SFDR versus performance classification: a clustering approach

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A B S T R A C T

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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ABSTRACT

The Sustainable Finance Disclosure Regulation (SFDR) imposes on investment companies the publication of sustainability-related profiles of the portfolio creation process. This obligation seeks to enhance the information provided to customers on financial products with regard to the Environmental, Social and Governance (ESG) criteria. In order to understand to which extent this information is relevant for investment decisions, the reliability of the classification among funds with a different ESG focus (articles 6, 8, and 9) is studied from a financial perspective and verified through a hierarchical cluster analysis on principal components of the performance measures of various funds distributed in Europe.

1. Introduction

In recent years the increasing attention to environmental, social and governance (ESG) issues has led to a rapid spread of financial instruments as well as investment decision-making processes linked to those activities or projects that take care of the environment and are beneficial to society.

Accordingly, specialised rating agencies have grown and have developed their own ESG scores algorithms through which issuers and financial investment instruments are classified and labelled at a certain degree of proximity to an ESG oriented approach. The purpose of rating agencies' ESG scores is to assist investors in more accurately assessing the non-financial performance of investment funds (Hartzmark and Sussman, 2019). In this context, the $10th$ of March 2021 came into force the Sustainable Finance Disclosure Regulation (SFDR) that was designed to enhance transparency in the market for sustainable investment products. Its primary objectives include mitigating greenwashing, fostering transparency and ensuring accuracy in sustainability-related assertions made by participants in financial markets.

The SFDR has harmonised rules for funds classification by indicating the modalities and explicitly providing information necessary for a clear taxonomy based on the declaration regarding the integration of ESG factors at the asset manager level. In particular, Article 6 Funds are those whose objectives are not aligned with ESG's themes, Article 8 Funds's interest is directed towards ESG themes but do not represent the main criteria of the fund, while Article 9 Fund's main objective is to comply with ESG issues. Recently, some authors have analyzed the impact of SFDR over different perspectives finding that investor attention to SFDR has strong predictive power over equity market prices especially during bearish markets (Birindelli et al., 2023), moreover a better ESG label leads to larger fund net inflows (Becker et al., 2022; Scherer and Hasaj, 2023) and investment funds with sustainability objectives have higher financial incentives (Cremasco and Boni, 2022). Few works have analyzed the alignment between investors' interest to performance and investment sustainability orientation in the light of the new SFDR classification, as in Cosma et al. (2023) that shows the outperformance of Article 9 funds over conventional funds during the two recent crises (Covid and Russia-Ukraine war) even if with a lack of performance persistence over the long run.

The aim of this paper is to contribute to the wide and still open debate on the alignment of investors' performance objectives and investment ESG orientation aiming at providing valuable information for inverstors' approach to ESG investments, asset managers' strategies correct implementation and policymakers' evaluations about the effectiveness of new regulation. Cluster methodology together with an unsupervised dimensionality reduction technique has been applied to examine the return, risk, and efficiency of funds subject to the SFDR classification using daily data, gathered from Refinitiv database, over the course of two years since the adoption of the SFDR. This is an innovative approach that instead of testing whether funds with a certain ESG classification exhibit common patterns of behavior in terms of return, risk, and efficiency deductively tests whether the data analysis provides homogeneous groups of funds characterized by the same ESG classification. The advantage of this approach is that while the inductive approach might be biased by secondary factors not considered (management style, costs, etc.), the deductive approach focuses only on the relevant metrics to identify patterns of behavior.

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2. Theoretical analysis and research hypothesis

The financial performance of ESG funds has stimulated a lively debate in the literature with respect to its connection with the ESG issues that has not yet reached a consensus and has developed three different theories that can be summarized in: negative, positive or absence of relationship.
Studies that support the theory of a negative relationship between ESG orientation and performance find their foundation on the argument that ESG funds are portfolios less efficient since the reduction of the universe of possible investments implies a lower diversification capable of excluding companies characterized by returns above the average (Hamilton et al., 1993; Adler and Kritzman, 2008). Similarly, other authors have demonstrated that ESG funds perform worse than conventional ones because of the higher screening activity that implies higher monitoring or agency costs (Bauer et al., 2007; Zeidan, 2022; Chegut et al., 2011; Fabozzi et al., 2008; Statman and Glushkov, 2008; Capelle-Blancard and Monjon, 2010).
Conversely, the idea of a positive relationship between financial performance and ESG funds orientation given by the possibility of obtaining higher returns by ESG investing in comparison to conventional investing (Luther et al., 1992; Mallin et al., 1995; Gil-Bazo et al., 2010; Becchetti et al., 2014; Braeken and van Assen, 2017). In this perspective, the commitment to social and environmental issues implies that screening techniques provide valuable information to fund managers about firms cost of debt and default risk (Atif and Ali, 2021).
On the other hand, numerous studies have also shown that the difference in performance between conventional funds and socially responsible funds is irrelevant or not significant (Goldreyer and Diltz, 1999; Hamilton et al., 1993; Shank et al., 2005; Statman, 2000).
This work reverts the analysis of the performances of ESG funds versus non ESG funds using the SFDR classification based on the asset manager's declaration. This approach overcomes most of the limits that affect sustainability ratings in the classification of funds (Berg et al., 2022) and permits to verify whether funds that belong to the same SFDR categories, as articles 6, 8 and 9, exhibit similar risk-adjusted performances. Indeed, different performances within the same category of funds could highlight important issues in the open debate on the performance of ESG funds by demonstrating that a relationship between ESG orientation and performance is absent or weak. Thus, the research hypothesis can be formulated as follows:

H1: the a priori SFDR funds classification provides information on the performance metrics of mutual funds and then on the performance expectations.

This paper proposes an innovative two step analysis to investigate this hypothesis. First of all, principal components analysis (PCA), which is an unsupervised dimensionality reduction method, has been used to find the most significant orthogonal linear combinations of the funds characteristics, namely the principal components PCs (Jolliffe, 2002). Then, these PCs have been included as new variables in the hierarchical clustering algorithm which has been performed by using the Ward criterion (Strauss and von Maltitz, 2017). The choice of this variables reduction is justified since it aims at identifying a smaller set of principal components that capture the most relevant information in the original dataset with minimal loss of information. The agglomerative hierarchical clustering based on principal components can help to improve the interpretation of the underlying data structure as well as can help to lead to a more stable clustering (Everitt et al., 2011). In the Supplementary materials, a brief review of the principal component analysis and the hierarchical clusterings, used in this paper, has been proposed, as well as external and internal clustering validation measures computed to evaluate the performance of clustering algorithm on the ESG dataset (Rousseeuw, 1987; Maulik and Bandyopadhyay, 2002) have been clarified (S.3).

3. Data and preliminary analysis

The dataset used in this study has been collected by Refinitiv Database from 10 March 2021 to 10 March 2023 and consists of 440 observations of various performance metrics referred to funds distributed in Europe and specialized on the European stock market with benchmarks coherent with a large cap blend style. The performance measures are classified into three macro sections: Return, Risk and Efficiency (Tab. 1). The first section is composed of 3 performance indicators assessing the absolute and relative return of each fund: the geometric mean of returns (GM), the excess return (ER) defined as the difference between the return of the fund and a risk free asset and the alpha indicator described as the difference between the return of the fund and the return of the MSCI Europe Net Return. The second section is composed by 3 risk indicators: the standard deviation (σ) as measure of dispersion of fund's returns around the average,

the tracking error (TE) that is the deviation from the benchmark of a fund and computed as standard deviation of alpha) and then maximum drawdown (MaxDD) defined ad a measure of asymmetric risk and computed as the fund's largest price drop from a peak to a valley. The last section is composed by 2 risk adjusted performance indicators assessing the ability to reward each unit of risk in addition to the risk free asset namely, in the case of the Sharpe ratio (SR) and to the benchmark in the case of the Information ratio (IR).
In addition, the classification variable defined as $SFDR$ describes the rules for the classification of funds, on the basis of the fund manager's attitude to a more or less sustainability-oriented portfolio composition and reporting (Fig. 1).

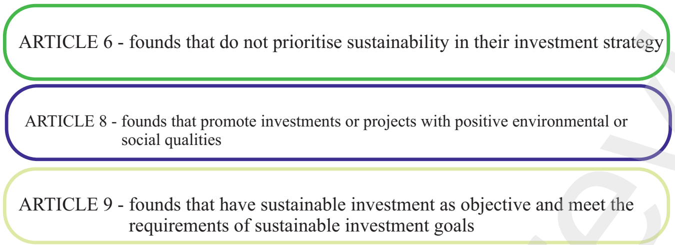

Figure 1: SFDR classification by article and definitions.

It is worth highlighting that the variable of classification $SFDR$ and the financial indicators used in this paper can be considered a valid syntheses of environmental, social and governance factors in the investment decision-making process.
In order to increase the accuracy of learning approach, a pre-processing data analysis has been performed to detect the presence of outliers values and removing funds with missing data. After the pre-processing phase, the dataset consists of 440 funds for which 9 performance measures are taken with respect to the original dataset.
The descriptive statistics in Tab. 1 show positive risk adjusted performance indicators SR and IR, with a mean of 0.41 and 0.28, and a standard deviation of 0.26 and 0.35 respectively. This means that the funds of the sample outperform on average the risk free asset and the benchmark. This is confirmed by the positive average of GM. The average value of standard deviation is consistent with the risk of the benchmark, even though the TE suggest an active strategy of the funds. The MaxDD is clearly affected by the negative performance of the european stock market in 2022.

3.1. Variables extraction method for hierarchical clustering algorithm in financial context

In this section, the PCA and the hierarchical clustering algorithm (HCA) have been applied to evaluate the specific hypothesis regarding the adequacy of the priori classification of funds ($SFDR$). More specifically, the paper proposes to check the null hypothesis that the priori classification is suitable to provide the economic information necessary for a correct classification with respect to the financial characteristics of mutual funds.
First of all, the PCA analysis on the observed dataset require preliminary:

- to compute the covariance matrix to identify correlations;
- to remove highly correlated variables before doing PCA analysis;
- to standardize the continuous original variables. This is justified since the PCA is sensitive to the relative scaling of the variables.

As regards the second step, the covariance matrix has shown that the variable Alpha is highly correlated, thus it has been removed. Consequently, the PCA has been carried out on the correlation matrix and the PCs with eigenvalues greater than one, based on Kaiser's rule (Kaiser, 1958; Braeken and van Assen, 2017), have been included as covariates of HCA algorithm. Table 2 presents the eigenvalues and the ratios of explained variances, from which it is evident as the PC variances are in progressive decline. Consequently, it is clear that the first two principal components can be selected, as the cumulative contribution rate exceeding the 84% is deemed to effectively reduce dimensionality while ensuring the preservation of sufficient information. Only the 15% of the variance remains unexplained.
The first PC of the data presents the highest eigenvalue (4.85); this component explains the greatest variation (69%) of the variables, making it the most significant. The influence is also equally distributed among all the variables. Similarly, the component with the second largest eigenvalue, (1.083) represents the second principal component. This component

Table 1
Description and descriptive statistics of relevant performance measures.

Sections	Performance measures	Formula	mean	std	min	max
Return Indicators	GM	$\sqrt[n]{\prod_{i=1}^{n}\left(1+\overline{R}_{pi}\right)}-1$	0.11	0.10	-0.26	0.61
	ER	$ER=\overline{R}_p-\overline{R}_f$	0.07	0.04	-0.12	0.26
	Alpha	$Alpha=\overline{R}_p-\overline{R}_{bmk}$	0.03	0.04	-0.16	0.22
Risk indicators	σ	$\sigma=Stdev\left(\overline{R}_p\right)$	0.17	0.02	0.07	0.29
	TE	$TE=Stdev\left(\overline{R}_p-\overline{R}_{bmk}\right)$	0.12	0.03	0.02	0.31
	MaxDD	$MaxDD=\frac{TroughValue-PeakValue}{PeakValue}$	0.24	0.06	0.11	0.51
Risk Adjusted Performance indicators	SR	$SR=\frac{\overline{R}_p-\overline{R}_f}{\sigma_p}$	0.41	0.26	-0.63	1.33
	IR	$IR=\frac{\overline{R}_p-\overline{R}_{bmk}}{TE}$	0.28	0.35	-0.82	1.23

* where $\overline{R}_p$ is the mean of the time series of the return of the mutual funds, $\overline{R}_f$ is the mean of the time series of the return of the risk -free asset and $\overline{R}_{bmk}$ is the mean of the times series of the return of the benchmark.

Table 2
Eingenvalues and percentange of explained variance

PC	Eingenvalues	% of explained variance	cumulative % of total variance
PC 1	4.851867677	69.31239538	69.31240
PC 2	1.082675030	15.46678615	84.77918
PC 3	0.886083156	12.65833081	97.43751
PC 4	0.103876709	1.48395299	98.92147
PC 5	0.054288125	0.77554464	99.69701
PC 6	0.018119349	0.25884785	99.95586
PC 7	0.003089953	0.04414219	100.00000

explains an additional 16% of the variation of the variables.
After checking the results in Tab. 3, it is reasonable the hypothesis according to which the first component provides a measure related to the performance assessment, where the SR and IR indices, together with GM and ER, are considered relevant for evaluating portfolios in comparison with the risk free asset and the benchmark returns. On the other hand, the second PC provides a measures related to risks indicators described by the variables: σ, TE and MaxDD. This second PC describes a relevant multidimensional aspect of risk management. Indeed, the PC component provides an information to interpret the dependence among the specific metrics that organizations use to monitor and assess potential risks with respect to the impact of the overall performance. In Fig. 2, the PCA analysis results have been displayed on the factor plane by focusing on the relations between PCs and financial variables (Gabriel, 1971). The graphical output allows detecting the variables (identified by arrows) which contribute to the construction of the axes on a circle, called the correlation circle. From Fig. 2 and Tab. 3, it is evident that PC1 best explains the variability of ER, GM, SR and IR variables. These values increase with as PC1 increase. On the contrary, PC2 best explains the variability of MaxDD, σ and TE variables. However, among these, the variables MaxDD and the σ have higher weights than the one for the variable TE (vectors with longer lengths). Indeed, it is important to point out that if the arrows identify the variables, the angles between the respective vectors indicate the different degree of collinearity between the variables. Therefore, the arrows indicate which variables account for most of PCs, while the length of the arrows corresponds to the intensity of the relationship.

Table 3
Pearson correlation coefficient between financial variables and the first two Principal Components (PCs)

Financial variables	PC 1	PC 2
GM	0.968	0.227
ER	0.956	0.263
σ	-0.574	0.653
TE	-0.282	0.595
MaxDD	-0.873	0.332
SR	0.974	0.176
IR	0.939	0.202

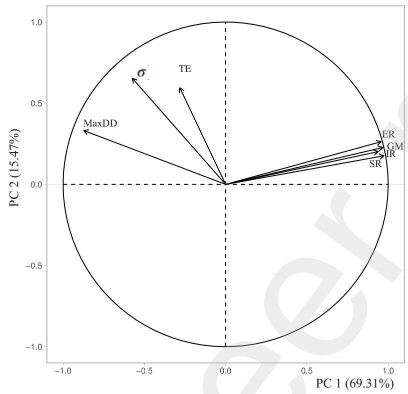

Figure 2: Projection of the 9 financial variables on the PC1 and PC2.

Within this context, the PCA has been used as a feature extraction to find the optimal subset of variables in terms of PCs ignoring redundant and irrelevant information. As a consequence, these PCs have been included as covariates of an HCA which aims to identify groups of similar observations according to a set of particular criteria. As previously mentioned, the cluster analysis, conducted on the PCs, is characterized by the estimation of the dissimilarity matrix associated with the distances between the 440 funds (Euclidean distance) and similarity between clusters measured by linkage methods (Ward type linkage). In addition, the optimal number of clusters has been defined to 3 in accordance with several indices that combine information regarding intra and inter cluster compactness. The findings of cluster analysis has been depicted graphically in a diagram, known as cluster dendrogram, as given in Fig. 3. Note that the horizontal axis indicates the funds and the vertical axis indicates the distance (level of similarity) at which the clusters are merged. Thus, the partitions obtained have the following size: cluster 1 (includes 213 funds), cluster 2 (includes 32 funds) and cluster 3 (includes 195 funds).

4. Comparison between the prior classification and classification based on clustering model

In this section, the hierarchical clustering based on PCA has been applied to assess the hypothesis that the SFDR classification provides a consistent information for the funds with respect to the classification obtained through the HCA. The choice to compare the partitions of $SDFR$, defined $Model_0$, and HCA, denoted as $Model_1$, is justified considering the lively debate on the impact of ESG orientation on performance results. Indeed, the performance of funds is heavily affected by factors (management style and costs) that are independent from ESG classification and thereby the aim is to analyze and measure the misalignment of the distribution of funds in $Model_0$ and in $Model_1$.
The validation criteria to assess the clustering partitions have been based on internal validation measures, as shown in Tab. 4. It is evident that $Model_1$ outperforms $Model_0$, in terms of separation and compactness. In particular, the optimal values (for k = 3) for the Average Silhouette Width and the Dunn index are 0.27 and 0.05, respectively. Similarly, the value of the Connectivity index equal to 51.73 suggests that the clustering structure, with k=3, is better (in terms of within-cluster variance) compared to other partition. Fig. 4 illustrates the colormaps of the partitions

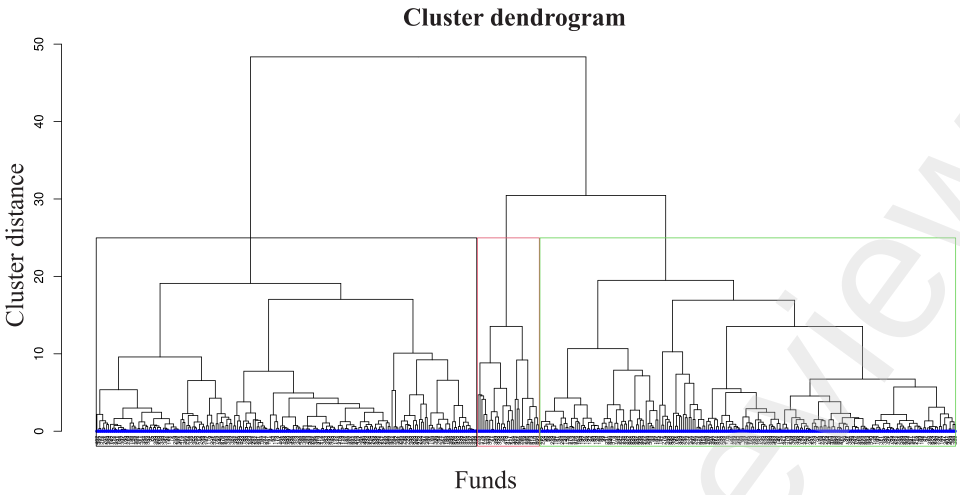

Figure 3: Dendrogram of the funds and financial indicators based on Ward linkage method of hierarchical clustering.

Table 4
performance metrics for the a prior classification based on $SFDR$ ($Model_0$) and HCA for $k = 3$ ($Model_1$)

Model	Silhouette	Dunn	Connectivity
$Model_0$	0.09	0.02	76.96
$Model_1$	0.27	0.05	51.73

achieved with $Model_1$ with respect to the $Model_0$. It is clear that the clusters partitions based on $Model_1$ provide a more compact result than those obtained considering only the priori information of $Model_0$.

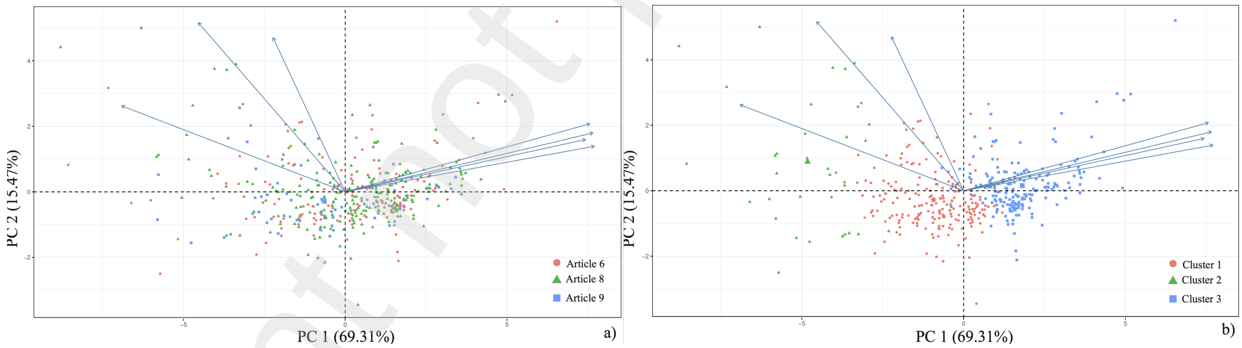

Figure 4: PCA plot regarding the multivariate variation among 50 funds in terms of financial variables. The colormaps of the partitions correspond to the partitions achieved with $Model_0$ a) with respect to the $Model_1$ b).

On the other hand, a key aspect has also been to compare the clustering procedure proposed in this paper with the a priori classification (or a priori knowledge) by using the external criteria. Thus, the ARI index, as a measure of similarity between these two different partitions, has been computed and its value equal to 0.05 has revealed that two cluster solutions can be considered independent. In other terms, the partitions provided by the classification $Model_0$ and the partitions provided by PCA based on HCA, $Model_1$ present a low agreement of clusters, as also evident from the contingency table (Tab 6), where there are the fund frequencies in relation to the partitions of the two models. The evident misalignment of the distribution of the funds in $Model_0$ and $Model_1$ highlights the poor predictive information about performance measures contained in the SFDR classification.
Finally, the performance of the obtained clusters ($Model_1$) and the a priori classification ($Model_0$) have been also evaluated with respect to the original financial data. To this aim, Fig. 5 shows the boxplots categorized according to

Table 5
Contingency table used to determine which funds have been correctly assigned to null ($Model_0$) and alternate distributions ($Model_1$).

		$Model_1$ Cluster 1	Cluster 2	Cluster 3	Total
$Model_0$	Article 6	65	6	86	157
	Article 8	115	19	89	223
	Article 9	33	7	20	60
Total		213	32	195	440

the three obtained clusters ($Model_1$) and with respect to the $SFDR$ classification ($Model_0$). From Fig. 5-b), it is evident that the classification obtained using the proposed method is able to identify clusters characterized by specific financial variables. In particular, the funds found in Cluster 3 are the most efficient (with the greatest value on average with respect to the Risk Adjusted performance indicators i.e. SR and IR), while Cluster 2 includes the most risky funds (with on average higher values with regards to risks metrics i.e. σ, TE and MaxDD). For what concerns the funds found in Cluster 1, it is important to point out that these funds are characterized by similar values in terms of TE to Cluster 3 but have lower average values of performance indicators compared to the latter.
On the other hand, the a priori classification based on $SFDR$ does not highlight the presence of significant differences among the theoretical clusters in terms of financial variables. This result is justified by the idea that the performance of funds is heavily affected by other factors (i.e. management style and costs) that can explain the heterogeneity of the performance patterns of fund showing the same SFDR classification. At the end, the averages associated to these

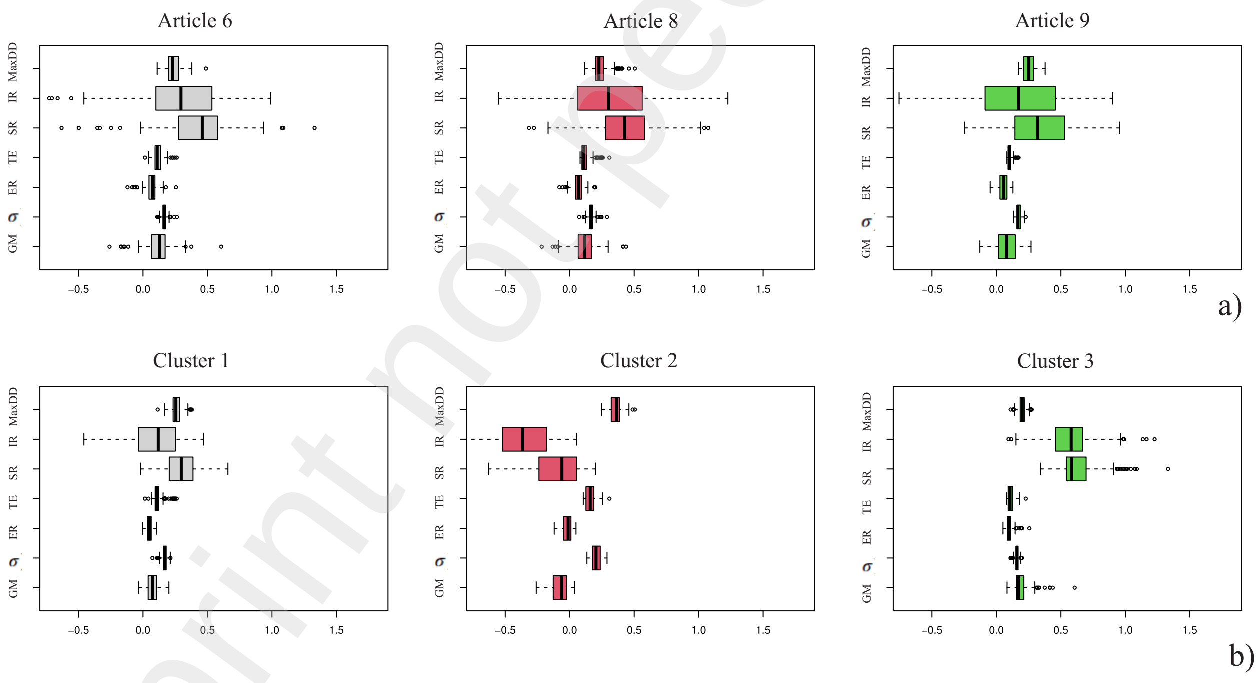

Figure 5: boxplots related to $p = 7$ financial variables classified by clusters with relation to a priori classification a) and with respect to classification based on the AHC procedure b)

financial variables have been compared with respect to both classifications by using the Kruskal-Wallis test. By fixing a significance level of 1%, this test checks for the validity of the null hypothesis that there is no difference among the partitions based on cluster hypothesis.
The results in Tab. 6 show statistically significant differences according to hierarchical partitions obtained by the

Table 6
Financial Variables of the "prior classification" and based on AHC algorithm.

Financial Variables	Kruskal-Wallis Statistics	df	*p-value*	Kruskal-Wallis Statistics	df	*p-value*
GM	8.324	2	0.016	323.458	2	0.00
ER	8.148	2	0.017	317.057	2	0.00
σ	4.414	2	0.110	74.780	2	0.00
TE	10.349	2	0.006	43.668	2	0.00
MaxDD	6.868	2	0.032	243.637	2	0.00
SR	8.612	2	0.013	322.245	2	0.00
IR	5.784	2	0.055	308.305	2	0.00

proposed method, while for what concerns the partitions based on $SFDR$ only the TE variable shows statistically significant differences among partitions.

5. Conclusions

The UE is leading the ESG deal at worldwide level and has decided to use the financial system as a transmission mechanism in order to improve the sustainability of the economic decisions. Also the asset management industry is part of this project and the investment companies have to disclose in the key information document the category of each mutual fund. This regulation came into force in March 2021 and the first reaction of the market has been a strong shift of Assets Under Management (AUM) towards art. 8 and art. 9 funds.
The academic research on this topic has been often based on the ESG ratings provided by different companies (Morningstar, Refinitv) that unfortunately present a great divergence. The SFDR imposes an official classification of the mutual funds, but it is founded on the declaration of the asset management companies and is exposed to the greenwashing risk (overstatement of the ESG orientation). The story telling around the ESG benefits not only on the sustainability, but also on better performances in terms of return, risk and efficiency, has driven many investors to select article 8 and article 9 funds. This study showed that the expectations of better performances only based on the SFDR classification is biased. The innovative approach of this study was to revert the analysis of the traditional performance metrics by creating clusters of funds with similar behaviors.
The clustering procedure was based on a PCA analysis of the performance metrics that allow to focus only on the variables able to explain the features of the sample of funds. It was found that the partitions are definitely better than the a prior one in terms of homogeneity and the contingency table show a low correlation of the classifications based on ESG declaration and on performances. The main finding of this research support the idea that using the SFDR classification to create expectations of better future performance could be misleading, since the different metrics seem to be affected by other factors. The assumption is that the management style (active versus passive) and the cost of the funds should be taken into account and could explain better (or together) with the ESG orientation the performance of mutual funds and future research oh this topic is needed. For the time being, regulators and asset management companies should pay attention to feed the idea that ESG investing is not only able to help the environment, to support social programs and to lead to better governance, but is also a good deal in terms of performance, because the data shows a different story.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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