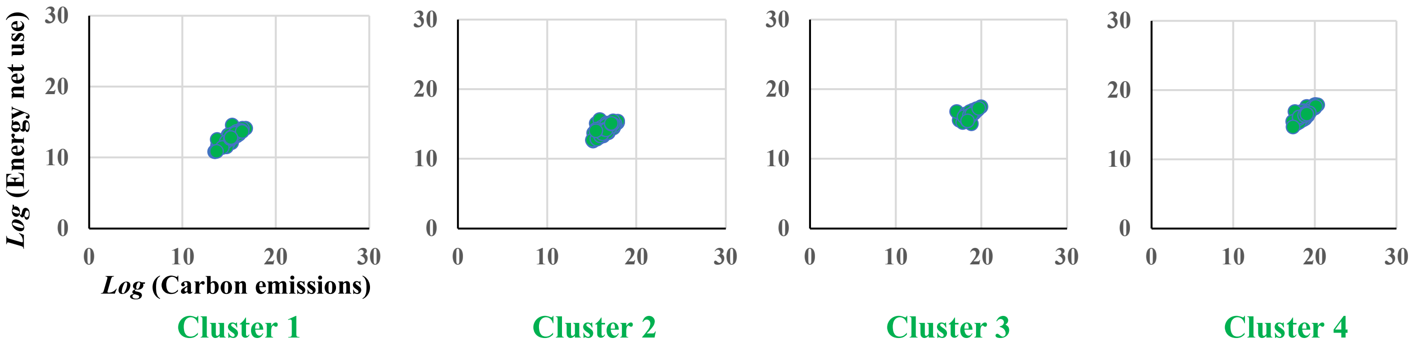


Figure 2. Energy net use vs. Carbon emissions – Scenario 6 variables

a) With 3 clusters

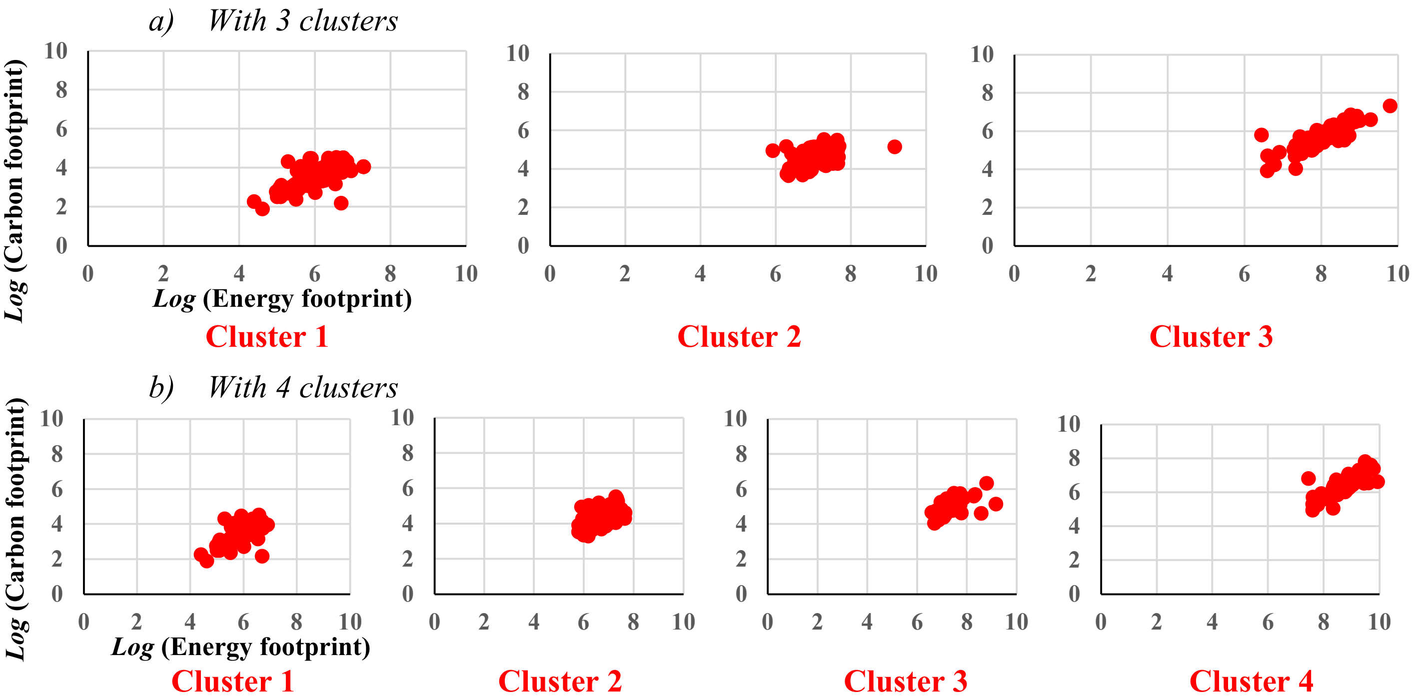


b) With 4 clusters



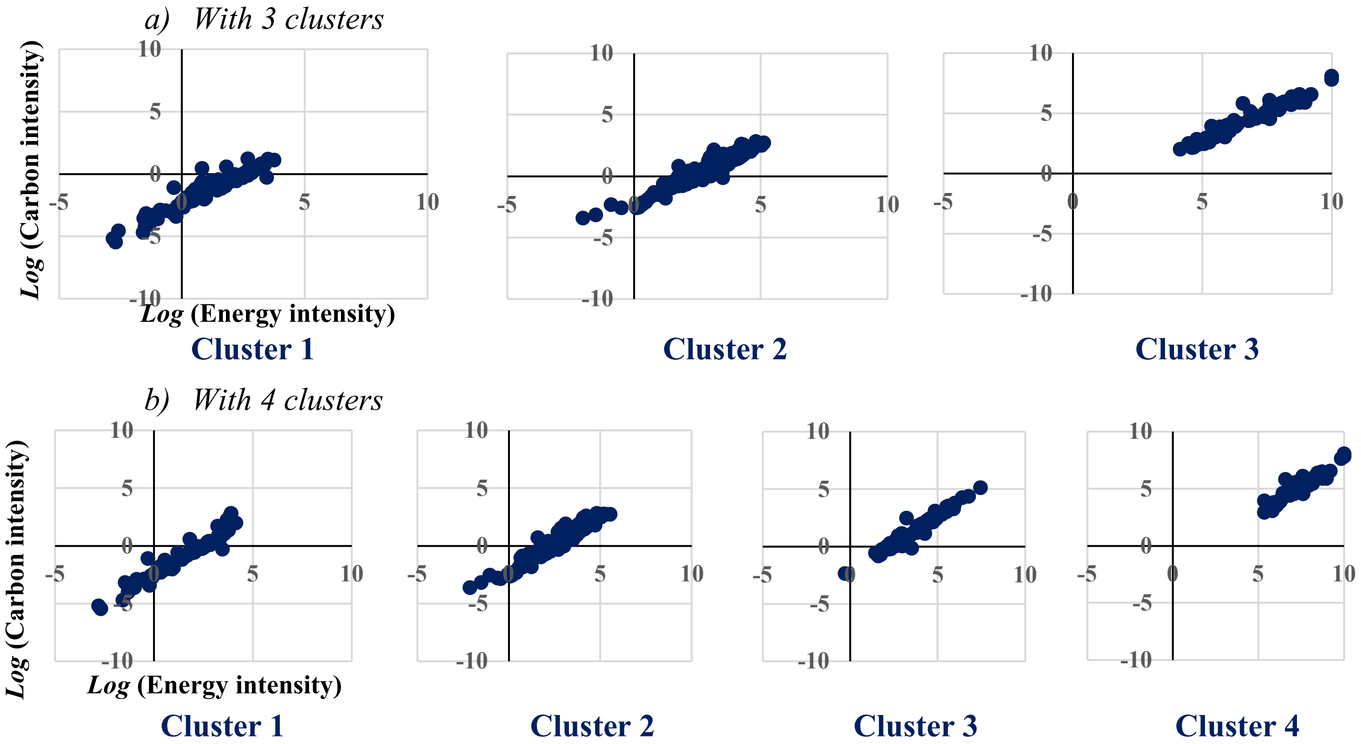
Note: The figures plot the logarithmic net Energy use with the logarithmic Carbon emissions averaged over the six-year period (2015-2020) of each fund belonging to their 3 (*resp*. 4) respective KM clusters obtained from six variables of interest. The sample of funds considered here is the full sample studied with **w** = **50%**.

Figure 3. Energy vs. Carbon footprint – Scenario 6 variables



Note: The figures graph the logarithmic Energy intensity ratio (*Energy use per dollar of sales*) with the logarithmic Carbon intensity (*Scope 1 &2 carbon emissions per dollar of sales*) ratio averaged over the six-year period (2015-2020) of each fund belonging to their 3 (*resp*. 4) respective KM clusters obtained from six variables of interest. The sample of funds considered here is the full sample studied with **w** = **50%**.

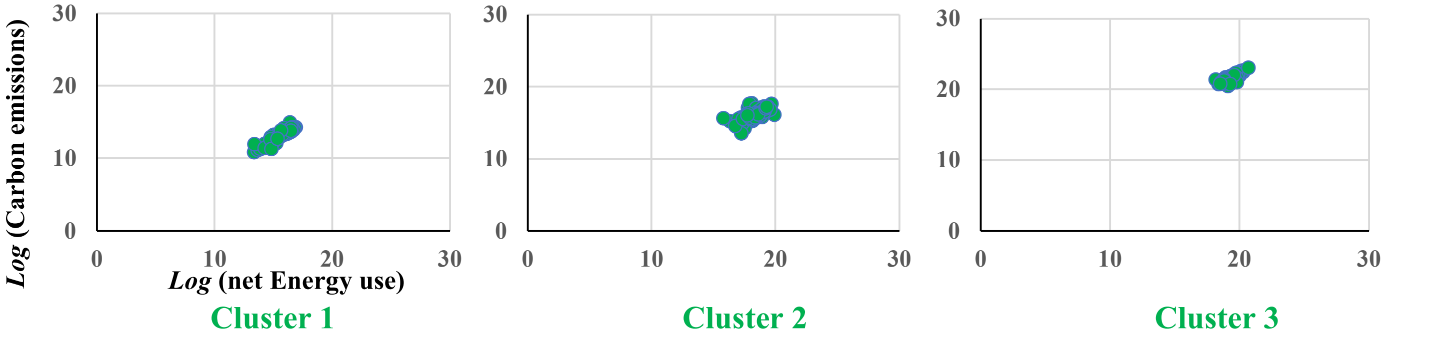
Figure 4. Energy vs. Carbon intensity – Scenario 6 variables



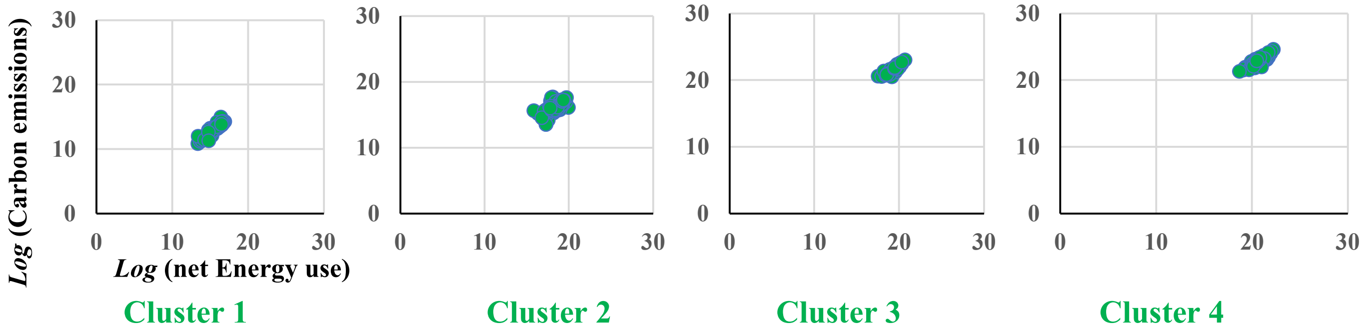
Note: The figures plot the logarithmic Energy intensity ratio (*Energy use per dollar invested*) with the logarithmic Carbon intensity (*Scope 1 &2 carbon emissions per dollar invested*) ratio averaged over the six-year period (2015-2020) of each fund belonging to their 3 (*resp*. 4) respective KM clusters obtained from six variables of interest. The sample of funds considered here is the full sample studied with **w** = **50%**.

Figure 5. Energy net use vs. Carbon emissions – Scenario 8 variables

a) With 3 clusters



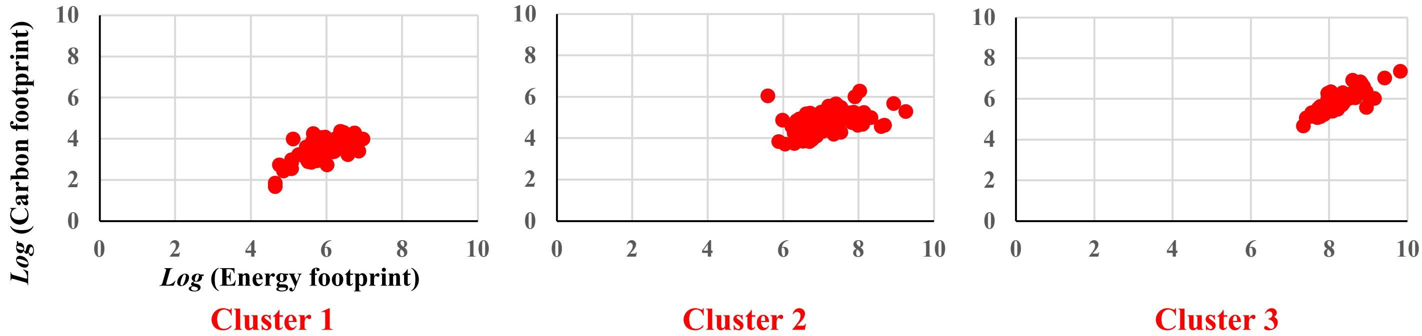
b) With 4 clusters



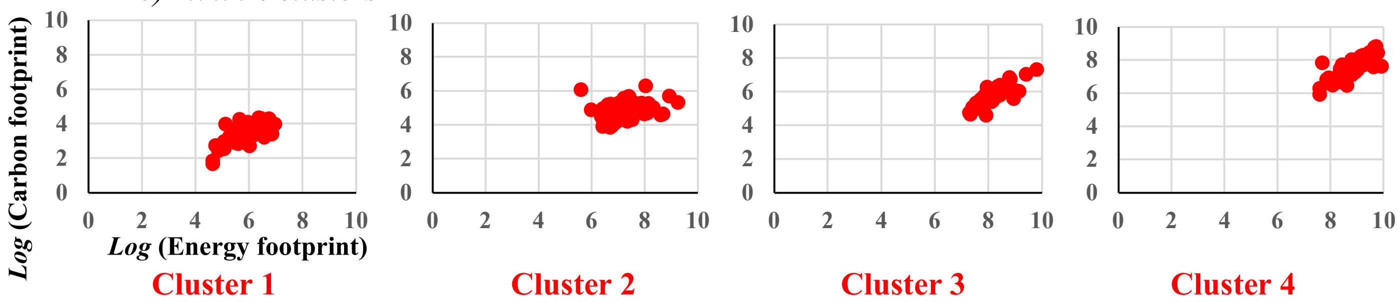
Note: The figures plot the logarithmic net Energy consumption with the logarithmic Carbon emissions averaged over the six-year period (2015-2020) of each fund belonging to their 3 (*resp*. 4) respective KM clusters obtained from eight variables of interest. The sample of funds considered here is the full sample studied with **w** = **50%**.

Figure 6. Energy vs. Carbon footprint – Scenario 8 variables

a) With 3 clusters



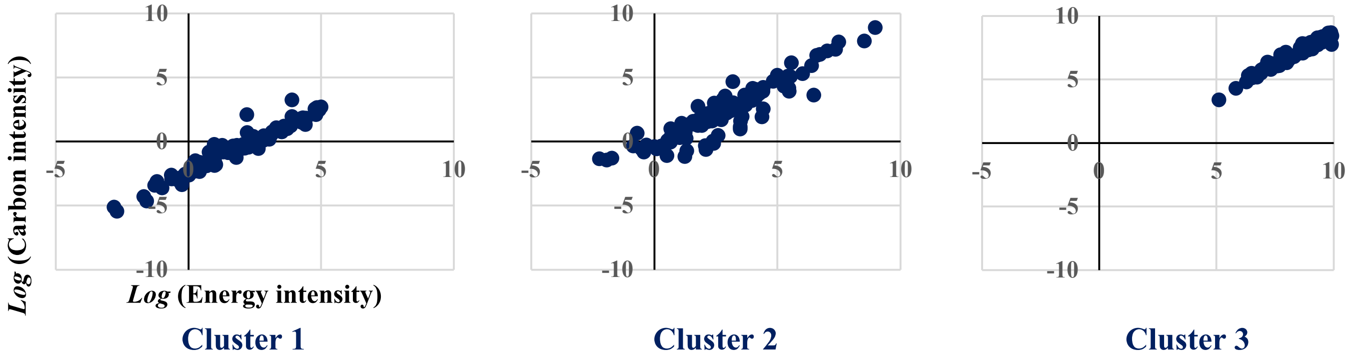
b) With 4 clusters



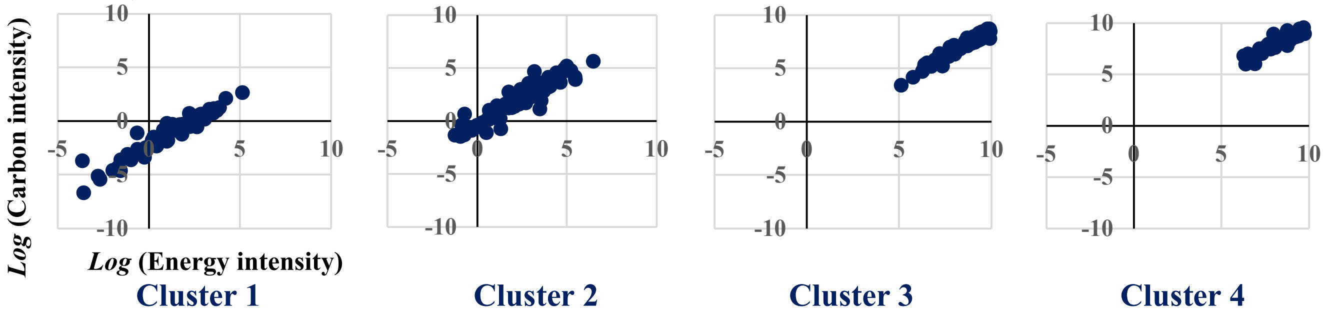
Note: The figures graph the logarithmic Energy intensity ratio (*Energy use per dollar of sales*) with the logarithmic Carbon intensity (*Scope 1 &2 carbon emissions per dollar of sales*) ratio averaged over the six-year period (2015-2020) of each fund belonging to their 3 (*resp*. 4) respective KM clusters obtained from eight variables of interest. The sample of funds considered here is the full sample studied with **w** = **50%**.

Figure 7. Energy vs. Carbon intensity – Scenario 8 variables

a) With 3 clusters



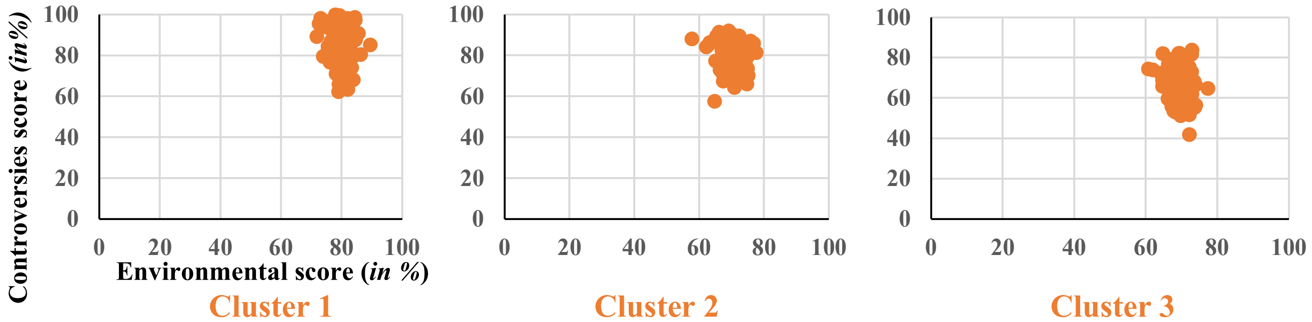
b) With 4 clusters



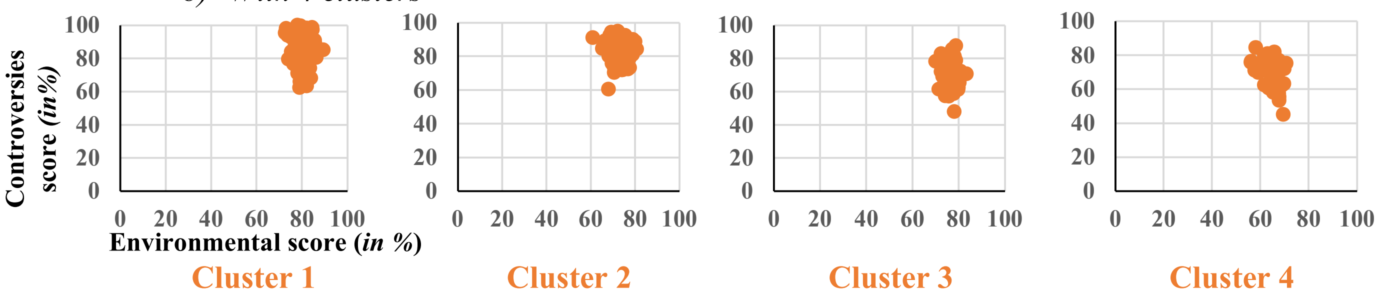
Note: The figures plot the logarithmic Energy intensity ratio (*Energy use per dollar invested*) with the logarithmic Carbon intensity (*Scope 1 &2 carbon emissions per dollar invested*) ratio averaged over the six-year period (2015-2020) of each fund belonging to their 3 (*resp*. 4) respective KM clusters obtained from six variables of interest. The sample of funds considered here is the full sample studied with **w** = **50%**.

Figure 8. Environmental score vs. Controversies score – Scenario 8 variables

a) With 3 clusters



b) With 4 clusters



Note: The figures plot the environmental score with the ESG controversies score averaged over the six-year period (2015-2020) of each fund belonging to their 3 (*resp*. 4) respective KM clusters obtained from eight variables of interest. The sample of funds considered here is the full sample studied with **w** = **50%**.

Table 1. Description of SRI labeled funds

		Full sample	SFDR categorized funds
	Nb of funds	380	323
	Avg number of funds per manager	4.7	4.3
	*Avg number of SRI labels held by fund**	1.21	1.27
Geographical Focus	*Europe*	233	215
	Emerging Markets	12	6
	North America (incl. U.S.)	17	11
	Asia (incl. China)	10	7
	Global	108	84
Invested amount *(in millions €)*	*Average*	373.3	382.8
	Min	10.2	15.1
	Max	3733.3	3733.3
Duration *(in years)*	*Average*	11.9	12.8
	Min	1	1.3
	Max	36	30

Note : * SRI labels includes the French SRI label

Table 2. Summary statistics – control variables

Panel A: Full sample

	2015		2016		2017		2018		2019		2020		Global period	
Nb of funds	169		185		199		222		251		281		295	
Nb of Equity per Fund	40		43		47		49		45		44		45	
	Avg	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**
Total Energy	28 451 208	28 018 723	33 219 684	30 119 740	34 405 051	29 741 929	33 520 618	33 298 374	26 497 477	24 265 101	22 833 119	19 288 555	29 845 352	27 512 579
Total Carbon Emissions	2 700 721	2 409 298	3 165 707	2 921 120	3 272 376	2 930 062	3 242 799	3 182 891	2 501 735	2 375 646	2 103 656	1 848 014	2 823 902	2 604 163
Energy footprint	1094.0x	1 008	1226.3x	1415.7	1132.9x	1012.1	1102.3x	965.1	887.6x	799.5	875.4x	753.1	1047.6x	987.1
Carbon footprint	113.6x	76	111.7x	73.5	109.9x	85.0	104.7x	82.5	84.0x	72.0	72.4x	62.3	98.4x	76.2
Energy intensity	8636.7x	7 881	8368.9x	4907.7	7832.6x	6030.2	6725.2x	4488.5	5108.4x	3650.1	4376.7x	3821.2	6838.4x	5128.0
Carbon intensity	881.3x	785	791.0x	583.3	762.1x	402.8	739.3x	439.8	671.3x	360.3	669.2x	543.2	753.9x	511.5
Environmental Score (%)	87.36	9.2	87.83	9.4	88.76	11.2	90.14	10.3	90.97	10.5	91.19	10.0	89.37	10.1
Controversies Score (%)	91.07	6.7	86.43	9.6	86.16	9.8	85.84	9.7	84.33	10.5	83.29	11.5	86.19	9.7

Panel B: Sample of SFDR categorized funds

	2015		2016		2017		2018		2019		2020		Average	
Nb of funds	145		160		174		192		223		248		191	
Nb of Equity per Fund	38		41		45		47		43		44		43	
	Avg	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**	**Avg**	**SD**
Total Energy	27 496 669	27 101 171	31 326 638	29 512 165	34 270 116	32 794 569	32 282 576	31 057 704	26 179 602	22 815 537	20 991 658	17 369 523	28 821 135	26 771 909
Total Carbon Emissions	2 596 487	2 364 372	2 976 316	2 827 554	3 205 282	3 068 020	3 114 562	3 028 958	2 491 851	2 258 250	1 974 297	1 706 273	2 750 945	2 565 361
Energy footprint	1081.3x	102	1213.7x	108.3	1120.9x	110.2	1098.6x	103.7	882.5x	84.5	850.2x	71.5	1038.8x	96.4
Carbon footprint	111.9x	77	108.3x	72.7	108.2x	88.2	103.7x	84.8	83.5x	74.9	71.5x	63.5	98.0x	77.8
Energy intensity	8591.4x	7 303	8253.5x	4567.4	6872.3x	5642.7	5840.1x	4178.6	4922.3x	4115.1	4351.2x	3549.1	6470.6x	4930.2
Carbon intensity	775.6x	648	757.0x	502.3	740.2x	427.5	736.5x	472.0	637.2x	382.5	635.9x	549.2	675.0x	535.9
Environmental Score (%)	87.54	9.3	87.88	9.6	88.85	10.5	91.13	9.6	91.31	9.4	91.45	8.7	89.73	9.5
Controversies Score (%)	91.25	6.5	88.23	9.4	87.14	6.7	86.10	9.7	85.07	10.4	84.08	11.7	86.98	9.2

Table 3. Cluster cross-tabulation between SFDR categories and 3 KM clusters – Scenario 6 variables

Panel A. Full sample

	w=50%						SFDR matching	w=60%						SFDR matching
	2015	***2016***	***2017***	***2018***	***2019***	***2020***		***2015***	***2016***	***2017***	***2018***	***2019***	***2020***	
Cluster 1	20 *(16.3%)*	20 *(14.1%)*	35 *(20.7%)*	47 *(22.8%)*	68 *(30.9%)*	80 *(34.2%)*	**100** ***(36.4%)***	14 *(13.9%)*	13 *(11.6%)*	25 *(17.5%)*	36 *(19.4%)*	55 *(29.6%)*	56 *(31.6%)*	**90** ***(39.6%)***
Cluster 2	64 *(52.0%)*	80 *(56.3%)*	88 *(52.1%)*	113 *(54.9%)*	111 *(50.5%)*	116 *(49.6%)*	**148** ***(53.8%)***	50 *(49.5%)*	63 *(56.3%)*	66 *(46.2%)*	100 *(53.8%)*	96 *(51.6%)*	86 *(48.6%)*	**129** ***(56.8%)***
Cluster 3	39 *(31.7%)*	42 *(29.6%)*	46 *(27.2%)*	46 *(22.3%)*	41 *(18.6%)*	38 *(16.2%)*	**8** ***(2.9%)***	37 *(36.6%)*	36 *(32.1%)*	52 *(36.4%)*	50 *(26.9%)*	35 *(18.8%)*	35 *(19.8%)*	**8** ***(3.5%)***

Panel B. Sample of SFDR categorized funds

	w=50%						SFDR matching	w=60%						SFDR matching
	2015	***2016***	***2017***	***2018***	***2019***	***2020***		***2015***	***2016***	***2017***	***2018***	***2019***	***2020***	
Cluster 1	20 *(20.2%)*	19 *(16.2%)*	35 *(24.3%)*	45 *(25.6%)*	72 *(37.5%)*	80 *(39.8%)*	**100** ***(36.4%)***	13 *(16.0%)*	12 *(13.2%)*	25 *(20.7%)*	35 *(22.3%)*	53 *(33.3%)*	55 *(36.4%)*	**90** ***(39.6%)***
Cluster 2	59 *(59.6%)*	80 *(68.4%)*	86 *(59.7%)*	109 *(61.9%)*	91 *(47.4%)*	92 *(45.8%)*	**148** ***(53.8%)***	44 *(54.3%)*	53 *(58.2%)*	58 *(47.9%)*	84 *(53.5%)*	75 *(47.2%)*	68 *(45%)*	**129** ***(56.8%)***
Cluster 3	20 *(20.2%)*	18 *(15.4%)*	23 *(16.0%)*	22 *(12.5%)*	29 *(15.1%)*	29 *(14.4%)*	**8** ***(2.9%)***	24 *(29.6%)*	26 *(28.6%)*	38 *(31.4%)*	38 *(24.2%)*	31 *(19.5%)*	28 *(18.5%)*	**8** ***(3.5%)***

Note: Table 3 provides the cross-tabulation of our 3 KM cluster's results obtained each year given 6 variables of interest, expressed in terms of number or *percentage (%)* under the two scenarios (weight (**w**)= **50%** and **60%**) and the SFDR categories self-reported by fund managers as of December 2020.
The columns SFDR matching report the number and the *percentage* of funds belonging to their closest associated cluster i.e., *Cluster 1*: Article 9 funds, *Cluster 2*: Article 8 funds, and *Cluster 3*: Article 6 funds respectively for the two scenarios.
The funds, which have been yet categorized by fund managers are not included in the calculation (i.e., 18 funds for w =50% and w=60%).

Table 4. Fund classification based on 3 KM clusters – European vs. non-European focused–Scenario 6 variables

Panel A. Full sample – **w = 50%**

	European focused						Out of Europe/World focused					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	9 *(10.2%)*	10 *(10.1%)*	16 *(15.0%)*	27 *(20.0%)*	38 *(26.8%)*	45 *(30.4%)*	11 *(31.4%)*	10 *(23.3%)*	19 *(29.7%)*	20 *(28.2%)*	30 *(38.5%)*	38 *(43.7%)*
Cluster 2	48 *(55.0%)*	58 *(59.0%)*	59 *(55.0%)*	77 *(57.0%)*	78 *(55.0%)*	79 *(53.0%)*	16 *(45.7%)*	22 *(51.2%)*	31 *(48.4%)*	37 *(52.1%)*	35 *(44.9%)*	37 *(42.5%)*
Cluster 3	31 *(35.2%)*	31 *(31.3%)*	32 *(29.9%)*	31 *(23.0%)*	26 *(18.3%)*	24 *(16.2%)*	8 *(22.9%)*	11 *(25.6%)*	14 *(21.9%)*	14 *(19.7%)*	13 *(16.7%)*	12 *(13.8%)*

Panel B. Full sample – **w = 60%**

	European focused						Out of Europe/World focused					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	5 *(6.4%)*	7 *(8.2%)*	12 *(11.8%)*	19 *(15.2%)*	32 *(23.9%)*	37 *(26.8%)*	9 *(39.1%)*	8 *(29.6%)*	13 *(31.7%)*	17 *(27.9%)*	21 *(40.4%)*	18 *(47.4%)*
Cluster 2	42 *(54.0%)*	46 *(54.0%)*	52 *(51.0%)*	70 *(56.0%)*	75 *(56.0%)*	76 *(55.0%)*	8 *(34.8%)*	15 *(55.6%)*	14 *(34.1%)*	30 *(49.2%)*	23 *(44.2%)*	15 *(39.5%)*
Cluster 3	31 *(39.6%)*	32 *(37.6%)*	38 *(37.2%)*	36 *(28.8%)*	27 *(20.1%)*	25 *(18.1%)*	6 *(26.1%)*	4 *(14.8%)*	14 *(34.1%)*	14 *(23.0%)*	8 *(15.4%)*	5 *(13.2%)*

Note: Table 4 presents the results of 3 KM clusters of funds that have either a European focus or outside Europe/World focus considering 6 variables of interest, expressed in terms of number or *percentage (%)* under two scenarios weight (**w**)= **50%** or **60%**.

Table 5. Level of diversification of 3 KM clustered funds – Scenario 6 variables

Panel A. Full sample

	w = 50%							w = 60%						
	2015	2016	2017	2018	2019	2020	*Avg*	2015	2016	2017	2018	2019	2020	***Avg***
Cluster 1	28	29	31	32	33	38	***33***	31	33	35	35	33	38	***35***
Cluster 2	47	46	48	49	48	43	***47***	50	49	50	50	50	44	***49***
Cluster 3	62	68	78	80	76	80	***74***	64	75	79	81	81	81	***77***

Panel B: Sample of SFDR categorized funds

	w = 50%							w = 60%						
	2015	2016	2017	2018	2019	2020	*Avg*	2015	2016	2017	2018	2019	2020	***Avg***
Cluster 1	27	27	31	33	34	39	***34***	28	31	33	35	34	39	***35***
Cluster 2	38	41	44	41	46	40	***42***	41	45	48	42	46	42	***44***
Cluster 3	60	59	67	70	72	72	***68***	62	63	68	70	73	73	***69***

Note: Table 5 reports the average number of equities invested by SRI labeled funds that are classified in 3 KM clusters year by year. The column ***"Avg"*** represents the mean number of equities averaged over the six-year period (2015-2020).

Table 6. Cluster stability – KM run with 3 clusters and 6 variables

Panel A: Full sample

	w = 50%			w = 60%		
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Cluster 1	85.3%	14.1%	0.6%	84.6%	13.8%	1.6%
Cluster 2	12.2%	83.3%	4.5%	11.5%	83.2%	5.3%
Cluster 3	3.9%	23.7%	72.5%	3.0%	21.3%	75.6%

Panel B: Sample of SFDR categorized funds

	w = 50%			w = 60%		
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Cluster 1	84.2%	14.6%	1.2%	82.5%	15.8%	1.7%
Cluster 2	14.1%	84.5%	1.5%	14.3%	81.8%	3.9%
Cluster 3	7.4%	22.2%	70.4%	4.0%	19.2%	76.8%

Note: Cluster stability (*resp*. instability) is measured by the average % similarity (*resp*. % change) of cluster composition assessed from the start (2015 or after if the fund was created after) to the end of the period (2020 or before if the fund was closed). The rows indicate the cluster that the fund belongs at the start of the period while the columns indicate the cluster that the fund belongs at the end of the period.
The percentages represent the probability of the fund to stay in the same cluster or to move to a given cluster at the end of the period considering it belongs to a given cluster at the start of the period.

Table 7. Cluster uncertainty – Membership grades of 3 fuzzy clusters (Scenario 6 variables)

Panel A. Full sample

	w=50%			**w=60%**		
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***
Cluster 1	**72.6%** *(2.3%)*	11.7% *(2.0%)*	8.1% *(1.9%)*	**72.4%** *(3.7%)*	11.5% *(2.2%)*	7.5% *(1.9%)*
Cluster 2	18.3% *(2.1%)*	**69.7%** *(1.3%)*	25.9% *(1.1%)*	18.3% *(2.1%)*	**69.4%** *(1.3%)*	25.6% *(2.6%)*
Cluster 3	9.2% *(0.5%)*	18.6% *(0.9%)*	**66.0%** *(2.2%)*	9.1% *(1.6%)*	19.1% *(1.7%)*	**66.7%** *(4.4%)*

Panel B. Sample of SFDR categorized funds

	w=50%			**w=60%**		
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***
Cluster 1	**72.8%** *(1.1%)*	12.9% *(3.2%)*	9.8% *(1.3%)*	**73.0%** *(2.7%)*	12.4% *(3.0%)*	8.6% *(2.0%)*
Cluster 2	17.3% *(1.3%)*	**70.8%** *(2.7%)*	22.4% *(2.4%)*	17.5% *(1.9%)*	**69.4%** *(2.2%)*	25.0% *(1.4%)*
Cluster 3	9.7% *(0.3%)*	16.3% *(0.9%)*	**67.9%** *(2.5%)*	9.1% *(1.3%)*	18.2% *(1.3%)*	**66.4%** *(3.1%)*

Note: Table 7 reports the mean membership grade for each cluster i.e., the probability (denoted *Prob.*) that a fund assigned to a specific cluster in a given year belongs to this cluster or move to another one. The reported percentage indicates the (mean) membership grades of each cluster averaged over the six-year period (2015-2020). The percentage in parentheses represents the standard deviation of the six annual percentages related to each cluster.

Table 8. Fund classification based on membership grades compared to SFDR categories

	w = 50%			**w = 60%**		
	Membership grades	Number of funds	SFDR categories matching	Membership grades	Number of funds	SFDR categories matching
Cluster 1	[90%-100%]	15	14	[90%-100%]	14	13
	[80%-90%]	19	14	[80%-90%]	18	14
	[70%-80%]	25	15	[70%-80%]	20	14
	[60%-70%]	32	16	[60%-70%]	20	12
	[50%-60%]	26	12	[50%-60%]	12	6
	< 50%	1	0	< 50%	1	0
Cluster 2	[90%-100%]	16	14	[90%-100%]	12	10
	[80%-90%]	25	18	[80%-90%]	25	18
	[70%-80%]	38	24	[70%-80%]	32	18
	[60%-70%]	46	23	[60%-70%]	36	18
	[50%-60%]	28	13	[50%-60%]	27	14
	< 50%	3	0	< 50%	3	0
Cluster 3	[90%-100%]	5	1	[90%-100%]	4	1
	[80%-90%]	10	1	[80%-90%]	8	1
	[70%-80%]	18	0	[70%-80%]	18	0
	[60%-70%]	11	0	[60%-70%]	12	1
	[50%-60%]	16	1	[50%-60%]	14	0
	< 50%	2	0	< 50%	2	0

Note: Membership grades are averaged over the period 2015-2020 for the two scenarios (weight (**w**) = **50%** or **60%**). The columns "Number of funds" indicate the number of funds that belong to a given cluster by interval of membership grades. The columns "SFDR matching" report the number of those now classified funds, which are consistently self-declared by fund managers according to the matching rule seen previously i.e., *Cluster 1*: Article 9 funds, *Cluster 2*: Article 8 funds, and *Cluster 3*: Article 6 funds.

Table 9. Fund classification based on 4 KM clusters – Scenario 6 variables

Panel A. Full sample

	w=50%						w=60%					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	13	15	22	33	49	59	9	10	16	27	39	40
	(10.6%)	*(10.6%)*	*(13.0%)*	*(16.0%)*	*(22.3%)*	*(24.8%)*	*(8.9%)*	*(8.9%)*	*(11.2%)*	*(14.5%)*	*(21.0%)*	*(22.7%)*
Cluster 2	32	37	50	65	86	109	25	30	39	64	75	80
	(26.0%)	*(26.1%)*	*(29.6%)*	*(31.6%)*	*(39.1%)*	*(45.8%)*	*(24.8%)*	*(26.8%)*	*(27.3%)*	*(34.4%)*	*(40.3%)*	*(45.5%)*
Cluster 3	62	72	77	85	61	44	50	54	68	73	50	35
	(50.4%)	*(50.7%)*	*(45.6%)*	*(41.3%)*	*(27.7%)*	*(18.5%)*	*(49.5%)*	*(48.2%)*	*(47.6%)*	*(39.2%)*	*(26.9%)*	*(19.9%)*
Cluster 4	16	18	20	23	24	26	17	18	20	22	22	21
	(13.0%)	*(12.7%)*	*(11.8%)*	*(11.2%)*	*(10.9%)*	*(10.9%)*	*(16.8%)*	*(16.1%)*	*(14.0%)*	*(11.8%)*	*(11.8%)*	*(11.9%)*

Panel B. Sample of SFDR categorized funds

	w=50%						w=60%					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	13	17	21	34	47	50	8	10	16	27	36	37
	(13.1%)	*(14.5%)*	*(14.6%)*	*(19.1%)*	*(24.5%)*	*(24.8%)*	*(9.9%)*	*(11.1%)*	*(13.2%)*	*(17.1%)*	*(22.6%)*	*(24.5%)*
Cluster 2	25	30	43	61	74	90	17	20	34	55	62	68
	(25.3%)	*(25.6%)*	*(29.9%)*	*(34.3%)*	*(38.5%)*	*(44.6%)*	*(21.0%)*	*(22.2%)*	*(28.1%)*	*(34.8%)*	*(39.0%)*	*(45.0%)*
Cluster 3	49	56	64	65	50	40	46	50	58	60	45	30
	(49.5%)	*(47.9%)*	*(44.4%)*	*(36.5%)*	*(26.0%)*	*(19.8%)*	*(56.8%)*	*(55.6%)*	*(47.9%)*	*(38.0%)*	*(28.3%)*	*(19.9%)*
Cluster 4	12	14	16	18	21	21	10	10	13	16	16	16
	(12.1%)	*(12.0%)*	*(11.1%)*	*(10.1%)*	*(10.9%)*	*(10.9%)*	*(12.3%)*	*(11.1%)*	*(10.7%)*	*(10.1%)*	*(10.1%)*	*(10.6%)*

Note: Table 9 presents the results of 4 KM clusters obtained each year considering 6 variables of interest.
They are expressed both in terms of number or *percentage (%)* under the two scenarios (weight **w**= 50% and 60%).

Table 10. Fund classification based on 4 KM clusters – European vs. non-European focused–Scenario 6 variables

Panel A. Full sample – **w = 50%**

	European focused						Out of Europe/World focused					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	7 *(7.8%)*	6 *(5.9%)*	10 *(8.8%)*	21 *(15.3%)*	27 *(19.4%)*	30 *(20.4%)*	6 *(22.2%)*	9 *(21.4%)*	12 *(21.8%)*	16 *(21.9%)*	22 *(27.2%)*	30 *(33.0%)*
Cluster 2	22 *(24.4%)*	24 *(23.5%)*	30 *(26.3%)*	37 *(27.0%)*	47 *(33.8%)*	60 *(40.8%)*	10 *(37.0%)*	15 *(35.7%)*	22 *(40.0%)*	31 *(42.5%)*	38 *(46.9%)*	43 *(47.3%)*
Cluster 3	44 *(48.9%)*	54 *(52.9%)*	56 *(49.1%)*	60 *(43.8%)*	47 *(33.8%)*	37 *(25.2%)*	8 *(29.6%)*	14 *(33.3%)*	16 *(29.1%)*	20 *(27.4%)*	15 *(18.5%)*	12 *(13.2%)*
Cluster 4	17 *(18.9%)*	18 *(17.6%)*	18 *(15.8%)*	19 *(13.9%)*	18 *(12.9%)*	20 *(13.6%)*	3 *(11.1%)*	4 *(9.5%)*	5 *(9.1%)*	6 *(8.2%)*	6 *(7.4%)*	6 *(6.6%)*

Panel B. Full sample – **w = 60%**

	European focused						Out of Europe/World focused					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	5 *(6.4%)*	6 *(7.1%)*	12 *(11.8%)*	17 *(13.6%)*	25 *(18.7%)*	30 *(21.6%)*	6 *(26.1%)*	7 *(25.9%)*	11 *(26.8%)*	17 *(27.9%)*	18 *(34.6%)*	15 *(39.5%)*
Cluster 2	19 *(24.4%)*	24 *(28.2%)*	29 *(28.4%)*	38 *(30.4%)*	52 *(38.8%)*	56 *(40.3%)*	8 *(34.8%)*	11 *(40.7%)*	16 *(39.0%)*	26 *(42.6%)*	23 *(44.2%)*	17 *(44.7%)*
Cluster 3	40 *(51.3%)*	40 *(47.1%)*	47 *(46.1%)*	54 *(43.2%)*	40 *(29.9%)*	37 *(26.6%)*	6 *(26.1%)*	7 *(25.9%)*	11 *(26.8%)*	14 *(23.0%)*	8 *(15.4%)*	4 *(10.5%)*
Cluster 4	14 *(17.9%)*	15 *(17.6%)*	14 *(13.7%)*	16 *(12.8%)*	17 *(12.7%)*	16 *(11.5%)*	3 *(13.0%)*	2 *(7.4%)*	3 *(7.3%)*	4 *(6.6%)*	3 *(5.8%)*	2 *(5.3%)*

Note: Table 10 presents the results of 4 KM clusters of funds that have either a European focus or outside Europe/World focus considering 6 variables of interest, expressed in terms of number or *percentage (%)* under two scenarios weight (**w**)= **50%** or **60%**.

Table 11. Level of diversification of 4 KM clustered funds– Scenario 6 variables

Panel A. Full sample

	w = 50%							w = 60%						
	2015	2016	2017	2018	2019	2020	*Avg*	2015	2016	2017	2018	2019	2020	*Avg*
Cluster 1	26	27	30	30	30	30	***29***	28	30	31	32	31	33	***32***
Cluster 2	38	39	37	38	46	45	***42***	41	44	41	39	48	44	***44***
Cluster 3	57	55	61	64	56	49	***58***	58	57	63	65	58	51	***60***
Cluster 4	69	70	83	83	76	88	***77***	71	81	86	84	83	93	***82***

Panel B: Sample of SFDR categorized funds

	w = 50%							w = 60%						
	2015	2016	2017	2018	2019	2020	*Avg*	2015	2016	2017	2018	2019	2020	*Avg*
Cluster 1	27	26	28	29	31	30	***29***	26	28	30	30	29	30	***29***
Cluster 2	37	40	43	40	44	41	***41***	40	45	47	41	44	42	***43***
Cluster 3	57	55	59	53	48	56	***55***	51	51	60	64	59	50	***56***
Cluster 4	69	72	78	75	76	82	***75***	68	79	85	81	79	88	***80***

Note: Table 11 reports the average number of equities invested by SRI labeled funds, which are classified in 3 clusters year by year. The column "Avg" represents the mean number of equities averaged over the six-year period (2015-2020).

Table 12. Cluster stability – KM run with 4 clusters and 6 variables

Panel A: Full sample

	w = 50%				w = 60%			
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Cluster 1	83.6%	15.6%	0.8%	0.0%	82.3%	15.9%	0.9%	0.9%
Cluster 2	11.6%	75.2%	12.8%	0.4%	13.8%	74.2%	11.1%	0.9%
Cluster 3	2.3%	20.8%	75.7%	1.2%	2.3%	23.3%	72.4%	1.9%
Cluster 4	3.1%	15.3%	11.2%	70.4%	3.1%	15.6%	10.4%	70.8%

Panel B: Sample of SFDR categorized funds

	w = 50%				w = 60%			
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Cluster 1	82.8%	16.1%	0.0%	1.1%	83.0%	15.9%	0.0%	1.1%
Cluster 2	13.6%	73.3%	12.1%	1.0%	15.6%	71.9%	11.4%	1.2%
Cluster 3	1.8%	23.4%	73.0%	1.8%	2.3%	24.4%	71.0%	2.3%
Cluster 4	2.5%	17.7%	8.9%	70.9%	2.5%	16.5%	8.9%	72.2%

Note: Cluster stability (*resp*. instability) measures the average % consistency (*resp*. % change) of cluster composition at the start (2015 or after if the fund was created after) and the end of the period (2020 or before if the fund was closed). The rows indicate the cluster that the fund belongs at the start of the period while the columns indicate the cluster that the fund belongs at the end of the period.
The percentages represent the probability of the fund to stay in the same cluster or to move to a given cluster at the end of the period considering it belongs to a given cluster at the start of the period.

Table 13. Cluster uncertainty – Membership grades of 4 fuzzy clusters (Scenario 6 variables)

Panel A. Full sample

	w=50%				**w=60%**			
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***
Cluster 1	**68.3%** *(4.1%)*	11.4% *(1.3%)*	3.5% *(0.4%)*	6.8% *(0.4%)*	**67.6%** *(5.9%)*	10.9% *(1.0%)*	3.6% *(0.2%)*	6.4% *(0.6%)*
Cluster 2	18.4% *(2.8%)*	**62.4%** *(1.7%)*	18.1% *(2.9%)*	13.8% *(0.8%)*	18.6% *(2.7%)*	**62.3%** *(2.7%)*	18.5% *(2.1%)*	13.8% *(0.7%)*
Cluster 3	6.8% *(0.8%)*	18.0% *(1.2%)*	**67.2%** *(3.9%)*	19.3% *(2.7%)*	6.9% *(1.2%)*	18.3% *(1.5%)*	**66.1%** *(2.9%)*	18.9% *(2.6%)*
Cluster 4	6.5% *(0.6%)*	8.2% *(0.5%)*	11.2% *(0.8%*	**60.1%** *(3.2%)*	6.9% *(2.4%)*	8.4% *(0.9%)*	11.9% *(1.0%)*	**60.9%** *(1.9%)*

Panel B. Sample of SFDR categorized funds

	w=50%				**w=60%**			
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***
Cluster 1	**67.9%** *(4.0%)*	12.1% *(1.4%)*	3.8% *(0.6%*	6.9% *(0.7%)*	**67.7%** *(4.5%)*	11.9% *(1.1%)*	3.7% *(0.4%)*	6.8% *(0.6%)*
Cluster 2	18.5% *(2.8%)*	**62.0%** *(1.6%)*	17.9% *(3.3%*	14.2% *(1.2%)*	18.8% *(2.0%)*	**62.2%** *(2.0%)*	18.0% *(2.9%)*	14.5% *(0.8%)*
Cluster 3	6.7% *(0.7%)*	17.3% *(1.5%)*	**66.6%** *(4.8%*	18.8% *(2.1%)*	6.6% *(0.8%)*	16.9% *(1.8%)*	**65.8%** *(4.2%)*	18.4% *(2.1%)*
Cluster 4	6.9% *(0.9%)*	8.7% *(0.6%)*	11.8% *(1.1%*	**60.0%** *(2.4%)*	6.9% *(2.2%)*	9.0% *(0.9%)*	12.5% *(1.1%)*	**60.3%** *(1.2%)*

Note: Table 13 reports the mean membership grade for each cluster i.e., the probability (denoted *Prob.*) that a fund assigned to a specific cluster in a given year belongs to this cluster or move to another cluster. The reported percentage indicates the (mean) membership grades of each cluster averaged over the six-year period (2015-2020). The percentage in parentheses represents the standard deviation of the six annual percentages related to each cluster.

Table 14. Cluster cross-tabulation between SFDR categories and 3 KM clusters – Scenario 8 variables

Panel A. Full sample

	w=50%						**SFDR matching**	w=60%						**SFDR matching**
	2015	***2016***	***2017***	***2018***	***2019***	***2020***		***2015***	***2016***	***2017***	***2018***	***2019***	***2020***	
Cluster 1	18 *(14.6%)*	23 *(16.2%)*	33 *(19.6%)*	42 *(20.5%)*	62 *(26.6%)*	75 *(28.5%)*	**100** ***(36.4%)***	14 *(14.0%)*	17 *(15.2%)*	23 *(16.2%)*	34 *(18.3%)*	53 *(24.5%)*	65 *(27.2%)*	**90** ***(39.6%)***
Cluster 2	48 *(39.0%)*	56 *(39.4%)*	67 *(39.9%)*	84 *(41.1%)*	106 *(45.5%)*	121 *(46.0%)*	**148** ***(53.8%)***	39 *(39.0%)*	45 *(40.2%)*	58 *(40.8%)*	77 *(41.4%)*	99 *(45.8%)*	112 *(46.9%)*	**129** ***(56.8%)***
Cluster 3	57 *(46.3%)*	63 *(44.4%)*	68 *(40.5%)*	79 *(38.5%)*	65 *(27.9%)*	67 *(25.5%)*	**8** **(2.9%)**	47 *(47.0%)*	50 *(44.6%)*	61 *(43.0%)*	75 *(40.3%)*	64 *(29.6%)*	62 *(25.9%)*	**8** ***(3.5%)***

Panel B. Sample of SFDR categorized funds

	w=50%						**SFDR matching**	w=60%						**SFDR matching**
	2015	***2016***	***2017***	***2018***	***2019***	***2020***		***2015***	***2016***	***2017***	***2018***	***2019***	***2020***	
Cluster 1	17 *(17.2%)*	21 *(17.9%)*	29 *(20.3%)*	43 *(24.6%)*	61 *(29.9%)*	73 *(32.2%)*	**100** ***(36.4%)***	12 *(14.6%)*	16 *(17.6%)*	22 *(18.3%)*	35 *(22.3%)*	56 *(29.6%)*	65 *(31.6%)*	**90** ***(39.6%)***
Cluster 2	42 *(42.4%)*	53 *(45.3%)*	66 *(46.2%)*	80 *(45.7%)*	94 *(46.1%)*	105 *(46.3%)*	**148** ***(53.8%)***	36 *(43.9%)*	40 *(44.0%)*	53 *(44.2%)*	70 *(44.6%)*	86 *(45.5%)*	94 *(45.6%)*	**129** ***(56.8%)***
Cluster 3	40 *(40.4%)*	43 *(36.8%)*	48 *(33.6%)*	52 *(29.7%)*	49 *(24.0%)*	49 *(21.6%)*	**8** **(2.9%)**	34 *(41.5%)*	35 *(38.5%)*	45 *(37.5%)*	52 *(33.1%)*	47 *(24.9%)*	47 *(22.8%)*	**8** ***(3.5%)***

Note: Table 14 provides the cross-tabulation of our 3 KM cluster's results obtained each year given 8 variables of interest, expressed in terms of number or *percentage (%)* under the two scenarios (weight **w**= 50% and 60%) and the SFDR categories self-reported by fund managers as of December 2020.
The columns SFDR matching report the number and the *percentage* of funds belonging to their closest associated cluster i.e., *Cluster 1*: Article 9 funds, *Cluster 2*: Article 8 funds, and *Cluster 3*: Article 6 funds respectively for the two scenarios.
The funds, which have been yet categorized by fund managers are not included in the calculation (i.e., 18 funds for w =50% and w=60%).

Table 15. Fund classification based on 4 KM clusters – Scenario 8 variables

Panel A. Full sample

	w=50%						w=60%					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	17 *(13.8%)*	20 *(14.1%)*	25 *(14.9%)*	35 *(17.1%)*	54 *(23.2%)*	64 *(24.3%)*	11 *(11.0%)*	12 *(10.7%)*	18 *(12.7%)*	30 *(16.1%)*	49 *(22.7%)*	57 *(23.8%)*
Cluster 2	32 *(26.0%)*	37 *(26.1%)*	47 *(28.0%)*	59 *(28.8%)*	70 *(30.0%)*	81 *(30.8%)*	23 *(23.0%)*	26 *(23.2%)*	38 *(26.8%)*	53 *(28.5%)*	64 *(29.6%)*	72 *(30.1%)*
Cluster 3	52 *(42.3%)*	61 *(43.0%)*	68 *(40.5%)*	80 *(39.0%)*	80 *(34.3%)*	89 *(33.8%)*	45 *(45.0%)*	52 *(46.4%)*	60 *(42.3%)*	75 *(40.3%)*	74 *(34.3%)*	81 *(33.9%)*
Cluster 4	22 *(17.9%)*	24 *(16.9%)*	28 *(16.7%)*	31 *(15.1%)*	29 *(12.4%)*	29 *(11.0%)*	21 *(21.0%)*	22 *(19.6%)*	26 *(18.3%)*	28 *(15.1%)*	29 *(13.4%)*	29 *(12.1%)*

Panel B. Sample of SFDR categorized funds

	w=50%						w=60%					
	2015	***2016***	***2017***	***2018***	***2019***	***2020***	***2015***	***2016***	***2017***	***2018***	***2019***	***2020***
Cluster 1	14 *(14.3%)*	18 *(15.4%)*	24 *(16.8%)*	36 *(20.6%)*	53 *(26.0%)*	62 *(27.3%)*	11 *(13.8%)*	13 *(14.3%)*	19 *(15.8%)*	30 *(19.1%)*	49 *(25.9%)*	56 *(26.9%)*
Cluster 2	26 *(26.5%)*	32 *(27.4%)*	41 *(28.7%)*	52 *(29.7%)*	66 *(32.4%)*	75 *(33.0%)*	20 *(25.0%)*	24 *(26.4%)*	33 *(27.5%)*	46 *(29.3%)*	60 *(31.7%)*	70 *(33.7%)*
Cluster 3	39 *(39.8%)*	45 *(38.5%)*	54 *(37.8%)*	61 *(34.9%)*	59 *(28.9%)*	64 *(28.2%)*	30 *(37.5%)*	34 *(37.4%)*	45 *(37.5%)*	55 *(35.0%)*	54 *(28.6%)*	56 *(26.9%)*
Cluster 4	19 *(19.4%)*	22 *(18.8%)*	24 *(16.8%)*	26 *(14.9%)*	26 *(12.7%)*	26 *(11.5%)*	19 *(23.8%)*	20 *(22.0%)*	23 *(19.2%)*	26 *(16.6%)*	26 *(13.8%)*	26 *(12.5%)*

Note: Table 15 presents the results of 4 KM clusters obtained each year considering 8 variables of interest.
They are expressed both in terms of number or *percentage (%)* under the two scenarios (weight **w**= 50% and 60%).

Appendix

Table A1. Cluster stability – KM run with 3 clusters and 8 variables

Panel A: Full sample

	w = 50%			**w = 60%**		
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Cluster 1	82.3%	13.4%	4.3%	82.4%	14.1%	3.5%
Cluster 2	9.2%	74.5%	16.2%	10.4%	87.1%	2.5%
Cluster 3	14.1%	20.1%	65.8%	18.1%	21.0%	60.9%

Panel B: Sample of SFDR categorized funds

	w = 50%			**w = 60%**		
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Cluster 1	84.1%	13.3%	2.7%	84.3%	13.8%	1.9%
Cluster 2	13.3%	84.3%	2.4%	13.7%	84.0%	2.3%
Cluster 3	10.3%	27.0%	62.7%	16.3%	19.2%	64.4%

Note: Cluster stability (*resp*. instability) measures the average % consistency (*resp*. % change) of cluster composition at the start (2015 or after if the fund was created after) and the end of the period (2020 or before if the fund was closed). The rows indicate the cluster that the fund belongs at the start of the period while the columns indicate the cluster that the fund belongs at the end of the period.
The percentages represent the probability of the fund to stay in the same cluster or to move to a given cluster at the end of the period considering it belongs to a given cluster at the start of the period.

Table A2. Membership grades of 3 fuzzy clusters – Scenario 8 variables

Panel A. Full sample

	w=50%			**w=60%**		
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***
Cluster 1	**63.2%** *(1.1%)*	18.5% *(1.3%)*	10.5% *(2.1%)*	**61.8%** *(3.6%)*	15.1% *(2.7%)*	16.3% *(1.4%)*
Cluster 2	23.2% *(1.1%)*	**57.7%** *(1.8%)*	24.9% *(2.5%)*	21.5% *(2.2%)*	**64.8%** *(3.3%)*	27.1% *(2.5%)*
Cluster 3	13.6% *(0.8%)*	23.8% *(0.9%)*	**64.6%** *(3.9%)*	16.8% *(1.8%)*	20.1% *(1.5%)*	**56.6%** *(2.2%)*

Panel B. Sample of SFDR categorized funds

	w=50%			**w=60%**		
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***
Cluster 1	**62.8%** *(2.2%)*	22.2% *(1.7%)*	15.0% *(0.8%)*	**61.9%** *(3.3%)*	21.7% *(2.0%)*	16.4% *(1.7%)*
Cluster 2	16.7% *(2.1%)*	**63.3%** *(2.3%)*	20.1% *(0.9%)*	16.2% *(2.6%)*	**64.6%** *(3.1%)*	19.2% *(1.3%)*
Cluster 3	14.8% *(1.5%)*	27.1% *(2.1%)*	**58.1%** *(1.7%)*	16.1% *(1.0%)*	25.7% *(2.5%)*	**58.1%** *(1.8%)*

Note: Table A2 reports the mean membership grade for each cluster i.e., the probability (denoted Prob.) that a fund assigned to a specific cluster in a given year belongs to this cluster or move to another cluster. The reported percentage indicates the (mean) membership grades of each cluster averaged over the six-year period (2015-2020). The percentage in parentheses represents the standard deviation of the six annual percentages related to each cluster.

Table B1. Cluster stability – KM run with 4 clusters and 8 variables

Panel A: Full sample

	w = 50%				w = 60%			
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Cluster 1	81.3%	12.9%	3.9%	1.9%	87.8%	8.1%	2.4%	1.6%
Cluster 2	8.2%	75.5%	15.5%	0.8%	8.9%	71.6%	17.9%	1.6%
Cluster 3	4.6%	8.9%	84.3%	2.3%	4.8%	7.9%	84.8%	2.5%
Cluster 4	4.0%	11.9%	23.8%	60.4%	7.9%	12.9%	16.8%	62.4%

Panel B: Sample of SFDR categorized funds

	w = 50%				w = 60%			
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Cluster 1	82.4%	11.5%	4.7%	1.4%	86.0%	8.3%	4.1%	1.7%
Cluster 2	10.4%	72.8%	16.3%	0.5%	13.5%	69.2%	16.0%	1.3%
Cluster 3	5.6%	9.7%	81.3%	3.4%	5.5%	9.3%	82.7%	2.5%
Cluster 4	4.8%	12.5%	25.0%	57.7%	7.0%	12.0%	16.0%	65.0%

Note: Cluster stability (*resp*. instability) measures the average % consistency (*resp*. % change) of cluster composition at the start (2015 or after if the fund was created after) and the end of the period (2020 or before if the fund was closed). The rows indicate the cluster that the fund belongs at the start of the period while the columns indicate the cluster that the fund belongs at the end of the period.
The percentages represent the probability of the fund to stay in the same cluster or to move to a given cluster at the end of the period considering it belongs to a given cluster at the start of the period.

Table B2. Membership grades of 4 fuzzy clusters – Scenario 8 variables

Panel A. Full sample

	w=50%				w=60%			
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***
Cluster 1	**58.5%** *(0.9%)*	20.5% *(1.0%)*	11.6% *(0.8%)*	9.3% *(0.8%)*	**57.5%** *(3.6%)*	20.9% *(1.6%)*	11.7% *(1.4%)*	9.8% *(1.6%)*
Cluster 2	15.4% *(1.2%)*	**52.5%** *(1.6%)*	19.9% *(1.1%)*	12.2% *(0.4%)*	15.9% *(1.7%)*	**52.3%** *(1.8%)*	18.9% *(1.5%)*	12.8% *(0.6%)*
Cluster 3	7.5% *(1.6%)*	18.9% *(2.4%)*	**59.5%** *(4.3%)*	14.1% *(1.2%)*	7.7% *(1.5%)*	18.2% *(2.6%)*	**59.5%** *(4.7%)*	14.6% *(1.6%)*
Cluster 4	9.3% *(0.7%)*	17.4% *(1.5%)*	20.4% *(2.6%)*	**52.9%** *(3.4%)*	9.6% *(0.6%)*	17.5% *(1.8%)*	20.9% *(2.0%)*	**52.0%** *(2.7%)*

Panel B. Sample of SFDR categorized funds

	w=50%				w=60%			
	Prob. (Cluster 1)	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***	***Prob. (Cluster 1)***	***Prob. (Cluster 2)***	***Prob. (Cluster 3)***	***Prob. (Cluster 4)***
Cluster 1	**58.4%** *(1.3%)*	20.2% *(1.1%)*	11.7% *(0.9%)*	9.6% *(0.7%)*	**57.4%** *(3.7%)*	20.6% *(2.1%)*	11.5% *(1.4%)*	10.4% *(1.5%)*
Cluster 2	16.2% *(1.6%)*	**51.6%** *(1.6%)*	19.5% *(1.6%)*	12.7% *(0.5%)*	16.8% *(1.8%)*	**51.4%** *(1.8%)*	18.6% *(2.1%)*	13.3% *(1.1%)*
Cluster 3	8.2% *(1.7%)*	18.5% *(2.6%)*	**58.7%** *(4.5%)*	14.7% *(1.4%)*	8.0% *(1.8%)*	18.1% *(3.1%)*	**58.9%** *(5.4%)*	15.0% *(1.5%)*
Cluster 4	9.7% *(0.7%)*	17.5% *(1.9%))*	20.7% *(2.5%)*	**52.1%** *(3.6%)*	10.2% *(0.6%)*	17.5% *(1.8%)*	20.9% *(2.3%)*	**51.4%** *(2.6%)*

Note: Table B2 reports the mean membership grade for each cluster i.e., the probability (Prob.) that a fund assigned to a specific cluster in a given year belongs to this cluster or move to another cluster. The reported percentage indicates the (mean) membership grades of each cluster averaged over the six-year period (2015-2020). The percentage in parentheses represents the standard deviation of the six annual percentages related to each cluster.