5 THE INFLUENCE OF ESG ON FINANCIAL PERFORMANCE. EVIDENCE FROM A COMBINED CLUSTER AND PANEL REGRESSION ANALYSIS

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Abstract

While most studies analyze the relationship between ESG and financial performance (FP) through a separate E, S and G spectrum, that approach fails to capture the risks behind a company's exposure to material ESG issues and its management. This study proposes a novel approach, based on ESG Risk and its two dimensions: Exposure and Management. To analyze their influence on financial performance, a combined cluster and panel regression analysis is employed on data for more than 2000 firms worldwide, between 2018 - 2022. Results show that companies tend to be grouped in ESG-FP performers and laggards. However, the GMM models employed at sample and cluster leve, respectively, reveal an inconclusive relationship between the financial and non-financial variables. Future research should explore alternative methodologies, data sources and longer time horizons to better understand the evolving dynamics between ESG risk dimensions and financial performance.

Keyword: ESG; financial performance; cluster analysis; panel regression analysis; risk mitigation.

JEL Classification: C33, C38, K32, Q56

1. Introduction

In recent years, the integration of Environmental, Social, and Governance (ESG) considerations into corporate strategies has drawn significant attention from investors, regulators and corporations themselves. While traditional financial metrics remain pivotal, there is an increasing belief that companies' performance must also be evaluated through the lens of their environmental, social and good governance practices, also driven by regulatory compliance. This paradigm shift has sparked interest among researchers, investors, and stakeholders alike, in exploring the relationship between ESG factors and financial performance. However, the precise nature of the relationship between ESG practices and financial outcomes remains a subject of debate. Moreover, while financial performance can be measured using well-established ratios, a

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consensus hasn't yet been reached when it comes to measuring ESG performance, as multiple ESG rating providers employ their own methodology in calculating these scores. Li and Polychronopoulos (2020) shows that ESG rating providers can be classified in 3 types, based on the data they provide: fundamental (e.g. Bloomberg), comprehensive (e.g. Morningstar Sustainalytics, LSEG, MSCI etc.) and specialist (e.g. Carbon Disclosure Project). Existing literature recognizes that multiple ESG rating providers might offer significantly different ESG scores for the same companies (Chatterji et al. (2016), Berg et al. (2022), Christensen et al. (2022)).

In this complex landscape, this paper aims to assess the influence of ESG on financial performance from a novel perspective, that of ESG Risk and its two dimensions: Exposure and Management, using a rigorous methodology that combines cluster analysis and panel regression techniques on a diverse sample of companies across industries and regions.

The rationale behind employing cluster analysis lies in its ability to identify distinct groups or clusters within a dataset based on similarities or differences in the variables under consideration. In the context of ESG-FP relationship, this methodology allows us to categorize companies into homogeneous groups based on their financial and ESG Risk profiles. By doing so, we can discern patterns and trends across these clusters, providing valuable insights into how different levels of ESG Risk, Exposure and Management may impact financial performance.

Complementing the cluster analysis, panel regression techniques offer a robust framework for quantitatively assessing the relationship between ESG and financial performance, while accounting for potential confounding variables and temporal dynamics.

This research seeks to address several key questions: What are the distinct clusters of companies based on their ESG Risk and financial profiles? Are there any patterns or trends in the relationship between ESG Risk and financial performance across these clusters and in the total sample? Additionally, how do contextual factors, such as firm size and leverage, influence this relationship?

Drawing upon a rich novel dataset and by employing a sound methodology, current study contributes to the ongoing dialogue surrounding sustainable investing, in general, and ESG and its impact on financial performance, in particular, fostering a positive impact for both businesses and society at large. Ultimately, this study upholds strategic decision-making for investors, asset managers, policymakers, and corporate leaders striving to create value through sustainable practices.

The rest of the paper is structured as follows: a critical review of the literature is presented next, followed by a comprehensive description of the data used in the empirical analysis, along with the methodological rationale. The final sections present and discuss the results obtained in the combined cluster and panel regression analysis, separately for each method employed. The paper concludes with managerial and policy implication, limitations and future study directions.

2. Literature review

One of the main reasons for which investors choose to integrate ESG considerations in their investment decisions is their long-studied influence on financial performance. An initial study of Friede et al. (2015) shows that researchers began looking for a link between social responsibility and corporate financial success around 1970s. After reviewing 2200 papers, the authors conclude that 90% of studies indicated a positive relationship between ESG and corporate financial performance. Eccles et al. (2014) delve into the impact of corporate sustainability on organizational processes and performance. Through a comprehensive analysis, they highlight the positive association between ESG practices and financial performance metrics, related to profitability and market valuation. Cheng et al. (2013) explore the relationship between corporate social responsibility (CSR) and access to finance. Their study employs panel regression analysis to assess how CSR practices influence firms' cost of capital and ability to attract investment. Their findings suggest that companies with strong CSR performance enjoy lower financing costs and greater access to capital markets, highlighting the financial benefits of ESG integration.

More recent studies, however, show mixed results when analysing the influence of ESG on financial performance. Alves et al. (2023), in a study of 16,000+ stocks over 2 decades, demonstrate that ESG investing did not systematically affect investment performance. On the other hand, Chen et al. (2023), on a dataset of 24,076 observations, find a significant ESG-FP relationship for large-scale companies and an insignificant relationship for small-scale companies. At industry level, some studies in automotive (Dincă et al. (2022)), industrials (Naimy et al. (2021)) or tourism (Uyar et al. (2020)), find mixed evidence on the relationship between ESG and financial performance, while others, such as in energy (Behl et al. (2021)), find a positive ESG-FP relationship. Liang and Renneboog (2020) conclude in a literature review on CSR and Sustainable Finance that “there is still no consensus about [whether] ESG-based investing helps or hurts performance”. Using a GMM-IV approach, Fain (2020) reveals that the relationship between financial and ESG performance is mostly neutral for companies in the MSCI ACWI index. Whelan et al. (2021), in a study of more than 1,000 papers on the ESG-FP relationship, also conclude that, while most studies show a positive relationship, the results indicate ongoing disagreement on the issue.

When it comes to the influence of ESG on financial performance from a risk and exposure perspective, we find very few studies that have approached this topic. Lopez de Silanes et al. (2019) find that ESG is correlated with decreased risk, but demonstrate that ESG scores have little or no impact on risk-adjusted financial performance. Hübel and Scholz (2019) construct three ESG risk factors (Environmental, Social and Governance) to quantify the ESG risk exposures of firms and find that strategically managing ESG risks may result in potential benefits for investors. From an ESG Risk, Exposure and Management perspective, especially, a gap in research is identified.

Regarding the variables used in the analysis of ESG-FP relationship, Margolis et al. (2009) conclude in their meta-analysis that most studies used either accounting-based measures (Return-on-Assets, Return-on-Equity) or market-based measures (stock returns, market-to-book value ratio) as dependent variables. Also, they noticed that most studies use firm size, firm risk and industry as control variables. Larger firms may have greater resources for ESG initiatives, while stable firms with lower risk generally appear more likely to engage in corporate sustainable practices. More recent studies (Velte (2017), Ahmad et al. (2021)) employ similar approaches, focusing on controlling firm-specific characteristics. Some authors suggest the existence of country-specific controls, such as GDP Growth (Diaye et al. (2022), Leogrande and Costantiello (2023)).

From a cluster analysis perspective, Vilas et al. (2022) use cluster analysis to detect differences among sustainability and conventional indices and suggest this method for validating the sustainable index classifications. Sariyer and Taşkın (2022) analyze Turkish-listed companies by performing a cluster analysis based on their environmental, social, and governance (ESG) scores using k-means clustering. They obtain a five-cluster solution.

Several studies have utilized panel regression analysis to explore the relationship between ESG and financial performance across diverse contexts. Khan et al. (2016) conducted a panel regression analysis of firms in emerging markets and observed a positive relationship between ESG performance and financial performance, albeit with variations across countries and industries. Their findings underscored the importance of considering contextual factors in assessing the impact of ESG practices on financial outcomes. Aydoğmuş et al. (2022) have employed a panel regression methodology with ROA and Tobin’s Q as dependent variables and E, S, G and combined ESG scores as independent variables, on data from Bloomberg and

Refinitiv. Authors also control for firm size and leverage and find a positive and significant influence of ESG scores on firm profitability.

From a combined machine learning and panel regression analysis methodological perspective, De Lucia et al. (2020) have run machine learning algorithms (k-nearest neighbour, neural networks etc.) to predict financial indicators such as ROA and ROE and apply an ordered logistic regression model to test whether any causal relationships between ESG investment decisions and ROA and ROE exist. Popa et al. (2022) performed a two-step cluster analysis in the first stage of the research and a regression analysis in the second stage on companies' financial and non-financial data. They identified a cluster of companies with good financial and non-financial outcomes and a cluster of companies with poor performance. Also, a direct, although weak in intensity but statistically significant correlation between ESEG disclosure index and financial performance has been found.

By reviewing the existing literature on the ESG-FP relationship, the following hyphothesis emerge:

H1. Based on ESG and financial performance, companies will be grouped 2 clusters: high-performers and low-performers.

H2. Higher ESG Risk has a negative effect of financial performance.

H3. Higher Exposure to material ESG issues has a negative effect on financial performance.

Additionally, due to the lack of existing research, a fourth exploratory hyphothesis is formulated:

H4. Better Management of ESG risks has a positive effect on financial performance.

3. Data

A novel dataset comprised of ESG and financial data for listed companies worldwide has been gathered at the beginning of 2024. ESG data has been obtained from Morningstar Sustainalytics, one of the largest ESG rating provider, while financial data was retrieved from the Morningstar Direct platform. ESG data refers to the following 3 variables: ESG Risk Score, Exposure Score, Management Score, all of which have been calculated monthly by Morningstar Sustainalytics starting with 2018 as part of their ESG Risk Rating product offering. In this study, we have calculated the yearly scores for the companies as the average of the monthly ESG scores in the 2018 – 2022 timeframe. Financial data was retrieved from the Morningstar Direct platform and refers to the following variables, calculated yearly: ROE, ROA, Tobin's Q, Total Assets and Leverage.

Below is a summary of the variables used in the analysis, along with the codification provided in paranthesis.

1. Return-on-Equity (*ROE*): The yearly Return-on-Equity is defined as Net Income / Average Total Common Equity and is expressed as percentage (%). It is considered an accounting-based measure of financial performance by expressing a company's ability to turn equity investments into profits.
2. Return-on-Assets (*ROA*): The yearly Return-on-Assets is defined as Net Income / Average Total Assets and is expressed as percentage (%). It is an accounting-based metric that indicates a company's profitability in relation to its total assets.
3. Tobin's Q (*TQ*): Also known as the Q ratio, is defined as Average Market Capitalization / Average Total Assets and expresed as percentage (%). It is a market-based indicator of financial performance that measures the market value of a company relative to its book value.
4. ESG Risk Score (*ESG_Risk_Score*): The ESG Risk Score is a measure of how well a company addresses risks and concerns related to corporate governance, material ESG

issues, and idiosyncratic issues. It applies the concept of risk decomposition to derive the level of unmanaged risk for a company, which is assigned to one of five risk categories. The score ranges from 0 and 100, with 0 indicating that risks have been fully managed (no unmanaged ESG risks) and 100 indicating the highest level of unmanaged risk. The scores are normalized by industry to allow for comparability between companies operating in the same sector.

5. Exposure Score (*Exposure_Score*): The Exposure score measures the extent to which a company is exposed to ESG Risks. The score ranges from 0 to 100, with 0 indicating no exposure and 100 indicating very high exposure.
6. Management Score (*Management_Score*): The Management score measures a company's ability to handle ESG risks across issues. The score ranges from 0 to 100, with 0 indicating no (evidence of) management and 100 very strong management.
7. Total Assets (*Total_Assets*): The reported value of a company's Total Assets each year, expressed in million US dollars. This variable is used to account for a firm's size.
8. Financial Leverage (*Leverage*): This measure is expressed by the Equity Multiplier, defined by Total Assets / Common Equity. A company with a low Equity Multiplier has financed a large portion of its assets with equity, meaning they are not highly leveraged. This variable will be used as a control variable, to account for firm risk.

The initial dataset contained 2375 companies for which we had complete ESG and financial data in the timeframe 2018 – 2022. After removing outliers, the final dataset contained data for 2177 companies across 5 years, resulting in 10885 firm-year observations. The companies' distribution by country and sector is found in Appendix A.

Table 1 below illustrates the descriptive statistics, while Table 2 shows the Pearson correlation coefficients between variables.

Table 1

Descriptive statistics

	n	Mean	Median	SD	Minimum	Maximum
ROE	10885	17.73	15.49	23.38	-222.03	452.20
ROA	10885	7.54	6.33	9.09	-64.56	103.72
TQ	10885	1.79	0.95	2.76	0.01	63.21
ESG_Risk_Score	10885	25.52	24.02	9.99	5.34	72.46
Management_Score	10885	39.22	38.96	15.00	1.00	85.55
Exposure_Score	10885	40.41	38.30	13.25	15.15	96.15
Total_Assets	10885	279145.66	79530	731662	451.84	12953062
Leverage	10885	3.26	2.34	3.66	1.01	93.53

Source: Morningstar Sustainalytics, authors' calculation in R Studio

The medians for the accounting-based measures, ROE and ROA, are of 15.49% and 6.33%, respectively, whilst Tobin's Q stands at 0.95. This suggests that our dataset contains companies efficient at generating profits and fairly valued. The correlation matrix shows high correlations between the ESG variables. Also, there is a high correlation between ROA and ROE and moderate correlations between Tobin's Q and ROA and Total Assets, respectively. Interestingly, there is a moderate correlation between the Management Score and Total Assets, suggesting that large companies have the necessary resources and invest in managing their ESG risks.

Table 2

Correlation matrix

	ROE	*ROA*	*TQ*	*Leverage*	*ESG Risk Score*	*Management Score*	*Exposure Score*	*Total Assets*
ROE	1.00							
ROA	0.77	1.00						
TQ	0.18	0.35	1.00					
Leverage	0.03	-0.18	-0.15	1.00				
ESG Risk Score	-0.06	-0.05	-0.02	-0.03	1.00			
Management Score	0.01	-0.07	-0.18	0.11	-0.50	1.00		
Exposure Score	-0.07	-0.11	-0.15	0.04	0.79	0.11	1.00	
Total Assets	-0.04	-0.24	-0.38	0.34	-0.07	0.41	0.20	1.00

Source: Morningstar Sustainalytics, authors' calculation in R Studio

4. Methodology

To study the influence of ESG factors on financial performance, a combined cluster and panel regression analysis was applied.

To determine which companies have similar ESG and financial characteristics, current study employs both hierarchical and partitional clustering methods on yearly-divided datasets, with standardized variables.

First, the hierarchical methods, as a means of unsupervised learning, help us identify the grouping of the companies without knowing the optimal number of clusters a priori. The analysis is first performed on the latest yearly dataset, i.e. 2022, and then on the previous years to test the stability of the clusters. To determine the optimal number of clusters, we calculate indices from R's NbClust package.

After determining the optimal number of clusters for our dataset using hierarchical methods, we also apply partitional methods – k-means, as a means of supervised learning, and compare the results to validate the stability of the clusters. Unlike hierarchical clustering methods, partitional methods require the a priori knowledge of the number of clusters.

Once our clusters are determined, we apply a panel regression methodology on both the full sample and the resulting clusters, with the goal of determining the influence of ESG factors on financial performance in both scenarios. Since the VIF factors for the ESG_Risk_Score, Exposure_Score and Management_Score variables are above 5 (Appendix A, Fig. A1), we run the following models at both full sample and cluster level:

$$ROE_{it} = \beta_0 + \beta_1 ESG\_Risk\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it} \quad (1)$$
$$ROE_{it} = \beta_0 + \beta_1 Exposure\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it} \quad (2)$$
$$ROE_{it} = \beta_0 + \beta_1 Management\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it} \quad (3)$$

$ROA_{it} = \beta_0 + \beta_1 ESG\_Risk\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it}$ (4)
$ROA_{it} = \beta_0 + \beta_1 Exposure\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it}$ (5)
$ROA_{it} = \beta_0 + \beta_1 Management\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it}$ (6)
$TQ_{it} = \beta_0 + \beta_1 ESG\_Risk\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it}$ (7)
$TQ_{it} = \beta_0 + \beta_1 Exposure\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it}$ (8)
$TQ_{it} = \beta_0 + \beta_1 Management\_Score_{it} + \beta_2 \log(Total\_Assets)_{it} + \beta_3 Leverage_{it} + \varepsilon_{it}$ (9)

As a preliminary step in the panel regression analysis, we run several tests/diagnostics to determine the most suitable panel regression model. The tests/diagnostics performed are shown below in Table 3.

Table 3

Test/diagnostics for panel data models

Test/Diagnostic	Hypothesis
Augmented Dickey-Fuller test (for each variable)	H0: Series has a unit root H1: No unit root is present
F test for individual effects	H0: Non-significant individual effects H1: Significant individual effects
Hausmann test	H0: RE and FE estimates are consistent H1: RE estimates are inconsistent
F test for time-fixed effects	H0: Non-significant time-fixed effects H1: Significant time-fixed effects
Lagrange Multiplier Test (Breusch-Pagan) for random effects	H0: No panel effect H1: Panel effect
Pesaran CD test for cross-sectional dependence in panels	H0: Non-correlation of residuals across entities H1: Correlation of residuals across entities
Breusch-Godfrey/Wooldridge test for serial correlation in panel models	H0: No serial correlation in idiosyncratic errors H1: Serial correlation in idiosyncratic errors
Breusch-Pagan test	H0: Homoskedasticity H1: Heteroskedasticity
Wu-Hausman test	H0: Exogenous regressor H1: Endogenous regressor

5. Results

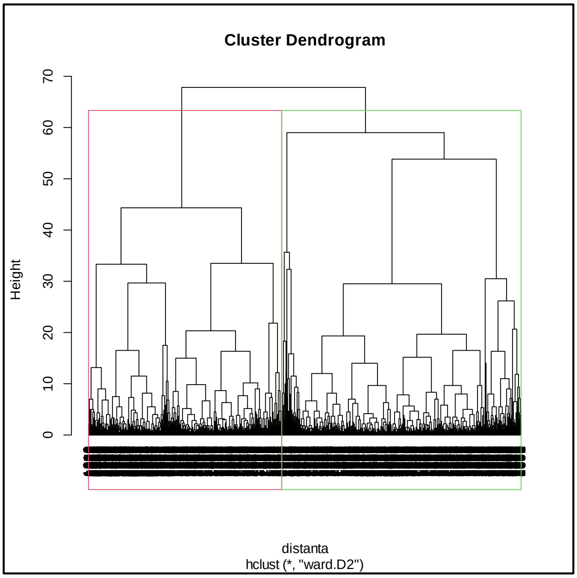
5.1. Cluster Analysis

5.1.1. Hierarchical clustering

Figure 1 below shows the cluster dendrogram obtained by applying the Ward method on Euclidean distances for the dataset with standardized variables for the year 2022. Visually, the figure highlights the existence of 2 clusters.

Figure 1

Cluster dendrogram for the 2022 dataset



Source: Created by authors in R Studio, based on Morningstar Sustainalytics data

The optimal number of clusters for this dataset, given by the NbClust indexes can be found in Appendix B. Among the 22 calculated indices of the NbClust packages:

- 5 proposed 2 as the best number of clusters;
- 3 proposed 3 as the best number of clusters;
- 4 proposed 4 as the best number of clusters;
- 2 proposed 5 as the best number of clusters;
- 2 proposed 6 as the best number of clusters;
- 5 proposed 8 as the best number of clusters;

In conclusion, according to the majority rule, the optimal number of clusters is 2. Therefore, we will continue the analysis with a pre-determined two-cluster solution, based on unsupervised methods.

5.1.2. Partitional clustering

Having determined a two-cluster solution, we run the k-means algorithm first on the da-taset for the year 2022, as the latest dataset, and then for the previous years. Table 4 below shows the differences in cluster allocation between hierarchical and k-means methods, for the year 2022.

Analyzing Table 4, we notice a clustering accuracy of approx. 85% using the two meth-ods. Similar results are found when comparing the accuracy for the datasets 2018, 2019, 2020 and 2021 (Appendix B, Tables B2 - B5). Therefore, we conclude that a two-cluster solution is optimal for our datasets.

Table 5 below shows the median values for the analyzed variables, by cluster, for the 2022 dataset.

Table 4

Cluster allocation for the 2022 dataset, by method

Clust. Accuracy = 84.8%		K-means	
		Cluster 1	Cluster 2
Hierarchical	Cluster 1	1042	164
	Cluster 2	167	804

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Table 5

Median values for the 2022 dataset variables, by cluster.

	Cluster 1: Laggards (n=968)	Cluster 2: Performers (n=1209)
ROE	13.35	19.26
ROA	4.67	8.26
TQ	0.59	1.14
ESG_Risk_Score	29.27	17.69
Management_Score	43.33	46.03
Exposure_Score	49.65	32.05
Total_Assets	13180.33	7277.23
Leverage	2.55	2.12

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Analyzing Table 5, we notice the following clusters:

1. Laggards: companies with below average performance both financially and in terms of ESG.
2. Performers: companies with above average performance both financially and in terms of ESG.

This result confirms our hyphothesis of a two-cluster solution, based on existing literature.

Therefore, we will continue the analysis with a two-cluster solution. The dataset for the panel regression analysis will be split according to the cluster allocation given by the k-means algorithm.

5.2. Panel regression analysis

5.2.1. Panel tests/diagnostics

First, several tests are conducted to determine the most suitable static panel model for the datasets, respectively pooled OLS, fixed effects (FE) or random effects (RE). The results of the F test for individual effects, Hausmann test and F test for time-fixed effects show that almost all models should be run under the specification of a time-fixed effects panel model, except for models (7), (8), (9) for the Laggards cluster, which should be run under a random effects panel model specification (Appendix C, Tables C1 – C3).

Secondly, the Pesaran CD and the Breusch-Godfrey/Wooldridge test results (Appendix C, Tables C1 – C3) show that all models have cross-sectional dependence and serial correlation in the error term. According to Baltagi (2008), cross-sectional dependence and serial correlation are problems in macro panels with long time series, but these are not problems in micro panels (few years and large number of cases) such as ours (T = 5, N1 = 2177, N2 = 968, N3 = 1209)

Lastly, the Breusch-Pagan test shows that heteroskedasticity is present in the models employed by this study, while the Wu-Hausman tests for all models show that the ESG variables present endogeneity.

Consequently, to address these problems, a difference Generalized Method of Moments (GMM) approach is employed, with the second lag of the ESG measures used as instrumental variables.

$$\Delta \text{ROE}_{it} = \beta_1 \Delta \text{ROE}_{i(t-1)} + \beta_2 \Delta \text{ESG\_Risk\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (1)$$

$$\Delta \text{ROE}_{it} = \beta_1 \Delta \text{ROE}_{i(t-1)} + \beta_2 \Delta \text{Exposure\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (2)$$

$$\Delta \text{ROE}_{it} = \beta_1 \Delta \text{ROE}_{i(t-1)} + \beta_2 \Delta \text{Management\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (3)$$

$$\Delta \text{ROA}_{it} = \beta_1 \Delta \text{ROA}_{i(t-1)} + \beta_2 \Delta \text{ESG\_Risk\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (4)$$

$$\Delta \text{ROA}_{it} = \beta_1 \Delta \text{ROA}_{i(t-1)} + \beta_2 \Delta \text{Exposure\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (5)$$

$$\Delta \text{ROA}_{it} = \beta_1 \Delta \text{ROA}_{i(t-1)} + \beta_2 \Delta \text{Management\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (6)$$

$$\Delta \text{TQ}_{it} = \beta_1 \Delta \text{TQ}_{i(t-1)} + \beta_2 \Delta \text{ESG\_Risk\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (7)$$

$$\Delta \text{TQ}_{it} = \beta_1 \Delta \text{TQ}_{i(t-1)} + \beta_2 \Delta \text{Exposure\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (8)$$

$$\Delta \text{TQ}_{it} = \beta_1 \Delta \text{TQ}_{i(t-1)} + \beta_2 \Delta \text{Management\_Score}_{it} + \beta_3 \Delta \log(\text{Total\_Assets}_{it}) + \beta_4 \Delta \text{Leverage}_{it} + \Delta \epsilon_{it} \quad (9)$$

5.2.1. Regression results

Regression results are provided at total sample, laggards and performers cluster level, with a total of 27 models, 9 for each dataset (Appendix D).

5.2.1.1. Total sample

The regression results for the total sample can be found in Appendix D, Table D1. Analysing this table, a non-significant relationship between the ESG and financial performance variables is generally observed, with the exception of the Exposure Score, which is found to positively affect companies' Return-on-Equity. Nevertheless, this relationship is not found in the case of the other two financial performance variables. These results are consistent with the large majority of recent studies on the ESG-FP relationship, where a clear relationship has not yet been found. The results of the Sargan and Arellano-Bond tests confirm that the instruments are valid when the dependent variables are ROE and ROA, while for the case of Tobin's Q, a more complex specification of the GMM is required.

5.2.1.2. Cluster 1: Laggards

The regression results for the Laggards cluster can be found in Appendix D, Table D2. Analysing this table, no significant relationship between ESG and FP variables are observed. Moreover, in the case of Tobin's Q as dependent variable, a more complex specification of the difference GMM is required, given the results of the Sargan and Arellano-Bond tests. As

5.2.1.3. Cluster 2: Performers

The regression results for the Performers cluster can be found in Appendix D, Table D2. At this cluster level, positive coefficients are identified only for ESG Risk Score and the Exposure Score, when the dependent variable is ROE,. Same as for the previous models, this positive relationship is not confirmed for the other 2 dependent variables, suggesting an overall unclear relationship between the ESG and financial performance variables. The results of the Sargan and Arellano-Bond tests confirm that the instruments are valid only when the dependent variables are ROE and ROA.

6. Conclusions

In this paper, a combined cluster and panel regression analysis assessed the influence of ESG Risk, Exposure and Management on financial performance, measured by ROE and ROA, as accounting-based measures, and Tobin's Q, as market-based measure, on a significant number of companies worldwide.

Through cluster analysis, namely using hierarchical and partitional methods, distinct groups of companies were identified, characterized by their financial and ESG risk profiles. This segmentation evidenced patterns and trends across these clusters, shedding light on the connection between financial and non-financial characteristics. An optimal two-cluster solution was obtained, with companies grouping in either a „Performers" cluster or „Laggards" cluster, confirming initial hyphothesis based on existing literature.

Complementing the cluster analysis, panel regression models provided quantitative evidence of the relationship between ESG risk and financial performance, both at total sample and cluster level. The findings underscored a largely statistically insignificant correlation between ESG v and financial performance variables, both at total sample and cluster levels. That is, companies with high ESG Risks and high Exposure to ESG Risks tend to neither underperform nor overperform financially. Interestingly, a significant, positive correlation between the ESG Risk and Exposure Scores and ROE was found at the total sample and the "performers" cluster level.

Reflecting on the implications of the findings, several key takeaways emerge. Firstly, the short-term effects of ESG factors on financial performance, measured by market-based and accounting-based indicators, are yet to be proven, both at total sample and cluster level. The results of this study are in line with the most recent research on the topic, that utilized approximately the same methodology – panel data regression. An unique contribution is the examination of the ESG-FP relationship from an ESG risk perspective, composed of ESG Exposure and ESG Management. This study significantly contributes to the existing literature by also leveraging an extensive database and sample of companies worldwide from one of the most important ESG data providers. Data from other ESG data providers, such as RepRisk, that measure ESG performance from a reputational risk perspective could also be utilized in future studies, as well as an improved GMM methodology or other techniques that provide evidence on the short- and long-term impact of ESG on financial performance.

Secondly, current research highlights the need for ongoing monitoring, evaluation, and adaptation of ESG practices to navigate evolving regulatory landscapes, market dynamics, and societal expectations. Even though there is no clear relationship between ESG factors and financial performance, companies that embrace a proactive and iterative approach to ESG integration should be better positioned to mitigate risks and build resilience in the face of uncertainty. An assessment of the ESG-FP relationship over more than 5-6 years is recommended, given the long-term aim of ESG – sustainability.

In conclusion, current study contributes to the growing literature on ESG and sustainable investing by offering a comprehensive analysis on the relationship between ESG Risks and financial performance. By leveraging a rigurous methodology, a combined cluster and panel regression analysis, this study deepens understanding of this complex relationship and provided valuable insights for investors, asset managers, policymakers, and organizations alike.

Appendix A

Table A1

Distribution of companies by Region/Country

Region/Country	Count of CompanyId
Africa / Middle East	**8**
Israel	7
South Africa	1
Asia / Pacific	**912**
Australia	131
China	230
Indonesia	17
Japan	358
New Zealand	9
Singapore	21
South Korea	80
Taiwan	65
Thailand	1
Europe	**513**
Austria	5
Belgium	4
Cyprus	1
Czech Republic	1
Finland	1
France	94
Germany	85
Gibraltar	1
Ireland	20
Italy	24
Luxembourg	13
Netherlands	31
Portugal	1
Russian Federation	1
Spain	26
Switzerland	51
United Kingdom	154
Latin America and Caribbean	**46**
Bermuda	12
Brazil	31
Mexico	1
Panama	1
Uruguay	1
United States and Canada	**698**
Canada	44
United States of America	654
Total	**2177**

Source: Morningstar Sustainalytics, authors' calculation in R Studio

Table A2

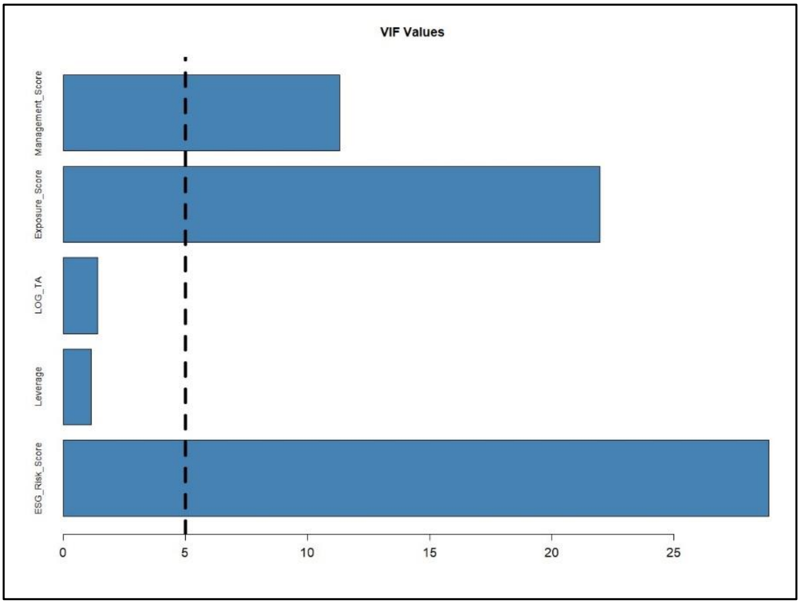
Distribution of companies by Sector

Sector	Count of CompanyId
Consumer Discretionary	306
Consumer Staples	160
Energy	81
Financials	139
Healthcare	193
Industrials	414
Information Technology	343
Materials	233
Real Estate	167
Telecommunication Services	37
Utilities	104
Total	**2177**

Source: Morningstar Sustainalytics, authors' calculation in R Studio

Figure A1

Variance inflation factors (VIF) for the independent variables



Source: Created by authors in R Studio, based on Morningstar Sustainalytics data

Appendix B

Table B1

Optimal number of clusters given by the NbClust indexes

NbClust index	Reference	Optimal number of clusters
KL index	Krzanowski & Lai (1988)	5
CH index	Calinski & Harabasz (1974)	4
Hartigan index	Hartigan (1975)	4
Cubic Clustering Criterion (CCC)	Sarle (1983)	2
Scott index	Scott & Symons (1971)	3
Marriot index	Marriot (1971)	6
TraceCovW index	Milligan & Cooper (1985)	3
TraceW index	Milligan & Cooper (1985)	4
Friedman index	Friedman & Rubin (1967)	8
Rubin index	Friedman & Rubin (1967)	5
C-index	Hubert & Levin (1976)	8
DB index	Davies & Bouldin (1979)	8
Silhouette index	Kaufman & Rousseeuw (1990)	6
Beale index	Beale (1969)	2
Ratkowsky index	Ratkowsky & Lance (1978)	4
Ball index	Ball & Hall (1965)	3
PtBiserial index	Milligan (1980,1981)	8
Frey index	Frey & Van Groenewoud (1972)	1
Mcclain index	McClain & Rao (1975)	2
Dunn index	Dunn (1974)	2
SDindex	Halkidi et al. (2000)	2
SDbw	Halkidi et al. (2001)	8

Source: Authors' calculation in R Studio, based on the NbClust package (Charrad et al. (2012) and Morningstar Sustainalytics data

Table B2

Cluster allocation for the 2021 dataset, by method

Clust. Accuracy = 81.2%		K-means	
		Cluster 1	Cluster 2
Hierarchical	Cluster 1	523	18
	Cluster 2	393	1243

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Table B3

Cluster allocation for the 2020 dataset, by method

Clust. Accuracy = 87.9%		K-means	
		Cluster 1	Cluster 2
Hierarchical	Cluster 1	766	146
	Cluster 2	117	1148

Table B4

Cluster allocation for the 2019 dataset, by method

Clust. Accuracy = 92.5%		K-means	
		Cluster 1	Cluster 2
Hierarchical	Cluster 1	922	149
	Cluster 2	14	1092

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Table B5

Cluster allocation for the 2018 dataset, by method

Clust. Accuracy = 82.8%		K-means	
		Cluster 1	Cluster 2
Hierarchical	Cluster 1	893	51
	Cluster 2	325	908

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Appendix C

Table C1

Tests/Diagnostics results for Total Sample initial models

	p-values								
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
F test for individual effects	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausmann test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F test for time-fixed effects	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pesaran CD test for cross-sectional dependence	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey/Wooldridge test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Pagan test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wu-Hausman test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Table C2

Tests/Diagnostics results for Cluster 1: Laggards initial models

	p-values								
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
F test for individual effects	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausmann test	0.000	0.000	0.000	0.000	0.000	0.000	0.789	0.408	0.055
F test for time-fixed effects	0.000	0.000	0.000	0.000	0.000	0.000	-	-	-
Lagrange Multiplier Test (Breusch-Pagan)	-	-	-	-	-	-	0.000	0.000	0.000
Pesaran CD test for cross-sectional dependence	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey/Wooldridge test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Pagan test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wu-Hausman test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Table C3

Tests/Diagnostics results for Cluster 2: Performers initial models

	p-values								
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
F test for individual effects	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausmann test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F test for time-fixed effects	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pesaran CD test for cross-sectional dependence	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey/Wooldridge test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Pagan test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wu-Hausman test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' calculation in R Studio, based on Morningstar Sustainalytics data

Appendix D

Table D1

Total sample panel regression results (GMM)

Dependent variable:	ROE			ROA			TQ		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Dependent (1)	0.51***	0.51***	0.51***	0.60***	0.604***	0.605***	2.330*	2.334*	2.328*
ESG_Risk_Score	0.12	-	-	0.043	-	-	-0.005	-	-
Exposure_Score	-	**0.220****	-	-	0.065	-	-	-0.013	-
Management_Score	-	-	0.006	-	-	-0.014	-	-	-0.007
Log(Total_Assets)	5.94	6.03*	5.823	3.993**	4.015**	3.978	-3.15**	-3.168**	-3.14**
Leverage	-2.66	-2.65*	-2.67*	-0.449**	-0.446**	-0.449	0.004	0.004	0.005
Sargan Test (p-value)	0.144	0.144	0.147	0.599	0.595	0.611	0.013	0.013	0.013
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.01	0.010	0.011
AR(2) (p-value)	0.11	0.115	0.117	0.066	0.064	0.066	0.24	0.243	0.245
Wald test for coefficients (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.035	0.020	0.058
Wald test for time dummies (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firm-year observations	10885	10885	10885	10885	10885	10885	10885	10885	10885

$* \, p < 0.1$; $** \, p < 0.05$; $*** \, p < 0.01$.

Table D2

Cluster 1: Laggards panel regression results (GMM)

Dependent variable:	ROE			ROA			TQ		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Dependent (1)	0.460***	0.459***	0.460***	0.553***	0.552***	0.553***	1.163	1.169	1.158
ESG_Risk_Score	-0.025	-	-	-0.003	-	-	0.003	-	-
Exposure_Score	-	0.117	-	-	0.035	-	-	-0.006	-
Management_Score	-		0.043	-		-0.005	-	-	-0.011
Log(Total_Assets)	12.947*	13.11*	12.958*	6.973***	7.01***	6.974***	-1.485	-1.503	-1.479
Leverage	-3.526**	-3.51**	-3.527**	-0.662**	-0.658**	-0.662	0.012	0.012	0.011
Sargan Test (p-value)	0.899	0.902	0.899	0.828	0.826	0.827	0.119	0.122	0.119
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.256	0.254	0.26
AR(2) (p-value)	0.412	0.40	0.409	0.59	0.572	0.591	0.570	0.568	0.57
Wald test for coefficients (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.537	0.431	0.000
Wald test for time dummies (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firm-year observations	4840	4840	4840	4840	4840	4840	4840	4840	4840

$*\ p < 0.1$; $**\ p < 0.05$; $***\ p < 0.01$.

Table D3

Cluster 2: Performers panel regression results (GMM)

Dependent variable:	ROE			ROA			TQ		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Dependent (1)	0.440***	0.482***	0.480***	0.667***	0.661***	0.661***	1.872*	1.877*	1.867*
ESG_Risk_Score	**0.366****			0.109			-0.019		
Exposure_Score		**0.294***			0.103			-0.018	
Management_Score			-0.087			-0.021			0.006
Log(Total_Assets)	4.003	2.85	2.816	1.264	1.233	1.243	-3.359*	-3.357*	-3.345
Leverage	-1.423	1.314	-1.322	-0.197	-0.199	-0.200	-0.026	-0.025	-0.026
Sargan Test (p-value)	0.115	0.0506	0.0507	0.681	0.674	0.706	0.027	0.027	0.026
AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.078	0.078	0.079
AR(2) (p-value)	0.065	0.071	0.068	0.051	0.042	0.038	0.287	0.286	0.289
Wald test for coefficients (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.062	0.065	0.108
Wald test for time dummies (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firm-year observations	6045	6045	6045	6045	6045	6045	6045	6045	6045

∗ $p < 0.1$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.

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