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What you see is not what you get: ESG scores and greenwashing risk

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ABSTRACT

This paper shows that ESG scores capture a company's greenwashing behavior. Greenwashing accusations are most prevalent among large companies with high ESG scores. We empirically employ a novel theoretical model that distinguishes between the communication of a company's environmental efforts (apparent environmental performance) and its actual environmental impact (real environmental performance). The correlation of the apparent (real) environmental performance with ESG scores is significantly positive (negative). Therefore, ESG scores are unsuitable for measuring real environmental impact. Thus, investors focusing on high ESG-rated companies may unknowingly increase their greenwashing risk exposure, and academics may use misleading information to assess greenwashing risk.

1. Introduction

This study examines the relationship between environmental, social, and governance (ESG) scores and greenwashing risk, focusing on whether high ESG scores reflect reduced greenwashing risk. This analysis is crucial for both investment decision-making and academic research, as it explores the extent to which ESG scores indicate sustainability practices. The growing sustainability awareness has led investors and consumers to consider ESG aspects in their decision-making (Liu et al., 2023). In this context, the ESG investment market has grown to $30 trillion in 2022 and is expected to cover about 25% ($40 trillion) of the entire global investment in 2040 (Bloomberg, 2024). A widely used source of information for investors in investment decision-making and for academics in research projects are ESG scores, which at the same time are unreliable and inconsistent (Benuzzi et al., 2023; Berg et al., 2022; Chatterji et al., 2016; Dorfleitner et al., 2015). The absence of reliable ESG scores may impede their consideration in investment decisions and mislead investors' decision-making (Li et al., 2024b). High ESG scores may result from manipulation driven by managerial incentives such as ESG-related compensation (Cohen et al., 2023), better access to capital (Amiraslani et al., 2023), high reputation (Galletta et al., 2023), and after index inclusion (Goyal et al., 2023). Additionally, a lack of transparency in rating methodologies exacerbates these inconsistencies (Berg et al., 2021). However, integrating ESG scores into investment decisions aims to mitigate risk (Lins et al., 2017; Pistolesi and Teti, 2024; Utz, 2018), yet misleading ESG scores may increase greenwashing risk (Sun, 2024).

Investors are willing to sacrifice returns to prevent greenwashing risk (Kleffel and Muck, 2023) and aim to avoid greenwashing companies in the long term (Li et al., 2024b). In this regard, we investigate whether investing in companies with high ESG scores

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helps mitigate greenwashing risk. To achieve this, we hand-collect greenwashing cases of the STOXX Europe 600 constituents from 2015 to 2023 and relate them to ESG scores from the data providers LSEG (formerly Refinitiv) and Bloomberg. Portfolios double-clustered by ESG score and company size quartiles reveal that companies with high ESG scores and large sizes contain the highest numbers of greenwashing cases. Tests, based on greenwashing risk estimated following the theoretical model of Dorfleitner and Utz (2023) show that ESG scores primarily reflect the apparent environmental performance that refers to the perceived strengths of a company's ecological efforts, reflecting the claims made in its reports. In contrast, the real environmental performance, i.e., a company's actual ecological effectiveness and impact based on quantifiable outcomes, correlates negatively with ESG scores.

Moreover, more analysts following a company mitigate the difference between a company's apparent and real environmental performance, particularly for small, CO_2-intensive companies, and those from brown industries. This supports previous findings that analyst coverage decreases information asymmetry and helps mitigate greenwashing risk (Liu et al., 2023).

The contribution of this paper to academia regards the assessment of greenwashing and its relationship with ESG scores. In general, greenwashing is difficult to detect (Kleffel and Muck, 2023), and companies' greenwashing strategies must be analyzed and examined accurately (Yuan et al., 2024). One common approach to identifying greenwashing behavior is to calculate the difference between standardized ESG disclosure and performance scores (Jin et al., 2024; Li et al., 2024a; Lin et al., 2023; Liu et al., 2023; Liu and Li, 2024; Peng and Xie, 2024; Sun, 2024; Yu et al., 2020; Zhang, 2023). We adopt this method as an additional measure of greenwashing risk and sort portfolios accordingly. The analysis reveals that this approach does not fully capture greenwashing cases in our sample.

2. Sample and methodology

2.1. Greenwashing cases and sample

According to Bloomberg (2024), Europe will remain the largest ESG market by 2030, with over \$18 trillion under management. Thus, we focus our analysis on the STOXX Europe 600 constituents from 2015 to 2023. This stock index covers approximately 90% of the free-float market capitalization in Europe. We match this sample with ESG-related data from LSEG, Bloomberg, RepRisk, and S&P Trucost and with financial data from LSEG. Our final sample includes 848 companies with 5,888 company-years.

To assess whether these companies engaged in greenwashing activities, research assistants conducted searches for greenwashing and related terms across web search engines, NGO websites, and social media platforms such as X (formerly Twitter) for each company-year. In the first step, we applied quality checks for the obtained greenwashing indications and retained 417 hand-collected greenwashing cases. We assess these information sources of greenwashing cases following our assessment framework (see Table A.1 in the appendix).

Table 1 shows the summary statistics of our sample. *United Kingdom*, *Germany*, and *France* account for almost 50% of the observations in the sample, but represent only about 30% of the greenwashing cases. The distribution of companies across individual sectors is balanced. The highest relative occurrences of greenwashing cases are in the *Utilities* (15.91%) and *Energy* (12.32%) sectors.

In the second step, four researchers (different from those in Step 1) independently assessed the severity of the hand-collected greenwashing cases. Table A.2 (appendix) describes the employed classification scheme, with a scale from 0% (no greenwashing) to 100% (greenwashing). This human judgment procedure leads to four greenwashing severity scores for each greenwashing case. We define the mean of the four assessments as the greenwashing severity score for each greenwashing case.

Table 1 (last two columns) shows the country and industry averages for the mean and standard deviation of greenwashing severity scores in the sample of greenwashing cases. Emissions-intensive sectors (*Basic Materials, Utilities, Energy*) and customer-related industries (*Consumer Discretionary, Consumer Staples*) show the highest greenwashing severity scores. Across countries and industries, higher average greenwashing severity scores tend to come with lower standard deviations across the four assessments.

2.2. ESG scores and greenwashing cases

Table 2 presents the number of greenwashing cases across double-sorted portfolios. Panel A shows portfolios sorted first by LSEG ESG scores and then by company size (log sales), both in ascending order from the lowest ("1 (low)") to the highest ("4 (high)") quartile. For example, portfolio "1-LSEG ESG scores" and portfolio "1-company size" represent 6.25% of company-years, containing the smallest companies within the lowest ESG scores company-years in our sample. Panels B–E follow the same logic but are sorted first by the variable mentioned at each panel's heading.

The most greenwashing cases in Panel A occur in high-ESG portfolios, with the frequency increasing as company size grows. A similar pattern is observed using Bloomberg ESG scores (Panel B). Thus, high ESG scores positively correlate with more greenwashing cases, especially for large companies.

Bloomberg ESG Disclosure scores (Panel C) reflect the extent of companies' disclosure of ESG-related information. We observe more greenwashing cases in portfolios with high disclosure, particularly as company size increases, i.e., these companies may be more likely to overstate their sustainable practices.

Moreover, as a benchmark, we determine greenwashing risk following the approach of recent studies (e.g., Jin et al., 2024; Li et al., 2024a; Lin et al., 2023; Liu et al., 2023; Liu and Li, 2024; Peng and Xie, 2024; Sun, 2024; Yu et al., 2020; Zhang, 2023) and classify portfolios accordingly. The high greenwashing portfolio in Panel D (E) accounts for only 98 (119) of the 391 (376) total

Table 1
Summary statistics of greenwashing cases per country and industry.

	Full sample		Subsample GW cases			
	N	Company-years	Company-years GW	GW obs. (%)	mean GW severity (%)	SD GW severity (%)
Panel A: Country						
Belgium	23	166	2	1.20	37.50	32.48
Denmark	26	183	11	6.01	72.16	22.82
Finland	27	190	4	2.11	84.38	16.34
France	91	671	65	9.69	58.17	21.86
Germany	100	679	81	11.93	76.00	15.22
Italy	43	279	11	3.94	74.43	16.45
Netherlands	47	309	13	4.21	68.27	17.70
Norway	25	167	7	4.19	87.50	17.99
Spain	40	294	21	7.14	60.12	20.89
Sweden	69	460	11	2.39	75.57	16.18
Switzerland	64	472	27	5.72	74.77	15.51
United Kingdom	207	1,395	122	8.75	72.85	18.89
Other	86	623	42	6.74	69.54	20.24
Panel B: Industry						
Basic materials	68	510	45	8.82	81.02	11.97
Consumer discretionary	141	961	98	10.20	71.17	17.95
Consumer staples	68	478	53	11.09	74.69	15.40
Energy	45	284	35	12.32	74.94	18.21
Financials	160	1,149	73	6.35	63.87	21.48
Health care	26	196	12	6.12	47.40	22.55
Industrials	178	1,243	52	4.18	64.78	23.36
Real estate	27	186	1	0.54	31.25	20.73
Technology	57	343	2	0.58	62.50	34.73
Telecommunications	40	274	4	1.46	67.19	26.55
Utilities	38	264	42	15.91	75.15	18.12
Total	**848**	**5,888**	**417**			

Notes: This table presents summary statistics of greenwashing (GW) cases and severity scores, categorized by country and industry, for companies in the STOXX Europe 600 index from 2015 to 2023. "Full sample" includes all companies in our sample, "Subsample GW cases" includes only the greenwashing company-year observations. Column "N" denotes the number of companies and Column "GW obs. (%)" contains the proportion of greenwashing cases compared to all companies in the sample. Column "mean GW severity (%)" ("SD GW severity (%)") shows the mean (standard deviation) of the greenwashing severity scores in percentage values based on the sample of greenwashing cases.

greenwashing cases.[1] Thus, these greenwashing risk measures do not reflect the actual greenwashing cases properly, highlighting the need for more reliable estimation approaches.

Table 3 shows the development of greenwashing and ESG-related variables over our sample period, separately for the greenwashing (GW) and non-greenwashing (non-GW) samples. The number of greenwashing cases increases over time. Moreover, the values of ESG variables in company-years with greenwashing accusations are, on average, higher than those in company-years without greenwashing accusations (Columns (4)–(9)).[2]

3. Greenwashing risk and estimation

3.1. Theoretical foundation

ESG data providers typically rely on publicly available information, such as SEC filings and company-generated sustainability reports, to construct their ratings. However, the information in these reports is often unaudited and may lack reliability (e.g., Yu et al., 2020). Long-term goals, such as emission reduction targets, can be particularly challenging for companies to substantiate, providing opportunities for potential greenwashing behavior. As shown in the previous section, ESG scores and the likelihood of engaging in greenwashing practices correlate positively.

From a theoretical perspective, the observed relationship can be explained through signaling theory (Spence, 1973), institutional theory (DiMaggio and Powell, 1983), and moral licensing theory (Merritt et al., 2010). Market pressure and reputational concerns can drive companies to greenwash as they face intense scrutiny from investors and other stakeholders. This scrutiny creates strong

[1] In Panels D and E of Table 2, we standardize the ESG Disclosure scores and ESG scores across the entire sample, following the widely adopted standardization method (e.g., Jin et al., 2024; Lin et al., 2023; Liu and Li, 2024; Peng and Xie, 2024) to calculate greenwashing behavior. For robustness, we also perform standardization by year (see Table A.5) and by industry-year (see Table A.6). The results remain similar across these alternative standardization approaches.

[2] Observations for 2023 are smaller because data providers have not yet fully updated their variables for this year, limiting our sample size.

Table 2
Portfolio double sorting of company-year greenwashing cases based on ESG-related variables and company size.

Portfolios	Number of company-year greenwashing observations					
	Portfolios (company size)					
	1 (low)	2	3	4 (high)	Obs. (GW)	Obs.
Panel A: LSEG ESG scores						
1 (low)	0	6	6	11	23	1,466
2	2	4	13	19	38	1,466
3	9	14	27	59	109	1,468
4 (high)	7	24	77	138	246	1,462
Panel B: Bloomberg ESG scores						
1 (low)	2	2	7	19	30	1,258
2	2	7	7	40	56	1,263
3	6	9	23	74	112	1,263
4 (high)	8	20	42	132	202	1,248
Panel C: Bloomberg ESG Disclosure scores						
1 (low)	0	3	6	8	17	1,423
2	3	3	14	25	45	1,421
3	7	16	20	75	118	1,421
4 (high)	8	27	41	134	210	1,421
Panel D: GW = Bloomberg ESG Disclosure scores − LSEG ESG scores						
1 (low)	0	8	15	66	89	1,417
2	1	10	10	65	87	1,416
3	4	7	19	87	117	1,417
4 (high)	6	6	22	64	98	1,416
Panel E: GW = Bloomberg ESG Disclosure scores − Bloomberg ESG scores						
1 (low)	1	11	10	58	81	1,217
2	2	8	18	61	89	1,217
3	4	5	16	62	87	1,217
4 (high)	5	10	26	78	119	1,217

Notes: This table presents the number of greenwashing cases across double-sorted portfolios for companies in the STOXX Europe 600 index from 2015 to 2023. In Panel A, portfolios are sorted first by LSEG ESG scores and then by company size, in ascending order from "1 (low)" to "4 (high)." The other panels follow the same logic but sort first based on different variables: Panel B uses Bloomberg ESG scores, Panel C uses Bloomberg ESG Disclosure scores, Panel D calculates greenwashing risk (GW) as the difference between standardized Bloomberg ESG Disclosure scores and standardized LSEG ESG scores, and Panel E calculates GW as the difference between standardized Bloomberg ESG Disclosure scores and standardized Bloomberg ESG scores. Panels D and E follow established academic methods (e.g., Jin et al., 2024; Lin et al., 2023; Liu and Li, 2024; Peng and Xie, 2024) for estimating a company's greenwashing risk. Columns "Obs. (GW)" and "Obs." show the number of greenwashing-related observations and the total company-year observations in the first sorted portfolios, respectively.

incentives to either maintain or improve their perceived sustainability performance (Delmas and Burbano, 2011). Companies with high ESG scores tend to be larger (e.g., Dobrick et al., 2023; Drempetic et al., 2020), attract more attention from analysts (e.g., Wu et al., 2024) and may be especially vulnerable to such pressures. Their desire to preserve or improve their market position and meet expectations can drive them to exaggerate their sustainability efforts, even when their actual practices do not align with these claims.

Moreover, regulatory pressures may lead companies to disclose positive environmental outcomes while concealing negative aspects selectively. This creates a misleading perception of sustainability (Lyon and Maxwell, 2011). By manipulating disclosures, companies can inflate their ESG score – often based on publicly available data – without making substantive improvements.

Lastly, companies with high ESG scores may justify misleading claims by relying on their overall positive impact from past actions. Parguel et al. (2011) argue that companies use their history of responsible behavior to legitimize less ethical practices, thereby maintaining a favorable public image.

To capture the mismatch between a company's sustainable claims and its actual environmental impact, which determines its greenwashing risk, we empirically implement and calibrate the theoretical model proposed by Dorfleitner and Utz (2023). This approach distinguishes between a company's apparent and real environmental performance to assess its greenwashing risk. Apparent environmental performance (AP) refers to the perceived environmental actions of a company as reflected in its environmental claims. For example, an oil company might pledge to reduce CO_2-emissions by 50% by 2040 in its sustainability report. These targets are challenging to quantify because they are forward-looking, with the actual business impact remaining uncertain. Real environmental performance (RP) refers to a company's actual, quantifiable environmental impact. It primarily relies on measurable quantities such as the number of environmental incidents involving a company as reported by the media and current CO_2-emissions.

Table 3
Number of greenwashing cases, severity scores, and ESG scores per year.

	Greenwashing cases	Greenwashing severity score	LSEG ESG score		Bloomberg ESG score		Bloomberg Disclosure score	
Year	GW	GW	GW	non-GW	GW	non-GW	GW	non-GW
2015	18	78.47	73.90	56.55	3.30	2.82	55.51	45.28
2016	23	74.73	75.37	57.73	3.56	3.06	57.53	46.73
2017	30	69.51	75.98	59.62	3.83	3.25	58.87	48.81
2018	32	69.08	73.57	61.53	4.13	3.39	57.18	49.55
2019	51	64.46	76.00	63.42	4.26	3.64	60.11	50.64
2020	46	78.13	78.87	65.83	4.94	3.95	63.70	52.12
2021	94	71.48	77.54	66.26	4.92	4.23	61.58	53.24
2022	94	71.17	77.62	66.62	4.82	4.26	61.02	53.60
2023	29	57.47	81.55	67.48	5.11	4.55	64.50	51.87
Mean	46	70.46	77.10	62.30	4.55	3.59	60.45	49.96
Obs.	417	417	417	5,445	401	5,032	391	5,295

Notes: This table presents summary statistics of greenwashing cases and ESG-related variables by year, covering companies from the STOXX Europe 600 index from 2015 to 2023. Greenwashing cases represent the number of hand-collected greenwashing incidents each year. ESG-related variables show the annual mean values from LSEG and Bloomberg ESG scores. The samples are divided into company-years with greenwashing accusations ("GW") and those without ("non-GW"). Row "Mean" displays the average value for each variable, and Row "Obs." reports the number of company-year observations for the corresponding sample.

The model evaluates a company's AP and RP across specified environmental dimensions. Each dimension contributes to a company's greenwashing risk only when the AP exceeds the real one.[3] To define the dimensions for our empirical analysis, we adopt an approach similar to that used by LSEG in its environmental pillar of the ESG score methodology.[4] Specifically, we focus on three dimensions: *Emissions*, *Environmental governance*, and *Resource use*.

3.2. Greenwashing risk estimation

We calibrate the model by identifying variables related to a company's greenwashing risk and then estimating a non-linear model using least squares regressions, as proposed by Dorfleitner and Utz (2023). The process for selecting variables included in our model estimation is as follows. First, we choose variables recognized in the literature as drivers of greenwashing behavior (e.g., Papoutsi and Sodhi, 2020, and references therein). This step provides a broad set of variables obtained from the four databases introduced in Section 2.1. Second, we ensure that the variables have sufficient coverage across our sample. Third, we address multi-collinearity by selecting variables with relatively low pairwise correlations. Finally, we categorize our selected variables into our predefined dimensions and distinguish between AP and RP.

This process results in the following independent variables for measuring the AP: *Emission target*, *Environmental partnerships*, *Eco-friendly products*, *Environmental restore initiatives*, *Water efficiency policy*, and *Energy efficiency policy*. It is important to emphasize that these variables reflect a company's perceived environmental performance and are difficult to quantify. In the case of the RP, we use *Scope 1 intensity*, *Scope 2 intensity*, *Misleading communications*, *Supply-chain-issues*, *Energy management*, and *Landscape impact*.[5] These variables are more easily quantifiable and reflect the actual environmental impact of a company. The variables taken from RepRisk (*Misleading communications*, *Supply-chain-issues*, *Energy management*, and *Landscape impact*) are defined as 1 minus the sum of a company's incidences within a year for each variable. The dependent variable is the greenwashing severity scores.

Table 4 presents the estimated coefficients and model statistics, along with categorizing whether a variable corresponds to AP or RP. Almost all variables (except for *Scope 2 intensity*) contribute to explaining the greenwashing severity scores. Variables linked to AP are associated with increased greenwashing risk, while RP-related variables are associated with a reduced risk.

We use the estimated coefficients to calculate a company's greenwashing risk. Higher values indicate a greater greenwashing risk. Over 90% of the estimated greenwashing risk values are below 0.1, and the median (mean) of the distribution is 0.027 (0.051). These figures coincide with the relatively low number (compared to the sample size) of detected greenwashing cases in our sample, and the distribution of greenwashing severity scores (see Table A.4). Furthermore, the receiver operating characteristic (ROC) curve analysis reveals an area under the curve of 0.86 (max: 1), indicating that the model performs significantly better than a random estimate (threshold: 0.50). The optimal cut-off point (0.04) from the analysis yields a sensitivity of 0.75 and a specificity of 0.82, demonstrating that the model accurately classifies company-years into greenwashing and non-greenwashing cases.

[3] A detailed description of the theoretical model can be found in Dorfleitner and Utz (2023).

[4] The LSEG ESG score methodology is described here: https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf (lastly accessed on Oct 10, 2024).

[5] Descriptions and sources of our used variables are provided in Table A.3. Summary statistics of these variables can be found in Table A.4.

Table 4
Regression results.

Variable	Greenwashing severity scores Coefficient	Standard error	T-Value	real/ apparent
Emissions				
Emission target	0.020***	0.004	4.589	apparent
Environmental partnerships	0.020***	0.006	3.355	
Scope 1 intensity	−0.125*	0.071	−1.765	real
Scope 2 intensity	−0.139	0.089	−1.555	
Environmental governance				
Eco-friendly products	0.239**	0.111	2.164	apparent
Environmental restore initiatives	0.335**	0.168	1.989	
Misleading communications	−0.283*	0.169	−1.675	real
Supply-chain-issues	−0.861***	0.202	−4.270	
Resource Use				
Water efficiency policy	0.385***	0.054	7.141	apparent
Energy efficiency policy	0.224***	0.067	3.334	
Energy management	−0.014**	0.007	−2.042	real
Landscape impact	−0.622***	0.072	−8.654	
Observations	5,888			
R^2	0.303			
Adj-R^2	0.302			
RMSE	0.168			

Notes: This table presents non-linear regression results with the mean greenwashing severity scores as the dependent variable and the selected independent variables to calculate the greenwashing risk ($[0,1]$), following the model approach by Dorfleitner and Utz (2023). The sample covers companies of the STOXX Europe 600 from 2015 to 2023. Variables are classified into distinct environmental dimensions and categorized based on whether they contribute to a company's real or apparent environmental performance. All continuous variables are winsorized at the 0.5% level. Independent variables are normalized to a scale ranging from 0 to 1 using the Min-Max normalization. For variable descriptions, see Table A.3. Standard errors are clustered at the company level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The advantage of the applied model is its feature to distinguish between a company's AP and RP. We calculate these figures for each company-year observation by using the estimated coefficients as the weights for the weighted sum of the company-level values of the independent variables.

Fig. 1 shows the development of the cross-sectional annual average AP and RP from 2015 to 2023, relative to 2015. While the average RP remains stable throughout the period, the apparent environmental performance shows a significant increase of roughly 40% by 2023 compared to 2015. Thus, while real environmental impact has been rather constant, the communication on companies' environmental strategies has substantially increased.

4. Greenwashing risk and ESG scores

Table 5 presents pairwise Pearson correlations between ESG scores and (1) apparent environmental performance, (2) real environmental performance, and (3) greenwashing risk. Pearson correlations between E(SG) (i.e., E individually and ESG) scores and AP range from 0.48 to 0.63 for LSEG ESG (Panel A). Consequently, ESG scores tend to be high when a company's AP is perceived as strong. In contrast, the correlations with the RP are negative and close to −0.25. Therefore, ESG scores are higher for companies with low RP. The correlations between greenwashing risk and E(SG) scores are positive and range between 0.32 and 0.41. Almost all correlations of the pairwise combinations are statistically significantly different from zero and display a relatively consistent pattern over time.

The findings provide two key insights. First, ESG scores partially reflect a company's greenwashing risk, which is critical as ESG information becomes increasingly embedded in investment decision-making (e.g., van Duuren et al., 2016) and executive compensation (e.g., Cohen et al., 2023). Second, the AP is strongly related to ESG performance. Thus, company-generated sustainable information may be unreliable and overestimate the environmental performance, inflating E(SG) scores. The reason for that could be that managers try to enhance ESG scores (e.g., Amiraslani et al., 2023; Cohen et al., 2023; Galletta et al., 2023) by increasing the AP, thereby increasing the company's greenwashing risk.

To rule out potential biases from using LSEG ESG scores, given provider discrepancies (e.g., Berg et al., 2022), we repeat the analysis with Bloomberg ESG scores. Panel B shows smaller, but still significant correlations, confirming the robustness of our

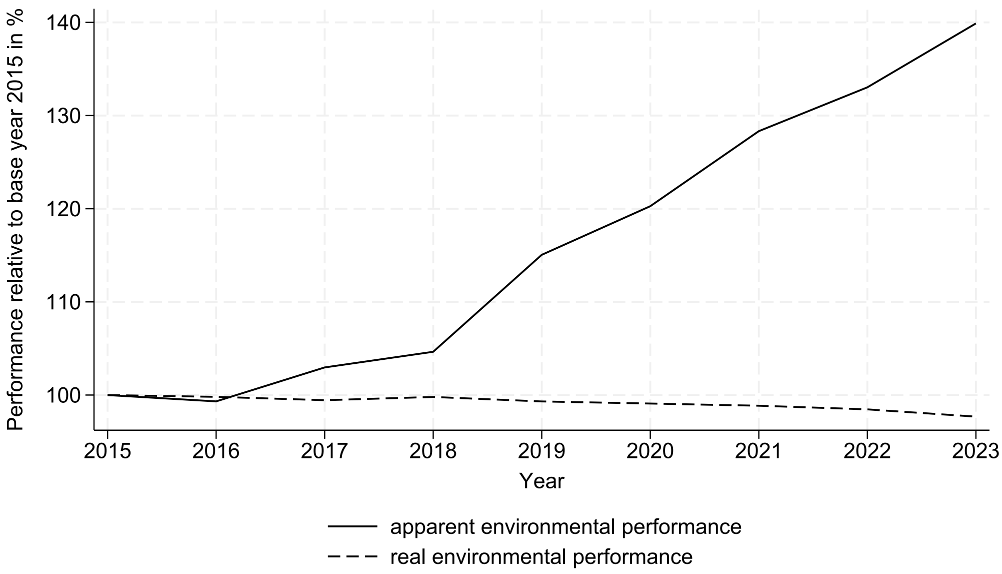

Fig. 1. This figure displays the development of sample companies' average apparent and real environmental performance over time. The *y*-axis measures environmental performance, either apparent (solid) or real (dashed line), expressed relative to the baseline year 2015. The *x*-axis shows the years.

Table 5
Pearson correlation between E(SG) scores and environmental performance of companies.

	Correlation between E(SG) scores and environmental performance of companies									
Variable/Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	All
Panel A: LSEG ESG score										
	apparent performance									
ESG score	0.60***	0.59***	0.58***	0.57***	0.55***	0.54***	0.49***	0.48***	0.51***	0.57***
E score	0.63***	0.62***	0.59***	0.62***	0.61***	0.59***	0.55***	0.55***	0.54***	0.60***
	real performance									
ESG score	−0.25***	−0.30***	−0.28***	−0.25***	−0.25***	−0.25***	−0.26***	−0.27***	−0.28***	−0.26***
E score	−0.22***	−0.27***	−0.25***	−0.21***	−0.23***	−0.24***	−0.24***	−0.26***	−0.29***	−0.24***
	greenwashing risk									
ESG score	0.39***	0.42***	0.41***	0.39***	0.37***	0.34***	0.34***	0.34***	0.33***	0.37***
E score	0.35***	0.39***	0.38***	0.36***	0.36***	0.33***	0.32***	0.32***	0.34***	0.35***
Panel B: Bloomberg ESG score										
	apparent performance									
ESG score	0.40***	0.39***	0.34***	0.37***	0.34***	0.34***	0.25***	0.23***	0.30***	0.38***
E score	0.34***	0.35***	0.33***	0.33***	0.30***	0.30***	0.24***	0.20***	0.22***	0.34***
	real performance									
ESG score	−0.16***	−0.12***	−0.13***	−0.17***	−0.18***	−0.21***	−0.19***	−0.21***	−0.11	−0.18***
E score	−0.14***	−0.10**	−0.11***	−0.15***	−0.19***	−0.20***	−0.17***	−0.21***	−0.13*	−0.17***
	greenwashing risk									
ESG score	0.31***	0.27***	0.28***	0.29***	0.31***	0.30***	0.28***	0.27***	0.19***	0.28***
E score	0.24***	0.21***	0.23***	0.24***	0.28***	0.27***	0.24***	0.25***	0.17***	0.25***
Panel C: Bloomberg ESG Disclosure score										
	apparent performance									
Discl. score	0.58***	0.57***	0.54***	0.54***	0.52***	0.51***	0.49***	0.50***	0.46***	0.55***
	real performance									
Discl. score	−0.23***	−0.24***	−0.22***	−0.22***	−0.21***	−0.22***	−0.21***	−0.21***	−0.19***	−0.22***
	greenwashing risk									
Discl. score	0.38***	0.39***	0.39***	0.38***	0.39***	0.35***	0.34***	0.34***	0.30***	0.37***

Notes: This table presents the pairwise Pearson correlations between E(SG) scores and companies' environmental performance, categorized into apparent and real, and companies' greenwashing risk. In Panel A (Panel B), the E(SG) scores are derived from LSEG (Bloomberg). Panel C employs the Bloomberg ESG Disclosure score. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Analyst coverage and environmental performance divergence.

	Diff-AP-to-RP$_{(t+1)}$						
	entire	company size		scope 1 intensity		industry	
	sample	large	small	high	low	brown	non-brown
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(1+No. Analysts)	−0.164**	−0.061	−0.137*	−0.432***	−0.008	−0.284**	−0.104
	(−2.02)	(−0.42)	(−1.90)	(−3.52)	(−0.07)	(−2.03)	(−1.07)
Company size (log sales)	0.118**	0.514***	−0.248***	0.337***	−0.082*	0.215**	0.053
	(2.17)	(4.52)	(−5.14)	(3.80)	(−1.80)	(2.36)	(0.82)
Log(1+M/B-ratio)	0.156*	0.004	0.152**	0.310**	0.048	0.185	0.186
	(1.82)	(0.03)	(2.05)	(2.19)	(0.49)	(1.34)	(1.58)
EBITDA-to-assets	0.009	1.460	−0.395	−0.739	0.321	−0.735	0.026
	(0.04)	(1.04)	(−1.32)	(−0.87)	(1.25)	(−0.69)	(0.10)
Net PPE-to-assets	−0.105	0.395	−0.670***	−0.028	0.804	−0.062	−0.049
	(−0.45)	(0.88)	(−3.59)	(−0.10)	(1.53)	(−0.18)	(−0.14)
Book-leverage-ratio	−0.123	0.403	−0.207	−0.744**	0.302	−1.051***	0.308
	(−0.67)	(1.17)	(−1.23)	(−2.32)	(1.46)	(−3.28)	(1.44)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,583	2,340	2,242	2,322	2,261	1,841	2,742
Adj-R2	0.085	0.181	0.237	0.128	0.091	0.123	0.043

Notes: This table presents results from fixed effect regressions, where the dependent variable is Diff-AP-to-RP. It is defined as the difference between the standardized estimated apparent (AP) and the standardized real (RP) environmental performance. This variable represents the one-year-lead values. Company-specific characteristics denote variables corresponding to the company's value in year t. Columns (2)–(7) display subsample analyses in which the sample is split at the median of company size (Columns (2) and (3)) and scope 1 intensity (Columns (4) and (5)). Column (6) shows the results for brown industries (Energy, Industrials, Utilities, and Basic Materials), and Column (7) for non-brown industries. All continuous variables are winsorized at the 0.5% level. All regressions include a constant. Standard errors are clustered at the company level, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

results. We also use Bloomberg's ESG Disclosure scores (Panel C), demonstrating that increased disclosure of ESG-related information correlates with a company's AP and risk of greenwashing.

Building on literature suggesting that analyst coverage can mitigate greenwashing behavior (e.g., Liu et al., 2023), we test whether higher analyst coverage reduces the gap between AP and RP. The rationale for this analysis is that in environments with high information asymmetry, companies can more easily exaggerate their environmental efforts, as stakeholders lack accurate data, reducing the likelihood of detection. Analyst coverage, however, can mitigate information asymmetry (e.g., Chan and Chan, 2014; Lee and So, 2017; Li et al., 2019). We use the number of analysts as a proxy for information asymmetry. The gap between AP and RP is defined by standardizing both variables using z-transformation and calculating their difference (*Diff-AP-to-RP*). However, we also account for the contextual differences in analyst coverage of environmental performance. For example, companies might strategically shape their environmental narratives to align with the expectations of analysts and investors. This implies that analysts not only reduce information asymmetry but also influence AP through their recommendations, reports, and media coverage. Therefore, we explore potential heterogeneity in the effects of analyst coverage across industries and company types through subsample analysis.

Table 6 presents the results for the relationship between *Diff-AP-to-RP* and *Log(1 + No. of analysts)* for the entire sample (Column (1)), and for subsamples based on "company size" (Columns (2)–(3)) and "scope 1 intensity" (Columns (4)–(5)), which are split at the median values of the respective variable. Columns (6) and (7) show the results for "brown" (*Energy, Industrials, Utilities, and Basic Materials*) and "non-brown industries."

The results reveal a statistically significant negative relationship between analyst coverage and the dependent variable for the entire sample (Column (1)). Furthermore, this effect persists in the subsamples of small companies (Column (3)), companies with high scope 1 intensity (Column (4)), and those from brown industries (Column (6)). As a result, reducing information asymmetry may decrease the gap between AP and RP, thereby lowering the risk of greenwashing.

5. Conclusion

Our study examines the relationship between real greenwashing allegations and ESG scores for the STOXX Europe 600 constituents. Companies with high ESG scores are more likely to face greenwashing accusations. This suggests that investors focusing on ESG may inadvertently increase their greenwashing risks exposure. From an academic perspective, our study highlights the need for a more nuanced approach to assessing greenwashing. While ESG scores provide valuable insights, they may not accurately reflect a company's real environmental performance.

Table A.1
Framework for assessing greenwashing information sources and greenwashing severity.

Description	Action
Information source provides a new greenwashing case	Assessment in the year of the information source
Greenwashing case of information source is already known from an earlier information source and does not provide new information	Drop information source
Greenwashing case of information source is already known from an earlier information source, but it provides new information	Assessment in the year of the information source
Numerous information sources indicate a pattern of repetitive greenwashing behavior associated with the same accusations/incidents	Assessments of repeated greenwashing behavior across all years, using interpolation where no information source exists between records from different years documenting the same case
Scientific papers and reports addressing the greenwashing behavior of specific companies	Assessments in the publication year of the information source
Collective reports covering multiple companies and multi-year greenwashing behavior	Assessments in the publication year of the information source
Information source accuses parent company and subsidiary	Assessment only for both companies if the greenwashing case can be clearly linked to both companies
Information source accuses sustainable funds of greenwashing for their holdings in companies with questionable environmental practices	Drop information source as it accuses the funds, not the company
Information sources accuse companies owing regarding social or governance misconduct	Drop information source
Information source does not directly reference the company	Drop information source
Information sources that cannot be translated into English (e.g., figures)	Drop information source

Notes: This table outlines the framework for assessing manually collected information sources related to greenwashing cases. Our sample's data selection regards specific aspects: (1) if multiple sources report different greenwashing cases within a year, we use the one with the highest severity score for our assessment, (2) for companies with persistent greenwashing behavior over multiple years, we evaluate all years of such behavior through interpolation (applied for ten greenwashing cases and 22 company-years), (3) specifically, when at least two sources from different years indicate consistent behavior, we apply the highest severity score from the recorded years to the interim years when no source was published.

CRediT authorship contribution statement

Manuel C. Kathan: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sebastian Utz:** Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Gregor Dorfleitner:** Writing – original draft, Supervision, Funding acquisition, Conceptualization. **Jens Eckberg:** Writing – original draft, Data curation. **Lea Chmel:** Data curation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Declaration of competing interest

The authors report there are no competing interests to declare.

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Appendix

See Tables A.1–A.6.

Table A.2
Assessment of greenwashing severity.

Rating	Assessment	Description
No greenwashing	0.00	The company demonstrates genuine sustainability practices or is a true/silent brown company
Light greenwashing	0.25	The company makes minor claims of sustainability but struggles to meet all stakeholder expectations
Medium greenwashing	0.50	There are vague sustainability claims accompanied by generic accusations of misleading practices
Moderate greenwashing	0.75	Some accusations of greenwashing are present, but they are not fully substantiated; practices may be misleading
Greenwashing	1.00	The company engages in deceptive practices, failing to fulfill sustainability commitments, often confirmed by NGOs

Notes: This table describes the framework for assessing the severity of greenwashing cases.

Table A.3
Definition of variables.

Variable	Description	Source
Dimension: Emissions (apparent performance)		
Emissions target (binary)	Has the company set targets or objectives to be achieved on emissions reduction? In scope are the short-term or long-term reduction target to be achieved on emissions to land, air or water from business operations.	Refnitiv
Environmental partnerships (score)	Does the company report on partnerships or initiatives with specialized NGOs, industry organizations, governmental or supra-governmental organizations, which are focused on improving environmental issues?	Refnitiv
Dimension: Emissions (real performance)		
Scope 1 intensity	Greenhouse gas (GHG) emissions from sources that are owned or controlled by the company (categorized by the Greenhouse Gas Protocol) divided by the company's revenue.	Trucost
Scope 2 intensity	Greenhouse gas (GHG) emissions from consumption of purchased electricity, heat or steam by the company (categorized by the Greenhouse Gas Protocol) divided by the company's revenue.	Trucost
Dimension: Environmental governance (apparent performance)		
Eco-friendly products (binary)	Does the company report on specific products which are designed for reuse, recycling or the reduction of environmental impacts?	Refnitiv
Environmental restore initiatives (score)	Does the company report or provide information on company-generated initiatives to restore the environment?	LSEG
Dimension: Environmental governance (real performance)		
Misleading communications	This issue refers to when a company manipulates the truth in an effort to present itself in a positive light, and in the meantime contradicts this self-created image through its actions.	RepRisk
Supply-chain-issues	This issue refers to companies who are held accountable for the actions of their suppliers. Both vendors and subcontractors are considered part of the supply chain.	RepRisk
Dimension: Resource use (apparent performance)		
Water efficiency policy (binary)	Does the company have a policy to improve its water efficiency? In scope are the various forms of processes/mechanisms/procedures to improve water use in operation efficiently.	LSEG
Energy efficiency policy (binary)	Does the company have a policy to improve its energy efficiency? In scope are the various forms of processes/mechanisms/procedures to improve energy use in operation efficiency.	LSEG
Dimension: Resource use (real performance)		
Energy management (Overuse and wasting resources)	Involves the management of energy consumption during operations, including energy efficiency and intensity. Energy consumption from the product use is outside of the scope.	RepRisk
Landscape impact (Impacts on landscapes, ecosystems and biodiversity)	This issue covers impacts of company activities on ecosystems or landscapes such as forests, rivers, seas, etc., contamination of groundwater and water systems, deforestation, impacts on wildlife, etc.	RepRisk

Notes: This table provides a detailed description, classification, and the corresponding data sources for each variable used in our empirical model to estimate a company's greenwashing risk.

Table A.4
Summary statistics of the used variables to calculate greenwashing risk.

Variables	Mean	Std.	5%	Q1	Median	Q3	95%
Mean greenwashing severity scores	0.05	0.20	0.00	0.00	0.00	0.00	0.56
Emission target	0.70	0.46	0.00	0.00	1.00	1.00	1.00
Environmental partnerships	47.49	41.00	0.00	0.00	74.53	84.73	90.25
Scope 1 intensity	128.13	428.72	0.24	1.59	8.19	38.59	665.86
Scope 2 intensity	38.43	87.23	0.61	3.79	10.70	33.03	180.47
Eco-friendly products	0.18	0.39	0.00	0.00	0.00	0.00	1.00
Environmental restore initiatives	22.84	38.35	0.00	0.00	0.00	74.15	92.62
Misleading communications	−0.21	2.40	−4.00	0.00	0.00	1.00	1.00
Supply-chain-issues	−0.39	3.27	−4.00	0.00	0.00	1.00	1.00
Water efficiency policy	0.63	0.48	0.00	0.00	1.00	1.00	1.00
Energy efficiency policy	0.92	0.28	0.00	1.00	1.00	1.00	1.00
Energy management	0.60	0.49	0.00	0.00	1.00	1.00	1.00
Landscape impact	−1.36	6.03	−9.00	0.00	0.00	1.00	1.00
Observations	5,888						

Notes: This table presents summary statistics of the variables used to calculate greenwashing risk, following the theoretical model approach by Dorfleitner and Utz (2023). The sample covers companies of the STOXX 600 Europe from 2015 to 2023. All continuous variables are winsorized at the 0.5% level. The variables taken from RepRisk (*Misleading communications*, *Supply-chain-issues*, *Energy management*, and *Landscape impact*) are defined as 1 minus the sum of a company's incidences within a year for each variable, respectively, to capture a company's environmental performance. For variable descriptions, see Table A.3.

Table A.5
Portfolio double sorting of company-year greenwashing cases based on alternative greenwashing approaches and company size (ESG and ESG Disclosure scores standardized by year).

Portfolios	Number of company-year greenwashing observations					
	Portfolios (company size)					
	1 (low)	2	3	4 (high)	Obs. (GW)	Obs.
Panel A: GW = Bloomberg ESG Disclosure scores − LSEG ESG scores						
1 (low)	1	11	16	76	104	1,417
2	0	7	7	63	77	1,416
3	4	9	20	81	114	1,417
4 (high)	6	5	23	61	95	1,416
Panel B: GW = Bloomberg ESG Disclosure scores − Bloomberg ESG scores						
1 (low)	2	10	11	48	71	1,217
2	3	5	14	59	81	1,217
3	1	5	17	70	93	1,217
4 (high)	8	9	29	84	130	1,217

Notes: This table presents the number of greenwashing cases across double-sorted portfolios for companies in the STOXX Europe 600 index from 2015 to 2023. The portfolios are sorted first by established academic methods (e.g., Jin et al., 2024; Lin et al., 2023; Liu and Li, 2024; Peng and Xie, 2024) for estimating a company's greenwashing risk, and then by company size, ranked in ascending order from "1 (low)" to "4 (high)." Panel A measures greenwashing risk (GW) as the difference between standardized Bloomberg ESG Disclosure scores and standardized LSEG ESG scores, while Panel B measures GW as the difference between standardized Bloomberg ESG Disclosure scores and standardized Bloomberg ESG scores. In both panels, the variables are standardized by year. The Columns "Obs. (GW)" and "Obs." indicate the number of greenwashing-related observations and the total company-year observations in the first sorted portfolio, respectively.

Table A.6
Portfolio double sorting of company-year greenwashing cases based on alternative greenwashing approaches and company size (ESG and ESG Disclosure scores standardized by industry and year).

Portfolios	Number of company-year greenwashing observations					
	Portfolios (company size)					
	1 (low)	2	3	4 (high)	Obs. (GW)	Obs.
Panel A: GW = Bloomberg ESG Disclosure scores − LSEG ESG scores						
1 (low)	0	11	15	70	96	1,416
2	2	11	12	82	107	1,416
3	4	7	25	75	111	1,416
4 (high)	5	6	13	52	76	1,416
Panel B: GW = Bloomberg ESG Disclosure scores − Bloomberg ESG scores						
1 (low)	1	11	12	53	77	1,217
2	3	4	24	62	93	1,216
3	2	8	18	69	97	1,217
4 (high)	5	7	15	81	108	1,216

Notes: This table presents the number of greenwashing cases across double-sorted portfolios for companies in the STOXX Europe 600 index from 2015 to 2023. The portfolios are sorted first by established academic methods (e.g., Jin et al., 2024; Lin et al., 2023; Liu and Li, 2024; Peng and Xie, 2024) for estimating a company's greenwashing risk, and then by company size, ranked in ascending order from "1 (low)" to "4 (high)." Panel A measures greenwashing risk (GW) as the difference between standardized Bloomberg ESG Disclosure scores and standardized LSEG ESG scores, while Panel B measures GW as the difference between standardized Bloomberg ESG Disclosure scores and standardized Bloomberg ESG scores. In both panels, the variables are standardized by industry and year. The Columns "Obs. (GW)" and "Obs." indicate the number of greenwashing-related observations and the total company-year observations in the first sorted portfolio, respectively.

Data availability

The data underlying this article were provided by Bloomberg, LSEG/Datastream, RepRisk, and S&P Trucost under license.

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