How to explain SRI funds' green performance? The influence of investment styles and experience of fund managers

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Abstract

This paper explores how the green performance of European SRI funds may be determined by investment styles, profiles and experiences of fund managers. For that purpose, we rely on k-means to cluster SRI funds based on a set of carbon risk and green performance indicators.

Overall, our results are consistent with a simple message: greening a SRI fund results from three combined effects: less diversification, sector allocation, salient experience of the lead manager in ESG. In particular, greener funds are less diversified and have a larger exposure to green (*resp*. fossil fuel) industries. Then, we find that the more the lead manager is experienced in ESG and the shorter her mandate, the greener the fund is. By contrast, the greenness of SRI funds is not related to the SMB factor and to the gender of the lead manager.

KEYWORDS: Socially Responsible Investment (SRI), Greenness, Investment styles, lead manager experience, K-means clustering

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1. Introduction

Climate change has potentially become the most important sustainability issue for asset managers (Morningstar, 2020). Investors are increasingly aware that greater climate variability and extreme weather events impact business activities and stock returns. Asset managers have responded to this new dynamic by launching dedicated climate-aware funds and tweaking their investment strategies to decarbonize their portfolios given a reduced (*resp*. greater) exposure to fossil fuels (*resp.* renewable energy) sectors (El Ghoul and Karoui, 2021).

Those climate-aware funds have emerged as a promising SRI segment in the past few years (Humphrey and Li, 2018; Morningstar, 2020). While SRI funds predominantly screen for firms with high ESG scores (Lesser et al., 2016; Alda, 2022), they are intended to invest at least 75 % of their assets in equities or equity-related securities issued by companies with activities related to green and low carbon industries (Agoraki et al., 2023) such as alternative fuels, clean technologies, renewable energies, and waste management (El Ghoul and Karoui, 2021). Some recent studies have investigated their characteristics in terms of portfolio composition and investment strategies. A report of Clarity AI indicates that Article 9 SFDR climate-branded funds have 15% of revenues classified as green under EU Taxonomy as compared to Article 8 funds, with 3.9% of green revenues (Clarity AI, 2022). Muñoz (2021) finds that they are less exposed to fossil fuel industries. Ceccarelli et al. (2022) show that fund managers reduced the exposure of their funds to carbon intensive firms when they missed the "low carbon designation" by Morningstar to attract larger fund flows. El Ghoul and Karoui (2021) show that greening the name of a SRI fund implies a substantial portfolio rebalancing. Rohleder et al. (2022) precise that larger SRI funds with larger holding positions spread trades over time rather than in specific quarters to avoid any signaling effects or important trading costs due to market impact.

Unlike those prior studies, we explore, in this paper, how investment styles and profiles of fund managers may jointly determine the green trajectories of SRI funds. Simultaneous investigation of fund manager experience, fund characteristics and investment styles are far more limited in number. Earlier studies on SRI concentrated on the impact of stock picking or market timing abilities of fund managers on financial performance (Leite and Cortez, 2014; Leite et al., 2018; Muñoz et al., 2021) without considering experience effects on investment styles that are significant in the mutual fund industry (Chen et al., 2021; Luo et al., 2021). To the best of our knowledge, we are the first to examine the effects of profile and experience of fund managers in ESG on their investment styles to explain SRI funds' portfolio green performance.

Our methodological framework relies on the use of k-means, an unsupervised machine learning technique to cluster SRI funds based on widely used carbon risk and environmental indicators. Empirically, we focus on a sample of European labelled equity funds over the period 2015-2022 during which the SRI market has gained importance and has been affected by the Covid-19 pandemic (Fang and Parida, 2022) and stronger regulation in Europe (Becker et al., 2022).

Overall, our results are consistent with a simple story: greening a SRI fund is a byproduct of three effects: less diversification, sector allocation, salient experience of the manager in ESG.

Our research makes three contributions to the mutual fund industry. First, we document that recently launched SRI funds are greener consistent with El Ghoul and Karoui (2022) but also larger SRI funds with lower expenses. Second, we show the influence of experience effects on investment styles. We find that the more the lead manager is experienced in ESG and the shorter her mandate, the greener the fund is. However, the greenness of SRI funds is not related to the SMB factor and to the gender of the lead manager. Finally, we complement the findings of Muñoz et al. (2021) regarding green performance in a sense that we find that greener funds are less diversified and have a larger exposure to green (*resp*. fossil fuel) industries especially since the Covid-19 pandemic and the introduction of SFDR.

Our paper proceeds as follows. Section 2 presents the data used and the methodology framework. Section 3 introduces our tests and empirical findings. Finally, Section 4 concludes.

2. Data and methodology

2.1. Data description

We focus on a comprehensive sample of SRI equity funds, which hold the French SRI at date of December 31, 2022. We extracted a sample of 462 equity funds after removing balanced, bond, money market, convertible funds and funds of funds from the initial list. We removed ETFs, ETNs, and funds whose names contain the word 'index', 'MSCI', 'ETF', and 'iShares' as well as funds, which have been fully reinvested in another existing fund to avoid overlapping issues consistent with Humphrey and Li (2018). We also excluded three SRI funds that only promote a specific social objective (e.g., diversity).

Our study starts in 2015 to account for the implications of the Paris summit on Climate Change (COP 21) on the SRI funds' strategies, which also coincides with the launch of the French SRI label. It covers a seven-year period between 2015 and 2021, implying 9,200 equities invested.

2.2. Fund clustering based on their greenness degree

We employ the k-means, which is a machine learning technique applied for clustering, to identify green vs. non-green portfolios comprising clean and environmentally toxic equity investments. Some finance papers already employed k-means (see e.g., Parnphumeesup and Kerr, 2011; Béreau et al., 2020; Liu and Pun, 2022) for clustering using financial variables. However, our study is, to the best of our knowledge, the first attempt of using k-means to differentiate SRI fund portfolios based on their green performance. The k-means algorithm presents two main advantages: (1) its ability to capture nonlinear features and its independence of data characteristics (sample size, etc.) (2) it does not impose any linearity conditions and avoid the issue of collinearity between factors to the contrary of traditional methods of ex-post classification (e.g., PCA or factor models).

We cluster SRI labeled funds in three and four greenness categories based on a set of environmental metrics including the weighted amount of carbon emissions, carbon footprints and intensities (Bolton and Kacperczyk, 2021; Rohleder et al., 2022); and the weighted environmental score (Joliet and Titova, 2018; Rahat and Nguyen, 2022).

Carbon emissions data or data related to environmental score could be incomplete or even not accessible due to the fact that the portfolio company is private. In this respect, we only consider the funds for which we have at least a weighted sum of 50% of equities for which this information is available in line with the methodological principles of Morningstar (2020). Based on this threshold of 50% minimum weight of equities for which all information is provided, we scrutinise a final sample of N = 298 equity funds.

We use the k-means algorithm to effectively partition those N fund-year pairs into C clusters based on M clustering variables. The algorithm inputs are the standardized logarithm of the variables (Milligan and Cooper, 1988) and the number of clusters is based to the well-known elbow method. In which the total inertias[5], measuring the compactness of each cluster (Nanda et al., 2010), and the silhouette score[6] are computed. According to the inflection points, we set the number of clusters to C= 3 & 4. Those numbers are in line with number of groups used in the mutual fund industry. Morningstar-Sustainalytics consider three levels of fund greenness (Low, Medium, High) based on portfolio carbon exposure measures, which result from a relative non-transparent methodology (Ceccarelli et al., 2022). Also, FNG Siegel, the manager of the German SRI label developed four grades to distinguish funds on the basis of their level of sustainability engagement.

[5] It sums the distance of all observations in a cluster to the cluster's mean.
[6] It sums the distance of all observations in a cluster to the cluster's mean compared to their distance to the second closest cluster's mean.

2.3. Variables

We use commonly fund characteristics including fund size (Gil-Bazo et al. 2010 ; Alda, 2022), fund age (Gil-Bazo et al. 2010; Humphrey and Lee 2011; Alda, 2022), total expense ratio (Muñoz, 2021 ; Fang and Parida, 2022). Fund age is the number of months in which the oldest share class in the fund is traded. We calculate fund-level TNA as the sum of TNA across all the share classes of a fund. The total expense ratio is the sum of the management, custodian, and sales fees divided by the sum of all share classes. All those data are gathered from Refinitiv.

Regarding investment styles, we measure the level of equity concentration using the Herfindhal index as it is commonly used to account for the level of portfolio diversification (e.g., Muñoz et al., 2021). We also consider two types of portfolio exposures: this to the SMB factor (Gregory and Whittaker 2007; Humphrey and Lee 2011) and this to specific sectors: green industries (classified green under the EU Taxonomy) and fossil fuel industries (Muñoz et al., 2021; Rahat and Nguyen, 2022). We determine the threshold of Small cap under 250 million euros and Big cap, more than 1 billion euros in accordance with the official definition of Eurolist (Euronext).

To account for fund managers' abilities and profiles, we use the experience of the lead manager in ESG, its team, its gender, its tenure as in Chen et al. (2021) and Luo et al. (2022). We collect fund managers' biographical information, including sex, professional background, and tenure by looking at DICI prospectus and Linkedin accounts. Tenure is the number of years the manager had been in the mutual fund industry. In circumstances with more than one lead manager, we assign the longest tenure and experience in ESG of the team as in Luo et al. (2022).

2.4. Regression design

We use an ordered logistic regression model, which is adapted to our restricted set of dependent variables (3 and 4 clusters). As those variables are ordinal and not normally distributed, we apply the ordered logistic regression based on the cumulative probabilities of the dependent variable to a pooled sample of funds measured yearly from 2015 to 2021 with missing observations. An ordered logit model for an ordinal dependent variable Y with C clusters is defined by a set of K-1 equations where the cumulative probabilities $P(Y \leq c)$ are related to a linear combination of predictors through the logit function.

We define our baseline multinomial ordered logit model as follows:

$$\begin{aligned}&\mathrm{logit}(\mathrm{P}(Y \leq c) = \beta_{o,c} + \beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{LargeCap} + \beta_3 \cdot \boldsymbol{SmallCap} + \beta_4 \cdot \boldsymbol{FossilFuel} \\ &+\beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} + \beta_7 \cdot \boldsymbol{FundSize} + \beta_8 \cdot \boldsymbol{FundAge} + \beta_9 \cdot \boldsymbol{ExpESG} + \beta_{10} \cdot \boldsymbol{Tenure}\end{aligned} \tag{1}$$

Where: ***HI*** is the Herfindhal index measuring the level of equity concentration, ***Large Cap*** stands for portfolio companies with a market capitalisation higher than 1 million euros, ***Small Cap*** stands for portfolio companies with a market capitalisation higher than 1 million euros, ***FossilFuel*** represents the weighted amount of equities belonging to the fossil fuel sector, ***Green*** accounts for the weighted amount of equities belonging to sectors which are classified green under the EU Taxonomy (see for instance Clarity AI, 2022). ***Expense***, ***FundSize***, ***FundAge*** are the level of expense ratio, the size in TNA and the age of the fund respectively. ***ExpESG*** is the number of years the lead manager had worked in the SRI industry. ***Tenure*** is the number of years the lead manager had been in the mutual fund industry. $\beta_{0,c}$ are cutpoints. c = {1, 2}, which stands for C=3 clusters and c = {1, 2, 3} for C =4 clusters.

Additionally, we use two variants of this model denoted (2) and (3), which include the dummy variables ***Team*** and ***Woman*** respectively as follows:

$$\begin{aligned}&\mathrm{logit}(\mathrm{P}(Y \leq c) = \beta_{o,c} + \beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{LargeCap} + \beta_3 \cdot \boldsymbol{SmallCap} + \beta_4 \cdot \boldsymbol{FossilFuel} \\ &+\beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} + \beta_7 \cdot \boldsymbol{FundSize} + \beta_8 \cdot \boldsymbol{FundAge} + \beta_9 \cdot \boldsymbol{ExpESG} + \beta_{10} \cdot \boldsymbol{Tenure} \\ &+\beta_{11} \cdot \boldsymbol{Team}\end{aligned} \tag{2}$$

$$\begin{aligned}&\mathrm{logit}(\mathrm{P}(Y \leq c) = \beta_{o,c} + \beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{LargeCap} + \beta_3 \cdot \boldsymbol{SmallCap} + \beta_4 \cdot \boldsymbol{FossilFuel} \\ &+\beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} + \beta_7 \cdot \boldsymbol{FundSize} + \beta_8 \cdot \boldsymbol{FundAge} + \beta_9 \cdot \boldsymbol{ExpESG} + \beta_{10} \cdot \boldsymbol{Tenure} \\ &+\beta_{11} \cdot \boldsymbol{Team} + \beta_{12} \cdot \boldsymbol{Female}\end{aligned} \tag{3}$$

$\beta_{0,c}$ are cutpoints. c = {1, 2}, which stands for C=3 clusters and c = {1, 2, 3} for C =4 clusters.

We estimate the parameters of logit functions of these two measures of dependent variable, for the whole sample. Then, we split the sample into two subperiods: 2015-2019 and 2020-2021 to account for the joint effects of Covid-19 pandemic and SFDR regulation discussed from November 2019, which comply fund managers to classify their funds into Article 9 with a clear environmental objective or Articles 8 and 6 (See Morningstar, 2020; Clarity AI, 2022).

3. Empirical results

3.1. Descriptive statistics

Table 1 reports the summary statistics of the independent variables previously described. For the whole sample period, the mean Herfindahl index (HI) is 2% which indicates that portfolio are well diversified on average. On average, if the fund maturity exceeds nine years, the experience of the lead manager in ESG is about four years and its tenure is about sixteen years. For the two sub-periods, we observe significant differences in terms of stock selectivity and investment styles, suggesting a possible effect of SFDR regulation and Covid-19 pandemic.

[INSER TABLE 1]

3.2. Regression results for 3 and 4 clusters - Full period

Table 2 presents the results of the ordered logit regression estimated for two scenarios: 3 clusters and 4 clusters. The three clusters may reflect either the three SFDR funds categories: Article 6 for the brown category; Article 8 for the light green one; and Article 9 for the dark green one (Morningstar, 2022; Clarity AI, 2022) or the three Morningstar categories of carbon risk portfolio exposure (High, Medium and Low). We also consider the scenario with four clusters because it corresponds to the level of inflection point for k-means clustering (see §2.3).

For both scenarios, we present the coefficient of explanatory variables included in models (1), (2), (3), which are reported in columns (1), (2), (3) respectively. Panel A of Table 2 reports the value and significance of coefficients while Panel B displays associated marginal effects.

We observe that the coefficient of *HI* is always negative and statistically significant at 1% level. This first result implies that funds with are less diversified and more concentrated deliver better green performance and are less carbon intensive. The negative coefficient on *HI* may be explained by the fact that managers of climate-aware funds applied screening approaches that restrict the investment universe (Lesser et al., 2016; Muñoz et al., 2021). This is in line with results found in the literature on SRI funds (i.e., Schröder, 2004 ; Gregory and Whittaker, 2007; Humphrey and Lee, 2011 and others), which indicates that the use of negative screens impact positively the environmental performance of funds. A complementary explanation is that fund managers deliberately invest in equities that are less exposed to carbon risks, which may be not diversifiable and require superior financial performance (Bolton and Kasperzcyk, 2021).

This explanation echoes to the positive and significant coefficient of Fossil fuel, which indicates that greener funds are less exposed to fossil fuel industries consistent with the findings of Muñoz (2021) and Rahrat and N'Guyen (2022).

As a result, two approaches of stock selection may co-exist among fund managers : negative screening and decarbonisation (Rohleder et al., 2022). However, this stock selectivity of greener portfolios does not result from better stock picking abilities in line with the findings of Muñoz (2021). Indeed, even if the coefficients of *Small Cap* (*resp*. *Large cap*) are negative (*resp*. positive), they remain insignificant. This result implies that stock selectivity is not due to stock picking abilities from fund managers and is unrelated to the SMB factor. Furthermore, the coefficient of *Green* is not significant, which indicates that allocation towards green and renewable energy sectors, which are aligned with EU Taxonomy does not really impact the green performance of SRI funds perhaps because the percentage of companies with activities that are classifies as green according to the EU Taxonomy is small (Clarity AI, 2022).

Regarding the effect of fund-specific characteristics, the coefficient of *Fund age* is significant and positive at 1% level, suggesting that the more recent the fund, the greener it is. This result suggests that newly launched SRI funds are more climate-aware and less carbon intensive than older funds, which tend to decarbonize their portfolios at a slower pace (Rohleder et al., 2022). Both coefficients of *Fund size* and *Expenses* are negative and significant. Interestingly, this result implies that larger SRI funds are less expensive for investors consistent with previous studies (Muñoz, 2021; Morningstar, 2022) but also they are greener and less exposed to carbon risks. It relates to the findings of Bolton and Kaspercyck (2021) in a sense that a fund with greater exposure to carbon risk may deliver superior financial performance, which may be associated with higher costs for investors.

From a manager skill perspective, our results reveal that lead managers with a salient experience in ESG make their fund portfolios greener given the negative sign of the coefficient *ExpESG* significant at 1% level. Then, the coefficient of *Tenure* is positive and significant indicating that the younger the lead manager is in the mutual fund industry, the more likely her fund portfolio is greener. The magnitude of *ExpESG* coefficient is larger implying that the greenness of SRI fund is more largely driven by the salient experience of fund manager in ESG.

Previous studies have found that the experience of fund managers may impact financial performance of SRI funds (Muñoz et al., 2014; Alda and Vicente, 2022). By contrast, our study is the first to detect two effects of salient experience of the lead manager on fund green performance, i.e., a positive (*resp*. negative) effect of her experience in ESG (*resp*. in the mutual fund industry).

From columns (2) and (3), we observe that the coefficient of *Team* is positive but non-significant. If the fund is team managed, the lead manager may have more difficulties to impose their convictions in terms of (green) stock selectivity and sector allocation but it does not really influence the green performance of SRI funds. There is also no significant relation between funds by *Female* managers and their greenness degree, suggesting that the gender do not impact the green performance of SRI funds.

All of the abovementioned results are robust to the scenarios selected (3 and 4 clusters). Also, the values for the cutpoints, while apparently merely constant, do contain information of interest. The difference between the first and second (*resp*. first and second or second and third) cutpoints for the three (*resp*. four) clusters scenarios is relatively small, suggesting that once the fund managers decide to decrease the greenness degree of SRI funds slightly, it does not take much more to precipitate a more substantial move. The difference between the second and third (third and fourth) cutpoints is relatively large, suggesting that the fund managers generally are reluctant to alleviate the greenness degree of SRI funds. In other words, it takes extreme values of the explanatory variables to push managers over one of these cutpoints.

Panel B of Table 2 presents the related marginal effects on the probabilities of belonging to each cluster, which allows to determine how these covariates affect the likelihood that a given SRI fund will be a member of a one of the clusters. On average, increases in *HI*, in *ExpESG*, in *Fund size* and in *Expenses* make memberships of Cluster 1 or 2 (*resp*. Cluster 3) more (*resp*. less) likely for the case of three clusters. Similar results are obtained for the case with four clusters. By contrast, the higher the exposure to *Fossil Fuel*, *Tenure* and *Fund age*, the greater (*resp*. lower) the probability of belonging to Cluster 3 (*resp*. Cluster 1 or 2) is for the case of three clusters. Similar results are obtained for the scenario with four clusters.

Taken together, Table 2 results highlight the joint influence of investment styles (sector allocation, lower diversification) and of manager's experience in ESG on the green performance of SRI funds. Nonetheless, they do not suggest that greener funds are due to better stock-picking abilities of fund managers that may be compensated by larger fees paid by investors.

[INSERT TABLE 2]

3.3. Regression results for 3 and 4 clusters - Sub period analysis

Agoraki et al. (2023) find that the COVID-19 pandemic has had a positive effect on the returns of green funds especially when the market was bearish. Becker et al. (2022) found that the entry into force of SFDR Regulation push asset managers to be better aligned with the sustainable and environmental objectives assigned to their SRI funds and to decarbonise them.

In order to take the effects of COVID-19 SFDR Regulation into consideration, we split the whole period in two subperiods: 2015-19, and 2020-21.

Tables 3 and 4 report the ordered logit model regression coefficients estimated for each of two subperiods. In both cases, and for each scenario, the coefficients of *HI*, *Fossil Fuel*, *Expenses*, *Fund size*, and *ExpESG* are significant and the signs are those obtained in Table 2. However, those of *Tenure* and *Fund age* appear to be insignificant in the two subperiods respectively.

Quite importantly, for the first sub-period, the coefficient value of the percentage of *Green* is positive and non-significant, while for the second sub-period is negative and statistically significant. This result confirms our initial intuition that SRI fund managers still invest little in green equities probably due to few sectors aligned with the EU Taxonomy especially before the entry in force of the EU Taxonomy and its SFDR pillar. However, with the the gradual exit from the pandemic Covid-19 and SDFDR discussions, fund managers are more likely to fully subscribe to a greening approach via much more ambitious thematic investment approaches.

Further, the coefficient of the variable Team become positive and significant in the period 2020-21. We interpret this result as a signal that the lead manager could benefit from the experience of her team members in ESG and stock picking to make their funds greener to accelerating portfolio decarbonisation (Rohleder et al., 2022) or even repackage them (El Ghoul and Karoui, 2021) in Article 9 climate-aware funds to attract larger fund flows (Morningstar, 2022).

[INSERT TABLE 3]

[INSERT TABLE 4]

4. Conclusion

The issue of low carbon and green performance has become essential for SRI fund managers since the Paris agreement on Climate Change (Morningstar, 2020). In this regard, our paper proposes to study the combined effects of fund managers' profiles and investment styles on SRI funds' green performance. Overall, our study provides a simple message: greening a SRI fund is due to less diversification, sector allocation, salient experience of the manager in ESG effects.

We provide three set of results that enrich the SRI and mutual fund literature. First, we document that recently launched SRI funds and larger SRI funds with lower expenses are greener. Second, we find that the more the lead manager is experienced in ESG and the shorter her mandate, the greener the fund is. However, the greenness of SRI funds is not related to the SMB factor and to the gender of the lead manager. Third, we complement the findings of Muñoz et al. (2021) regarding green performance in a sense that we find that greener funds are less diversified and have a larger exposure to green (*resp*. fossil fuel) industries especially since the Covid-19 pandemic and the introduction of SFDR.

Like any study, our paper is, however, not exempt from limits. For instance, asessing the green performance of SRI funds given a set of carbon risk and environmental metrics may be imperfect and short-term focused. Avenues for further research may consider both ESG and impact metrics to better explain fund green performance.

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Table 1. Summary statistics

	Whole period (2015-21)		First subperiod (2015-19)		Second subperiod (2015-19)		Mean diff
	Mean	SD	Mean	SD	Mean	SD	
HI	0.02	0.01	0.02	0.01	0.02	0.01	-0.00** *(0.00)*
Large cap	0.89	0.12	0.87	0.1	0.93	0.14	-0.06** *(0.00)*
Small Cap	0.00	0.02	0.00	0.02	0.00	0.1	0.00** *(0.00)*
Fossil fuel industries	0.03	0.03	0.04	0.03	0.03	0.03	0.01** *(0.00)*
Green industries	0.10	0.06	0.09	0.06	0.10	0.06	-0.01** *(0.00)*
Expenses	1.66	0.61	1.66	0.60	1.64	0.64	0.03 *(0.03)*
Fund Size	4.90	1.43	4.76	1.44	5.17	1.35	-0.41** *(0.07)*
Fund Age	9.34	8.85	8.47	8.63	11.51	9.04	-3.04** *(0.42)*
ESG Exp	4.05	4.54	4.05	4.54	4.05	4.54	0 *(0.22)*
Tenure	16.22	4.94	16.22	4.94	16.22	4.84	0 *(0.24)*
Team	0.26	0.44	0.26	0.44	0.26	0.44	0 *(0.21)*
Female	0.27	0.44	0.27	0.44	0.27	0.44	0 *(0.21)*

Note: Table 1 shows summary statistics of the SRI funds sample. The Herfindahl index (HI) measures the concentration of SRI funds' portfolios expressed in %, the exposure to Large cap and Small cap as well as the exposure to fossil fuel industries and green industries expressed in%, Expenses are expressed in % of TNA, the fund are expressed in logarithms, the fund age expressed in years, the ESG experience and Tenure in years. Team is a dummy variable that equals 1 if the fund is team-managed and 0 otherwise. Female is a dummy variable that equals 1 if the fund is managed by a women and 0 otherwise. ** denotes statistical significance at the 1% level.

Table 2. Regression results – Whole period (2015-2021)

Panel A. Coefficient results

	3 clusters			4 clusters		
	(1)	(2)	(3)	(1)	(2)	(3)
HI	-60.62**	-59.66**	-59.87**	-61.22**	-60.65**	-60.53**
	(7.47)	*(7.55)*	*(7.55)*	*(6.45)*	*(6.50)*	*(6.50)*
Large cap	-0.12	-0.11	-0.10	-0.29	-0.30	-0.31
	(1.02)	*(1.03)*	*(1.03)*	*(1.07)*	*(1.07)*	*(1.08)*
Small Cap	-12.10	-12.20	-11.96	-23.62	-23.68	-23.84
	(14.92)	*(14.94)*	*(15.02)*	*(15.73)*	*(15.73)*	*(15.60)*
Fossil fuel industries	28.15**	28.29**	28.35**	25.14**	25.21**	25.18**
	(2.49)	*(2.50)*	*(2.50)*	*(2.31)*	*(2.31)*	*(2.31)*
Green industries	-0.43	-0.50	-0.48	-0.32	-0.38	-0.39
	(1.17)	*(1.18)*	*(1.17)*	*(1.14)*	*(1.15)*	*(1.15)*
Expenses	-0.50**	-0.48**	-0.48**	-0.47**	-0.46**	-0.46**
	(0.12)	*(0.13)*	*(0.13)*	*(0.12)*	*(0.12)*	*(0.12)*
Fund Size	-0.68**	-0.68**	-0.68**	-0.74**	-0.74**	-0.74**
	(0.05)	*(0.05)*	*(0.05)*	*(0.05)*	*(0.05)*	*(0.05)*
Fund Age	0.03**	0.03**	0.03**	0.03**	0.03**	0.27**
	(0.01)	*(0.01)*	*(0.007)*	*(0.01)*	*(0.01)*	*(0.05)*
ESG Exp	-0.12**	-0.12**	-0.12**	-0.1**	-0.1**	-0.1**
	(0.02)	(0.02)	(0.02)	(0.01)	(0 .01)	(0.01)
Tenure	0.04**	0.45**	0.04**	0.03*	0.03*	0.03*
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
Team		0.18	0.18	0.12	0.12	0.12
		(0.14)	*(0.13)*	*(0.13)*	*(0.13)*	*(0.13)*
Female			-0.09			0.07
			(0.13)			*(0.12)*
Cutoff 1 (1-2)	*-6.21*** *(1.00)*	*-6.06*** *(1.01)*	*-6.06*** *(1.01)*	*-8.39*** *(1.06)*	*-8.30*** *(1.06)*	*-8.31*** *(1.07)*
Cutoff 2 (2-3)	*-3.52*** *(0.99)*	*-3.37*** *(0.10)*	*-3.37*** *(0.99)*	*-6.10*** *(1.06)*	*-6.01*** *(1.06)*	*-6.01*** *(1.06)*
Cutoff 3 (3-4)				*-4.04*** *(1.05)*	*-3.95*** *(1.05)*	*-3.96*** *(1.05)*
Obs.	1247	1247	1247	1247	1247	1247
Log Pseudo-Likelihood	-987.06	-986.24	-986.03	-1248.10	-1247.68	-1247.51
Pseudo R^2	0 t.25	0.26	0 .26	0.23	0.22	0.22

Note: This table presents the results of the determinant analysis of the Ordered Logit Model for the whole sample period (2015-2021). For the three clusters scenario, the dependent variable is the number of funds belonging to their 3 closest associated clusters i.e., Cluster 1: Article 9 funds, Cluster 2: Article 8 funds, and Cluster 3: Article 6 funds respectively. For the four clusters scenario, the dependent variable is the number of funds belonging to their 4 clusters. Robust standard errors are in parentheses.
**, and * denote statistical significance at the 1%, and 5% levels, respectively.

Panel B. Marginal effects

	3 clusters			**4 clusters**			
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 4
HI	6.91**	2.24**	-9.15**	3.51**	5.33**	0.47**	-9.31**
	(0.85)	*(0.34)*	*(1.08)*	*(0.47)*	*(0.59)*	*(0.20)*	*(0.96)*
Large cap	0.01	0.00	-0.02	0.02	0.03	0.00	-0.05
	(0.12)	*(0.04)*	*(0.16)*	*(0.06)*	*(0.09)*	*(0.01)*	*(0.17)*
Small Cap	1.40	0.45	-1.83	1.38	2.10	0.18	-3.66
	(1.74)	*(0.55)*	*(2.29)*	*(0.93)*	*(1.34)*	*(0.15)*	*(2.39)*
Fossil fuel	-3.27**	-1.06**	4.33**	-1.46**	-2.22**	-0.19*	3.87**
Industries	*(0.28)*	*(0.12)*	*(0.32)*	*(0.17)*	*(0.21)*	*(0.08)*	*(0.32)*
Green	0.06	0.02	-0.07	0.02	0.03	0.00	-0.06
Industries	*(0.14)*	*(0.04)*	*(0.18)*	*(0.07)*	*(0.10)*	*(0.01)*	*(0.18)*
Expenses	0.06**	0.02**	-0.07**	0.03**	0.04**	0.00*	-0.07**
	(0.01)	*(0.00)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.02)*
Fund Size	0.08**	0.03**	-0.10**	0.04**	0.07**	0.01*	-0.11**
	(0.01)	*(0.00)*	*(0.01)*	*(0.00)*	*(0.01)*	*(0.00)*	*(0.01)*
Fund Age	-0.00**	-0.00**	0.00**	-0.00**	-0.00**	-0.00*	0.00**
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
ESG Exp	0.01**	0.00**	-0.02**	0.01**	0.01**	0.00*	-0.01**
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Tenure	-0.01**	-0.00**	0.01**	-0.00*	-0.00*	-0.00	0.00*
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Team	-0.02	-0.01	0.03	-0.01	-0.01	-0.00	0.02
	(0.02)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.02)*
Female	0.01	0.00	-0.01	-0.00	-0.01	-0.00	0.01
	(0.02)	*(0.00)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.02)*

Note: This table presents present the associated marginal effects on the probabilities of belonging to each cluster of the Ordered Logit for the whole sample period (2015-2021). Robust standard errors are in parentheses. **, *, and * denote statistical significance at the 1%, and 5% levels, respectively.

Table 3. Regression results – 1st sub-period (2015-2019)

	3 clusters			4 clusters		
	(1)	(2)	(3)	(1)	(2)	(3)
HI	-72.97**	-72.97**	-72.91**	-72.34**	-73.01**	-72.93**
	(9.62)	*(9.70)*	*(9.77)*	*(8.09)*	*(8.14)*	*(8.16)*
Large cap	0.94	0.94	0.94	0.11	0.12	0.12
	(1.35)	*(1.35)*	*(1.35)*	*(1.37)*	*(1.37)*	*(1.37)*
Small Cap	-5.64	-5.64	-5.72	-17.11	-17.14	-17.31
	(20.90)	*(20.89)*	*(20.88)*	*(21.30)*	*(21.24)*	*(21.16)*
Fossil fuel industries	30.12**	30.12**	30.11**	26.90**	26.87**	26.85**
	(2.13)	*(3.09)*	*(3.09)*	*(2.93)*	*(2.93)*	*(2.93)*
Green industries	2.13	2.13	2.13	2.25	2.28	2.29
	(1.28)	*(1.30)*	*(1.30)*	*(1.19)*	*(1.2)*	*(1.2)*
Expenses	-0.52**	-0.52**	-0.52**	-0.51**	-0.52**	-0.52**
	(0.18)	*(0.18)*	*(0.18)*	*(0.16)*	*(0.16)*	*(0.16)*
Fund Size	-0.77**	-0.77**	-0.77**	-0.85**	-0.86**	-0.86**
	(0.07)	*(0.07)*	*(0.07)*	*(0.07)*	*(0.07)*	*(0.07)*
Fund Age	0.04**	0.05**	0.05**	0.04**	0.04**	0.04**
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
ESG Exp	-0.14**	-0.14**	-0.14**	-0.1**	-0.1**	-0.1**
	(0.02)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*
Tenure	0.03	0.03	0.03	0.01	0.01	0.01
	(0.02)	*(0.02)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.02)*
Team		-0.00	-0.00		-0.11	-0.12
		(0.17)	*(0.17)*		*(0.17)*	*(0.17)*
Female			0.02			0.05
			(0.18)			*(0.16)*
Cutoff 1 (1-2)	*-5.79***	*-5.79***	*-5.79***	*-9.09***	*-9.19***	*-9.19***
	(1.28)	*(1.29)*	*(1.29)*	*(1.34)*	*(1.34)*	*(1.34)*
Cutoff 2 (2-3)	*-3.08**	*-3.08**	*-3.08**	*-6.49***	*-6.59***	*-6.59***
	(1.28)	*(1.27)*	*(1.27)*	*(1.33)*	*(1.32)*	*(1.32)*
Cutoff 3 (3-4)				*-4.44***	*-4.53***	*-4.53***
				(1.31)	*(1.30)*	*(1.30)*
Obs.	817	817	817	817	817	817
Log Pseudo-Likelihood	-601.53	-601.53	-601.52	-759.39	-759.15	-759.11
Pseudo R^2	0.29	0.29	0.29	0.24	0.24	0.24

Note: This table presents the results of the determinant analysis of the Ordered Logit Model for the sub-period (2015-2019). For the three clusters scenario, the dependent variable is the number of funds belonging to their 3 closest associated cluster i.e., Cluster 1: Article 9 funds, Cluster 2: Article 8 funds, and Cluster 3: Article 6 funds respectively. For the four clusters scenario, the dependent variable is the number of funds belonging to their 4 clusters. Robust standard errors are in parentheses. **, and * denote statistical significance at the 1%, and 5% levels, respectively.

Table 4. Regression results – 2nd sub-period (2020-2021)

	3 clusters			4 clusters		
	(1)	(2)	(3)	(1)	(2)	(3)
HI	-34.06**	-31.73**	-32.16**	-40.51**	-38.67**	-38.49**
	(11.43)	*(11.42)*	*(11.34)*	*(10.30)*	*(10.42)*	*(10.39)*
Large cap	-0.97	-0.89	-0.80	0.71	0.87	0.81
	(2.17)	*(2.20)*	*(2.18)*	*(2.15)*	*(2.11)*	*(2.15)*
Small Cap	-23.59	-25.61	-25.21	-29.62	-31.19	-31.33
	(24.72)	*(25.27)*	*(25.17)*	*(20.71)*	*(20.26)*	*(20.53)*
Fossil fuel industries	22.67**	22.87**	23.01**	22.84**	23.23**	23.19**
	(4.67)	*(4.71)*	*(4.71)*	*(4.35)*	*(4.40)*	*(4.41)*
Green industries	-6.72*	-7.23*	-7.10*	-6.00*	-6.32*	-6.41*
	(3.55)	*(3.50)*	*(3.50)*	*(2.78)*	*(2.72)*	*(2.74)*
Expense Ratio	-0.51**	-0.45*	-0.45*	-0.41*	-0.36*	-0.37*
	(0.17)	(0.17)	(0.18)	(0.17)	(0.18)	(0.17)
Fund Size	-0.52**	-0.52**	-0.52**	-0.57**	-0.56**	-0.56**
	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)
Fund Age	-0.01	-0.01	-0.00	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ESG Exp	-0.11**	-0.11**	-0.11**	-0.1**	-0.1**	-0.1**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Tenure	0.06**	0.06**	0.06**	0.05*	0.05*	0.05*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Team		0.58**	0.59**		0.55*	0.54*
		(0.23)	(0.23)		(0.21)	(0.21)
Female			-0.22			0.20
			(0.22)			(0.21)
Cutoff 1 (1-2)	*-6.41**	*-6.02***	*-5.97***	*-6.18***	*-5.72***	*-5.75***
	(2.21)	*(2.23)*	*(2.22)*	*(2.14)*	*(2.12)*	*(2.15)*
Cutoff 2 (2-3)	*-3.63**	*-3.21*	*-3.15*	*-4.14*	*-3.65*	*-3.67*
	(2.19)	*(2.20)*	*(2.20)*	*(2.13)*	*(2.11)*	*(2.15)*
Cutoff 3 (3-4)				*-1.98*	*-1.47*	*-1.49*
				(2.13)	*(2.11)*	*(2.15)*
Obs.	430	430	430	430	430	430
Log Pseudo-Likelihood	-365.47	-362.29	-361.79	-470.19	-466.39	-466.85
Pseudo R^2	0.20	0.21	0.21	0.18	0.18	0.18

Note: This table presents the results of the determinant analysis of the Ordered Logit Model for the sub-period (2020-2021). For the three clusters scenario, the dependent variable is the number of funds belonging to their 3 closest associated cluster i.e., Cluster 1: Article 9 funds, Cluster 2: Article 8 funds, and Cluster 3: Article 6 funds respectively. For the four clusters scenario, the dependent variable is the number of funds belonging to their 4 clusters. Robust standard errors are in parentheses. **, and * denote statistical significance at the 1%, and 5% levels, respectively.