How do socially responsible investment funds go green? The influence of investment styles and managers' experience

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Abstract

We provide an holdings-based analysis of socially responsible investment (SRI hereafter) funds' greenness and its determinants in Europe over eight years (2015-22). To this end, a segmentation of SRI funds by greenness degree based on k-means clustering is developed.

Our results reveal that SRI funds' greenness depends on specific investment styles and the salient experience of managers in SRI. We verify that greening an SRI fund implies a higher stock selectivity leading managers to underweight their portfolios with fossil fuel stocks and raise the weight of green stocks once SRI market regulations in Europe have been implemented. Also, we find that active investment styles make SRI funds greener. Moreover, we provide evidence of counteracting experience effects provided that the more (resp. less) the manager is experienced in SRI (resp. mutual fund industry), the greener the fund is. In addition to those experience effects, we detect a gender diversity effect provided that a greater gender diversity in fund management teams contributes to increase SRI funds' greenness.

Overall, our findings support the argument that the experience and abilities of fund managers are important factors for investors to consider when they choose SRI funds notably because skilled professionals with more experience in SRI are more likely to adapt to regulatory shifts.

Keywords: Socially Responsible Investment (SRI); Mutual funds; Greenness; K-means clustering; Manager Experience; Active strategies

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1. Introduction

Climate change has become the highest sustainability priority for investors since the Paris Agreement, which has invited investors and non-governmental actors to serve as catalysts for expediting the transition to a low carbon economy (Bolton and Kacperczyk, 2021). This milestone combined with the higher frequency of extreme weather events have raised investors' awareness of climate risks (Krueger et al., 2020) and the negative environmental impacts of fossil fuels (Muñoz, 2021). This increase in awareness has, in turn, led asset managers to launch green funds (El Ghoul and Karoui, 2021) or decarbonise their existing fund portfolios (Rohleder et al., 2022) with the aim to attract net money inflows (Liang and Renneboog, 2021).

Although the role of asset managers to achieve climate goals has been acknowledged, both their profiles and their ability to make their funds greener remain understudied (Krueger et al., 2020; Humphrey and Li, 2021). To bridge this gap in the literature, we investigate the greenness of SRI funds from the double perspective of managers' experience and their investment styles.

Green investing has emerged as a promising subset of SRI in the past few years. Although SRI funds predominantly screen for firms with high ESG scores (Kim and Yoon, 2022), green funds should invest at least 75 % of their assets in equities issued by firms with low carbon activities (Agoraki et al., 2023) such as alternative fuels, clean technologies, and renewable energies. Despite the growing importance of green funds for the SRI industry (see e.g., Liang and Renneboog, 2021), only a handful of papers have explored their characteristics. Ibikunle and Steffen (2017) argue that green SRI funds are more exposed to small caps and growth stocks because they face less carbon risks. If Muñoz (2021) finds that greener US SRI funds are less exposed to fossil fuel industries, El Ghoul and Karoui (2021) show that greening US SRI funds also involves a substantial portfolio rebalancing, which leads to a greater exposure to the renewable energy sector. For Rohleder et al. (2022), this rebalancing is slow especially for larger SRI funds to avoid important market impact. Despite those advances, it remains unclear whether the profile and skills of managers may explain the green trajectories of their SRI funds. Notably, if the literature on managers' experience effects in finance is vast (Chen et al., 2021), no papers, to our knowledge, have examined their influence in the SRI context.

Previous studies concentrated on SRI's investment styles, stock picking and market timing abilities of managers to explain financial performance. Capelle-Blancard and Monjon (2014) show that environmental screens decrease SRI funds' financial performance while governance and social screens do not impact. Regarding investment styles, Joliet and Titova (2018) show that actively SRI managed funds are less diversified than passive managed SRI funds. In terms of stock selectivity, research has shown that SRI funds tend to invest more in large caps and have lower exposure to momentum stocks (Gregory and Whittaker, 2007; Humphrey and Lee, 2011). If screening may help SRI fund managers find undervalued stocks (Leite and Cortez, 2014), Humphrey and Lee (2011) precise that positive (*resp*. negative) screening bias SRI funds to the selection of larger (*resp*. smaller) stocks. Leite and Cortez (2014) add that European SRI best-in-class funds applying positive screens are less exposed to small caps. Leite and Cortez (2015) highlight higher abilities of managers of French SRI funds to time the market during good economic states. By contrast, Muñoz et al. (2014) find that green SRI fund managers are generally unable to implement successful stock-picking and market-timing strategies. In terms of managerial abilities, Alda and Vicente (2020) argue that non-specialist SRI managers exhibit better performance than SRI specialist managers because they benefit from broader market knowledge, consider financial and non-financial aspects of SRI funds, and may share knowledge between SRI and conventional fund markets. Interestingly, they find that the more experienced the specialist SRI fund manager is, the lower the financial performance she delivers.

Unlike those studies, our paper aims to examine the joint effects of investment styles and manager experience on the green trajectories of SRI funds in Europe where important regulations on SRI have been recently implemented (Becker et al., 2022).

We focus on the French SRI market, which has been the leading European SRI fund market in terms of the number of funds and assets under management (AuM hereafter) since its launch in 2015. Recent statistics also indicate that, from 2019 to 2021, the weight of the French SRI label on the total European AuM has increased from 46% to 59% (Novethic & Fair, 2022). Moreover, recent research has shown that different types of screens may affect the financial performance of SRI funds (Muñoz, 2021; Ibikunle and Martí-Ballester, 2022) and its green performance (Ceccarelli et al., 2023). While US and UK funds are generally focused on negative screens, leading them to exclude sector-specific firms from SRI portfolios, SRI funds in continental Europe use mostly positive screens, notably "best-in-class" screening strategies, which implies to choose leader firms on environmental issues within each sector (Leite and Cortez, 2015). In this context, the French SRI market appears to be highly relevant since it is the European SRI market where "best-in-class" strategies are employed to a larger extent (Leite end Cortez, 2014).

In this paper, we study a comprehensive sample of 307 French SRI labelled funds over an eight-year period (2015-22) covering the Paris Summit on Climate Change, the Covid-19 pandemic (Agoraki et al., 2023), and the implementation of two SRI market regulations in Europe: the EU Taxonomy and the Sustainable Finance Disclosure Regulation (Becker et al., 2022).

Our main contribution is twofold. Methodologically, our paper is the first, to our knowledge, to use the k-means clustering technique to group SRI fund portfolios based on their "green" performance that is assessed using widely used carbon and environmental variables. From our clustering, we obtain degrees of fund greenness based on homogeneous groups (3 or 4 degrees), which does not *ex ante* penalise investment into carbon intensive sectors in contrast to fund ranking methods based on carbon risk and/or environmental scores (e.g. Morningstar). With those degrees, we can also provide a dynamic assessment of green trajectories of SRI funds.

Empirically, we contribute to the literature on SRI in four respects. First, we verify that greener SRI funds are less diversified but attract more money inflows as it was already reported by El Ghoul and Karoui (2021) for the case of US SRI funds. Second, we show that greening an SRI fund implies a higher stock selectivity related to negative screening and/or thematic approaches leading managers not only to underweight their portfolios with fossil fuel stocks but also to step up the weight of green stocks in them once market regulations have been implemented. Regarding investment styles, managers who conduct active strategies make SRI funds greener without any effect on fees required to clients, which highlights their market-timing abilities. Third, by showing that greener funds are older when SRI market regulations have been established, our results suggest that managers have used those regulations as a selling point to their clients for expediting the decarbonisation of their mature funds, which are longer to execute (Rohleder et al., 2022). Fourth, we provide evidence of counteracting "experience effects" on SRI funds greenness provided the fact that the more (*resp*. less) the manager is experienced in SRI (*resp*. mutual fund industry), the greener the fund is. Interestingly, the positive impact of the manager's experience in ESG on fund greenness is found to be three times larger than the negative influence of her experience in the mutual fund industry.[5] Also, we detect "gender diversity effects", i.e., a greater gender diversity in the fund management teams allows to increase SRI fund greenness while the gender of the manager has no influence.

Overall, our findings support the argument that the experience and skills of managers are important factors to consider when selecting green SRI funds especially since experienced and skilled managers are particularly better positioned to benefit from regulatory opportunities.

[5] ESG refers to the environmental, social, and governance criteria for evaluating corporate behavior and screening investments. SRI involves selecting or disqualifying investments based on a set of those ESG criteria.

The rest of the paper proceeds as follows. Section 2 presents the data and the clustering methodology employed. Section 3 describes our empirical framework. In Section 4, we discuss our empirical results. Section 5 concludes.

2. Data and Methodology

2.1. Mutual fund data

Our sample of French SRI labelled funds covers the 2015-2022 period that accounts for the potential effects of the Paris Summit on Climate Change, the Covid-19 pandemic (Agoraki et al., 2023), and stronger SRI market regulation in Europe (Becker et al., 2022).[6]

We start with an initial sample of equity funds holding the French SRI label as of December 2022. We exclude from this sample ETFs, ETNs, funds whose names contain the word 'index', 'MSCI', and 'iShares', as well as funds that have been fully reinvested in another fund to avoid overlapping issues as in Humphrey and Li (2021).[7] We also remove three funds that only promote a specific social objective (e.g., gender diversity).

After applying these different filters, a sample of 347 equity funds is retained.

2.2. Stock level emissions data and environmental score

Emissions data are extracted from Refinitiv database at a stock level. We refer to the GHG Protocol's scope 1, 2, and 3 classifications of carbon emissions (see Bolton and Kacperczyk, 2021). Scope 1 emissions are direct emissions from firms' operations like combustion and use of vehicles. Scope 2 emissions are indirect emissions from firms' purchased electricity. Scope 3 emissions are indirect emissions from firms' activities, but emitted by other firms (or people). As in Humphrey and Li (2021), we focus on Scope 1 and 2 emissions for two reasons. First,

[6] The two SRI market regulations namely the EU Taxonomy and SFDR are complementary. If the EU taxonomy (implemented in 2020) helps to identify the truly green share of investments, the SFDR has enabled a distinction between SRI funds based on their sustainability characteristics and goals since 2021.

[7] Exchange-traded funds (ETFs) and exchange-traded notes (ETNs) track the performance of a benchmark like an index (e.g., MSCI sustainability index). Unlike mutual funds, they do not sell or redeem shares directly to retail investors. IShares is a vast collection of ETFs managed by Blackrock, the largest provider of ETFs and ETNs.

Scope 3 emissions are difficult to estimate and firms rarely report them. Second, we aim to avoid the risk of carbon emissions' double counting, as one portfolio firm's Scope 1 and 2 emissions may become another portfolio firm's Scope 3 emissions.

From those data, we calculate for each stock that belongs to SRI fund portfolios the level of (Scope 1 and 2) emissions, its carbon footprint (emissions/annual sales) and intensity (emissions/invested capital) as in Bolton and Kacperczyk (2021) and Humphrey and Li (2021).

As the world's largest ESG rating database, we also use Refinitiv ESG scores, in particular the environmental pillar score that is calculated based on three complementary aspects: *i) resource use* (i.e., water, energy use, sustainable packaging, environmental supply chain); *ii) emissions* (i.e., waste, emissions, biodiversity, environmental management systems) and *iii) innovation* (i.e., product innovation, green research, and development or capital expenditures).

2.3. Clustering variables

For each fund at a given year-end, we compute the weighted amount of its portfolio's Scope 1 and 2 carbon emissions as the weighted average of the stock-level emissions consistent with Humphrey and Li (2021). We employ an identical method for calculating the weighted carbon footprints, weighted carbon intensities, and weighted environmental pillar scores. Those variables are standardised and then used for clustering SRI fund portfolios.

Since carbon emissions and environmental score data may be incomplete or unavailable, we obtain a final sample of 307 SRI funds that collectively invest in 11,326 equities. From this final sample, we consider two scenarios for clustering: a first (*resp*. second) scenario with at least a weighted sum of 60% (**w=60%**) (*resp*. 50% (**w=50%**)) of equities for which this information is available that correspond to a fund portfolio where 70% (*resp*. 64%) of assets are informed, which is in line with the threshold of two-third of assets informed applied by Morningstar when it calculates its carbon score (see Ceccarelli et al., 2023).

A critical aspect of our methodology lies in the identification of fund styles that are responsible for producing green fund portfolios. A fund style governs the broad direction of a green investment strategy, which may rely on the exclusion of polluting sectors (Muñoz et al., 2014; Muñoz, 2021) and on a thematic approach e.g., water management (Ibikunle and Martí-Ballester, 2022). Thus, within a style, a green fund can depart from its peers by making decisions depending on the skills of its managers, or the specificity of its strategy. Therefore, pairing funds according to their greenness is a pivotal step in subsequently assessing the specificity of investment strategy relative to style-based peers. For fund managers, peer funds following a similar style are particularly relevant for comparison purposes since they are viewed as natural "rivals" or "competitors" (Leite and Cortez, 2014; Coleman, 2023). To pair funds according to SRI funds according to their greenness (or brownness), we run a k-means algorithm over a significant eight-year period (2015-22) to group (or cluster) funds into homogeneous peer groups. In the forthcoming paragraph, we elaborate on this approach.

Few papers already used the k-means algorithm, an unsupervised machine learning technique for clustering sustainability stock indices (Vilas et al., 2022) or mutual fund portfolios according to financial returns (Béreau et al., 2020; Soleymani and Vasighi, 2020). Like those papers, we use the k-means to group fund portfolios based on their "green" performance which is assessed using our set of carbon and environmental clustering variables (described in §2.2). To our knowledge, our study is the first attempt at using the k-means to cluster funds into homogeneous (peer) groups based on their green performance.

Ample evidence exists in Morningstar reports and recent evidence exists in the academic literature that self-reporting of SRI funds as SDFR Article 9 "green" funds —can provide a misleading picture of their green credentials that poses greenwashing risks (e.g., Becker et al., 2022). The simple reason is that a financial institution may have a strategic interest in greening SRI funds to attract money inflows (El Ghoul and Karoui, 2021). In response, several data providers have developed their proprietary carbon risk or environmental scores. For instance, Morningstar has measured a carbon risk score for many fund portfolios since 2018 and ranks them in terms of greenness accordingly (Ceccarelli et al., 2023). However, this ranking method based on scores suffers from two important limitations. First, some SRI fund managers focus on environmental scores performing a static assessment of green performance. Accordingly, they select companies with good environmental scores but they are unlikely to cause future improvements in their green performance, nor do they reward companies for past improvements (Heath et al., 2023). Second, this ranking method is subjected to biases due to the existence of green window dressing techniques that occurred when quarterly fund reportings are publicly disclosed leading data providers to update scores simultaneously (Parise and Rubin, 2023).

Our approach to assessing fund greenness through clustering departs from this ranking method.

We build on the intuition that SRI funds that are similar to each other in terms of greenness should be placed in a common group, while those appearing more distant should be in different groups. Equipped with distance measures for all funds, we use clustering techniques to allocate them into consistent groups. In contrast to Morningstar and environmental scores, our approach does not *ex ante* penalise investment into fossil fuel or carbon intensive sectors (Ceccarelli et al., 2023) consistent with the principles of the French SRI label that favoured Best-in-class strategies over sector exclusion (Leite and Cortez, 2014). Also, the degrees of fund greenness resulting from clustering allows us to provide a dynamic assessment of SRI fund decarbonization, which may smooth the effects of their green window dressing strategies (Parise and Rubin, 2023) provided that clustering is run collectively over an eight-year period.[8]

[8] We cluster funds based on a set of eight year-observations (or eight portfolios) while ranking methods assess fund using one year-observation (or single portfolio) independently. Our clustering approach may smooth the effects due to potential green window dressing techniques along the eight-year period provided that their magnitude significantly varies according to changes in the annual fund performance (Parise and Rubin, 2023).

The popular "k-means" algorithm (Hartigan, 1975) presents a simple and intuitive rationale. Considering a set of n observations and k clusters determined *ex ante*, it seeks a partition such that the squared difference between the empirical mean of each cluster (called centroid) and the points in the cluster is minimised. Put simply, the observations are grouped into k clusters such that each belongs to the group with which the associated mean has the closest distance.

Algorithm 1 presents the application of the k-means in two steps as in Parnphumeesup and Kerr (2011). It relies on an iterative process assigning data points to clusters (**Step 1**) and updating the cluster centroids (**Step 2**) until convergence. Once the algorithm has delivered the clusters, we rank them according to the sum of the centroids' values.

Algorithm 1: The algorithm of k-means

Step 1. Each observation (i.e, SRI fund for a given year) $\boldsymbol{x}_i \in \mathbb{R}^M$ is assigned to its closest centroid $\boldsymbol{c}_j \in \mathbb{R}^M$ out of k possible clusters as expressed with the below loss function.[9]

$$\mathrm{f}(\boldsymbol{c}_j) := \sum_{i=1}^{N} \operatorname{argmin} d(\boldsymbol{x}_i, \boldsymbol{c}_j)$$

Where: $d(\boldsymbol{x}_i, \boldsymbol{c}_j)$ is computed using the Euclidean distance. The observations 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 j[th] cluster, as follows:

$$\boldsymbol{c}_j = \frac{\sum x_i \in S_j x_i}{Card(S_j)}$$

[9] M corresponds to the number of clustering variables.

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

In theory, using k-means presents three immediate advantages. First, it is considered as a fast, reliable, stable, algorithm for partitioning data related to funds into clusters (Hartigan, 1975). Second, it is effective for capturing linear relationships between clustering (here carbon and environmental) variables and demonstrates a degree of adaptability in capturing non-linear relationships between them to some extent. Finally, it does not require prior information about the structure of the data and is not restricted to any specific distribution of data.

In practice, the allocation of funds into accurate similarity-based groups may be challenging. The number of clusters k is generally set using a tradeoff between the decrease in inertia and the increase in the number of clusters via the elbow method. Another method is the silhouette score, which assesses the compactness within clusters and the separation between clusters.

Figure 1 displays the silhouette score, indicating that the optimal trade-off point may be found between three and five clusters for both portfolio weights (**w=50%** or **w=60%**) studied. Additionally, domain knowledge, which is relevant for the k-means parametrization, allows us to identify three and four clusters. This latest number corresponds to the German SRI label that delivers up to four stars to assess the sustainability performance of their labelled funds.

[INSERT FIGURE 1]

Another potential risk is related to the selection of initial centroids. As in Soleymani and Vasighi (2020), we mitigate this risk by applying the k-means++ algorithm to create compact and well-separated clusters. Indeed, the k-means++ developed by Arthur & Vassilvitskii (2007) helps choose the initial values for the k-means in order to avoid the potential risk of poor clustering results by applying a simple random selection of the initial centroids.

3. Empirical analysis

Our empirical analysis aims to explore the drivers of different levels of SRI fund greenness. Based on our k-means clustering, we identify three or four groups of SRI funds that refer to the number of clusters selected (3 or 4) and examine their trajectories over the 2015-2022 period.

Pooled data regressions are used to test the influence of independent variables on the dependent variable i.e., the level of SRI fund greenness that can take either 3 values (for the case of three clusters) or 4 (for the case of four clusters).

3.1. Independent variables

An important number of papers has shown that fund characteristics including fund size (Gil-Bazo et al., 2010; Alda and Vicente, 2020), fund age (Gil-Bazo et al., 2010; Humphrey and Lee, 2011; Alda and Vicente, 2020), expense ratio (Alda and Vicente, 2020; Muñoz, 2021) impact the financial performance of SRI funds. Consistent with this literature, we consider the size of the fund approached by the log of the total net assets (TNA hereafter); the age of the fund expressed in years and computed as the difference between the month t and the inception date of fund's oldest share class; the net expense ratio; the level of portfolio diversification (*resp*. concentration) approached by the Herfindahl index (HI), which may be affected by the restriction of investment universe due to the application of screens (Muñoz, 2021). Data related to those variables are gathered from Refinitiv Eikon as shown in Table A1 (See Appendix).

We assess the influence of investment styles with a dummy variable that is equal to 1 when the fund is actively managed and 0 otherwise. Specifically, we use a proprietary database of Novethic that classify French SRI funds in terms of investment styles using a textual analysis of their Document d'Information Clé pour l'Investisseur (DICI hereafter) and fund reportings.[10] As a result, we are able to divide our sample of SRI funds into two investment style categories:

[10] The DICI is a three-page "fact-sheet" style document presenting the critical information about a fund and managers that is updated once a year. It is the equivalent of the Anglo-Saxon Key Information Document (KID).

passive and active funds as in Joliet and Titova (2018). Passive funds track the behavior of an underlying index while active funds aim to maximise total returns (capital appreciation and income) by investing on undervalued stocks to generate alpha (see Chen and Scholtens, 2018). As in El Ghoul and Karoui (2021), we also identify funds that have switched to a sustainability-related appellation over the period 2015-2022. This new appellation should include one of the following words: 'environment', 'ESG', 'green', 'biodiversity', 'impact', 'responsible', 'SRI', 'sustainable', and 'sustainability'. It is likely to affect the (green) fund investment strategy. Consistent with the literature, we consider a first type of exposure of SRI fund portfolios to the Small Minus Big (SMB) factor i.e., small vs. large capitalisations (e.g., Humphrey and Lee 2011).[11] We also consider a second type of exposure: this to the Brown Minus Green (BMG) factor i.e., fossil fuel (brown) (Muñoz, 2021) vs. green sectors. The EU Taxonomy provides an official definition of green activities, which determine the level of greenness of firms. It follows the NACE classification, which contains a list of economic activities for the relevant technical screening criteria (TAC hereafter), i.e. the conditions under which the activity is green, and their rationale is indicated. We follow the method developed by Alessi and Battiston (2022) to construct the Green variable by applying the TAC relevant to each portfolio firm.

To account for the manager profile, we use the experience of the lead managers in ESG, their gender, their team, their tenure as Luo et al. (2022) and Alda and Vicente (2020). We hand-collect fund managers' biographical information, including sex, professional background, and tenure from their LinkedIn accounts but also their CV published on the websites of their asset management companies and on DICI. In circumstances with more than one lead manager, we assign with the longest tenure and experience in ESG of the team (Luo et al., 2022). Finally, we consider the fact that the fund is team-managed or not. As shown by Kim and Yoon (2022), team-managed funds may have difficulty agreeing on details of ESG implementation and asset

[11] We define a small (*resp*. large) cap given a market capitalisation under 250 million euros (*resp*. above 1 billion euros) in accordance with the definition of Euronext (Eurolist) where most equities have been traded.

allocation but may also be more open to diverse opinions (Gangi et al., 2021). The meaning and the calculation of those variables are summarised in Table A1 (see Appendix).

[INSERT TABLE A1]

3.2. Ordered logistic regression models

We implement an ordered logistic data regression model to investigate the role of those explanatory variables in affecting the different levels of SRI fund greenness since our dependent variables are ordinal and not normally distributed.

An ordered logit model for an ordinal dependent variable Y with *K* categories is defined by a set of *K*-1 equations where the cp^{th} cumulative probability $\text{logit}(\text{P}(Y \le cp)) = \ln\left(\frac{\text{Prob}(Y \le cp)}{1-\text{Prob}(Y \le cp)}\right)$ is related to a linear combination of predictors through the logit function as follows:

$$\text{logit}(\text{P}(Y \le cp)) = \beta_{o,cp} - (\beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{Large\,Cap} + \beta_3 \cdot \boldsymbol{Small\,Cap} + \beta_4 \cdot \boldsymbol{Fossil\,Fuel} + \beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} + \beta_7 \cdot \boldsymbol{Fund\,Size} + \beta_8 \cdot \boldsymbol{Fund\,Age} + \beta_9 \cdot \boldsymbol{ESG\,Exp} + \beta_{10} \cdot \boldsymbol{Tenure})$$

(1)

Where : $\beta_{o,cp}$ are cut points with cp = {1, 2} for 3 clusters and cp = {1, 2, 3} for 4 clusters (for a number of clusters k, cp = k-1); ***HI*** is the Herfindahl index ; ***Large Cap*** *(resp.* ***Small Cap****)* are the weighted percentage of Large (*resp*. small) capitalisations, proxy of portfolio exposure to SMG factor; ***Fossil Fuel*** *(resp.* ***Green****)* is the weighed percentage of equities belonging to fossil fuel (*resp.* green) industries, proxy of exposure to BMG factor; ***Expense*** is the expense ratio ; ***Fund Size*** is the sum of TNA across all the share classes of a fund ; ***Fund Age*** is the number of years in which the oldest share class in the fund is traded ; ***ESG Exp*** is the number of years the lead manager had worked in ESG ; ***Tenure*** is the number of years she had been in the mutual fund industry. See Table A1 for a description of those independent variables.

We also consider three enriched regression models: (2) which includes a dummy variable ***Team*** that adopts the value 1 if the fund is team-managed, 0 otherwise; (3) which includes the dummy variable ***Female*** that adopts the value 1 if the fund is managed by a female manager; (4) which includes the dummy Name Change if the fund has changed its appellation written as follows:

$$\text{logit}(P(Y \leq cp)) = \beta_{o,cp} - (\beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{Large\,Cap} + \beta_3 \cdot \boldsymbol{Small\,Cap} + \beta_4 \cdot \boldsymbol{Fossil\,Fuel} + \beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} + \beta_7 \cdot \boldsymbol{Fund\,Size} + \beta_8 \cdot \boldsymbol{Fund\,Age} + \beta_9 \cdot \boldsymbol{ESG\,Exp} + \beta_{10} \cdot \boldsymbol{Tenure} + \beta_{11} \cdot \boldsymbol{Team}) \quad (2)$$

$$\text{logit}(P(Y \leq cp)) = \beta_{o,cp} - (\beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{Large\,Cap} + \beta_3 \cdot \boldsymbol{Small\,Cap} + \beta_4 \cdot \boldsymbol{Fossil\,Fuel} + \beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} + \beta_7 \cdot \boldsymbol{Fund\,Size} + \beta_8 \cdot \boldsymbol{Fund\,Age} + \beta_9 \cdot \boldsymbol{ESG\,Exp} + \beta_{10} \cdot \boldsymbol{Tenure} + \beta_{11} \cdot \boldsymbol{Team} + \beta_{12} \cdot \boldsymbol{Female})$$

$$(3) \quad \text{logit}(P(Y \leq cp)) = \beta_{o,cp} - (\beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{Large\,Cap} + \beta_3 \cdot \boldsymbol{Small\,Cap} + \beta_4 \cdot \boldsymbol{Fossil\,Fuel} + \beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} + \beta_7 \cdot \boldsymbol{Fund\,Size} + \beta_8 \cdot \boldsymbol{Fund\,Age} + \beta_9 \cdot \boldsymbol{ESG\,Exp} + \beta_{10} \cdot \boldsymbol{Tenure} + \beta_{11} \cdot \boldsymbol{Team} + \beta_{12} \cdot \boldsymbol{Female} + \beta_{13} \cdot \boldsymbol{Name\,Change})$$

(4)

We estimate the parameters of (1), (2), (3), and (4) for our final sample of SRI equity funds.

4. Results

4.1. Descriptive statistics

Figure 2 (*resp*. Figure 3) shows the distribution of SRI funds among 3 clusters (*resp*. 4 clusters). Our clusters (degrees) of clusters reflects differences in terms of greenness, which is captured along its two dimensions: *i)* low carbon performance (carbon emissions, carbon footprint and intensity); and *ii)* broader environmental impact captured by the environmental score. We follow the Morningstar's denomination to distinguish funds according to their greenness degree. Cluster 1 is the greenest cluster i.e., the *dark green* cluster, Cluster 2 is the *light green* cluster while Cluster 3 (*resp*. Clusters 3 and 4) are *light brown* and *dark brown* clusters, respectively.[12]

While the share of *dark green* funds has increased fourfold, the share of brown funds has been cut in half from 2015 to 2022. This evolution coincides with the overall decarbonisation trend of SRI funds documented by Rohleder et al. (2022) after the ratification of Paris Agreement.

[12] We use the spectral clustering as an alternative to the KM clustering like Vilas et al. (2022). We obtain a similar distribution of funds between clusters whatever the scenario considered. Results are available upon request.

[INSERT FIGURE 2]

[INSERT FIGURE 3]

Table 1 reports the summary statistics of these independent variables. The mean Herfindahl index (HI) is 2.35% indicating that equity portfolios are well diversified but a little less diversified as compared to the HI estimations of Muñoz (2021) for US SRI funds. Those portfolios have a lower exposure to the fossil fuel sector (3.5%) than US SRI funds estimated at 5.3% by Muñoz (2021) but have a greater exposure to the green sector: 9.3% on average. Interestingly, if the average maturity of our sampled funds exceeds twelve years, the experience of the managers in ESG is four years and their tenure is about seventeen years on average. Finally, 28% of funds are managed by women, while 63% of them are managed by a team.

[INSERT TABLE 1]

4.2. Regression results - Full period analysis

Panel A of the Table 2 presents the coefficients of explanatory variables included in models (1), (2), (3) and (4) estimated from the sample of funds with at least 60% of equities informed (**w=60%**) for both 3 and 4 KM clusters.

We observe that the coefficient of *HI* is always negative and statistically significant at 1% level. This first result implies that less (*resp*. more) diversified funds have a higher (*resp*. lower) degree of greenness. Given managers of greener funds applied screens or even follow thematic approaches that restrict the investment universe (Leite and Cortez, 2015; Liang and Renneboog, 2021), they have lower potential for diversification (Muñoz, 2021). This reduced diversification may also result from a higher stock selectivity of better-informed managers who select stocks of companies, which face lower carbon risks and are even innovative environmental pioneers (Ibikunle and Steffen, 2017) as thematic approaches may promise.

The significantly positive coefficients of *Fossil Fuel* indicate that greener funds are less exposed to fossil fuel industries, which should result from the application of negative screens by fund managers (Ibikunle et Steffen, 2017; Muñoz, 2021). By contrast, those of *Green* are negative and significant implying that greener funds have a greater allocation in green sectors suggesting a severe stock selectivity provided the fact that the share of companies with activities classified as green according to the EU Taxonomy is relatively small.

Also, the coefficients of *Small Cap* are negative and statistically significant for the 4 clusters scenario (*Panel B*), which provide evidence of stock picking abilities from fund managers who can more invest in smaller equities to green their SRI funds, which is not the case in the US SRI market according to Muñoz (2021). As for the coefficients of *Large Cap*, they are positive but insignificant, which imply that greener funds are less diversified but do not have a significantly lower portfolio exposure to large capitalisations especially.

The coefficients of *Fund size* are negative and significant suggesting that greener SRI funds attract more fund inflows and are larger in line with the findings of El Ghoul and Karoui (2021). This result echoes to the rising practice of repurposing mutual funds toward sustainable and environmental strategies with the aim to classify them into SFDR Article 9 climate-aware funds given positive outcomes in terms of fund inflows (Becker et al., 2022 ; Morningstar, 2022). However, this practice appears to be independent from a change of the fund name as in the US market (El Ghoul and Karoui, 2021) since the coefficient of *Name Change* is not significant.

The coefficients of *Expenses* are negative and significant for model (1) suggesting that greener (*resp*. less green) SRI funds are more (*resp*. less) expensive for investors. This result may be interpreted in two ways. On the one hand, greener SRI funds bear higher search costs in relation to more stringent stock selectivity policies. Those funds may also have higher engagement costs since stronger engagement policies are necessary to decarbonise Best-in-class firms. Combined together, higher search and engagement costs may result in higher management fees relatively. On the other hand, less green funds are managed by well-developed firms that are not SRI specialists (Alda and Vicente, 2020) that, with economies of scale, can charge lower fees.

From a manager skill perspective, the coefficients *ESG Exp* are negative and significant indicating that a manager with a salient experience in ESG makes her fund greener. Probably, managers with greater ESG experience are likely to apply thematic environmental approaches, which allow them to make their funds greener. Those thematic investment styles are related to environmental themes such as water management (Ibikunle and Martí-Ballester, 2022).

Besides, managers with more ESG experience may have informational advantages that help them select environmental pioneers or firms that are engaged to a net zero commitment strategy. They may dialogue with their corporate boards and managers more easily and in a constructive way given their experience and close relationships with other SRI managers to accelerate portfolio companies' decarbonisation through collective engagement.

Conversely, the coefficients *Tenure* are significantly positive implying that the higher the amount of time a manager has spent in the mutual fund industry, the lower the degree of greenness of her fund is. Managers with a greater experience in the mutual fund industry may be non-SRI specialists who are primarily focused on the financial performance of SRI funds they manage (Alda and Vicente, 2020) rather than green performance. Also, they are likely to run their SRI funds from a market risk management perspective leading to increase portfolio diversification (which explains the negative sign of *HI*) without ESG risk assessment because they are not sufficiently educated to extra-financial analysis.

From columns (2), (3), and (4), we note that the coefficients of *Team* are positive and always significant indicating that team-managed funds are likely to be less green while Chen et al. (2020) obtained that teamwork mitigates the adverse effect associated with managerial multi-tasking of single fund managers, which allows delivering superior financial performance.

Finally, the coefficients of *Female* are also not significant suggesting that the gender of the manager does not influence the green performance of SRI funds, which contrasts with the case of financial performance provided that female managers may deliver lower returns because they adopt more conservative investment strategies (see Alda and Vicente, 2020).

Overall, Panel A of Table 2 results highlight that greening a fund implies lower portfolio diversification, higher stock selectivity towards small cap equities and green sectors as well as more (*resp.* less) managers' experience in ESG (*resp.* mutual fund industry) management.

Panel B of Table 2 presents the marginal effects associated with the variables included in the (4) regression model) given the probabilities of belonging to each cluster (3 or 4). We first verify that SRI funds, which adopt higher stock selectivity leading managers to build lower diversified portfolios with a lower (*resp*. greater) exposure to fossil fuels (*resp*. green sector) are more likely to be greener. Considering the 3 clusters (*resp*. 4 clusters) scenario, we can estimate that one unit decrease in the Fossil Fuel percentage leads to a probability increase of 1.06% (*resp*. 0.54%) for belonging to the dark green cluster and 0.95% (*resp*. 0.58%) to the light green cluster. Thus, considering the scenario with 3 clusters (*resp*. 4 clusters), one unit increase of HI percentage is associated with a probability increase of 3.26% (*resp*. 2.79%) for belonging to the dark green cluster and 2.94% (resp. 2.95%) to the light green cluster.

Moreover, the experience of managers appears to be a key determinant of the SRI fund greenness degree. We obtain that increasing the manager's ESG experience (*ESG Exp*) by one year is associated with a probability increase of 2.07% (*resp*. 1.44%) to the dark green cluster and a probability increase of 1.86% (*resp*. 1.52%) to the light green cluster considering the 3 clusters (*resp*. 4 clusters) scenario. The opposite effect was observed for the experience of the manager in the mutual fund industry (*Tenure*). Indeed, our estimation reveals that a one-year increase in the time spent by a manager in the mutual fund industry leads to a probability decrease of 0.75% (*resp*. 0.5%) for belonging to the dark green cluster and 0.68% (*resp*. 0.53%) for belonging to the light green cluster given the 3 clusters (*resp*. 4 clusters) scenario. Taken together, these two latest results indicate that the magnitude of *ESG Exp* marginal effects is three times higher than those of *Tenure* for both scenarios, meaning that the positive influence of manager's experience in ESG on fund greenness clearly dominates the negative impact of manager's experience in the mutual fund industry.

[INSERT TABLE 2]

Panel A of Table A2 presents the coefficients of variables included in (1), (2), (3) and (4) estimated from the sample of funds with at least 50% of informed equities. Panel B presents the marginal effects of variables included in (4). Similar results to Table A2 are observable.

[INSERT TABLE A2]

4.3. Regression results – Sub-period analysis

In order to test the influence of stricter SRI market regulation on greening SRI funds and their managers' investment styles, we split the period in two sub-periods: 2015-19 and 2020-22. The second period is concomitant to the implementation of SFDR by fund managers and the COVID-19 pandemic. As shown by Becker et al. (2022), SFDR with early discussions dated back to November 2019 has prompted SRI fund managers to push the ESG performance of European funds up in order to advertise them as climate-aware Article 9 funds with the aim to attract new money inflows (Morningstar, 2022). Also, Agoraki et al. (2023) find that the COVID-19 pandemic has positively affected the returns of green funds from 2020 to 2021. Therefore, we consider the two above mentioned sub-periods to capture the potential effects of SFDR and COVID-19 on the greenness of European SRI funds.

Tables 3 and 4 report the coefficients of models (1), (2), (3), (4) estimated from the sample of funds composed of at least 60% of informed equities for the two sub-periods, respectively. In both sub-periods, whatever the number of clusters, the coefficients of *HI*, *Fossil Fuel*, *Fund size*, *ESG Exp* are significant and the signs are those obtained in Table 2 while those of *Expenses* are only significant in the period 2015-19 for the 3 clusters' scenario.

Although insignificant in the first sub-period, the coefficients of *Green* are negative and significant in the second sub-period (2020-22), which coincides with the application of SFDR principles in Europe by fund managers. This result indicates that greener funds invest in green stocks in greater proportion in this period offering a better hedge against climate risks (Bolton and Kacperczyk, 2021). In parallel, the coefficients of *Fossil Fuel* remain to be positive and statistically significant at 1% level implying that greener funds underweight fossil fuel stocks in their portfolios. Because fund managers are willing to package their funds as SFDR Article 9 climate-aware funds to attract larger fund inflows (Morningstar, 2022), they can decide to increase (*resp*. decrease) portfolio exposure to green (*resp*. fossil fuel) equities. These two results suggest that managers have intensified their use of negative screens and their recourse to thematic environmental strategies to make their funds greener in the second sub-period. Remarkably, these two complementary strategies are used to decarbonise funds in Europe where emissions trading schemes are the most active in a period of the price of carbon soared.

The coefficients of *Team* are significantly positive in both sub-periods but their magnitude is twice as high in the second sub-period. This suggests that a single manager is likely to adopt a greening strategy for her SRI fund more easily with the aim to benefit from new market regulations, which allows more transparency on her sustainability efforts. Instead, a team of fund co-managers may be more concentrated on maintaining the financial performance during this period marked by market downturns due to Covid (Chen et al., 2020).

Also, the fact that *Fund age* coefficients are negative (*resp*. positive) in the first (*resp*. second) sub-period) confirms the existence of shifts in the managers' (green) investment strategies attributed to changes in the SRI regulatory landscape in Europe. In the first sub-period, greener funds are more likely to be recent as in the US SRI market where no specific SRI market regulations have been designed (El Ghoul and Karoui, 2021). Instead, older funds tend to be greener in the period 2020-22 indicating that their managers have used the implementation of

SRI market regulation in Europe as an important selling point to their clients for accelerating the decarbonisation of their SRI funds that they have already started (Rohleder et al., 2022).

[INSERT TABLE 3]

[INSERT TABLE 4]

Tables A3 and A4 displays the value of coefficients of models (1), (2), (3), (4) estimated from the sample of funds composed of at least 50% of informed equities for the two sub-periods, respectively. Similar results to Tables 3 and 4 are obtained.

[INSERT TABLE A3]

[INSERT TABLE A4]

4.4. Influence of an active investment style on fund greenness

In the previous section, we found that the influence of (green) stock selectivity on fund greenness is important but regulatory state dependent. However, since differences in fund greenness may also be due to investment styles based on market timing abilities, we now examine whether SRI funds' greenness may also depend on active management styles.

Specifically, we follow Muñoz et al. (2014), Leite and Cortez (2015) and incorporate a dummy *Active* in (3) that allows an investigation of timing abilities in relation to the market and to the active investment style as shown in the following expression:[13]

$$\begin{aligned}\text{logit}(\text{P}(Y \le cp)) = \beta_{o,cp} - (&\beta_1 \cdot \textbf{\textit{HI}} + \beta_2 \cdot \textbf{\textit{Large Cap}} + \beta_3 \cdot \textbf{\textit{Small Cap}} + \beta_4 \cdot \textbf{\textit{Fossil Fuel}} + \beta_5 \cdot \textbf{\textit{Green}} + \beta_6 \cdot \textbf{\textit{Expense}} \\ &+ \beta_7 \cdot \textbf{\textit{Fund Size}} + \beta_8 \cdot \textbf{\textit{Fund Age}} + \beta_9 \cdot \textbf{\textit{ExpESG}} + \beta_{10} \cdot \textbf{\textit{Tenure}} + \beta_{11} \cdot \textbf{\textit{Team}} \\ &+ \beta_{12} \cdot \textbf{\textit{Female}} + \beta_{13} \cdot \textbf{\textit{Name Change}} + \beta_{14} \cdot \textbf{\textit{Active}})\end{aligned}$$

(5)

[13] As explained by Chen and Scholtens (2018), an active strategy aims to generate higher alpha that is likely to be achieved by adopting market-timing investment styles. Moreover, an active strategy may be motivated by the necessity to maintain holdings eligible to SRI label standards, which should rely on higher stock selectivity.

Panels A and B of Table 5 display the value and significance of coefficients belonging to model (5) estimated for the full period and the two sub-periods (2015-19 and 2020-22) based on the scenario of 3 and 4 clusters, respectively. We first note that the coefficient of *Active* is negative and significant for the two sub-periods. It is also significant for the full period when the 4 clusters scenario is considered. This result suggests that a specific investment style i.e., an active strategy contributes to the greening of SRI fund both in normal economic conditions (2015-19) and in a crisis period (2020-22)). This underscores the market timing abilities of active fund managers who can time the market all in greening their funds.

Consistent with our previous findings, the coefficient of *Green* is insignificant in 2015-19 period while it is negative and statistically significant in the 2020-22 period, which implies that SRI fund portfolios tilted toward green equities in greater proportions during this period.

Taken together, these two results suggest that an investment style *i.e.*, an active strategy based on market timing abilities contributes to increasing fund greenness whatever the period considered while higher selectivity positively affects fund greenness only in period marked by market downturns (i.e., Covid) and regulatory shifts. This finding complements Leite and Cortez (2015) who found that market-timing abilities managers of French SRI labelled funds have contributed to increase the financial performance of their funds during crisis periods.

Another interesting result is that the coefficients of *Expenses* are not significant for the three periods and the two cluster scenarios considered. This finding disproved the hypothesis that greener active strategies are more expensive due to higher search and information costs (Chen and Scholtens, 2018; Coleman, 2023) and/or higher engagement costs (Kim and Yoon, 2022). Potentially, the relationship between *Expenses* and *Active* would be different if the financial performance of SRI funds instead of their greenness was considered (Chen and Scholtens, 2018).

Overall, the signs and significance of other coefficients observed in Tables 3 and 4 are similar, which provide evidence of the stability of our model. This confirms that greening a fund also depends on fund characteristics and on salient manager experience in ESG as seen previously.

[INSERT TABLE 5]

Table 6 presents the marginal effects associated with the model (5) regressions for the full period. Overall, we obtain similar marginal effects for all coefficients both in signs and in magnitude as compared to those reported in Panel B of Table 2. Additionally, our results emphasise the importance of an active investment style to make SRI funds greener. Considering the scenario with 3 clusters (*resp*. 4 clusters), we can estimate that one unit increase of *Active* is associated with a probability increase of 5.8% (*resp*. 3.9%) for belonging to the *dark green* cluster and a probability increase of 5.6% (*resp*. 4.3%) for belonging to the *light green* cluster.

[INSERT TABLE 6]

Table A5 presents the coefficients of variables included in (5) estimated from the sample of funds with at least 50% of informed equities. Similar results to Table 5 are obtained. Also, Table A6 results related to the marginal effects of variables present in (5) estimated from the sample of at least 50% informed equities are qualitatively similar to those of Table 6.

[INSERT TABLE A5]

[INSERT TABLE A6]

4.5. Diversity analysis of the team-managed funds

Our previous results indicate that team-managed funds are comparatively less green, although a comprehensive explanation has not been found. In this respect, we posit the hypothesis that gender diversity of management teams may affect the green degree of funds. Indeed, Gangi et al. (2021) find that a greater gender diversity in the fund management team positively impacted

ESG ratings of European fund portfolios between 2014 and 2018.[14] To consider the influence of gender diversity, we consider two proxies: *Blau index* and *Critical Mass*. Similar to Gangi et al. (2021), we calculate the *Blau index* as follows: $1-\sum_{i=1}^{n} p_i^{\,2}$ where p_i^2 is the share of managers in each gender and n =2 is the number of genders. We also select a 30% threshold of women presence in the team to define *Critical Mass* consistent with Gangi et al. (2021). Focusing on the subsample of team-managed funds, we run the following equation:

$$\begin{aligned}\text{logit}(\text{P}(Y \le cp)) = \beta_{o,cp} - (\beta_1 \cdot \boldsymbol{HI} + \beta_2 \cdot \boldsymbol{Large\,Cap} + \beta_3 \cdot \boldsymbol{Small\,Cap} + \beta_4 \cdot \boldsymbol{Fossil\,Fuel} + \beta_5 \cdot \boldsymbol{Green} + \beta_6 \cdot \boldsymbol{Expense} \\ + \beta_7 \cdot \boldsymbol{Fund\,Size} + \beta_8 \cdot \boldsymbol{Fund\,Age} + \beta_9 \cdot \boldsymbol{ExpESG} + \beta_{10} \cdot \boldsymbol{Tenure} + \beta_{11} \cdot \boldsymbol{Blau\,Index} + \beta_{12} \cdot \boldsymbol{Critical\,Mass})\end{aligned} \quad (6)$$

Where: ***HI***, ***Large Cap, Small Cap, Fossil Fuel, Green, Expense***, ***Fund Size***, ***Fund Age***, ***ESG Exp***, ***Tenure*** are defined previously; ***Blau index*** proxies the gender diversity of funds' management teams; ***Critical Mass*** is equal to 1 if the share of women in the management team is higher than 30% (0 otherwise) (see Table A1 for a description of those variables).

Panels A and B of Table 7 show the coefficients included in model (6) estimated for the full period and the two sub-periods based on the scenario of 3 and 4 clusters, respectively.
The coefficients of *Blau index* are negative and statistically significant for both the full period and the second sub-period (2020-22), indicating that greater diversity in management teams leads to increase greenness of an SRI fund during those periods. We explain this result through two complementary arguments. First, the advantage of managing a fund with a team is related to the level of diversification of investment style, tenure and judgments leading to enhance the effectiveness of investment styles and stock selectivity applied (Gangi et al., 2021). Second, we argue that a greater diversity in a fund management team contributes to improve the collective SRI experience of managers that is individually short (on average 4.4 years; see Table 1), knowledge on the recent SRI market regulations, and increase expertise on environmental

[14] We thank the anonymous reviewer for this suggestion and informing us about the Gangi et al. (2021)'s study.

claims that are often technical (e.g., climate, biodiversity). However, this positive impact of gender diversity on SRI fund greenness is unrelated to whether women represent a critical mass (30%) of the management team as the variable *Critical Mass* remains insignificant.

Overall, the variables *HI, Fossil Fuel, Green, Fund Size* and those related to experience (*Exp ESG* and *Tenure*) exhibit significant coefficients with identical signs and similar magnitude whatever the period or clusters scenarios considered. This is another ample evidence of their importance to explain the greenness of SRI funds.

[INSERT TABLE 7]

Table A7 outlines the coefficients of variables included in (6) estimated from the sample of funds with at least 50% of informed equities. Similar results to Table 7 are obtained.

[INSERT TABLE A7]

5. Conclusion

Recently, El Ghoul and Karoui (2021) explained that greening a SRI fund generates positive effects in terms of inflows. However, little is known about the determinants of greening SRI funds, i.e, the "how". To fill this gap, our paper proposes to examine how SRI funds' greenness depend on fund characteristics, investment styles and experience of managers.

Our main contribution is twofold. Methodologically, our study, is the first, to our knowledge, to use the k-means to group SRI fund portfolios based on their "green" performance. From this clustering, we derive three and four degrees of fund greenness based on homogeneous groups. Empirically, we enrich the literature on SRI in four respects. First, we find that greener European SRI funds are less diversified but attract more fund flows as it is the case with US SRI funds (El Ghoul and Karoui, 2021). Second, we verify that greening a fund induces higher stock selectivity leading fund managers to underweight their portfolios with fossil fuel stocks and increase the share of stocks belonging to green sectors when market regulations have been implemented. Regarding investment styles, our results highlight that managers who conduct active strategies make SRI funds greener, which emphasises their market-timing abilities.

Third, we document that greener funds tend to be older when those regulations have been implemented, indicating that managers have used those regulations as a selling point to their clients for accelerating the decarbonisation of their mature fund that are longer to execute (Rohleder et al., 2022). This "regulation effect" offers a positive outlook on how EU regulations applied to SRI have accelerated the transition to a low carbon economy by providing greater transparency on fund management strategies, which contributes to level the playing field.

Fourth, we show that the manager's experience in ESG is a major driver of SRI fund greenness. Notably, we estimate that the positive impact of the manager's experience in ESG on fund greenness is three times larger than the negative influence of her experience in the mutual fund industry. In addition to those "experience effects", we provide evidence of "gender diversity effects", i.e., a greater gender diversity in the fund management teams contributes to increase SRI fund greenness while the gender of the lead manager has no influence.

Our findings hold significant implications for the mutual fund industry and policy makers. By showing that the higher the amount of time manager has spent in the mutual fund industry, the lower the greenness of her fund is, this study raises clear concerns about her interest on recommendations made by their ESG analysts and about the sufficiency of industry training especially in a period marked by important regulatory shifts. Besides, the fact that a greater gender diversity contributes to increase the greenness of SRI fund may encourage fund management companies to favour the promotion of females within management teams. By increasing gender diversity, they could also enhance their image as more inclusive firms, which address the demands of different stakeholders. Finally, our study highlights that the best-in-class investment strategy promoted by the French SRI label should be coupled with negative screening and/or thematic approaches to improve the greenness of its labelled funds. In either case, the French Minister of Economy and Finance in charge of managing the label may decide to exclude some carbon intensive sectors (e.g., fossil fuels) or fix maximum investment thresholds for those sectors, helping fund managers to enhance the trust and confidence of their clients and potential investors, which could be affected by greenwashing concerns.

Our study opens up avenues for further research, such as assessing how conventional (or non-SRI) funds may also have hastened their portfolio decarbonisation after the implementation of SRI market regulations in Europe. This question may be explored by investigating whether our results are applicable to French conventional mutual funds. Moreover, further studies may be undertaken to assess the potential impact of the Covid-19 measures (Agoraki et al., 2023) on SRI fund greenness and compare it to the influence of SRI market regulations in Europe. Finally, studying other SRI markets like the US SRI market could give further insights on the influence of managers’ profiles and investment styles in terms of greenness (Muñoz et al., 2014).

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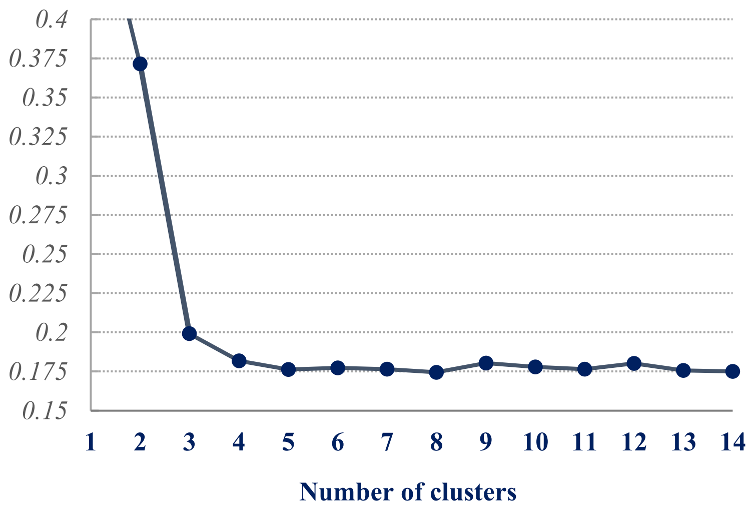
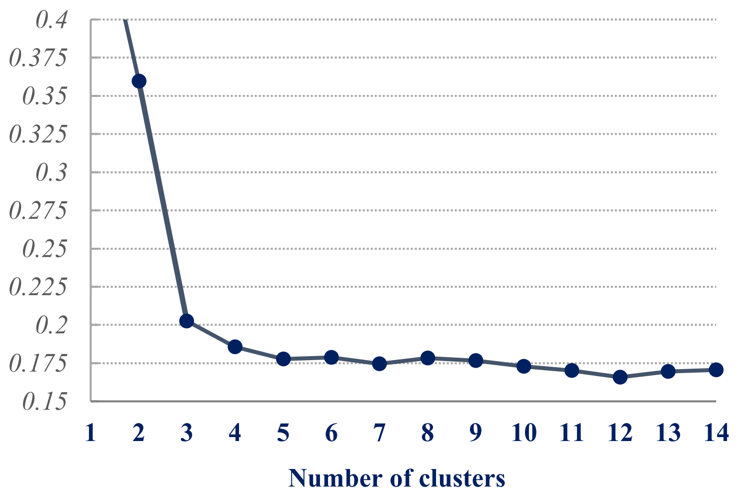
List of Tables and Figures

Figure 1. Determination of the optimal number of clusters according to the silhouette score

a) Silhouette score for w=60%

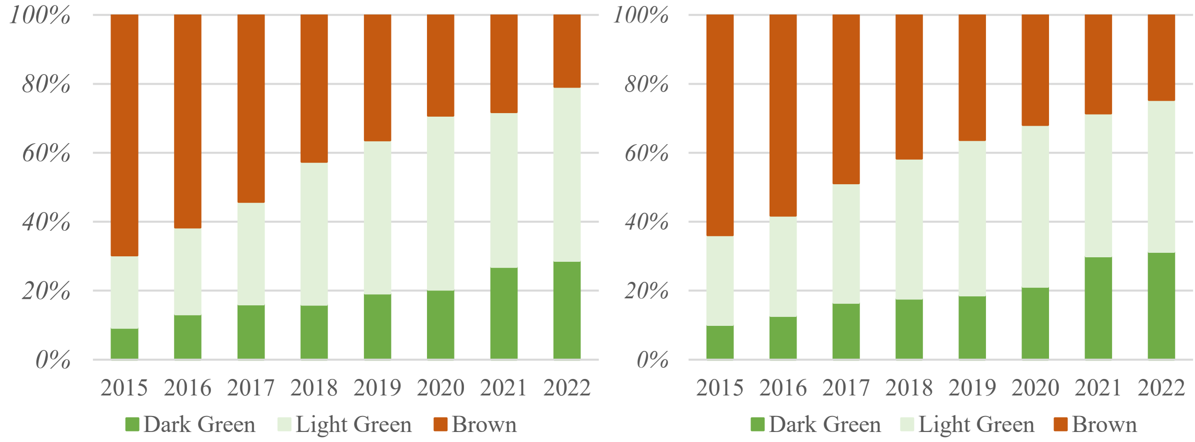


b) Silhouette score for w=50%



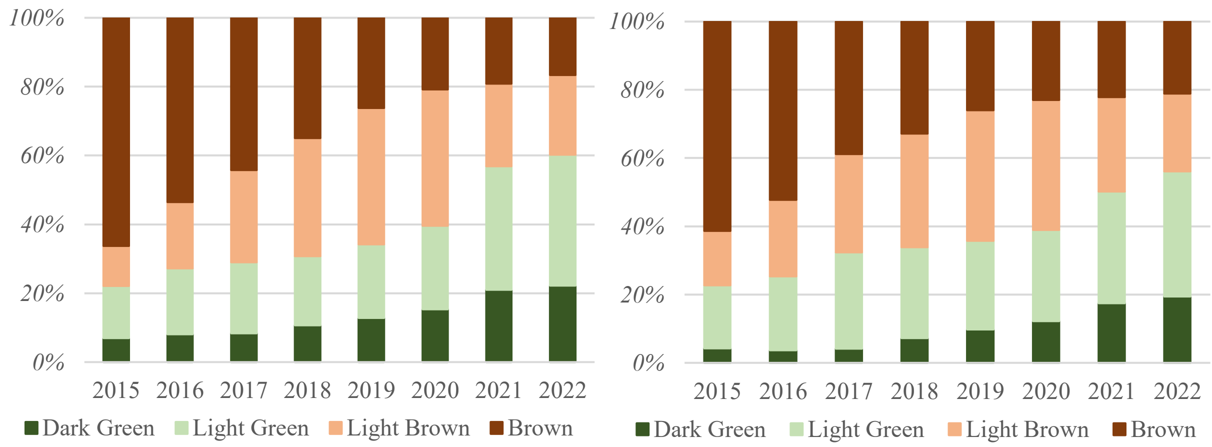
Note: These two graphs display the silhouette scores for a number of clusters ranging from 1 to 14, which are related to two clustering scenarios: w (weight) = 60% and w = 50% respectively.
The silhouette score assesses how similar a point is to its own cluster compared to other clusters, in function of the number of clusters. Regarding the trade-off between the silhouette and the numbers of clusters, we choose 3 clusters as the optimal point. Beyond this value, the improvement of the silhouette is not found significant.

Figure 2. Distribution of SRI funds among three KM clusters (2015-2022)



w=60% *w=50%*

Figure 3. Distribution of SRI funds among four KM clusters (2015-2022)



w=60% *w=50%*

Table 1. Summary statistics

	Mean	**SD**	**Median**	**Q1**	**Q4**
HI (%)	2.35	0.90	2.23	1.72	2.83
Large Cap (%)	89.15	12.95	92.33	86.34	96.70
Small Cap (%)	0.47	1.77	0.00	0.00	0.00
Fossil Fuel (%)	3.54	3.42	3.05	0.00	5.71
Green (%)	9.33	6.00	8.76	6.10	11.30
Expense (%)	1.56	0.57	1.63	1.20	1.93
Fund Size (in million)	365.32	842.79	149.84	52.71	401.90
Fund Age (in years)	12.95	9.04	11.32	5.24	19.25
ESG Exp (in years)	4.39	4.30	1.00	0.00	9.00
Tenure (in years)	17.59	5.10	17.00	14.00	21.00
Team (%)	63.1	48.2	NS	NS	NS
Female (%)	28.0	45.1	NS	NS	NS
Name Change (%)	18.4	38.1	NS	NS	NS

Note: *HI* is the Herfindahl index, which proxies the level of portfolio diversification (*resp*. concentration); *Large Cap* are the weighted percentage of large capitalisations (market capitalisation >1 billion euros); *Small Cap* are the weighted percentage of small capitalisations (market capitalisation < 250 million euros); *Fossil Fuel* is the weighed percentage of equities belonging to fossil fuel industries; *Green* is the weighed percentage of equities belonging to industries classified as green under EU Taxonomy; *Expense* is the expense ratio ; *Fund Size* is the sum of TNA across all the share classes of a fund ; *Fund Age* is the number of years in which the oldest share class in the fund is traded ; *ESG Exp* is the number of years the lead manager had worked in the ESG industry ; *Tenure* is the number of years she had been in the mutual fund industry ; *Team* is a dummy variable, which is set to 1 when the fund is managed by two managers or more (0 when the fund is managed by one fund manager). *Female* is a dummy variable, which take the values of 1 if the lead manager is a woman. *Name change* is a dummy variable, which takes the value of 1 if the fund has switched to a green and/or sustainability-related appellation. NS indicates non-significant values.

Table 2. Regression results – Full period (2015-2022)

Panel A. Coefficient results

	3 clusters				4 clusters			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
HI	-43.33** *(8.30)*	-47.72** *(8.54)*	-48.05** *(8.55)*	-47.99** *(8.55)*	-51.71** *(7.05)*	-56.54** *(7.07)*	-56.53** *(7.07)*	-56.55** *(7.06)*
Large cap	0.10 *(1.22)*	0.51 *(1.21)*	0.56 *(1.21)*	0.56 *(1.21)*	-0.08 *(1.06)*	0.27 *(1.07)*	0.26 *(1.07)*	0.26 *(1.07)*
Small Cap	-15.31 *(10.76)*	-9.95 *(10.79)*	-9.52 *(10.92)*	-9.61 *(10.95)*	-23.89** *(8.88)*	-20.22* *(8.92)*	-20.25* *(8.90)*	-20.24* *(8.89)*
Fossil Fuel	16.24** *(2.22)*	15.72** *(2.25)*	15.63** *(2.26)*	15.57** *(2.27)*	11.68** *(1.51)*	10.94** *(1.98)*	10.97** *(1.99)*	11.02** *(2.00)*
Green	-15.38** *(3.94)*	-14.74** *(4.05)*	-14.60** *(4.04)*	-14.61** *(4.04)*	-19.09** *(3.91)*	-17.95** *(3.87)*	-17.99** *(3.86)*	-17.95** *(3.87)*
Expense	-0.26* *(0.13)*	-0.40 *(0.06)*	-0.23 *(0.13)*	-0.24 *(0.13)*	-0.05 *(0.11)*	-0.03 *(0.11)*	-0.03 *(0.11)*	-0.03 *(0.11)*
Fund Size	-0.40** *(0.07)*	-0.40** *(0.06)*	-0.41** *(0.06)*	-0.41** *(0.06)*	-0.34** *(0.05)*	-0.34** *(0.05)*	-0.33** *(0.05)*	-0.33** *(0.05)*
Fund Age	0.00 *(0.01)*	0.00 *(0.01)*	0.00 *(0.01)*	0.00 *(0.01)*	-0.00 *(0.01)*	-0.00 *(0.01)*	-0.00 *(0.01)*	-0.00 *(0.01)*
ESG Exp	-0.34** (0.03)	-0.30** (0.03)	-0.30** (0.03)	-0.30** (0.03)	-0.32** (0.03)	-0.29** (0.03)	-0.29** (0.03)	-0.29** (0.03)
Tenure	0.10** *(0.02)*	0.11** *(0.02)*	0.11** *(0.02)*	0.11** *(0.02)*	0.09** *(0.01)*	0.10** *(0.01)*	0.10** *(0.01)*	0.10** *(0.01)*
Team		0.91** *(0.16)*	0.96** *(0.17)*	0.96** *(0.17)*		1.01** *(0.15)*	1.01** *(0.16)*	1.01** *(0.16)*
Female			-0.26 (0.15)	-0.26 (0.15)			0.04 (0.13)	0.04 (0.13)
Name Change				0.06 *(0.17)*				-0.06 *(0.16)*
Cut point 1 (Clusters 1-2)	-6.04** *(1.18)*	-4.89** *(1.18)*	-4.91** *(1.17)*	-4.92** *(1.17)*	-7.69** *(1.04)*	-6.54** *(1.06)*	-6.54** *(1.06)*	-6.53** *(1.06)*
Cut point 2 (Clusters 2-3)	-2.00 *(1.15)*	-0.73 *(1.16)*	-0.73 *(1.15)*	-0.74 *(1.15)*	-4.50** *(1.01)*	-3.16** *(1.04)*	-3.15** *(1.04)*	-3.15** *(1.04)*
Cut point 3 (Clusters 3-4)					-2.09* *(0.99)*	-0.70 *(1.02)*	-0.69 *(1.02)*	-0.69 *(1.03)*
Obs.	1249	1249	1249	1249	1249	1249	1249	1249
Log Pseudo-Likelihood	-780.94	-763.89	-762.31	-762.25	-1077.29	-1052.63	-1052.58	-1052.51
Pseudo R²	0.41	0.42	0.42	0.42	0.35	0.37	0.37	0.37

Note: This table presents the results of the ordered logit models (1), (2), (3), (4) run for the full period (2015-22). The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female* and *Name Change* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eqs.(1), (2), (3) and (4) respectively). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Panel B. Marginal effects

	3 clusters			**4 clusters**			
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 4
HI	3.26** *(0.56)*	2.94** *(0.51)*	-6.19** *(1.05)*	2.79** *(0.35)*	2.95** *(0.38)*	1.78** *(0.27)*	-7.52** *(0.87)*
Large cap	-0.04 *(0.08)*	-0.03 *(0.07)*	0.72 *(0.16)*	-0.01 *(0.05)*	-0.01 *(0.06)*	-0.01 *(0.03)*	0.03 *(0.14)*
Small Cap	0.65 *(0.74)*	0.59 *(0.67)*	-1.24 *(1.41)*	1.00* *(0.44)*	1.06* *(0.48)*	0.64* *(0.28)*	-2.69* *(1.19)*
Fossil fuel	-1.06** *(0.16)*	-0.95** *(0.12)*	2.01** *(0.27)*	-0.54** *(0.11)*	-0.58** *(0.11)*	-0.35** *(0.07)*	1.47** *(0.26)*
Green	0.99** *(0.25)*	0.89** *(0.25)*	-1.88** *(0.49)*	0.89** *(0.16)*	0.94** *(0.22)*	0.57** *(0.12)*	-2.39** *(0.48)*
Expense	0.02 *(0.01)*	0.01 *(0.01)*	-0.03 *(0.01)*	0.00 *(0.01)*	0.00 *(0.01)*	0.00 *(0.00)*	-0.00 *(0.01)*
Fund Size	0.03** *(0.00)*	0.03** *(0.00)*	-0.05** *(0.01)*	0.02** *(0.00)*	0.02** *(0.00)*	0.01** *(0.00)*	-0.04** *(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	0.02** *(0.00)*	0.02** *(0.00)*	-0.04** *(0.00)*	0.01** *(0.00)*	0.02** *(0.00)*	0.01** *(0.00)*	-0.04** *(0.00)*
Tenure	-0.01** *(0.00)*	-0.01** *(0.00)*	0.01** *(0.00)*	-0.00** *(0.00)*	-0.01** *(0.00)*	-0.00** *(0.00)*	0.01** *(0.00)*
Team	-0.07** *(0.01)*	-0.06** *(0.01)*	0.12** *(0.02)*	-0.05** *(0.01)*	-0.05** *(0.01)*	-0.03** *(0.00)*	0.13** *(0.02)*
Female	0.02 *(0.01)*	0.02 *(0.01)*	-0.03 *(0.02)*	-0.00 *(0.01)*	-0.00 *(0.01)*	-0.00 *(0.00)*	0.00 *(0.02)*
Name Change	-0.00 *(0.01)*	-0.00 *(0.01)*	0.00 *(0.02)*	0.00 *(0.01)*	0.00 *(0.01)*	0.01 *(0.01)*	-0.01 *(0.02)*

Note: This table presents the associated marginal effects on the probabilities of belonging to each cluster obtained from the ordered logit regression model (4) run on the full sample period (2015-22).
Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Cluster 3 (*resp*. Cluster 3 and 4) are considered as brown clusters for the 3 clusters (*resp*. 4 clusters) scenario.

Robust standard errors are in parentheses.
**, and * denote statistical significance at the 1%, and 5% levels, respectively.

Table 3. Regression results – 1st sub-period (2015-19)

	3 clusters				4 clusters			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
HI	-53.44** *(12.42)*	-54.96** *(12.59)*	-55.27** *(12.70)*	-55.35** *(12.64)*	-67.44** *(9.72)*	-69.19** *(9.65)*	-69.33** *(9.70)*	-69.34** *(9.72)*
Large cap	-0.15 *(1.85)*	0.38 *(1.83)*	0.40 *(1.84)*	0.51 *(1.84)*	-1.68 *(1.63)*	-1.15 *(1.61)*	-1.14 *(1.61)*	-1.13 *(1.62)*
Small Cap	-6.40 *(18.65)*	-1.92 *(18.97)*	-1.39 *(20.25)*	-2.00 *(20.94)*	-7.86 *(17.75)*	-3.77 *(18.11)*	-3.41 *(18.17)*	-3.42 *(18.79)*
Fossil Fuel	18.52** *(3.77)*	17.68** *(3.82)*	17.79** *(3.81)*	17.73** *(3.79)*	17.43** *(3.26)*	16.27** *(3.24)*	16.27** *(3.24)*	16.27** *(3.24)*
Green	-9.29 *(7.20)*	-8.42 *(7.58)*	-8.47 *(7.76)*	-8.38 *(7.72)*	-12.21 *(7.42)*	-10.99 *(7.56)*	-11.08 *(7.63)*	-11.07 *(7.63)*
Expense	-0.37* *(0.18)*	-0.37* *(0.18)*	-0.35* *(0.18)*	-0.38* *(0.18)*	-0.17 *(0.15)*	-0.16 *(0.15)*	-0.15 *(0.15)*	-0.15 *(0.15)*
Fund Size	-0.42** *(0.08)*	-0.41** *(0.08)*	-0.41** *(0.08)*	-0.41** *(0.08)*	-0.46** *(0.08)*	-0.46** *(0.08)*	-0.45** *(0.08)*	-0.45** *(0.08)*
Fund Age	0.03* *(0.01)*	0.03* *(0.01)*	0.03* *(0.01)*	0.03* *(0.01)*	0.01* *(0.00)*	0.01* *(0.00)*	0.01* *(0.00)*	0.01 *(0.01)*
ESG Exp	-0.40** *(0.04)*	-0.38** *(0.04)*	-0.38** *(0.04)*	-0.38** *(0.05)*	-0.31** *(0.03)*	-0.29** *(0.03)*	-0.29** *(0.03)*	-0.29** *(0.03)*
Tenure	0.11** *(0.02)*	0.11** *(0.03)*	0.11** *(0.02)*	0.11** *(0.02)*	0.09** *(0.02)*	0.10** *(0.02)*	0.10** *(0.02)*	0.10** *(0.02)*
Team		0.62** *(0.22)*	0.67** *(0.22)*	0.66** *(0.22)*		0.68** *(0.22)*	0.70** *(0.22)*	0.70** *(0.22)*
Female			-0.27 *(0.22)*	-0.26 *(0.22)*			-0.13 *(0.20)*	-0.13 *(0.20)*
Name Change				0.20 *(0.24)*				0.01 *(0.22)*
Cut point 1 (Clusters 1-2)	-5.72** *(1.59)*	-4.61** *(1.63)*	-4.65** *(1.61)*	-4.56** *(1.62)*	-8.85** *(1.39)*	-7.76** *(1.43)*	-7.78** *(1.43)*	-7.78** *(1.43)*
Cut point 2 (Clusters 2-3)	-1.79 *(1.58)*	-0.61 *(1.61)*	-0.64 *(1.59)*	-0.55 *(1.60)*	-6.01** *(1.36)*	-4.81** *(1.40)*	-4.83** *(1.39)*	-4.83** *(1.40)*
Cut point 3 (Clusters 3-4)					-3.60* *(1.33)*	-2.38* *(1.37)*	-2.40* *(1.36)*	-2.40* *(1.37)*
Obs.	670	670	670	670	670	670	670	670
Log Pseudo-Likelihood	-394.02	-390.05	-389.17	-388.80	-556.58	-550.85	-550.59	-550.58
Pseudo R^2	0.41	0.42	0.42	0.42	0.34	0.35	0.35	0.35

Note: This table presents the results of the ordered logit models (1), (2), (3), (4) run for the sub-period: 2015-19. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female* and *Name Change* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eqs.(1), (2), (3) and (4) respectively). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Table 4. Regression results – 2nd sub-period (2020-22)

	3 clusters				4 clusters			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
HI	-24.21*	-33.34**	-33.51**	-33.26**	-24.10**	-32.38**	-32.69**	-32.94**
	(11.73)	*(12.29)*	*(12.24)*	*(12.24)*	*(10.96)*	*(11.15)*	*(11.21)*	*(11.19)*
Large Cap	1.08	1.70	1.99	1.88	3.60	4.36	4.17	4.32*
	(2.35)	*(2.26)*	*(2.22)*	*(2.28)*	*(2.22)*	*(2.21)*	*(2.23)*	*(2.26)*
Small Cap	-30.73*	-22.23	-21.12	-21.35	-45.98**	-40.51**	-41.64**	-41.31**
	(13.51)	*(12.22)*	*(11.88)*	*(12)*	*(12.09)*	*(11.51)*	*(11.83)*	*(11.81)*
Fossil Fuel	12.69**	12.92**	12.52**	12.36**	6.31*	6.42*	6.80*	6.99*
	(3.01)	*(3.00)*	*(3.03)*	*(3.07)*	*(2.84)*	*(2.94)*	*(2.99)*	*(3.05)*
Green	-20.74**	-20.37**	-19.85**	-19.91**	-24.12**	-23.36**	-23.83**	-23.70**
	(3.09)	*(3.03)*	*(3.03)*	*(3.05)*	*(3.88)*	*(3.64)*	*(3.71)*	*(3.77)*
Expense	-0.24	-0.20	-0.20	-0.21	0.03	0.07	0.07	0.08
	(0.19)	*(0.20)*	*(0.20)*	*(0.20)*	*(0.16)*	*(0.16)*	*(0.16)*	*(0.16)*
Fund Size	-0.36**	-0.36**	-0.37**	-0.38**	-0.21**	-0.18*	-0.18*	-0.17*
	(0.09)	*(0.09)*	*(0.09)*	*(0.09)*	*(0.07)*	*(0.07)*	*(0.07)*	*(0.07)*
Fund Age	-0.03*	-0.03*	-0.03*	-0.03*	-0.03*	-0.03*	-0.03*	-0.03*
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
ESG Exp	-0.29**	-0.24**	-0.24**	-0.24**	-0.33**	-0.29**	-0.29**	-0.29**
	(0.04)	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.04)*
Tenure	0.10**	0.11**	0.11**	0.11**	0.09**	0.09**	0.09**	0.09**
	(0.02)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*
Team		1.37**	1.46**	1.46**		1.55**	1.51**	1.51**
		(0.26)	*(0.27)*	*(0.27)*		*(0.25)*	*(0.25)*	*(0.25)*
Female			-0.36	-0.36			0.24	0.24
			(0.24)	(0.24)			*(0.20)*	*(0.20)*
Name Change				0.09				-0.11
				(0.27)				*(0.25)*
Cut point 1	-5.41**	-3.86	-3.66	-3.79	-4.17	-2.33	-2.48	-2.32
(Clusters 1-2)	*(2.43)*	*(2.32)*	*(2.28)*	*(2.37)*	*(2.30)*	*(2.27)*	*(2.28)*	*(2.34)*
Cut point 2	-1.12	0.70	0.92	0.79	-0.55	1.65	1.53	1.69
(Clusters 2-3)	*(2.39)*	*(2.30)*	*(2.28)*	*(2.36)*	*(2.29)*	*(2.28)*	*(2.29)*	*(2.35)*
Cut point 3					1.99	4.32	4.19	4.35
(Clusters 3-4)					*(2.27)*	*(2.28)*	*(2.29)*	*(2.34)*
Obs.	579	579	579	579	579	579	579	579
Log Pseudo-Likelihood	-365.09	-348.27	-347	-346.94	-494.29	-469.87	-469.16	-469.06
Pseudo R^2	0.40	0.43	0.43	0.43	0.37	0.40	0.40	0.40

Note: This table presents the results of the ordered logit models (1), (2), (3), (4) run for the sub-period: 2020-22. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female* and *Name Change* (see Table AI for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eqs.(1), (2), (3) and (4) respectively). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Table 5. Results of model (5) regression – the influence of active strategies

Panel A. 3 clusters scenario

	Full period 2015-22	1st sub-period 2015-19	2nd sub-period 2020-22
HI	-45.71** *(8.54)*	-51.05** *(12.67)*	-33.66** *(12.29)*
Large Cap	0.03 *(1.25)*	-0.08 *(1.95)*	0.83 *(2 .39)*
Small Cap	-6.24 *(10.50)*	0.36 *(18.75)*	-19.13 *(12.03)*
Fossil Fuel	14.90** *(2.27)*	17.65** *(3.85)*	11.46** *(3.08)*
Green	-13.81** *(3.10)*	-6.74 *(8.11)*	-19.53** *(2.94)*
Expense	-0.12 *(0.14)*	-0.28 *(0.19)*	-0.08 *(0.21)*
Fund Size	-0.45** *(0.06)*	-0.45** *(0.09)*	-0.42** *(0.09)*
Fund Age	-0.00 *(0.01)*	0.03* *(0.01)*	-0.03* *(0.01)*
ESG Exp	-0.30** *(0.03)*	-0.37** *(0.54)*	-0.23** *(0.04)*
Tenure	0.10** *(0.02)*	0.10** *(0.02)*	0.11** *(0.02)*
Team	0.94** *(0.17)*	0.58* *(0.31)*	1.49** *(0.27)*
Female	-0.24 *(0.15)*	-0.26 *(0.21)*	-0.32 *(0.23)*
Name Change	0.08 *(0.17)*	0.21 *(0.24)*	0.12 *(0.28)*
Active	-0.89** *(0.18)*	-0.92** *(0.28)*	-0.92** *(0.27)*
Cut point 1 (Clusters 1-2)	-5.66** *(1.19)*	-5.41** *(1.64)*	-5.01* *(2.48)*
Cut point 2 (Clusters 2-3)	-1.44* *(1.17)*	-1.36 *(1.63)*	-0.38 *(2.44)*
Obs.	1249	670	579
Log Pseudo-Likelihood	-748.51	-381.58	-340.29
Pseudo R^2	0.43	0.43	0.44

Panel B. 4 clusters scenario

	Full period 2015-22	1st sub-period 2015-19	2nd sub-period 2020-22
HI	-54.83** *(7.01)*	-66.12** *(9.78)*	-33.41** *(11.22)*
Large cap	-0.19 *(1.10)*	-1.64 *(1.71)*	3.68 *(2.36)*
Small Cap	-18.23* *(8.51)*	-2.99 *(17.75)*	-37.71** *(11.65)*
Fossil Fuel	10.40** *(2.00)*	15.96** *(3.27)*	6.38* *(3.04)*
Green	-17.17** *(3.77)*	-9.84 *(7.66)*	-23.36** *(3.56)*
Expense	0.08 *(0.11)*	-0.08 *(0.16)*	0.22 *(0.18)*
Fund Size	-0.36** *(0.05)*	-0.48** *(0.08)*	-0.21** *(0.07)*
Fund Age	-0.00	0.02*	-0.03*

	(0.01)	*(0.01)*	*(0.01)*
ESG Exp	-0.29**	-0.29**	-0.28**
	(0.02)	(0.03)	(0.04)
Tenure	0.10**	0.09**	0.09**
	(0.01)	*(0.02)*	*(0.02)*
Team	1.02**	0.66**	1.56**
	(0.16)	*(0.22)*	*(0.26)*
Female	0.06	-0.12	0.29
	(0.13)	*(0.20)*	*(0.20)*
Name Change	-0.03	0.04	-0.08
	(0.16)	*(0.23)*	*(0.25)*
Active	-0.81**	-0.80**	-0.85**
	(0.17)	*(0.24)*	*(0.25)*
Cut point 1 (Clusters 1-2)	-7.23**	-8.59**	-3.20
	(1.07)	(1.48)	(2.40)
Cut point 2 (2-3)	-3.72**	-5.54**	0.96
	(1.06)	(1.45)	(2.41)
Cut point 3 (3-4)	-1.25	-3.09*	3.64
	(1.04)	(1.42)	(2.40)
Obs.	1249	670	579
Log Pseudo-Likelihood	-1038.79	-543.85	-301.65
Pseudo R²	0.38	0.36	0.41

Note: This table presents the results of the ordered logit regression model (5) run for the full period and the two sub-periods: 2015-19 and 2020-22. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female, Name Change,* and *Active* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eq.(5)). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Table 6. Marginal effects related to model (5) regression results

	3 clusters			**4 clusters**			
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 4
HI	2.97**	2.85**	-5.82**	2.61**	2.91**	1.67**	-7.19**
	(0.54)	*(0.53)*	*(1.04)*	*(0.33)*	*(0.38)*	*(0.25)*	*(0.86)*
Large cap	-0.00	-0.00	0.00	0.01	0.01	0.01	-0.03
	(0.08)	*(0.08)*	*(0.16)*	*(0.05)*	*(0.06)*	*(0.03)*	*(0.14)*
Small Cap	0.41	0.38	-0.79	0.87*	0.97*	0.56*	-2.39*
	(0.68)	*(0.66)*	*(1.34)*	*(0.40)*	*(0.47)*	*(0.26)*	*(1.12)*
Fossil fuel	-0.97**	-0.92**	1.90**	-0.50**	-0.55**	-0.32**	1.36**
	(0.15)	*(0.13)*	*(0.27)*	*(0.10)*	*(0.10)*	*(0.07)*	*(0.26)*
Green	0.90**	0.86**	-1.76**	0.82**	0.91**	0.52**	-2.25**
	(0.25)	*(0.26)*	*(0.50)*	*(0.15)*	*(0.21)*	*(0.12)*	*(0.47)*
Expense	0.01	0.01	-0.02	-0.00	-0.00	-0.00	0.01
	(0.01)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.01)*
Fund Size	0.03**	0.03**	-0.06**	0.02**	0.02**	0.01**	-0.48**
	(0.00)	*(0.00)*	*(0.01)*	*(0.00)*	*(0.00)*	*(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	0.02**	0.02**	-0.04**	0.01**	0.02**	0.01**	-0.04**
	(0.00)	*(0.00)*	*(0.03)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Tenure	-0.01**	-0.01**	0.01**	-0.00**	-0.01**	-0.00**	0.01**
	(0.01)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Team	-0.06**	-0.06**	0.12**	-0.05**	-0.05**	-0.03**	0.13**
	(0.01)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.02)*
Female	0.02	0.01	-0.03	-0.00	-0.00	-0.00	0.01
	(0.01)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.01)*
Name Change	-0.01	-0.00	0.01	0.00	0.00	0.00	-0.00
	(0.01)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.00)*	*(0.02)*
Active	0.06**	0.06**	-0.11**	0.04**	0.04**	0.02**	-0.11**
	(0.01)	*(0.01)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.02)*

Note: This table presents the associated marginal effects on the probabilities of belonging to each cluster obtained from the ordered logit regression model (5) run on the whole sample period (2015-2022).
Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Cluster 3 (*resp*. Cluster 3 and 4) are considered as brown clusters for the 3 clusters (*resp*. 4 clusters) scenario.

Robust standard errors are in parentheses.
** and * denote statistical significance at the 1% and 5% levels respectively

Table 7. Results of model (6) – the impact of gender diversity in fund management teams

Panel A. 3 clusters scenario

	Full period	**1st sub-period**	**2nd sub-period**
	2015-22	2015-19	2020-22
HI	-50.80**	-54.61**	-45.87**
	(11.02)	*(17.19)*	*(14.98)*
Large cap	0.49	0.77	-1.11
	(1.47)	*(2.13)*	*(2.81)*
Small Cap	2.49	-13.98	7.44
	(19.49)	*(23.88)*	*(19.57)*
Fossil Fuel	17.53**	16.57**	16.92**
	(2.87)	*(4.37)*	*(4.01)*
Green	-23.58**	-24.21**	-25.61**
	(3.34)	*(4.85)*	*(4.78)*
Expense	-0.15	-0.24	-0.11
	(0.17)	*(0.24)*	*(0.24)*
Fund Size	-0.53**	-0.53**	-0.53**
	(0.08)	*(0.02)*	*(0.13)*
Fund Age	0.01	0.03	-0.01
	(0.01)	*(0.02)*	*(0.01)*
ESG Exp	-0.36**	-0.48**	-0.27**
	(0.05)	*(0.07)*	*(0.06)*
Tenure	0.10**	0.10**	0.10**
	(0.02)	*(0.03)*	*(0.03)*
Blau index	-1.69**	-1.42	-1.85*
	(0.59)	*(0.76)*	*(0.90)*
Critical Mass	0.36	0.13	0.60
	(0.29)	*(0.37)*	*(0.45)*
Cut point 1 (Clusters 1-2)	-7.89**	-8.01**	-9.39**
	(1.51)	*(2.02)*	*(2.96)*
Cut point 2 (Clusters 2-3)	-3.14**	-3.15	-4.61
	(1.46)	*(1.96)*	*(2.88)*
Obs.	834	459	375
Log-Pseudo-Likelihood	-461.87	-231.68	-222.61
Pseudo R^2	0.40	0.40	0.38

Panel B. 4 clusters scenario

	Full period	**1st sub-period**	**2nd sub-period**
	2015-22	2015-19	2020-22
HI	-50.39**	-62.98**	-38.09**
	(8.78)	*(11.80)*	*(13.85)*
Large cap	0.14	0.77	1.09
	(1.25)	*(1.70)*	*(2.82)*
Small Cap	-10.11	5.81	-34.91
	(12.57)	*(20.04)*	*(22.04)*
Fossil Fuel	11.80**	12.88**	10.88**
	(2.50)	*(3.50)*	*(3.74)*
Green	-28.45**	-30.99**	-28.89**
	(3.34)	*(4.43)*	*(5.27)*
Expense	0.11	0.12	-0.15
	(0.14)	*(0.19)*	*(0.22)*
Fund Size	-0.55**	-0.58**	-0.52**
	(0.07)	*(0.10)*	*(0.10)*
Fund Age	0.01	0.02	-0.00
	(0.01)	*(0.01)*	*(0.01)*
ESG Exp	-0.34**	-0.38**	-0.32**
	(0.03)	*(0.05)*	*(0.05)*
Tenure	0.08**	0.08**	0.08**
	(0.02)	*(0.02)*	*(0.03)*
Blau index	-1.26**	-1.02	-1.52*
	(0.60)	*(0.77)*	*(0.68)*
Critical Mass	0.34	-0.06	0.78
	(0.29)	*(0.38)*	*(0.49)*
Cut point 1	-10.40**	-11.40**	-9.45**
(Clusters 1-2)	*(1.30)*	*(1.68)*	*(2.84)*
Cut point 2	-6.57**	-7.98**	-5.25
(Clusters 2-3)	*(1.24)*	*(1.61)*	*(2.83)*
Cut point 3	-3.63**	-4.98**	-2.28
(Clusters 3-4)	*(1.21)*	*(1.54)*	*(2.79)*
Obs.	834	459	375
Log-Pseudo-	-461.87	-325.88	
Likelihood	-461.87	-325.88	-300.90
Pseudo R^2	0.35	0.34	0.34

Note: This table presents the results of the ordered logit regression model (6) run for the full period and the two sub-periods: 2015-19 and 2020-22. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Blau index*, and *Critical Mass* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the “baseline” or “reference” shape of the relative frequency distribution of cases across clusters of *Y* (see Eq.(6)). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Appendix

Table A1. Definition of independent variables

Variable	Definition	Source
HI	Measures the fund portfolio concentration in equities i.e., a higher value of HI means higher portfolio concentration and lower diversification.	Data from Refinitiv
Large Cap (%)	Percentage of large cap equities (market cap > 1 billion euros) in the portfolio	Data from Refinitiv
Small cap (%)	Percentage of Small cap equities (market cap < 250 million euros) in the portfolio	Data from Refinitiv
Fossil fuel (%)	Percentage of equity from portfolio companies belonging to fossil fuel industries	Data from Refinitiv
Green (%)	Percentage of equity from portfolio companies with activities considered as green under the EU Taxonomy.	Data from Refinitiv and the European Unio
Expense (%)	Annual operating costs of running a fund (i.e., the sum of management, custodian, and sales fees) as a percentage of the fund TNA computed across all the fund share classes.	Data from Refinitiv
Fund Size	Logarithm of fund TNA computed across all the share classes of a fund.	Data from Refinitiv
Fund Age	Number of years of fund existence computed as the difference between the month t and the inception date of fund's oldest share class.	Data from Refinitiv
ESG Exp	Number of years the lead manager had worked in ESG industry	Data from DICI, public CVs and Linkedin profiles
Tenure	Number of years the fund manager had been in the mutual fund industry	Data from DICI, public CVs and Linkedin profiles
Team	1 denotes a fund managed by two managers at least, 0 denotes a fund managed by one manager.	Data from DICI and fund reportings
Female	The gender of the lead fund manager, 1 denotes Female, 0 otherwise	Data from DICI, public CVs and Linkedin profiles
Active	The nature of investment strategies, 1 denotes active, 0 passive.	Data from Novethic
Name Change	1 denotes the fact that the fund has changed its name for a green and/or sustainability appellation. 0 otherwise.	Data from the French SRI Label list and Refinitiv
Blau index	Index that proxies the gender diversity of funds' management teams. It ranges from 0, when there is only one gender on the fund's management team, to 0.5, when the team has an equal number of women and men.	Data from DICI and Refinitiv
Critical Mass	1 indicates that the percentage of women on the fund's management team is higher than 30%, 0 otherwise.	Data from DICI and Refinitiv

Table A2. Regression results – Full period (2015-2022)

Panel A. Coefficient results

	3 clusters				4 clusters			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
HI	-49.64**	-51.86**	-51.96**	-52.05**	-60.19**	-62.48**	-62.50**	-62.45**
	(8)	*(8.15)*	*(8.16)*	*(8.55)*	*(6.85)*	*(6.90)*	*(6.91)*	*(6.91)*
Large cap	1.14	1.33	1.36	1.35	1.49	1.50	1.47	1.48
	(1.04)	*(1.05)*	*(1.05)*	*(1.05)*	*(1)*	*(1.01)*	*(1.01)*	*(1.01)*
Small Cap	-9.44	-5.58	-5.25	-5.22	-28.38**	-25.45**	-25.68**	-25.69**
	(8.26)	*(8.54)*	*(8.57)*	*(8.55)*	*(8.31)*	*(8.34)*	*(8.27)*	*(8.27)*
Fossil Fuel	14.94**	14.42**	14.39**	14.45**	11.65**	11.17**	11.21**	11.18**
	(2.01)	*(2.03)*	*(2.03)*	*(2.05)*	*(1.88)*	*(1.88)*	*(1.89)*	*(1.89)*
Green	-14.55**	-13.98**	-13.94**	-13.92**	-26.63**	-25.88**	-25.95**	-25.69**
	(3.06)	*(3.14)*	*(3.14)*	*(3.14)*	*(3.70)*	*(3.79)*	*(3.79)*	*(3.821)*
Expense	-0.21	-0.19	-0.19	-0.18	-0.09	-0.09	-0.09	-0.10
	(0.13)	*(0.12)*	*(0.12)*	*(0.12)*	*(0.11)*	*(0.11)*	*(0.11)*	*(0.11)*
Fund Size	-0.41**	-0.42**	-0.42**	-0.42**	-0.51**	-0.52**	-0.52**	-0.52**
	(0.05)	*(0.05)*	*(0.05)*	*(0.05)*	*(0.05)*	*(0.05)*	*(0.05)*	*(0.05)*
Fund Age	0.00	0.00	0.00	0.00	-0.01	-0.00	-0.00	-0.00
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
ESG Exp	-0.34**	-0.31**	-0.31**	-0.31**	-0.35**	-0.33**	-0.33**	-0.33**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Tenure	0.12**	0.12**	0.12**	0.12**	0.10**	0.11**	0.11**	0.11**
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
Team		0.77**	0.79**	0.79**		0.76**	0.74**	0.74**
		(0.14)	*(0.15)*	*(0.15)*		*(0.14)*	*(0.14)*	*(0.14)*
Female			-0.10	-0.09			0.11	0.11
			(0.14)	(0.14)			(0.13)	(0.13)
Name Change				-0.06				0.05
				(0.16)				*(0.15)*
Cut point 1 (Clusters 1-2)	-5.22**	-4.46**	-4.45**	-4.44**	-9.49**	-8.95**	-8.96**	-8.96**
	(1.04)	*(1.05)*	*(1.04)*	*(1.04)*	*(1.02)*	*(1.03)*	*(1.04)*	*(1.04)*
Cut point 2 (Clusters 2-3)	-1.07	-0.19	-0.17	-0.17	-5.22**	-4.56**	-4.56**	-4.56**
	(1)	*(1.01)*	*(1.01)*	*(1.01)*	*(0.96)*	*(0.97)*	*(0.97)*	*(0.97)*
Cut point 3 (Clusters 3-4)					-2.19*	-1.49	-1.49	-1.49
					(0.94)	*(0.94)*	*(0.95)*	*(0.95)*
Obs.	1447	1447	1447	1447	1447	1447	1447	1447
Log Pseudo-Likelihood	-893.87	-879.01	-878.79	-878.71	-1086.11	-1070.23	-1069.87	-1069.80
Pseudo R^2	0.43	0.44	0.44	0.44	0.44	0.45	0.45	0.45

Note: This table presents the results of the ordered logit models (1), (2), (3), (4) run for the full period (2015-22). The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female* and *Name Change* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eqs.(1), (2), (3) and (4) respectively). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Panel B. Marginal effects

	3 clusters			4 clusters			
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 4
HI	3.63** *(0.55)*	2.68** *(0.42)*	-6.32** *(0.95)*	2.41** *(0.27)*	2.90** *(0.34)*	1.67** *(0.19)*	-6.98** *(0.71)*
Large cap	-0.09 *(0.07)*	-0.07 *(0.05)*	0.16 *(0.13)*	-0.06 *(0.04)*	-0.07 *(0.05)*	-0.04 *(0.03)*	0.17 *(0.11)*
Small Cap	0.36 *(0.60)*	0.27 *(0.44)*	-0.63 *(1.04)*	0.99** *(0.32)*	1.19** *(0.40)*	0.69** *(0.23)*	-2.87** *(0.93)*
Fossil fuel	-1.01** *(0.15)*	-0.74** *(0.09)*	1.75** *(0.23)*	-0.43** *(0.08)*	-0.52** *(0.09)*	-0.30** *(0.05)*	1.25** *(0.21)*
Green	0.97** *(0.20)*	0.72** *(0.18)*	-1.69** *(0.36)*	1** *(0.11)*	1.21** *(0.19)*	0.69** *(0.10)*	-2.90** *(0.37)*
Expense	0.01 *(0.01)*	0.01 *(0.01)*	-0.02 *(0.01)*	0.00 *(0.00)*	0.00 *(0.01)*	0.00 *(0.00)*	-0.01 *(0.01)*
Fund Size	0.03** *(0.00)*	0.03** *(0.00)*	-0.05** *(0.01)*	0.02** *(0.00)*	0.02** *(0.00)*	0.01** *(0.00)*	-0.06** *(0.01)*
Fund Age	-0.00 *(0.00)*	-0.00 *(0.00)*	0.00 *(0.00)*	0.0 *(0.00)*	0.00 *(0.00)*	0.00 *(0.00)*	-0.00 *(0.00)*
ESG Exp	0.02** *(0.00)*	0.02** *(0.00)*	-0.04** *(0.00)*	0.01** *(0.00)*	0.02** *(0.00)*	0.01** *(0.00)*	-0.04** *(0.00)*
Tenure	-0.01** *(0.00)*	-0.01** *(0.00)*	0.01** *(0.00)*	-0.00** *(0.00)*	-0.01** *(0.00)*	-0.00** *(0.00)*	0.01** *(0.00)*
Team	-0.06** *(0.01)*	-0.04** *(0.01)*	0.10** *(0.02)*	-0.03** *(0.01)*	-0.03** *(0.01)*	-0.02** *(0.00)*	0.08** *(0.02)*
Female	0.01 *(0.01)*	0.00 *(0.01)*	-0.01 *(0.02)*	-0.00 *(0.01)*	-0.00 *(0.01)*	-0.00 *(0.00)*	0.01 *(0.01)*
Name Change	0.00 *(0.01)*	0.00 *(0.01)*	-0.00 *(0.02)*	-0.00 *(0.01)*	-0.00 *(0.01)*	-0.00 *(0.01)*	-0.01 *(0.02)*

Note: This table presents the associated marginal effects on the probabilities of belonging to each cluster obtained from the ordered logit regression model (4) run on the full sample period (2015-22).
Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Cluster 3 (*resp*. Cluster 3 and 4) are considered as brown clusters for the 3 clusters (*resp*. 4 clusters) scenario.

Robust standard errors are in parentheses.
**, and * denote statistical significance at the 1%, and 5% levels, respectively.

Table A3. Regression results – 1st sub-period (2015-19)

	3 clusters				4 clusters			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
HI	-69.12**	-69.26**	-69.24**	-69.25**	-69.73**	-70.31**	-70.26**	-70.24**
	(11.79)	*(11.86)*	*(11.87)*	*(11.88)*	*(9.28)*	*(9.20)*	*(9.16)*	*(9.17)*
Large cap	1.45	1.71	1.75	1.75	1	1.09	1.10	-1.09
	(1.61)	*(1.61)*	*(1.63)*	*(1.64)*	*(1.54)*	*(1.51)*	*(1.52)*	*(1.54)*
Small Cap	1.11	4.47	4.99	4.99	-8.03	-4.63	-4.46	-4.45
	(13.35)	*(13.59)*	*(13.92)*	*(13.91)*	*(14.12)*	*(14.38)*	*(14.54)*	*(14.50)*
Fossil Fuel	17.69**	17.04**	17.04**	17.04**	13.77**	12.98**	12.97**	12.97**
	(3.18)	*(3.19)*	*(3.19)*	*(3.18)*	*(2.97)*	*(2.87)*	*(2.89)*	*(2.87)*
Green	-9.79	-9.28	-9.30	-9.30	-21.27**	-20.43**	-20.45**	-20.44
	(5.25)	*(5.41)*	*(5.46)*	*(5.46)*	*(6.86)*	*(6.95)*	*(6.99)*	*(6.99)*
Expense	-0.18	-0.18	-0.17	-0.17	-0.18	-0.18	-0.18	-0.18
	(0.16)	*(0.16)*	*(0.16)*	*(0.17)*	*(0.14)*	*(0.15)*	*(0.15)*	*(0.15)*
Fund Size	-0.44**	-0.44**	-0.44**	-0.44**	-0.61**	-0.62**	-0.62**	-0.62**
	(0.07)	*(0.08)*	*(0.08)*	*(0.08)*	*(0.07)*	*(0.07)*	*(0.07)*	*(0.07)*
Fund Age	0.04**	0.04**	0.04**	0.04**	0.00	0.00	0.00	0.01
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
ESG Exp	-0.39**	-0.37**	-0.37**	-0.37**	-0.34**	-0.32**	-0.32**	-0.32**
	(0.04)	*(0.04)*	*(0.04)*	*(0.04)*	*(0.03)*	*(0.03)*	*(0.03)*	*(0.03)*
Tenure	0.13**	0.14**	0.13**	0.13**	0.11**	0.12**	0.12**	0.12**
	(0.02)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.02)*
Team		0.49*	0.50*	0.50*		0.60**	0.61**	0.61**
		(0.20)	*(0.20)*	*(0.20)*		*(0.20)*	*(0.20)*	*(0.20)*
Female			-0.09	-0.09			-0.03	-0.03
			(0.20)	*(0.20)*			*(0.18)*	*(0.18)*
Name Change				-0.00				-0.03
				(0.21)				*(0.21)*
Cut point 1	-4.33**	-3.67**	-3.65**	-3.65**	-9.97**	-9.44**	-9.43**	-9.44**
(1-2)	*(1.50)*	*(1.52)*	*(1.52)*	*(1.54)*	*(1.44)*	*(1.43)*	*(1.43)*	*(1.43)*
Cut point 2	-0.01	0.74	-0.76	0.76	-5.60**	-4.98**	-4.98**	-4.99**
(2-3)	*(1.45)*	*(1.47)*	*(1.47)*	*(1.49)*	*(1.33)*	*(1.31)*	*(1.31)*	*(1.31)*
Cut point 3					-2.58*	-1.92	-1.92	-1.93*
(3-4)					*(1.30)*	*(1.27)*	*(1.27)*	*(1.28)*
Obs.	817	817	817	817	817	817	817	817
Log Pseudo-Likelihood	-454.03	-451.05	-450.95	-450.95	-583.25	-577.90	-577.89	-577.88
Pseudo R^2	0.44	0.45	0.45	0.45	0.42	0.43	0.43	0.43

Note: This table presents the results of the ordered logit models (1), (2), (3), (4) run for the sub-period: 2015-19. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female* and *Name Change* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the “baseline” or “reference” shape of the relative frequency distribution of cases across clusters of *Y* (see Eqs.(1), (2), (3) and (4) respectively). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Table A4. Regression results – 2nd sub-period (2020-22)

	3 clusters				4 clusters			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
HI	-21.07 *(11.40)*	-26.88* *(11.86)*	-27.15* *(11.86)*	-26.99* *(11.85)*	-45.25** *(10.74)*	-50.96** *(11.18)*	-50.73** *(11.26)*	-50.30** *(11.28)*
Large cap	-0.38 *(1.87)*	-0.05 *(1.79)*	-0.14 *(1.78)*	0.10 *(1.81)*	3.13 *(1.89)*	3.42 *(1.87)*	3.24 *(1.87)*	3.13 *(1.89)*
Small Cap	-33.88* *(15.73)*	-29.19 *(17.10)*	-28.62 *(16.90)*	-28.73 *(16.96)*	-50.20** *(12.85)*	-46.24** *(13.93)*	-47.60** *(14.45)*	-47.91** *(14.55)*
Fossil Fuel	11.38** *(2.82)*	11.45** *(2.88)*	11.29** *(2.90)*	11.20** *(2.95)*	10.80** *(2.70)*	10.98** *(2.79)*	11.35** *(2.81)*	11.12** *(2.84)*
Green	-19.59** *(2.81)*	-18.89** *(2.87)*	-18.65** *(2.89)*	-18.70** *(2.92)*	-31.06** *(3.92)*	-30.19** *(4.06)*	-30.91** *(4.15)*	-31.10** *(4.25)*
Expense	-0.33 *(0.17)*	-0.32 *(0.18)*	-0.31 *(0.18)*	-0.32 *(0.18)*	0.03 *(0.16)*	0.03 *(0.16)*	0.03 *(0.16)*	0.01 *(0.16)*
Fund Size	-0.37** *(0.07)*	-0.38** *(0.08)*	-0.39** *(0.08)*	-0.39** *(0.08)*	-0.42** *(0.07)*	-0.41** *(0.07)*	-0.40** *(0.07)*	-0.41** *(0.07)*
Fund Age	-0.04** *(0.01)*	-0.04** *(0.01)*	-0.04** *(0.01)*	-0.04** *(0.01)*	-0.02* *(0.00)*	-0.02* *(0.00)*	-0.02* *(0.00)*	-0.02* *(0.00)*
ESG Exp	-0.31** *(0.04)*	-0.26** *(0.04)*	-0.26** *(0.04)*	-0.26** *(0.04)*	-0.36** *(0.04)*	-0.32** *(0.04)*	-0.33** *(0.04)*	-0.33** *(0.37)*
Tenure	0.11** *(0.02)*	0.12** *(0.02)*	0.12** *(0.02)*	0.12** *(0.02)*	0.09** *(0.02)*	0.09** *(0.02)*	0.10** *(0.02)*	0.10** *(0.02)*
Team		1.22** *(0.23)*	1.26** *(0.23)*	1.26** *(0.23)*		1.05** *(0.21)*	0.98** *(0.21)*	0.98** *(0.21)*
Female			-0.19 (0.22)	-0.19 (0.22)			0.37* *(0.19)*	0.37* *(0.19)*
Name Change				0.05 *(0.27)*				0.13 *(0.24)*
Cut point 1 (Clusters 1-2)	-7.16** *(1.94)*	-5.95** *(1.84)*	-5.89** *(1.84)*	-5.95** *(1.88)*	-7.83** *(2.04)*	-6.88** *(2.05)*	-7.03** *(2.06)*	-7.18** *(2.10)*
Cut point 2 (Clusters 2-3)	-2.93 *(1.90)*	-1.49 *(1.83)*	-1.43 *(1.82)*	-1.48 *(1.87)*	-3.50 *(1.99)*	-2.35 *(1.99)*	-2.45 *(2.01)*	-2.60 *(2.04)*
Cut point 3 (Clusters 3-4)					-0.41 *(1.96)*	-0.80 *(1.97)*	0.70 *(1.98)*	0.56 *(2.01)*
Obs.	660	660	660	660	660	660	660	660
Log Pseudo-Likelihood	-409.77	-393.74	-393.37	-393.34	-486.87	-473.97	-472.21	-472.03
Pseudo R^2	0.42	0.44	0.44	0.44	0.45	0.47	0.47	0.47

Note: This table presents the results of the ordered logit models (1), (2), (3), (4) run for the sub-period: 2020-22. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female* and *Name Change* (see Table A1 for definition) are displayed in this table. Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eqs.(1), (2), (3) and (4) respectively). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Table A5. Results of model (5) regression – the influence of active strategies

Panel A. 3 clusters scenario

	Full period	**1st sub-period**	**2nd sub-period**
	2015-22	2015-19	2020-22
HI	-49.61** *(8.20)*	-65.39** *(12.07)*	-26.08* *(11.84)*
Large cap	1.06 *(1.06)*	1.46 *(1.65)*	-0.65 *(1.86)*
Small Cap	-2.83 *(8.46)*	5.53 *(13.60)*	-26.20 *(16.07)*
Fossil Fuel	14.36** *(2.04)*	17.99** *(3.25)*	10.34** *(2.94)*
Green	-13.22** *(3.20)*	-8.00 *(5.80)*	-18.13** *(2.84)*
Expense	-0.08 *(0.13)*	-0.10 *(0.18)*	-0.21 *(0.19)*
Fund Size	-0.46** *(0.06)*	-0.49** *(0.08)*	-0.43** *(0.09)*
Fund Age	0.00 *(0.01)*	0.05** *(0.01)*	-0.04** *(0.01)*
ESG Exp	-0.30** *(0.03)*	-0.35** *(0.04)*	-0.25** *(0.04)*
Tenure	0.12** *(0.01)*	0.12** *(0.02)*	0.12** *(0.02)*
Team	0.77** *(0.15)*	0.43* *(0.20)*	1.27** *(0.24)*
Female	-0.09 *(0.14)*	-0.10 *(0.21)*	-0.17 *(0.21)*
Name Change	-0.05 *(0.17)*	0.01 *(0.22)*	0.08 *(0.27)*
Active	-0.87** *(0.16)*	-0.98** *(0.25)*	-0.80** *(0.25)*
Cut point 1 (Clusters 1-2)	-5.01** *(1.04)*	-4.30** *(1.50)*	-6.85** *(1.93)*
Cut point 2 (Clusters 2-3)	-0.67 *(1.01)*	-0.16 *(1.46)*	-2.33 *(1.90)*
Obs.	1477	817	660
Log Pseudo-Likelihood	-862.57	-440.96	-387.16
Pseudo R²	0.44	0.47	0.45

Panel B. 4 clusters scenario

	Full period	**1st sub-period**	**2nd sub-period**
	2015-22	2015-19	2020-22
HI	-60.54** *(6.99)*	-67.02** *(9.34)*	-51.51** *(11.51)*
Large cap	1.26 *(1.05)*	0.85 *(1.59)*	2.63 *(1.93)*
Small Cap	-23.44** *(8.68)*	-3.71 *(14.49)*	-44.86** *(14.71)*
Fossil Fuel	10.93** *(1.88)*	13.13** *(2.87)*	10.43** *(2.96)*
Green	-25.16** *(3.87)*	-19.53** *(7.09)*	-30.34** *(4.20)*
Expense	-0.02 *(0.11)*	-0.14 *(0.15)*	0.16 *(0.17)*

Fund Size	-0.56** *(0.05)*	-0.65** *(0.07)*	-0.45** *(0.08)*
Fund Age	-0.01 *(0.01)*	0.01 *(0.01)*	-0.02* *(0.01)*
ESG Exp	-0.32** (0.02)	-0.32** (0.03)	-0.32** (0.04)
Tenure	0.10** *(0.01)*	0.11** *(0.02)*	0.10** *(0.02)*
Team	0.73** *(0.14)*	0.56** *(0.20)*	1.03** *(0.22)*
Female	0.13 *(0.13)*	-0.03 *(0.18)*	0.41* *(0.19)*
Name Change	0.08 *(0.15)*	0.01 *(0.21)*	0.14 *(0.24)*
Active	-0.80** *(0.16)*	-0.71** *(0.21)*	-0.94** *(0.23)*
Cut point 1 (Clusters 1-2)	-9.53** *(1.05)*	-10.03** *(1.45)*	-8.05 *(2.10)*
Cut point 2 (Clusters 2-3)	-4.97** *(0.99)*	-5.47** *(1.34)*	-3.21 *(2.06)*
Cut point 3 (Clusters 3-4)	-1.88 *(0.97)*	-2.39* *(1.31)*	-0.05 *(2.03)*
Obs.	1477	817	660
Log Pseudo-Likelihood	-1054.89	-571.78	-463.12
Pseudo R²	0.46	0.43	0.48

Note: This table presents the results of the ordered logit regression model (5) run for the full period and the two sub-periods: 2015-19 and 2020-22. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Team, Female, Name Change,* and *Active* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eq.(5)). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.

Table A6. Marginal effects related to (5) regression results

	3 clusters			**4 clusters**			
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 4
HI	3.31** *(0.53)*	2.65** *(0.44)*	-5.96** *(0.95)*	2.27** *(0.26)*	2.79** *(0.34)*	1.66** *(0.19)*	-6.66** *(0.71)*
Large cap	-0.07 *(0.07)*	-0.06 *(0.06)*	0.13 *(0.13)*	-0.05 *(0.03)*	-0.06 *(0.05)*	-0.03 *(0.03)*	0.14 *(0.12)*
Small Cap	0.19 *(0.57)*	0.15 *(0.45)*	-0.34 *(1.02)*	0.88** *(0.32)*	1.08** *(0.41)*	0.62** *(0.24)*	-2.58** *(0.96)*
Fossil fuel	-0.96** *(0.14)*	-0.77** *(0.10)*	1.72** *(0.23)*	-0.41** *(0.08)*	-0.50** *(0.08)*	-0.29** *(0.05)*	1.20** *(0.20)*
Green	0.88** *(0.20)*	0.71** *(0.17)*	-1.59** *(0.37)*	0.94** *(0.11)*	1.16** *(0.19)*	0.66** *(0.10)*	-2.77** *(0.38)*
Expense	0.01 *(0.01)*	0.01 *(0.01)*	-0.01 *(0.02)*	0.00 *(0.01)*	0.00 *(0.01)*	0.00 *(0.00)*	-0.01 *(0.01)*

Fund Size	0.03** *(0.00)*	0.02** *(0.00)*	-0.06** *(0.01)*	0.02** *(0.00)*	0.03** *(0.00)*	0.01** *(0.00)*	-0.06** *(0.00)*
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	0.02** *(0.00)*	0.02** *(0.00)*	-0.04** *(0.03)*	0.01** *(0.00)*	0.01** *(0.00)*	0.01** *(0.00)*	-0.04** *(0.00)*
Tenure	-0.01** *(0.00)*	-0.01** *(0.00)*	0.01** *(0.00)*	-0.00** *(0.00)*	-0.01** *(0.00)*	-0.00** *(0.00)*	0.01** *(0.00)*
Team	-0.05** *(0.01)*	-0.04** *(0.01)*	0.09** *(0.02)*	-0.03** *(0.01)*	-0.03** *(0.01)*	-0.02** *(0.00)*	0.08** *(0.02)*
Female	0.00 *(0.01)*	0.00 *(0.01)*	-0.01 *(0.02)*	-0.00 *(0.01)*	-0.01 *(0.01)*	-0.00 *(0.00)*	0.01 *(0.01)*
Name Change	0.00 *(0.01)*	0.00 *(0.01)*	-0.01 *(0.02)*	-0.00 *(0.01)*	-0.00 *(0.01)*	0.00 *(0.00)*	0.00 *(0.02)*
Active	0.06** *(0.01)*	0.04** *(0.01)*	-0.10** *(0.02)*	0.03** *(0.01)*	0.04** *(0.01)*	0.02** *(0.00)*	-0.09** *(0.02)*

Note: This table presents the associated marginal effects on the probabilities of belonging to each cluster obtained from the ordered logit regression model (5) run on the whole sample period (2015-2022).
Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Cluster 3 (*resp*. Cluster 3 and 4) are considered as brown clusters for the 3 clusters (*resp*. 4 clusters) scenario.

Robust standard errors are in parentheses.
** and * denote statistical significance at the 1% and 5% levels respectively

Table A7. Results of model (6) – the impact of gender diversity in fund management teams

Panel A. 3 clusters scenario

	Full period	**1st sub-period**	**2nd sub-period**
	2015-22	2015-19	2020-22
HI	-56.30**	-68.52**	-43.73**
	(1.55)	*(16.30)*	*(14.44)*
Large cap	2.90*	2.28	0.33
	(1.30)	*(1.93)*	*(2.36)*
Small Cap	-13.79	-14.74	-32.26
	(18.34)	*(25.30)*	*(29.57)*
Fossil Fuel	15.64**	16.74**	14.03**
	(2.64)	*(3.88)*	*(3.75)*
Green	-20.87**	-19.88**	-24.08**
	(3.13)	*(4.09)*	*(4.81)*
Expense	-0.12	-0.11	-0.22
	(0.16)	*(0.21)*	*(0.24)*
Fund Size	-0.59**	-0.63**	-0.58**
	(0.07)	*(0.10)*	*(0.11)*
Fund Age	0.01	0.06**	-0.02
	(0.01)	*(0.02)*	*(0.01)*
ESG Exp	-0.33**	-0.43**	-0.26**
	(0.04)	*(0.06)*	*(0.05)*
Tenure	0.12**	0.12**	0.12**
	(0.02)	*(0.03)*	*(0.03)*
Blau index	-2.21**	-2.16**	-2.15*
	(0.61)	(0.80)	(0.99)
Critical Mass	0.91**	0.69	1.16*
	(0.29)	*(0.38)*	*(0.48)*
Cut point 1	-5.62**	-6.21**	-8.29**
(Clusters 1-2)	(1.34)	(1.89)	(2.45)
Cut point 2	-0.95	-1.18	-3.65
(Clusters 2-3)	(1.29)	(1.80)	(2.39)
Obs.	943	535	408
Log-Pseudo-Likelihood	-509.04	-259.11	-236.92
Pseudo R^2	0.41	0.44	0.39

Panel B. 4 clusters scenario

	Full period	**1st sub-period**	**2nd sub-period**
	2015-22	2015-19	2020-22
HI	-73.73**	-87.60**	-62.94**
	(9.20)	*(12.52)*	*(13.93)*
Large cap	3.01*	2.43	2.70
	(1.46)	*(2.19)*	*(2.69)*
Small Cap	-43.84*	-25.88	-79.14**
	(22.21)	*(24.27)*	*(27.24)*
Fossil Fuel	12.66**	11.82**	14.32**
	(2.70)	*(3.81)*	*(3.85)*
Green	-33.88**	-37.06**	-33.34**
	(3.84)	*(4.99)*	*(5.86)*
Expense	0.07	0.05	0.16
	(0.15)	*(0.19)*	*(0.23)*
Fund Size	-0.80**	-0.87**	-0.75**
	(0.08)	*(0.11)*	*(0.12)*
Fund Age	0.01	0.02	0.01
	(0.01)	*(0.01)*	*(0.01)*
ESG Exp	-0.38**	-0.42**	-0.36**
	(0.04)	*(0.05)*	*(0.06)*
Tenure	0.10**	0.13**	0.07*
	(0.02)	*(0.03)*	*(0.03)*
Blau index	-0.46*	-0.46	-0.44*
	(0.27)	*(0.32)*	*(0.25)*
Critical Mass	0.21	-0.07	0.56
	(0.28)	*(0.34)*	*(0.47)*
Cut point 1	-11.58**	-12.82**	-11.53**
(Clusters 1-2)	*(1.51)*	*(2.27)*	*(2.84)*
Cut point 2	-6.32**	-7.41**	-6.33*
(Clusters 2-3)	*(1.42)*	*(2.06)*	*(2.77)*
Cut point 3	-2.70**	-3.65	-2.73
(Clusters 3-4)	*(1.39)*	*(1.99)*	*(2.72)*
Obs.	943	535	408
Log-Pseudo-Likelihood	-601.20	-314.67	-278.31
Pseudo R^2	0.45	0.45	0.44

Note: This table presents the results of the ordered logit regression model (6) run for the full period and the two sub-periods: 2015-19 and 2020-22. The coefficient of independent variables *HI, Large cap, Small Cap, Fossil Fuel, Green, Expense, Fund Size, Fund Age, ESG Exp, Tenure, Blau index, Critical Mass* (see Table A1 for definition) are displayed in this table.

Robust standard errors are in parentheses.

** and * denote statistical significance at the 1% and 5% levels respectively.

The cut point coefficients represent the expected ratios of cases across the cut points in the distribution of clusters when all independent variables are zero. This can be understood as the "baseline" or "reference" shape of the relative frequency distribution of cases across clusters of *Y* (see Eq.(6)). Cluster 1 represents the dark green cluster while Cluster 2 is the light green cluster. Clusters 3 and 4 are the light and dark brown clusters, respectively.