Journal of Economic Behavior and Organization 241 (2026) 107354

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Research Paper

Determinants and forecasting of corporate greenwashing behavior

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ARTICLE INFO

Keywords:
Greenwashing
ESG scores
Corporate misconduct
Risk management
Forecasting
Machine learning
Information asymmetry

ABSTRACT

This paper empirically analyzes the determinants of corporate greenwashing behavior to enhance forecasting and mitigation of greenwashing practices, particularly in the context of stakeholder decision-making. Using company-level characteristics from a sample of STOXX Europe 600 constituents, we show that ESG and environmental (E) scores exhibit a U-shaped relationship with greenwashing, indicating that companies with both low and high (E)SG scores are more likely to engage in greenwashing. Additionally, ESG disclosure score, company size, cash-to-assets, and capital intensity are positively associated with greenwashing behavior. Furthermore, greenwashing behavior is more prevalent in consumer-related industries than in other industries. Building on the identified determinants of greenwashing behavior, we develop machine learning models grounded in economic theory to forecast greenwashing risk. Overall, our analyses demonstrate how current and future greenwashing risks can be effectively assessed. This enables stakeholders such as investors and policymakers to better identify corporate greenwashing behavior and incorporate the associated risks into their decision-making.

1. Introduction

Concerns about corporate greenwashing have grown among investors and other stakeholders. According to the Ernst & Young 2024 Institutional Investor Survey, 85 % of investors view greenwashing as a greater challenge today than five years ago (EY , 2024). Greenwashing, defined as the misrepresentation of a company's environmental performance, creates information asymmetry because companies know their true environmental performance while stakeholders remain unaware until misconduct is revealed. This asymmetry exposes stakeholders, particularly investors, to hidden financial and reputational risks, as greenwashing undermines corporate legitimacy (Seele and Gatti, 2017) and can result in costly litigation and reputational damage (Pizzetti et al., 2021; Siano et al., 2017; Torelli et al., 2020; Walker and Wan, 2012).

To address these risks, this paper examines two main research objectives. The first is to identify which company-level characteristics, such as ESG scores, company size, and industry context, are associated with corporate greenwashing behavior among European companies. The second is to develop and evaluate forecasting models of greenwashing risk (i.e., the risk of future greenwashing

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https://doi.org/10.1016/j.jebo.2025.107354
Received 4 April 2025; Received in revised form 17 November 2025; Accepted 23 November 2025
Available online 4 December 2025
0167-2681/

behavior of a company) within a decision-oriented framework grounded in economic theory. Addressing these objectives enables sustainability-oriented stakeholders to incorporate greenwashing risk into their decision-making. These stakeholders include customers, employees, suppliers, and investors, all of whom have a strong interest in detecting greenwashing risks early. For investors in particular, timely detection supports more effective management of idiosyncratic risk, reduces the likelihood of stock price declines following greenwashing revelations, and mitigates reputational damage, especially for ESG-focused mutual funds.

We measure and forecast greenwashing behavior by examining the relationship between company characteristics and observed greenwashing accusations. Prior studies have identified various company characteristics as potential determinants of greenwashing, mostly derived from theoretical arguments (e.g., Delmas and Burbano, 2011; Lyon and Montgomery, 2015). However, a comprehensive empirical investigation of these determinants at the company level is still lacking. To address this gap, we identify relevant company-level determinants based on the existing literature on corporate greenwashing, environmental and social performance, and corporate misconduct. We organize these variables into categories that reflect distinct channels through which company characteristics influence greenwashing behavior. Both the categories and variables are grounded in economic theory, providing a robust theoretical foundation for our analysis.

Our measure of greenwashing behavior is a score derived from hand-collected greenwashing accusations that assesses the severity of each incident for every company-year on a discrete scale from 0 % (no greenwashing) to 100 % (greenwashing) based on human judgment. Using a panel dataset of STOXX Europe 600 constituents from 2011 to 2023, we analyze how company characteristics relate to greenwashing behavior. To identify its determinants, we estimate regression models with year, industry, and country fixed effects.

We find that greenwashing behavior is most prevalent among companies with both low and high ESG ratings. This U-shaped relationship remains when focusing specifically on environmental scores. Thus, even companies perceived as environmental leaders may engage in greenwashing, posing risks that investors may not fully consider in their decisions. In addition to sustainability ratings, greenwashing behavior is also associated with company size, the cash-to-asset ratio, capital intensity, and the level of ESG disclosure.

To explore whether the determinants of greenwashing behavior vary across industries, we conduct an industry-level analysis using industry dummies instead of industry fixed effects. The results indicate that greenwashing behavior is more prevalent in industries that interact directly with consumers, whereas the telecommunications, real estate, and technology industries exhibit a lower propensity for such behavior.

After identifying the determinants of greenwashing behavior, we employ machine learning models to forecast greenwashing risk. These models draw on the identified determinants and environmental corporate misconduct variables that reflect a company's actual environmental performance in terms of its environmental standards and practices. Machine learning models are well-suited to capturing complex, non-linear relationships and often outperform traditional regression approaches. We optimize the models within an economic framework that accounts for sustainability-oriented stakeholders. Using a validation dataset, we then assess out-of-sample predictive accuracy to evaluate model performance under realistic conditions.

Regarding greenwashing forecasting, we find that correctly identifying greenwashing cases (i.e., avoiding false negatives) yields greater cost savings than reducing false positives. The consequences of undetected greenwashing behavior, such as reputational damage or stock price declines, are substantially higher than the opportunity or review costs associated with incorrectly flagged companies. When the models are optimized within an economic framework that considers these cost imbalances confirms that larger cost gaps increase potential savings.

Among the tested models, the Recurrent Neural Network (RNN) achieves the best and most robust out-of-sample forecasting performance, with true positive rates between 70 % and 100 % and true negative rates between 46 % and 89 % across high and moderate false-negative cost settings. The feature importance analysis further identifies the ESG disclosure score, energy management issues, the one-year lagged greenwashing severity score, and company size as the most influential predictors of greenwashing cases.

Our findings contribute to a deeper understanding of corporate greenwashing and its relevance for both academic research and practice. First, we empirically identify the company-level determinants and industry-level variation of greenwashing behavior and thereby extend the literature on (environmental) corporate misconduct (e.g., Chen and Chu, 2024; Dorfleitner et al., 2022; Peng et al., 2024; Ruiz-Blanco et al., 2022; Zhang, 2022; Zhang et al., 2024). Second, we build on research on corporate misconduct forecasting (e.g., Antulov-Fantulin et al., 2021; Liu et al., 2015; Wang et al., 2020) by demonstrating how greenwashing risk can be estimated, enabling sustainability-oriented stakeholders such as investors to incorporate a company's exposure to greenwashing into decision-making. Finally, policymakers can use our findings to identify greenwashing companies and strengthen regulatory frameworks to curb such practices.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework for analyzing company-level determinants of greenwashing behavior, industry-level variation, and forecasting approaches. Section 3 describes the greenwashing accusations and the sample construction. Section 4 presents the empirical results on the determinants of greenwashing behavior, while Section 5 reports the forecasting analysis. Section 6 discusses the practical implications of our findings and concludes.

2. Theoretical foundation

Understanding the determinants and risk of corporate greenwashing behavior is crucial for a wide range of stakeholders because greenwashing entails substantial financial and reputational risks, including litigation and loss of legitimacy (Pizzetti et al., 2021; Siano et al., 2017; Torelli et al., 2020; Walker and Wan, 2012). To effectively manage these risks, it is necessary to identify the determinants of greenwashing behavior and develop methods to forecast the risk of such behavior. While some stakeholders may focus on assessing current greenwashing risk based on observable company characteristics, others, such as investors, may prioritize forecasting future greenwashing risk using predictive models. Stakeholders concerned with the current greenwashing risk include customers, employees, and suppliers. For example, customers may consider company-level characteristics when selecting suppliers for purchasing decisions and avoiding those more likely to greenwash. To provide a theoretical foundation, the following sections examine the theory on (1) the determinants of greenwashing behavior, (2) industry-level variation, and (3) the forecasting of greenwashing.

2.1. Determinants of company-level greenwashing behavior

Companies operate in a complex and evolving environment defined by increasing regulatory, stakeholder, and societal pressures to adopt sustainable practices. Drawing on institutional, legitimacy, signaling, and stakeholder theory, greenwashing emerges as a strategic response by companies to manage external pressures and the information asymmetries related to their environmental performance (Cho et al., 2015; Delmas and Burbano, 2011; Lyon and Montgomery, 2015; Walker and Wan, 2012).

In this regard, institutional theory posits that companies are subject to normative, coercive, and mimetic pressures arising from their institutional environment, including expectations from industry norms, legal frameworks, and peer behavior, which influence companies to adopt practices that enhance their legitimacy and align with prevailing societal standards (DiMaggio and Powell, 1983). When genuine environmental improvements are costly or complex, symbolic actions such as greenwashing offer a low-cost means to appear compliant and socially responsible (Bansal and Clelland, 2004).

Legitimacy theory deepens this perspective by emphasizing the importance of perceived conformity with societal expectations (Aldrich and Fiol, 1994; Ashforth and Gibbs, 1990; Suchman, 1995). Within this framework, companies may engage in greenwashing to protect or restore their legitimacy in the eyes of stakeholders. Corporate environmental performance has become a critical dimension of organizational legitimacy (Cho and Patten, 2007). When a gap exists between a company's actual environmental performance and stakeholder expectations, greenwashing serves as a legitimacy management mechanism. Companies use it to exaggerate or misrepresent their environmental efforts to maintain stakeholder trust and preserve social acceptance amid growing scrutiny (Bansal and Clelland, 2004).

Stakeholder theory highlights that companies must balance the diverse and sometimes conflicting expectations of investors, customers, employees, suppliers, regulators, and non-governmental organizations (NGOs) (Freeman, 2010). Greenwashing thus functions as a deliberate strategy to manage stakeholder perceptions by tailoring disclosures to satisfy influential stakeholders, mitigate conflicts, and secure critical resources. Through selective or exaggerated environmental claims, companies can maintain stakeholder support while avoiding the costs of full transparency or substantive organizational change (Lyon and Maxwell, 2011).

Signaling theory interprets greenwashing as a response to information asymmetry between companies and external stakeholders. Companies possess private information about their true environmental performance, while external stakeholders rely on observable signals (Spence, 1973). In this context, greenwashing enables companies to convey exaggerated or misleading signals about their environmental efforts. These signals aim to influence stakeholder perceptions, gain competitive advantages, and attract investment or customer loyalty even in the absence of substantive environmental improvement (Lyon and Montgomery, 2015).

Taken together, these perspectives position greenwashing as a deliberate strategic response aimed at maintaining legitimacy, managing information asymmetry, and balancing stakeholder demands, often through symbolic rather than substantive environmental actions. However, the likelihood of engaging in greenwashing varies across companies, influenced by internal characteristics and contextual factors that affect the costs and benefits of such behavior.

Accordingly, we identify several key categories derived from these theoretical perspectives that may influence a company's engagement in greenwashing. A company with a strong *green reputation* often faces intensified scrutiny, which can both pressure it to maintain its image and incentivize defensive exaggeration of environmental efforts, particularly when discrepancies between actual and apparent environmental performance are difficult to verify (Delmas and Burbano, 2011; Kathan et al., 2025; Marquis et al., 2016). Similarly, *size and visibility* increase stakeholder exposure and public attention, thereby raising the risk of detection and the motivation to engage in symbolic environmental claims to preserve a responsible image (Aouadi and Marsat, 2018; Drempetic et al., 2020; Fiss and Zajac, 2006). *Capital dependency* further affects greenwashing incentives. Companies reliant on ESG-sensitive investors may overstate their sustainability credentials to secure financing, while companies with abundant financial resources may prioritize symbolic actions driven by managerial incentives and external expectations (Cheng et al., 2014; Freeman, 2010; Schreck and Raithel, 2018). Financial considerations related to *risk and return* factors may also play a crucial role, as companies under financial pressure can use greenwashing to signal stability and long-term commitment while managing reputational and legal risks (Delmas and Burbano, 2011; Lyon and Montgomery, 2015; Qu, 2024). Finally, *other factors* such as capital intensity, ownership structure, and foreign sales influence greenwashing behavior by affecting environmental risks, governance mechanisms, and regulatory pressures in diverse contexts (Burkart et al., 1997; Ioannou and Serafeim, 2012, 2019; Marquis et al., 2016). Capital-intensive companies may face higher environmental risks, which can encourage symbolic compliance strategies (Marquis et al., 2016). Ownership structure can influence corporate behavior through governance mechanisms. While concentrated ownership can reduce greenwashing through increased monitoring, it can also increase it when dominant shareholders pursue reputational gains or access to ESG-sensitive capital (Burkart et al., 1997; Ioannou and Serafeim, 2012). Foreign operations may expose companies to heterogeneous environmental expectations, influencing both behavior and disclosure (Ioannou and Serafeim, 2019). Table 1 summarizes the theoretical foundations corresponding to each category, specifying the theories that underpin our conceptualization of greenwashing determinants at the company level.

The identification of empirical variables within these categories draws on prior literature, including foundational studies on greenwashing drivers (Delmas and Burbano, 2011; Marquis et al., 2016; Zhang, 2022), and broader research on corporate environmental and social performance as well as corporate misconduct (Chen and Chu, 2024; Clarkson et al., 2011; Cormier and Magnan, 1999;

Table 1
Theoretical foundations of greenwashing determinants.

Category	Related theories	Rationale
Green reputation	legitimacy, stakeholder	Companies with strong green reputations face increased stakeholder scrutiny. Greenwashing helps to manage expectations and preserve legitimacy when actual environmental performance is hard to verify.
Size and visibility	institutional, legitimacy, stakeholder	Larger and more visible companies are subject to stronger institutional and stakeholder pressures. Greenwashing serves to maintain legitimacy and conform to expected environmental standards.
Capital dependency	stakeholder, signaling	ESG-sensitive investors exert pressure on companies. Greenwashing enables companies to signal their alignment with stakeholder expectations and secure critical capital in the face of information asymmetry.
Risk and return	signaling, stakeholder	Companies under financial pressure may use greenwashing to signal stability and long-term responsibility while addressing stakeholder concerns over reputation and risk.
Other factors	institutional, stakeholder	Structural characteristics (e.g., ownership, industry, international exposure) influence the company's institutional context and stakeholder environment, influencing symbolic compliance behavior.

Notes: This table presents the theoretical frameworks linked to each category that might influences corporate greenwashing behavior.

Dorfleitner et al., 2022; Ioannou and Serafeim, 2012; Peng et al., 2024). These studies provide the foundation for selecting measurable company-level characteristics that serve as proxies for the conceptual categories outlined above and guide the operationalization of our empirical analysis. The specific variables are introduced in Section 4.1.

2.2. Industry-level variation in greenwashing behavior

Company-level characteristics account for variation in greenwashing behavior, whereas industry-level dynamics define the broader context in which this behavior is more likely. Accordingly, differences in regulatory scrutiny, consumer awareness, and environmental impact across industries help explain systematic variation in greenwashing, consistent with the theoretical framework outlined above. In this regard, recent studies show that high-emitting industries such as energy, utilities, and materials, are more prone to greenwashing, driven by their significant environmental footprints and increased public scrutiny (Chen and Chu, 2024; Keresztúri et al., 2025). In contrast, industries subject to stricter regulations and higher consumer environmental awareness tend to experience more frequent detection of greenwashing practices (Ruiz-Blanco et al., 2022). Similarly, companies in clean production industries and those operating in regions with well-developed green financial instruments are generally less prone to greenwashing (Zhang, 2023).

Based on these observations, we argue that greenwashing is more prevalent (1) in consumer-related industries and (2) in industries with high environmental impact. Companies operating in consumer markets face stronger public scrutiny, which increases their exposure to greenwashing allegations. Media outlets and NGOs also play a crucial role in amplifying public accusations of greenwashing. Moreover, business-to-consumer (B2C) companies often invest in green marketing to strengthen legitimacy and promote perceptions of environmental and social responsibility (Nyilasy et al., 2014; Prakash, 2002). Through these efforts, they aim to improve brand image and influence consumer purchasing decisions, but exaggerated claims increase the risk of being perceived as engaging in greenwashing. By contrast, companies with significant environmental impacts may use greenwashing as a cost-effective strategy to manage external perception of their environmental performance. Since genuine environmental improvements are often costly, short-term-oriented managers may instead rely on selective disclosure and overstated claims as faster, less expensive alternatives.

2.3. Forecasting of greenwashing risk

For sustainability-oriented stakeholders, forecasting corporate greenwashing risk is essential for identifying and mitigating exposure to sustainability-related financial, reputational, and strategic risks. Accurate forecasts help distinguish companies genuinely pursuing environmental goals from those engaging in symbolic communication, thereby supporting more informed decision-making and resource allocation. The proposed forecasting framework serves as a decision-oriented tool that balances statistical accuracy with the economic implications of prediction errors, providing practical value for diverse stakeholder groups, including customers, suppliers, and investors.

Accordingly, we define a framework to evaluate the economic significance of a greenwashing forecasting method and introduce the expected loss function

$$EL = FN \cdot c + FP \cdot (1 - c), \tag{1}$$

where FN and FP denote the number of false negatives and false positives, respectively, and c and $(1 - c)$ represent their associated expected costs. Without loss of generality, both costs are assumed to sum to 1. If N denotes the number of all cases considered in a forecasting application, and q denotes the fraction of greenwashing cases, then, using the performance metrics recall (R) and specificity (S),[1] we can express FN and FP as $FN = (1 - R) \cdot N \cdot q$ and $FP = (1 - S) \cdot N \cdot (1 - q)$. Substituting FN and FP in Eq. (1) accordingly, we obtain:

$$EL = (1 - R) \cdot N \cdot q \cdot c + (1 - S) \cdot N \cdot (1 - q) \cdot (1 - c) \tag{2}$$

for the expected loss function, which is minimized by choosing an optimal forecasting method. By defining the weight

$$w := \frac{Nqc}{Nqc + N(1-q)(1-c)} = \frac{qc}{1 - q - c + 2qc},$$

we obtain the directly proportional function (to be minimized)

$$EL^* = w \cdot (1 - R) + (1 - w) \cdot (1 - S) = 1 - (w \cdot R + (1 - w) \cdot S).$$

Thus, a positive target function (to be maximized) can be expressed as

$$w \cdot R + (1 - w) \cdot S \rightarrow \max! \tag{3}$$

Note that this expression is the weighted average of recall and specificity, where the weights depend on the cost of false negatives and positives, and the relative number of greenwashing cases in the sample under investigation.

We assume that $c > 1 - c$, reflecting that an undetected case of greenwashing (false negative) causes much greater damage than a false positive, where a company is falsely accused of greenwashing (e.g., Gatti et al., 2019; Walker and Wan, 2012).[2] In an investment context, the cost of an undetected greenwashing case may take the form of reputational losses or stock price declines. By contrast, the lower cost of a false positive can be viewed as an opportunity cost, such as the lost diversification benefit or forgone returns from falsely excluded companies, as well as review expenses. For illustration, if $c = 0.99$ and $(1 - c) = 0.01$ (i.e., a cost ratio of $99 : 1$) with $q = 0.05$, the weight on recall is $w = 0.8390$; for a cost ratio of $9 : 1$, the weight is $w = 0.3214$.

This framework enables sustainability-oriented stakeholders to balance the trade-off between recall and specificity based on economic considerations. A perfect forecast (where recall and specificity both equal one) is generally unachievable given the complexity of greenwashing behavior and the inherent difficulty of detecting all cases.

3. Greenwashing accusations and sample construction

Following the theoretical discussion of greenwashing behavior determinants and forecasting, this section introduces the dataset used in the empirical analysis. We examine STOXX Europe 600 constituents from 2011 to 2023 because of Europe's leadership in global sustainable finance,[3] which provides an ideal setting to study corporate greenwashing behavior from the perspective of investors and other stakeholders.

Our initial sample comprises 1031 companies that were index constituents during the sample period. For each company-year observation, eight research assistants conducted systematic searches for greenwashing accusations using web search engines, NGO websites, and social media platforms such as X (formerly Twitter). These searches yielded 1254 information sources containing greenwashing allegations. Following a structured quality review based on a predefined classification framework (see Table A.1, Appendix A), we excluded 356 sources. In particular, we removed redundant entries that referred to already documented accusations without adding new information to ensure the dataset contains only unique content. This procedure helps mitigate the risk of overrepresenting specific companies and inflating the number of accusations.

Next, four trained researchers independently evaluated the 898 information sources to assess the severity of the greenwashing accusations, which varied in clarity and strength of evidence. A predefined classification scheme with scores ranging from 0 (no greenwashing) to 1 (greenwashing) was applied to ensure consistent and balanced assessments across heterogeneous sources. Table A.2 in Appendix A provides a detailed description of the greenwashing severity score categories and illustrative examples. We then calculated the mean of the four individual assessments to derive a composite company-level greenwashing severity score for each information source.

Based on these company-level greenwashing severity scores, we construct a company-year panel dataset by retaining the highest composite severity score within each year for companies with multiple greenwashing accusations. For companies exhibiting recurring greenwashing behavior across non-consecutive years, we applied interpolation to fill potential gaps, adding 43 company-year observations to reflect the likely continuation of such behavior. The resulting dataset includes 595 company-year observations with greenwashing accusations and 8864 without, represented by a greenwashing severity score of zero. We excluded observations with missing data when merging the dataset with control variables.[4] The final sample consists of 6654 company-year observations across 746 unique companies, including 377 company-years associated with greenwashing accusations.

Table 2 presents descriptive statistics for the final sample. In the "Full sample" columns, the overall industry distribution is relatively balanced with the largest share of companies belonging to the *Industrial* and *Consumer discretionary* industries. In the columns of "Subsample GW accusations", "GW obs. (%)" shows the proportion of greenwashing accusations in each industry relative

[1] See Appendix D for the definitions of the recall and specificity metrics.

[2] This assumption is independent of the decision maker's risk aversion. For simplicity, we assume risk neutrality in our considerations. However, even for a risk-averse decision maker, minimizing expected costs is a rational strategy.

[3] https://www.alfi.lu/en-gb/news/europe-remains-a-global-leader-in-sustainable-fina (lastly accessed on June 23, 2025)

[4] Table A.3 in Appendix A reports the number of missing observations for each control variable.

Table 2
Descriptive statistics of greenwashing accusations across industries.

	Full sample		Subsample GW accusations			
Industry	N	Comp.-years	Comp.-years GW	GW obs. (%)	Mean GW sev. (%)	Std. GW sev. (%)
Basic materials	67	664	50	13.26	79.04	24.91
Consumer discretionary	130	1182	111	29.44	72.75	25.80
Consumer staples	60	566	61	16.18	69.30	30.25
Energy	41	368	40	10.61	76.82	25.59
Financials	40	331	6	1.59	62.50	37.71
Health care	66	556	10	2.65	56.25	34.23
Industrials	166	1515	50	13.26	65.50	26.49
Real estate	53	426	1	0.27	31.25	-
Technology	49	361	1	0.27	56.25	-
Telecommunications	37	335	3	0.80	60.42	30.83
Utilities	37	350	44	11.67	75.57	22.35
Total	**746**	**6654**	**377**			

Notes: This table presents summary statistics of greenwashing (GW) accusations and GW severity scores by industry for companies in the STOXX Europe 600 index from 2011 to 2023. The "Full sample" columns include all companies in our sample, whereas "Subsample GW accusations" include only company-year observations with greenwashing accusations. The column "N" denotes the number of companies, and "GW obs. (%)" shows the proportion of greenwashing accusations in each industry relative to the total number of accusations across all industries. The columns "Mean GW sev. (%)" and "Std. GW sev. (%)" present the mean and standard deviation of GW severity scores, respectively, based on the subsample of greenwashing accusations.

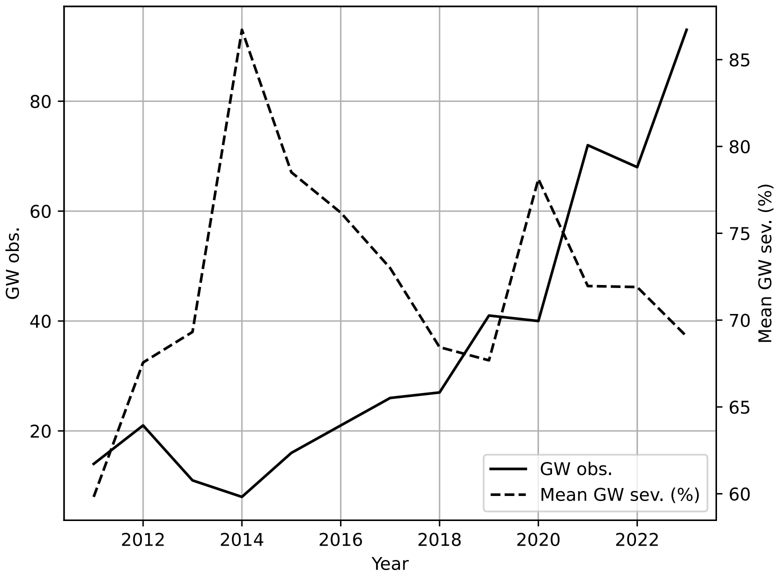

Fig. 1. Annual development in greenwashing accusations (GW obs.) and mean greenwashing severity scores (Mean GW sev. (%)) within the subsample of greenwashing accusations, 2011–2023.

to the total number of greenwashing accusations across all industries. Most greenwashing accusations occur in the consumer-related industries—*Consumer discretionary* (29.4 %) and *Consumer staples* (16.2 %)—as well as in emission- and resource-intensive industries such as *Basic materials*, *Industrials*, *Utilities*, and *Energy*, which together account for roughly 50 % of all accusations. The column "Mean GW sev. (%)" reports the average greenwashing severity score by industry, which is highest in *Basic materials* (79.0 %), *Energy* (76.8 %), and *Utilities* (75.6 %). Finally, the column "Std. GW sev. (%)" shows that the standard deviation of severity scores decreases as the mean severity increases, indicating greater assessment consistency for more severe accusations.

Fig. 1 illustrates the annual distribution of greenwashing accusations from 2011 to 2023. The number of accusations increases from 14 in 2011 to 93 in 2023. While greenwashing accusations remain relatively low before 2015, their number rise sharply thereafter. This post-2015 increase likely reflects growing institutional pressures and greater scrutiny from media and NGOs (e.g., Delmas and Burbano, 2011), coinciding with stronger attention to corporate environmental performance following the Paris Agreement. In contrast, mean greenwashing severity scores remain within a range of 60 % to 87 % across years.

4. Determinants of greenwashing behavior in European companies

4.1. Company-level characteristics

To empirically identify the company-level determinants of greenwashing behavior, we estimate models that relate company characteristics to the greenwashing severity score while controlling for year, industry, and country fixed effects. Because the severity score is bounded between 0 and 1 and exhibits a substantial mass at zero (i.e., left-censored), we apply Tobit model regressions that account for this censoring and prevent bias from truncation at the lower bound. For comparison, we also estimate OLS models, which do not correct for censoring but allow straightforward interpretation of marginal effects.

Following our theoretical framework, we operationalize the conceptual categories through a set of company-level variables. The category *green reputation* includes the E(SG) scores, the ESG disclosure score, and emission intensities. *Size and visibility* consists of company size and analyst coverage. *Capital dependency* is represented by cash-to-assets, leverage and capex-to-assets, while *risk and return* comprises return-on-assets, earnings variability, price volatility, and market-to-book ratio. Finally, *other factors* include capital intensity, ownership concentration, and foreign sales.[5]

Since prior research suggests that greenwashing behavior may occur among companies with low and high apparent environmental performance, we include squared terms for the ESG and E scores to capture potential non-linear relationships. While Kathan et al. (2025) show that companies with high ESG scores are particularly prone to greenwashing due to overstated apparent environmental performance, legitimacy theory also implies that poor ESG performers may use symbolic communication to compensate for weak sustainability outcomes (Delmas and Burbano, 2011; Lyon and Montgomery, 2015).

Building on these considerations, Table 3 presents the regression results. Models 1–3 report Tobit estimations, and Models 4–6 report OLS estimations. The first two models in each set of columns use the full 2011–2023 sample (Models 1, 2, 4, and 5), whereas Models 3 and 6 are based on the 2017–2023 subsample due to the availability of *GHG Scope 3 up + down* data from 2017 onward.

Beginning with the *green reputation* category, the results show that the squared *ESG score* is positively and the linear term negatively correlated with the greenwashing severity score, and both coefficients are highly statistically significant. This pattern indicates a U-shaped relationship, suggesting greenwashing behavior is more common among companies with high or low ESG scores. Thus, companies perceived as top or poor ESG performers may employ greenwashing to manage environmental expectations and increased scrutiny. These findings provide further evidence to the literature (e.g., Kathan et al., 2025) showing that ESG scores are an important determinant of greenwashing.

To further disentangle the ESG-greenwashing relationship, we replace the aggregated *ESG score* with linear and quadratic *E scores* in Models 2 and 5. Consistent with the previous results, we again find a U-shaped relationship between the *E score* and greenwashing severity score. From a Tobit-model perspective, this implies that companies with both low and high *E scores* are more likely to have a positive greenwashing severity score and, on average, exhibit higher greenwashing risk. Hence, the *E score* appears to account for much of the overall ESG-greenwashing link, with companies perceived as either environmentally weak or strong showing a higher propensity to engage in greenwashing. The calculated vertex points for the U-shaped relationships across all models lie above 0.5, suggesting that companies with below-average E(SG) scores face a higher greenwashing risk than those with higher scores.

In addition to the ESG scores, the coefficient for the *ESG disclosure score* is positive and statistically significant across all models—at the 5 % level in Models 1, 3, 4, and 6 and at the 10 % level in Models 2 and 5. A likely explanation is that extensive ESG reporting can create an impression of superior environmental performance, thus deepening the gap between a company's communicated image and its actual environmental practices. Turning to GHG intensities, *Scope 1* is positively associated with greenwashing behavior in Tobit Models 1–3, and in OLS this effect appears only in the 2017–2023 subsample (Model 6). By contrast, *Scope 2* is negative and significant but only in the subsample regression (Models 3 and 6), while *Scope 3* variables are not statistically significant. The positive association for *Scope 1* may suggest that companies with higher direct emissions tend to have higher greenwashing severity scores. This pattern aligns with the idea that emission-intensive companies, being subject to greater public scrutiny, may use symbolic environmental communication to mitigate reputational risks linked to visible pollution. Because reducing such emissions typically involves costly operational changes, these companies may instead rely on greenwashing behavior to demonstrate environmental commitment without undertaking substantive improvements.

We proceed by discussing the variables in the *size and visibility* category. *Company size* shows a positive relationship with observed greenwashing incidents, whereas *analyst coverage* is not statistically significant. To further examine the insignificant results for *analyst coverage*, we note its moderate correlation with *company size* (0.39, see Table B.3 in Appendix B). Untabulated results show that *analyst coverage* becomes highly statistically significant with a positive coefficient when we re-estimate regression models excluding the size variable. This suggests that *company size* absorbs part of *analyst coverage's* explanatory power because their visibility dimensions overlap. Together with the results for ESG-related variables, these findings indicate that larger—and therefore more visible—companies tend to display higher levels of greenwashing intensity, consistent with prior evidence on size-related effect in ESG performance (Dobrick et al., 2023; Drempetic et al., 2020).

We now turn to the *capital dependency* category. The positive and significant coefficients of *cash-to-assets* indicates that companies with higher internal liquidity and lower reliance on external capital markets exhibit higher greenwashing severity scores. This finding

[5] Table B.3 in Appendix B reports Pearson correlation coefficients. Company size, ESG score, ESG disclosure score, and analyst coverage are positively correlated with the greenwashing severity score. To assess multicollinearity, we calculate Variance Inflation Factors (VIF) from an OLS model, which yields a mean VIF of 1.78, indicating no significant collinearity.

is consistent with the free cash flow hypothesis (e.g., Jensen, 1986), suggesting that financial slack may enable managers to pursue symbolic rather than substantive ESG initiatives. By contrast, financially constrained companies face stronger market discipline, which limits their ability to engage in opportunistic sustainability communication. This interpretation aligns with the evidence of Zhang (2023), who show that financially constrained companies are less likely to greenwash.

None of the variables in the *risk and return* category show consistently significant coefficients across models. Thus, greenwashing behavior does not appear to be systematically related to companies' market or risk characteristics. Regarding the remaining factors, only *capital intensity* shows positive and statistically significant coefficients for the dependent variable. This finding aligns with Marquis et al. (2016), who find that capital-intensive companies are more prone to environmental damage and to selective disclosure that relates to greenwashing.

To further strengthen the robustness of our results, we conduct two additional analyses. First, to mitigate potential simultaneity concerns, we re-estimate the main Tobit and OLS models using one-year-lagged explanatory variables (see Table B.4 in Appendix B). The results show that coefficient signs, magnitudes, and significance remain largely unchanged, supporting the robustness of our findings. Second, we estimate equivalent OLS models with a binarized version of the greenwashing severity score as the dependent variable, which yields consistent results and confirms the stability of our conclusions (see Table B.5 in Appendix B).

4.2. Industry-level variation

The previous analysis includes industry fixed effects to account for industry heterogeneity. However, these controls do not identify how industries are associated with the observed variation in greenwashing behavior. To address this, we next analyze greenwashing behavior across industries. Specifically, we modify Model 1 from Table 3 by introducing industry dummies as separate regressors and iteratively excluding one to serve as the reference category. This approach enables a direct comparison of greenwashing occurrence across industries. The resulting coefficients are presented in Table 4.

The results reveal distinct industry patterns. In Model 2, where *Consumer discretionary* serves as the reference category, coefficients for all other industries except *Basic materials*, *Consumer staples*, *Energy*, and *Utilities* are negative and statistically significant. We find similar results when *Consumer staples* is used as the reference category (Model 3). Together, these findings suggest that companies in consumer-facing industries exhibit higher levels of greenwashing behavior than those in most other industries. This supports our hypothesis that companies in consumer-oriented industries are more prone to greenwashing due to greater public scrutiny and reputational exposure.

In contrast, companies in the *Telecommunications* industry exhibit the lowest level of greenwashing behavior, followed by those in the *Real estate* and *Technology* industries, as shown in Models 8–10. The positive and significant coefficients indicate that these industries display relatively less greenwashing behavior compared to others. However, these results should be interpreted cautiously, as the number of observations in *Real estate* and *Technology* (one company-year each) and *Telecommunications* (three company-years) is very limited, restricting the reliability of these estimates.

Furthermore, Models 1 and 11 show that companies in the *Basic materials* and *Utilities* industries, which are characterized by high environmental externalities, exhibit higher greenwashing severity scores compared with those in *Telecommunications*, *Technology*, *Real estate*, and *Health care*. At the same time, coefficients for most other industries remain insignificant in these models. Moreover, we find mixed results when the industries *Energy* and *Industrials* serve as reference categories (Models 4 and 7). Taken together, these findings provide only limited support for the hypothesis that greenwashing behavior is more prevalent in environmentally intensive industries.

5. Forecasting greenwashing risk in European companies

Having identified company characteristics associated with greenwashing behavior, we now develop a forecasting framework to predict greenwashing risk based on our developed framework for sustainable-oriented stakeholders (see Section 2.3). To ensure a realistic out-of-sample setting, we validate model performance using greenwashing accusations from the year 2023.[6] Following common forecasting terminology, we refer to the explanatory variables as "features," which represent the company characteristics analyzed in Section 4. We classify observations as "positive" when the greenwashing severity score exceeds 0 and as "negative" when it equals 0.

We apply a suite of machine learning models that capture relationships from simple linear patterns to complex non-linear and sequential dynamics. Prior studies show these approaches perform well in economic forecasting, including stock price prediction (Chong et al., 2017; Fischer and Krauss, 2018; Ghosh et al., 2022; Hoseinzade and Haratizadeh, 2019), default forecasting (Antulov-Fantulin et al., 2021; Jones, 2023), and portfolio optimization (De Prado, 2018; Ghosh et al., 2022; Yun et al., 2020). Similar methods have also been applied successfully to forecast corporate misconduct and environmental disclosure (Frost et al., 2023; Liu et al., 2015; Serafeim and Caicedo, 2022; Wang et al., 2020). We describe the models used in our study in detail in Appendix C.

For the forecasting models, we also include corporate misconduct variables that were deliberately excluded from the determinant analysis in the previous section to avoid multicollinearity with the greenwashing measure. For forecasting, however, these variables are valuable because past environmental controversies can help predict future greenwashing behavior. We therefore expand the

[6] For the regression models, we use the full 2011–2023 sample, whereas this section focuses on forecasting models trained on 2012–2022 data and validated on 2023 accusations.

Table 3
Main regression results.

		Tobit			OLS		
		Full sample		Year > 2016	Full sample		Year > 2016
Category	Variable	(1)	(2)	(3)	(4)	(5)	(6)
Green reputation	ESG score × ESG score	6.574***		6.347***	0.450***		0.573***
		(1.400)		(1.662)	(0.094)		(0.156)
	ESG score	−8.373***		−8.551***	-0.564***		-0.760***
		(1.781)		(2.174)	(0.104)		(0.185)
	E score × E score		3.477***			0.254***	
			(1.077)			(0.059)	
	E score		−3.884***			-0.295***	
			(1.328)			(0.056)	
	ESG disclosure score	1.613**	1.405*	1.941**	0.101**	0.087*	0.165**
		(0.773)	(0.791)	(0.864)	(0.047)	(0.050)	(0.076)
	GHG scope 1	0.030***	0.029***	0.044***	0.001	0.001	0.004**
		(0.011)	(0.010)	(0.011)	(0.001)	(0.001)	(0.002)
	GHG scope 2	−0.108	−0.089	−0.240**	−0.005	-0.004	−0.010*
		(0.096)	(0.096)	(0.122)	(0.004)	(0.004)	(0.005)
	GHG scope 3 up	−0.040	−0.035		0.000	0.001	
		(0.038)	(0.038)		(0.002)	(0.002)	
	GHG scope 3 up + down			0.002			0.000
				(0.002)			(0.000)
Size and visibility	Size	0.571***	0.562***	0.474***	0.035***	0.035***	0.043***
		(0.063)	(0.061)	(0.062)	(0.006)	(0.006)	(0.007)
	Analyst coverage	0.169	0.109	0.285	0.000	−0.001	−0.001
		(0.174)	(0.175)	(0.182)	(0.007)	(0.007)	(0.010)
Capital dependency	Cash-to-assets	2.111***	2.084***	1.552**	0.115***	0.103***	0.144***
		(0.659)	(0.673)	(0.656)	(0.025)	(0.025)	(0.035)
	Leverage	−0.005	−0.005	−0.001	0.000	0.000	0.000
		(0.004)	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)
	Capex-to-assets	−0.021	−0.018	−0.095	−0.005	−0.004	−0.008
		(0.118)	(0.121)	(0.126)	(0.005)	(0.005)	(0.009)
Risk and return	Return-on-assets	−0.011	−0.011	−0.003	0.000	0.000	0.000
		(0.009)	(0.008)	(0.008)	(0.000)	(0.000)	(0.001)
	Earnings variability	−0.060	−0.047	−0.086	0.006	0.007*	0.005
		(0.079)	(0.079)	(0.081)	(0.004)	(0.004)	(0.006)
	Price volatility	−0.018*	−0.022*	−0.016	−0.000	−0.001	−0.001
		(0.011)	(0.011)	(0.012)	(0.001)	(0.001)	(0.001)
	Market-to-book ratio	0.052	0.021	−0.084	−0.001	-0.002	−0.003
		(0.132)	(0.132)	(0.121)	(0.008)	(0.008)	(0.010)
Other factors	Capital intensity	1.306***	1.236***	1.700***	0.081***	0.082***	0.129***
		(0.426)	(0.430)	(0.428)	(0.028)	(0.028)	(0.040)
	Owner concentration	−0.021	−0.025	−0.022	−0.003	−0.003	−0.004
		(0.057)	(0.056)	(0.059)	(0.004)	(0.004)	(0.005)
	Foreign sales	−0.017	−0.017	−0.010	0.000	−0.000	0.001
		(0.054)	(0.055)	(0.055)	(0.002)	(0.002)	(0.003)
	Constant	−6.064***	−7.050***	−5.184***	−0.048	−0.116	0.024
		(1.291)	(1.147)	(1.174)	(0.083)	(0.085)	(0.104)
	Year	Yes	Yes	Yes	Yes	Yes	Yes
	Industry	Yes	Yes	Yes	Yes	Yes	Yes
	Country	Yes	Yes	Yes	Yes	Yes	Yes
	N	6654	6654	3711	6654	6654	3711
	Pseudo R^2 / Adj. R^2	0.324	0.322	0.343	0.153	0.151	0.198

Notes: This table presents results of Tobit and OLS regression models, where the dependent variable is the greenwashing severity score. All continuous variables are winsorized at the 0.5 % level at both ends. Standard errors are clustered at the company level and reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

forecasting dataset with corporate environmental issue indicators from LSEG and RepRisk, which capture historical patterns of misconduct. To prevent look-ahead bias, all features, including the corporate misconduct variables, enter the models in lagged form. We also add the lagged greenwashing severity score to capture temporal dependencies, as past greenwashing behavior is likely to persist and indicate increased future greenwashing risk. This extended feature set enables the forecasting models to integrate static company characteristics with dynamic, historically driven risk factors. We provide descriptive statistics for the complete set of features used in the forecasting models, including determinants and corporate misconduct[7] in Table B.7 of Appendix B. To ensure consistent inter-

[7] Definitions of the corporate misconduct variable are provided in Table B.6 of Appendix B.

Table 4
Tobit regression results across industries.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	Basic materials		−0.199	−0.305	0.169	0.389	1.013*	0.426	1.204*	1.263*	1.674***	−0.008
			(0.303)	(0.343)	(0.374)	(0.481)	(0.544)	(0.310)	(0.618)	(0.673)	(0.488)	(0.371)
2	Consumer discretionary	0.199		−0.106	0.368	0.588*	1.211***	0.625***	1.403**	1.461**	1.873***	0.190
		(0.303)		(0.223)	(0.306)	(0.352)	(0.443)	(0.186)	(0.581)	(0.634)	(0.422)	(0.281)
3	Consumer staples	0.305	0.106		0.474	0.694*	1.317***	0.731***	1.508**	1.567**	1.979***	0.296
		(0.343)	(0.223)		(0.328)	(0.394)	(0.467)	(0.246)	(0.604)	(0.664)	(0.439)	(0.302)
4	Energy	−0.169	−0.368	−0.474		0.220	0.844	0.257	1.035	1.094	1.505***	−0.177
		(0.374)	(0.306)	(0.328)		(0.459)	(0.526)	(0.340)	(0.651)	(0.681)	(0.477)	(0.362)
5	Financials	−0.389	−0.588*	−0.694*	−0.220		0.624	0.037	0.815	0.874	1.285**	−0.398
		(0.481)	(0.352)	(0.394)	(0.459)		(0.515)	(0.368)	(0.654)	(0.718)	(0.534)	(0.440)
6	Health care	−1.013*	−1.211***	−1.317***	−0.844	−0.624		−0.587	0.191	0.250	0.662	−1.021*
		(0.544)	(0.443)	(0.467)	(0.526)	(0.515)		(0.448)	(0.707)	(0.737)	(0.566)	(0.524)
7	Industrials	−0.426	−0.625***	−0.731***	−0.257	−0.037	0.587		0.778	0.837	1.248***	−0.434
		(0.310)	(0.186)	(0.246)	(0.340)	(0.368)	(0.448)		(0.581)	(0.637)	(0.419)	(0.307)
8	Real estate	−1.204*	−1.403**	−1.508**	−1.035	−0.815	−0.191	−0.778		0.059	0.470	−1.212*
		(0.618)	(0.581)	(0.604)	(0.651)	(0.654)	(0.707)	(0.581)		(0.825)	(0.685)	(0.629)
9	Technology	−1.263*	−1.461**	−1.567**	−1.094	−0.874	−0.250	−0.837	−0.059		0.412	−1.271*
		(0.673)	(0.634)	(0.664)	(0.681)	(0.718)	(0.737)	(0.637)	(0.825)		(0.734)	(0.676)
10	Telecommunications	−1.674***	−1.873***	−1.979***	−1.505***	−1.285**	−0.662	−1.248***	−0.470	−0.412		−1.683***
		(0.488)	(0.422)	(0.439)	(0.477)	(0.534)	(0.566)	(0.419)	(0.685)	(0.734)		(0.470)
11	Utilities	0.008	−0.190	−0.296	0.177	0.398	1.021*	0.434	1.212*	1.271*	1.683***	
		(0.371)	(0.281)	(0.302)	(0.362)	(0.440)	(0.524)	(0.307)	(0.629)	(0.676)	(0.470)	
	N	6654	6654	6654	6654	6654	6654	6654	6654	6654	6654	6654

Notes: This table reports the industry coefficients from the Tobit regression Model 1 reported in Table 3, estimated with year and country fixed effects, while controlling for company–level characteristics. Each specification includes alternating industry dummies, one of which serves as the reference category. All regressions include a constant. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

pretation, the RepRisk variables are defined as 1 minus the total number of incidents for each variable within a year, so that higher values represent better (that is, less harmful) environmental behavior.

We preprocess the data to ensure high quality and comparability across models. First, we binarize the target variable using an initial threshold of 0 to enable classification performance metrics. Second, we encode categorical variables using one-hot encoding, mapping each categorical feature to integer values represented as binary vectors. Third, to scale continuous features appropriately, we generate a normal quantile-quantile (*Q-Q*) plot for each feature to visualize its relationship with randomly generated standard normal distributed data. The plots indicate that the *ESG disclosure score* follows a normal distribution. Therefore, we standardize this feature using Z-score normalization, which scales it to unit variance with a mean of zero. All other continuous features are scaled using min-max normalization. This preprocessing step ensures that all models are trained on normalized data, facilitating fair comparisons (e.g, Chawla et al., 2004). Fourth, we generate one-year-lagged versions of all features to establish a forecasting setting and avoid data leakage from future information. Fifth, we randomly and stratifically split the 2012–2022 dataset into training (70 %) and test (30 %) subsets, maintaining an equal distribution between positive and negative classes in both datasets.[8] Sixth, we define the 2023 greenwashing accusations as our validation set to evaluate model performance on unseen data. This setup enables us to examine greenwashing risk forecasting in a real-world setting.

Using the preprocessed dataset, we train all models on the training set and evaluate the forecasting accuracy on both the test (in-sample) and validation (out-of-sample) sets. To optimize model performance, we select the classification threshold that maximizes our economically motivated target function (TF), defined in Eq. (3) in Section 2.3 on the test set. The selected threshold is then applied to compute performance metrics on the validation set and compared with a naive forecast that assumes the greenwashing severity score of 2022 as the forecasting value for 2023. We further include a no-information benchmark that predicts “positive” or “negative” outcomes by sampling according to the observed prevalence of the positive class in the training data. This provides a minimal baseline that does not rely on any feature information. For optimization, we estimate the models under multiple specifications, using *k*-fold cross-validation (*k*-fold CV) to improve forecasting accuracy and generalization. We also vary optimizers and loss functions for neural network models and address class imbalance through ClassWeights, Up-sampling, and Random Over-Sampling Examples (ROSE) (Chawla et al., 2004; López et al., 2013; Lunardon et al., 2014; Menardi and Torelli, 2014). Finally, all models are estimated with both default parameters and hyperparameter-tuned (HT) specifications.

Regarding descriptive statistics, the training set contains 3864 observations, including 235 positive and 3629 negative cases. The test dataset consists of 1656 observations, including 101 from the positive class and 1555 from the negative class. Thus, in both datasets, 6 % of all company-year observations contain greenwashing severity scores greater than 0. The 2023 validation set contains 386 observations, 43 positive and 343 negative. Given this class imbalance, we assume that for sustainability-oriented stakeholders the cost of a false negative is substantially higher than that of a false positive. Accordingly, we optimize the classification threshold

[8] We use 2012 as the starting year rather than 2011 because our models rely on one-year-lagged features.

Table 5
Forecasting performance on the test set (2012–2022).

Panel A - TF: Cost for FN $c = 0.99$					
Model	TF	P-diff	Recall	Specificity	Specification
No-information benchmark	0.172		0.059	0.936	
Logistic Regression	0.926	0.000	0.970	0.628	HT
Random Forest	0.913	0.000	0.941	0.728	*k*-fold CV
KNN	0.872	0.000	1.000	0.000	*k*-fold CV
SVM	0.919	0.001	0.960	0.640	Up-sampling HT
Decision Tree	0.872	0.000	1.000	0.000	*k*-fold CV
Gradient Boosting	0.911	0.000	0.980	0.442	*k*-fold CV
FNN	0.917	0.042	0.970	0.554	Up-sampling HT
RNN	**0.929**	0.000	0.980	0.579	ROSE HT
LSTM	0.911	0.000	0.950	0.641	ROSE HT
Panel B - TF: Cost for FN $c = 0.90$					
Model	TF	P-diff	Recall	Specificity	Specification
No-information benchmark	0.601		0.059	0.936	
Logistic Regression	0.850	0.000	0.842	0.855	Up-sampling HT
Random Forest	0.862	0.000	0.772	0.917	*k*-fold CV
KNN	0.763	0.000	0.644	0.838	*k*-fold CV
SVM	0.858	0.000	0.723	0.942	HT
Decision Tree	0.781	0.000	0.485	0.964	ClassWeights HT
Gradient Boosting	0.860	0.000	0.743	0.932	ClassWeights HT
FNN	0.860	0.000	0.812	0.890	ROSE HT
RNN	**0.869**	0.000	0.792	0.916	Up-sampling
LSTM	0.857	0.000	0.812	0.885	Up-sampling
Panel C - TF: Cost for FN $c = 0.50$					
Model	TF	P-diff	Recall	Specificity	Specification
No-information benchmark	0.879		0.059	0.936	
Logistic Regression	0.951	0.000	0.356	0.992	*k*-fold CV
Random Forest	**0.952**	0.000	0.436	0.987	*k*-fold CV HT
KNN	0.945	0.000	0.297	0.990	ClassWeights HT
SVM	0.949	0.000	0.287	0.995	Up-sampling HT
Decision Tree	0.933	0.000	0.485	0.964	ClassWeights HT
Gradient Boosting	0.950	0.000	0.505	0.981	Up-sampling HT
FNN	0.948	0.000	0.257	0.995	Up-sampling HT
RNN	0.950	0.000	0.287	0.995	Up-sampling
LSTM	0.946	0.000	0.297	0.990	ROSE

Notes: “No-information benchmark” refers to a stratified prediction where the probability of predicting greenwashing equals the empirical prevalence, i.e., $P(\hat{y} = 1) = P(y = 1)$. TF denotes the cost-weighted accuracy (target function). FN represents false negatives. HT reflects hyperparameter-tuned models. P-diff reports the p-value of a two-sided paired t-test comparing each model’s per-observation misclassification cost to that of the no-information benchmark. Each panel corresponds to a different cost specification ($c = 0.99$, 0.90, 0.50), and the best-performing model within each panel is highlighted in bold.

by setting the cost parameter c to 0.99 and 0.90 in our TF, corresponding to cost ratios of 99 : 1 and 9 : 1. These two specifications represent high- and moderate-cost settings, respectively.

As the cost parameter c increases, false negatives become more detrimental in economic terms, making recall increasingly more important than specificity. However, optimizing recall is challenging in imbalanced datasets because greenwashing accusations are relatively rare. To address this issue, we adapt our imbalance handling strategy to each cost setting. When c is high (0.99), methods such as ROSE and Up-sampling perform better because they are known to improve recall. For lower c values (0.90), the models maintain a more balanced trade-off between recall and specificity. Under moderate cost settings, methods that address imbalance more conservatively, such Up-sampling and ClassWeights, tend to achieve better overall performance. Up-sampling remains effective across cost levels but serves different purposes: at high c, it emphasizes the minority class to improve the detection of greenwashing cases, whereas at moderate c, it maintains a balanced relationship between recall and specificity.

We now evaluate how the different forecasting models perform under varying cost assumptions. This step allows us to assess which approaches best balance recall and specificity from an economic decision-making perspective. Table 5 presents the forecasting performance of all models on the test set. Panel A shows models optimized under a high cost weight ($c = 0.99$) in our TF, Panel B corresponds to a moderate cost setting ($c = 0.90$), and Panel C provides results for a balanced cost scenario ($c = 0.50$) as a robustness

Table 6
Forecasting performance on the validation set (2023).

Panel A - TF: Cost for FN $c = 0.99$					
Model	TF	P-diff	Recall	Specificity	Specification
No-information benchmark	0.120		0.000	0.933	
Naive forecast	0.608		0.558	0.945	
Logistic Regression	0.910	0.000	0.953	0.612	HT
Random Forest	0.884	0.000	0.907	0.726	*k*-fold CV
KNN	0.872	0.000	1.000	0.000	*k*-fold CV
SVM	0.915	0.000	0.953	0.656	Up-sampling HT
Decision Tree	0.872	0.000	1.000	0.000	*k*-fold CV
Gradient Boosting	0.925	0.000	0.977	0.571	*k*-fold CV
FNN	0.920	0.000	1.000	0.379	Up-sampling HT
RNN	**0.931**	0.000	1.000	0.464	ROSE HT
LSTM	0.919	0.000	0.977	0.531	ROSE HT
Panel B - TF: Cost for FN $c = 0.90$					
Model	TF	P-diff	Recall	Specificity	Specification
No-information benchmark	0.577		0.000	0.933	
Naive forecast	0.797		0.558	0.945	
Logistic Regression	0.791	0.000	0.651	0.878	Up-sampling HT
Random Forest	**0.846**	0.000	0.767	0.895	*k*-fold CV
KNN	0.827	0.000	0.744	0.878	*k*-fold CV
SVM	0.802	0.000	0.605	0.924	HT
Decision Tree	0.756	0.000	0.465	0.939	ClassWeights HT
Gradient Boosting	0.818	0.000	0.651	0.921	ClassWeights HT
FNN	0.825	0.000	0.744	0.875	ROSE HT
RNN	0.818	0.000	0.698	0.892	Up-sampling
LSTM	0.816	0.000	0.744	0.860	Up-sampling
Panel C - TF: Cost for FN $c = 0.50$					
Model	TF	P-diff	Recall	Specificity	Specification
No-information benchmark	0.873		0.000	0.933	
Naive forecast	0.920		0.558	0.945	
Logistic Regression	0.935	0.000	0.419	0.971	*k*-fold CV
Random Forest	0.933	0.000	0.419	0.968	HT
KNN	0.941	0.000	0.372	0.980	ClassWeights HT
SVM	0.943	0.000	0.372	0.983	Up-sampling HT
Decision Tree	0.906	0.001	0.465	0.936	ClassWeights HT
Gradient Boosting	0.936	0.000	0.512	0.965	Up-sampling HT
FNN	0.938	0.000	0.419	0.974	Up-sampling HT
RNN	**0.944**	0.000	0.419	0.980	Up-sampling
LSTM	0.935	0.000	0.419	0.971	ROSE

Notes: “No-information benchmark” refers to a stratified prediction where the probability of predicting greenwashing cases equals the empirical prevalence, i.e., $P(\hat{y} = 1) = P(y = 1)$. The naive forecast assumes no change in severity score between 2022 and 2023, i.e., the greenwashing severity score in 2022 equals that in 2023. TF denotes the cost-weighted accuracy (target function). FN represents false negatives. HT reflects hyperparameter-tuned models. P-diff reports the p-value of a two-sided paired *t*-test comparing each model’s per-observation misclassification cost to that of the no-information benchmark. Each panel corresponds to a different cost specification ($c = 0.99, 0.90, 0.50$), and the best-performing model within each panel is highlighted in bold.

check. The models listed in each panel are those with the highest TF values among all estimated models for the respective cost specifications. Details on model configurations, including imbalance handling strategies, tuning approach, and holdout treatment, are shown in the “Specification” column.

Across all panels, the selected machine learning models significantly outperform the no-information benchmark, which achieves a TF of only 0.172 at $c = 0.99$, 0.601 at $c = 0.90$, and 0.879 at $c = 0.50$. These performance differences are statistically significant for all models, as indicated by the paired t-test results in the “P-diff” column. The improvements are particularly pronounced in recall and specificity, highlighting the models’ ability to detect greenwashing while maintaining a low false positive rate.

Among the individual models, *Logistic Regression* performs consistently well, achieving a TF of 0.926 at $c = 0.99$ and 0.850 at $c = 0.90$, outperforming several more complex models across both recall and specificity. The best-performing model at each cost

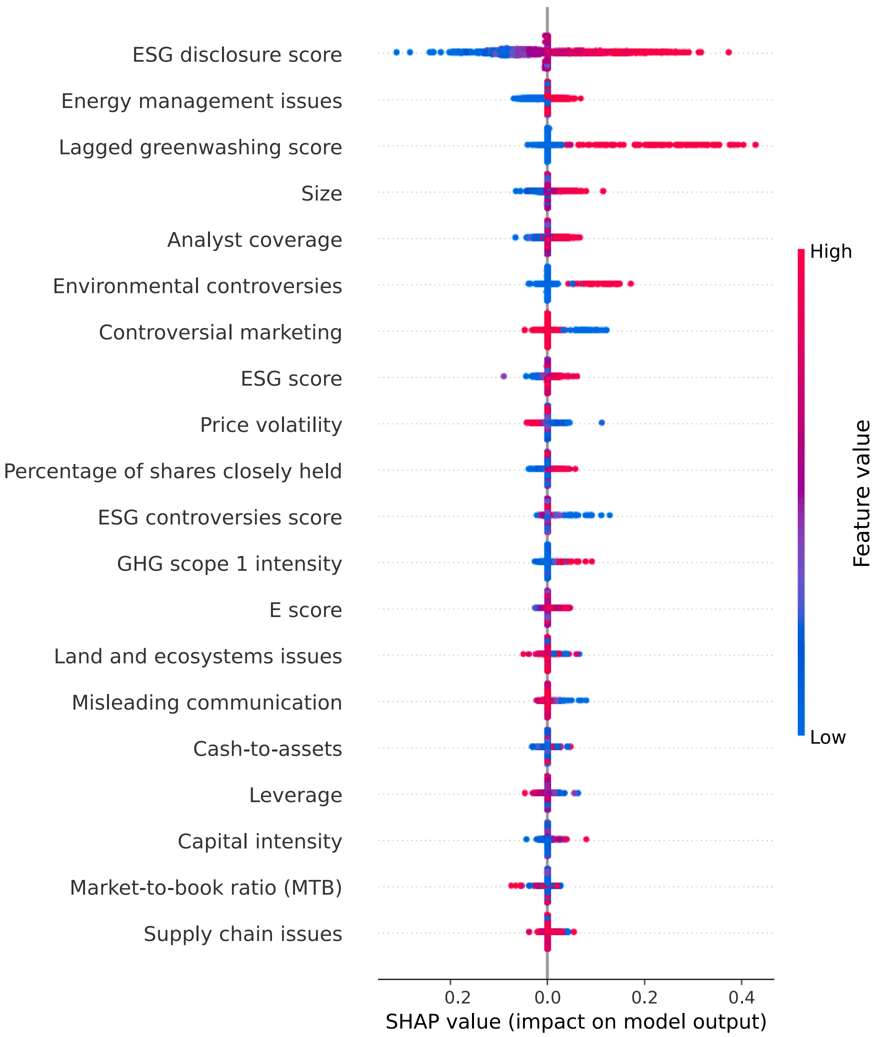

Fig. 2. Feature importance for the *RNN* model at $c = 0.99$. This figure shows the SHAP values for the best-performing *RNN* model trained in the high-cost setting. Each point represents a SHAP value for one observation-feature pair, showing the direction and magnitude of that feature's contribution to the predicted probability of greenwashing. Features are ranked by their overall importance (mean absolute SHAP value), and colors indicate the original feature value from low to high. For interpretability, all dummy variables (year, industry, and country indicators) are excluded from the plot.

level, however, varies: the *Recurrent Neural Network (RNN)* achieves the highest TF values of 0.929 and 0.869 at $c = 0.99$ and $c = 0.90$, respectively, while at $c = 0.50$, *Random Forest* yields the best performance with a TF of 0.952.

In the high-cost setting ($c = 0.99$), the *RNN* achieves a recall of 0.980 and specificity of 0.579, i.e., it correctly identifies 98 % of all greenwashing observations and 58 % of non-greenwashing observations. At $c = 0.90$, it maintains strong performance with a recall of 0.792 and specificity of 0.916. These results demonstrate that the *RNN* effectively prioritizes greenwashing detection according to the cost function. Imbalance handling strategies such as Up-sampling and ROSE are particularly beneficial for neural networks, substantially enhancing recall. The performance of other models is more variable and depends on their interaction with the model architecture and cost setting.

To validate the models' out-of-sample predictive ability, we re-estimate them using the 2023 validation set. Specifically, for each cost factor c, we apply the model specification that achieved the highest TF value on the test set. For benchmarking, we also consider a naive forecasting model that assumes the greenwashing severity score of 2022 as the forecast for 2023. The performance metrics are shown in Table 6.

Across all panels, almost all models substantially outperform both the naive forecast, which assumes no change in greenwashing severity between 2022 and 2023, and the no-information benchmark, which represents a stratified guess based on empirical prevalence. In Panel A ($c = 0.99$), the no-information benchmark achieves a TF of only 0.120, while the naive forecast reaches 0.608. All machine learning models exceed 0.870, with the *RNN* achieving the highest TF of 0.931. These results imply a cost reduction of approximately 92 % relative to the no-information benchmark and over 82 % relative to the naive forecast, as measured by the TF complement (1 − TF). In Panel B ($c = 0.90$), the benchmark shows a TF score of 0.577, the naive forecast 0.797, and the best-performing model, *Random Forest*, 0.846. Panel C ($c = 0.50$) differs from the previous results. The naive forecast achieves a TF of 0.920, slightly exceeding the benchmark (0.873), yet all machine learning models continue to perform better, with the *RNN* again achieving the highest TF of 0.944.

Overall, the naive forecast has high specificity (0.945) but only moderate recall (0.558). This indicates that the benchmark correctly identifies companies as non-greenwashing in most cases, which is consistent with the predominance of this group in the sample. In contrast, machine learning models achieve substantially higher recall, up to 1.000 in several cases at $c = 0.99$, making them particularly valuable when the cost of false negatives is high. These results highlight the practical advantage of data-driven classification methods, both traditional and learning-based, in identifying greenwashing, especially when calibrated to stakeholder-specific cost preferences.

Panel A confirms that the *RNN* is most effective when the cost of missing a greenwashing case is high ($c = 0.99$), achieving a recall of 1.000 and specificity of 0.464. At moderate cost sensitivity ($c = 0.90$, Panel B), *Random Forest* performs best with a recall of 0.767 and specificity of 0.895. Under balanced cost conditions ($c = 0.50$, Panel C), the *RNN* again provides the strongest performance. These findings highlight the importance of aligning model selection with stakeholder cost preferences and sustainability objectives.

To ensure that our results are not mechanically driven by persistence in greenwashing behavior, we conduct a robustness check excluding the lagged greenwashing severity score from the feature set. Untabulated results indicate that model performance remains stable, with only minor reductions in TF values. Even without the lagged score, our models outperform the benchmark classifiers across all cost-sensitive evaluation settings. This confirms that the predictive power of our approach is not solely due to past greenwashing activity but also reflects broader company-level characteristics and performance indicators.

To conclude our analysis of greenwashing forecasting, we examine which features contribute most to the predictions of the *RNN* model in the high-cost setting ($c = 0.99$). To this end, we generate a SHapley Additive exPlanations (SHAP) summary plot based on the validation set, as shown in Fig. 2. The plot illustrates both the magnitude and direction of each feature's influence on the model output, providing a detailed view of feature relevance and behavior. For interpretability, all dummy variables (year, industry, and country indicators) are excluded from the SHAP plot.

The top predictors are the *ESG disclosure score*, *energy management issues*, the one-year lagged *greenwashing severity score*, *company size*, *analyst coverage*, and *environmental controversies*. This ranking indicates that large companies with extensive ESG disclosures, notable energy management challenges, and a history of greenwashing behavior are the most influential in predicting future greenwashing risk. Moreover, several variables identified as greenwashing behavior determinants in Section 4 also show strong SHAP contributions, with *ESG disclosure score*, *company size*, and *ESG score* emerging as the most relevant within that group.

6. Concluding remarks and discussion

This study investigates corporate greenwashing behavior by (1) identifying its company-level determinants and industry-level variation and (2) forecasting greenwashing risk using machine learning models grounded in economic theory. The findings contribute to both academic research and practical applications.

From an academic perspective, this study offers a comprehensive empirical analysis of company characteristics associated with greenwashing behavior. It extends the corporate misconduct literature by integrating greenwashing as a critical aspect of organizational behavior and demonstrating that it can be forecasted with high accuracy. Specifically, the results show that companies with low or high ESG scores, and those perceived as environmentally "poor" (low E score) or "top" (high E score) performers, are more likely to engage in greenwashing. Other critical determinants include company size, ESG disclosure score, cash-to-assets ratio, and capital intensity. At the industry level, greenwashing behavior is more prevalent in consumer-facing industries, while industries such as real estate, technology, and telecommunications have a lower risk of greenwashing. Our findings support recent evidence that machine learning models achieve high accuracy in forecasting corporate misconduct (Antulov-Fantulin et al., 2021; Liu et al., 2015; Wang et al., 2020). Specifically, we achieve similar recall-specificity levels as Liu et al. (2015), who identify financial fraud. Moreover, we complement the findings of Khan et al. (2024), who show that the internal use of artificial intelligence in corporate environmental reporting can reduce greenwashing behavior.

From a practical perspective, the findings offer valuable guidance for sustainability-oriented decision-makers. Several machine learning models, particularly sequential neural networks such as RNNs, deliver strong predictive performance and outperform simple benchmarks, including a naive forecast based on recent outcomes and a stratified no-information baseline. At the same time, logistic regression, despite its simplicity and interpretability, remains competitive and in some cases rivals or surpasses more complex models. This demonstrates that both traditional and modern forecasting approaches add value depending on stakeholders' cost preferences and transparency requirements. Feature importance analysis identifies ESG disclosure score, energy management issues, prior greenwashing behavior, and company si-ze as the most influential drivers of model performance.

The results highlight that when the cost of false negatives (i.e., failing to detect greenwashing) is high, optimized machine learning models can generate substantial cost savings. This is particularly relevant for sustainability-focused practitioners, including portfolio and fund managers and capital providers, who face financial and reputational risks when greenwashing is detected in their portfolios.

Specifically, the proposed economic forecasting framework enables investors to tailor model weightings to their specific cost structure, adjusting forecasts to reflect the severity of false negatives. For example, ESG-branded mutual fund managers may face high false-negative costs due to potential capital outflows and reputational damage if a constituent company is later exposed to greenwashing. Impact investors such as retailers or private equity companies may typically face moderately high false-negative costs linked to reputation and alignment with sustainability objectives. By contrast, capital providers such as banks and pension funds generally face lower false negative costs, as their exposure to reputational or stakeholder-driven sustainability risks tends to be less direct and immediate. Thus, the optimal model and specification depend on the relative cost of false negatives and can be selected using historical data. Once identified, this model can then be applied to forecast greenwashing risk tailored to specific stakeholder needs.

More broadly, the findings provide valuable insights for stakeholders such as customers, employees, suppliers, NGOs, and media organizations by identifying determinants that act as red flags for companies with increased greenwashing risk. These determinants include large companies with extreme E(SG) scores, ESG disclosure scores, companies with large cash reserves, and high capital intensity. This information enables more targeted scrutiny and can influence stakeholder decisions, such as consumer purchasing behavior. A key advantage of the determinant analysis is its low data requirements, which make it fast and practical to apply.

Finally, the study provides actionable insights for policymakers seeking to refine regulatory frameworks aimed at curbing greenwashing. Evidence shows that stronger environmental oversight and better corporate governance can reduce greenwashing tendencies (Driss et al., 2024; Zhang, 2023; Zhang et al., 2024). Policymakers can draw on these findings to identify high-risk companies and to evaluate and improve the effectiveness of existing regulations.

Regulators could integrate the greenwashing risk forecasting framework into supervisory toolkits, using model predictions to prioritize inspections or disclosures for companies with elevated risk scores. The company-level determinants that were identified, such as extreme ESG scores, high capital intensity, and environmental controversy, could also inform risk-based reporting thresholds. Under this system, companies that exceed certain risk levels would face enhanced scrutiny or more detailed disclosure requirements. Moreover, the approach could be formalized into regulatory sandboxes or stress-testing frameworks for green claims, enabling early detection of greenwashing trends across industries.

In summary, the ability to estimate and forecast greenwashing risk can inform a wide range of stakeholders, from investors and regulators to civil society, and ultimately promote more transparent and sustainable corporate behavior.

Data availability

The authors do not have permission to share data.

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.

Appendix A. Greenwashing sample

We provide illustrative examples for each greenwashing category below. In the case of *Light greenwashing*, our researchers rated an instance in 2012 involving Puma, a German multinational sportswear and athletic apparel company. While Puma promotes the use of sustainably sourced cotton and markets certain products as "eco-friendly," a study cited in the information source revealed that these products had a higher water footprint than conventional alternatives. This discrepancy suggests that, although Puma makes genuine efforts towards sustainability, the company struggles to fully meet stakeholder expectations and faces challenges in fully

Table A.1
Framework for assessing greenwashing information sources.

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 of 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 describes the framework for assessing manually collected information sources relating to greenwashing accusations. The framework was initially presented in Kathan et al. (2025).

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 accusations. The framework was initially presented in Kathan et al. (2025).

Table A.3
Missing observations of determinant variables.

Category	Variable	Missing obs.
Green reputation	ESG score	880
	E score	836
	ESG disclosure score	857
	GHG scope 1	1096
	GHG scope 2	1096
	GHG scope 3 up	1096
	GHG scope 3 up + down	6069
Size and visibility	Size	153
	Analyst coverage	443
Capital dependency	Cash-to-assets	1406
	Leverage	206
	Capex-to-assets	734
Risk & return	Return-on-assets	256
	Earnings variability	239
	Price volatility	206
	Market-to-book ratio	320
Other factors	Capital intensity	193
	Owner concentration	640
	Foreign sales	702

Notes: This table reports on missing observations of control variables used in the construction of the sample and the examination of the determinants of greenwashing behavior. Note that the variable *GHG scope 3 up + down* is only available from 2017 to 2023.

delivering on its environmental claims. Therefore, the case exemplifies light greenwashing, with a mean severity score of 0.25 based on independent assessments by four researchers. This reflects minor sustainability claims accompanied by shortcomings in actual environmental performance.

A case reflecting *Medium greenwashing* involves Barclays' $10 billion sustainability-linked revolving credit facility provided to Shell in 2023. Barclays, a British multinational universal bank headquartered in London, operates across retail banking, credit cards, corporate and investment banking, and wealth management. The bank positions this financing as a key part of its commitment to supporting clients' transitions to a low-carbon economy by linking loan terms to Shell's carbon intensity reduction targets for its energy products. While Shell, a major British oil and gas company, has made public commitments to reduce its carbon footprint, it continues to invest heavily in fossil fuel exploration and production. Critics argue that such investments undermine the credibility of its climate goals. While Barclays emphasizes that sustainability-linked loans are designed to integrate environmental goals into broader financial products and actively engage clients on sustainability, some critics question the effectiveness and transparency of these initiatives, given Shell's continued fossil fuel investments and the use of asset sales to meet emissions targets. This tension between intent and impact illustrates the challenges in defining genuine sustainability in complex industries. Given the general nature of the accusations directed at Barclay and the limited clarity surrounding how Shell applies the loan, our researchers rated this case with a mean greenwashing severity score of 0.50. This indicates medium greenwashing, characterized by vague sustainability claims and broad concerns about potentially misleading practices.

With regard to *Moderate greenwashing*, an example is Glencore in 2023, a Swiss multinational commodity trading and mining company, whose lobbying activities appear to conflict with its public climate commitments. This assessment is based on information from a report published by the non-profit think tank "InfluenceMap" and cited in a newspaper, which evaluates corporate alignment between climate commitments and policy engagement. According to the report, Glencore has publicly expressed support for net-zero emissions targets while simultaneously opposing key climate policy initiatives in several jurisdictions. It highlights Glencore's resistance to climate policy developments within the European Union, as well as its opposition to the design of Australia's Safeguard Mechanism Reform, a regulatory framework aimed at limiting industrial greenhouse gas emissions. Although Glencore asserts its commitment to reducing its carbon footprint, its lobbying behavior indicates a reluctance to support binding regulatory measures needed to achieve these reductions. This misalignment between Glencore's stated environmental objectives and its policy advocacy underscores broader concerns about the credibility and integrity of corporate net-zero pledges. In this context, the United Nations has stressed the need for companies to align their lobbying practices with their climate commitments to ensure the legitimacy of their sustainability claims. Given the presence of specific but not fully substantiated accusations of greenwashing, particularly in relation to policy influence, our researchers rated this case with an average greenwashing severity score of 0.75, indicating moderate greenwashing. This rating reflects scenarios where corporate sustainability claims may be misleading due to underlying practices that conflict with publicly stated environmental goals.

For the *Greenwashing* category, Volkswagen in 2015 serves as a representative example. Volkswagen, a major German automotive manufacturer, was found to have installed a “defeat device”, software in diesel engines that detected emissions testing conditions and altered engine performance to produce artificially low pollution readings. This manipulation affected approximately 11 million vehicles worldwide, undermining Volkswagen's public claims about the environmental benefits of its diesel cars. Despite aggressive marketing campaigns promoting low emissions, the affected vehicles emitted nitrogen oxides up to 40 times above legal limits when driven under normal conditions. Volkswagen admitted to cheating on emissions tests, leading to regulatory investigations, executive resignations, massive recalls, and significant financial penalties. This scandal illustrates how Volkswagen failed to fulfill its sustainability commitments, leading our researchers to assign it an average greenwashing severity score of 1.00, indicating deliberate and confirmed deceptive practices.

Appendix B. Additional tables

Table B.1
Variable definitions, measures, and data sources.

Category	Variable	Measurement	Source
Dependent variable	Greenwashing severity score	Mean severity of individual greenwashing accusation assessments.	Own collection
Green reputation	ESG score	Environmental, social, governance (ESG) score reflecting a company's ESG performance, ranging from 0 to 1.	LSEG
	E score	Environmental (E) score reflecting a company's environmental performance, ranging from 0 to 1.	LSEG
	ESG disclosure score	The extent of a company's disclosure on environmental, social, and governance (ESG) data, with industry-specific weighting and relevance adjustments, ranging from 0 to 1.	Bloomberg
	GHG scope 1	Greenhouse gas (GHG) emissions from sources that are owned or controlled by the company divided by the company's revenue (and divided by 100).	Trucost
	GHG scope 2	GHG emissions from consumption of purchased electricity, heat or steam by the company divided by the company's revenue (and divided by 100).	Trucost
	GHG scope 3 up	GHG emissions from other upstream activities not covered in Scope 2 divided by the company's revenue (and divided by 100).	Trucost
	GHG scope 3 up + down	Downstream indirect GHG emissions associated with the use of sold goods and services as a multiple of revenue plus upstream GHG emissions divided by the company's revenue (and divided by 100).	Trucost
Size and visibility	Company size	(Natural logarithm of one plus) net sales.	LSEG
	Analyst coverage	(Natural logarithm of one plus) total number of analysts providing forecasts regarding earnings per share.	LSEG
Capital dependency	Cash-to-assets	The sum of cash and short-term investments divided by total assets.	LSEG
	Leverage	Book leverage-to-assets.	LSEG
	Capex-to-assets	(Natural logarithm of one plus) capital expenditure divided by total assets times 100.	LSEG
Risk & return	Return-on-assets.	Net income divided by total assets.	LSEG
	Earnings variability	(Natural logarithm of one plus) standard deviation of net income before extra items/preferred dividends of the previous five years over total assets.	LSEG
	Price volatility	Average annual stock price movement to a high and low from a mean price for each year.	LSEG
	Market-to-book ratio	(Natural logarithm of one plus) market value of equity over book value of equity calculated at fiscal year-end.	LSEG
Other factors	Capital intensity	Ratio of net property, plant, and equipment to total assets.	LSEG
	Owner concentration	(Natural logarithm of one plus) percentage of shares held by investors owing more than 5 %.	LSEG
	Foreign sales	(Natural logarithm of one plus) percentage of sales to non-headquarters countries.	LSEG

Notes: This table reports variable definitions, measurements, and data sources.

Table B.2
Descriptive statistics of determinant variables.

Category	Variable	Obs.	Mean	Std.	Min	Median	Max
Dependent variable	Greenwashing severity score	6654	0.04	0.18	0.00	0.00	1.00
Green reputation	ESG score	6654	0.62	0.18	0.02	0.64	0.96
	E score	6654	0.60	0.24	0.00	0.64	0.99
	ESG disclosure score	6654	0.49	0.13	0.03	0.49	0.84
	GHG scope 1	6654	1.61	5.68	0.00	0.13	80.95
	GHG scope 2	6654	0.46	1.09	0.00	0.15	19.57
	GHG scope 3 up	6654	1.81	1.97	0.15	1.19	22.75
	GHG scope 3 up + down	3711	10.50	34.51	0.15	2.64	826.52
Size and visibility	Size	6654	14,032.37	31,365.01	26.40	4246.46	487,275.10
	Analyst coverage	6654	17.05	8.00	0.00	17.00	51.00
Capital dependency	Cash-to-assets	6654	0.12	0.11	0.00	0.09	0.99
	Leverage	6654	26.05	16.01	0.00	25.30	154.04
	Capex-to-assets	6654	4.20	4.62	0.00	3.22	210.84
Risk and return	Return-on-assets	6654	6.83	12.40	-70.08	5.65	269.11
	Earnings variability	6654	42.80	88.14	0.18	27.15	3871.60
	Price volatility	6654	24.19	7.77	8.52	22.95	64.46
	Market-to-book ratio	6654	3.96	18.83	-0.92	2.28	1070.46
Other factors	Capital intensity	6654	0.29	0.25	0.00	0.22	0.99
	Owner concentration	6654	23.92	23.30	0.00	16.67	99.00
	Foreign sales	6654	60.99	36.47	0.00	71.23	421.10

Notes: This table reports summary statistics on the determinant variables for the full sample prior to data manipulation, such as log transformations and winsorization.

Table B.3
Correlations.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Greenwashing severity score	1.00																			
2	ESG score	0.18	1.00																		
3	E score	0.17	0.82	1.00																	
4	ESG disclosure score	0.21	0.72	0.64	1.00																
5	GHG scope 1	0.06	0.02	0.05	0.10	1.00															
6	GHG scope 2	−0.01	0.04	0.05	0.11	0.31	1.00														
7	GHG scope 3 up	0.06	0.07	0.11	0.11	0.28	0.20	1.00													
8	GHG scope 3 up + down	0.06	0.07	0.07	0.10	0.18	0.02	0.15	1.00												
9	Size	0.39	0.34	0.32	0.28	0.05	−0.04	0.09	0.06	1.00											
10	Analyst coverage	0.16	0.42	0.39	0.29	0.07	0.01	0.03	0.01	0.39	1.00										
11	Cash−to−assets	0.01	−0.08	−0.12	−0.10	−0.03	−0.05	−0.05	0.00	−0.04	−0.00	1.00									
12	Leverage	0.03	0.14	0.13	0.15	0.08	0.14	−0.10	−0.04	0.03	0.02	−0.29	1.00								
13	Capex−to−assets	0.02	−0.03	0.02	0.00	0.06	0.13	0.04	−0.01	0.05	0.05	−0.09	0.07	1.00							
14	Return−on−assets	−0.03	−0.09	−0.10	−0.08	−0.08	−0.11	−0.03	−0.03	−0.06	−0.03	0.13	−0.21	0.02	1.00						
15	Earnings variability	−0.02	−0.06	−0.08	−0.06	0.00	0.11	−0.03	0.02	−0.05	−0.03	0.15	−0.07	−0.01	0.13	1.00					
16	Price volatility	−0.07	−0.20	−0.19	−0.18	0.11	0.15	0.03	0.08	−0.13	−0.17	0.25	−0.07	0.02	−0.09	0.25	1.00				
17	Market−to−book ratio	−0.02	−0.05	−0.06	−0.04	−0.02	−0.01	−0.03	−0.02	−0.04	−0.01	0.08	−0.02	−0.01	0.53	0.18	0.02	1.00			
18	Capital intensity	0.06	0.09	0.19	0.12	0.20	0.25	0.03	0.00	0.03	−0.01	−0.30	0.31	0.41	−0.10	−0.01	−0.11	−0.06	1.00		
19	Owner concentration	−0.02	−0.08	0.05	−0.05	0.14	0.07	0.09	0.03	−0.03	−0.07	−0.00	−0.01	0.11	−0.07	−0.04	0.01	−0.03	0.11	1.00	
20	Foreign sales	0.05	0.14	0.03	0.13	0.01	0.05	0.22	0.09	0.10	0.13	0.11	−0.09	−0.06	−0.05	−0.03	0.11	−0.03	−0.28	−0.10	1.00

Notes: This table reports the pairwise Pearson correlation coefficients. The mean Variance Inflation Factor (VIF) as a diagnostic for multicollinearity, estimated from an OLS regression model, is 1.78. The highest VIF value is 3.73.

Table B.4
Main regression results with lagged determinants.

		Tobit			OLS		
		Full sample		Year > 2016	Full sample		Year > 2016
Category	Variable	(1)	(2)	(3)	(4)	(5)	(6)
Green reputation	ESG score × ESG score	6.414***		6.019***	0.491***		0.574***
		(1.466)		(1.690)	(0.106)		(0.169)
	ESG score	−8.121***		−8.132***	−0.616***		−0.788***
		(1.791)		(2.200)	(0.115)		(0.201)
	E score × E score		4.260***			0.281***	
			(1.015)			(0.066)	
	E score		−4.761***			−0.327***	
			(1.238)			(0.063)	
	ESG disclosure score	1.792**	1.669**	1.798**	0.111**	0.094	0.173**
		(0.811)	(0.815)	(0.871)	(0.054)	(0.057)	(0.084)
	GHG scope 1	0.033***	0.033***	0.041***	0.001	0.001	0.004**
		(0.010)	(0.010)	(0.010)	(0.001)	(0.001)	(0.002)
	GHG scope 2	−0.096	−0.075	−0.263**	−0.005	−0.003	−0.013**
		(0.089)	(0.089)	(0.112)	(0.004)	(0.004)	(0.006)
	GHG scope 3 up	−0.060	−0.057		−0.000	−0.000	
		(0.039)	(0.039)		(0.003)	(0.003)	
	GHG scope 3 up + down			0.002			0.000
				(0.002)			(0.000)
Size and visibility	Size	0.547***	0.537***	0.469***	0.038***	0.038***	0.048***
		(0.067)	(0.064)	(0.064)	(0.006)	(0.006)	(0.007)
	Analyst coverage	0.181	0.118	0.304	0.001	−0.000	−0.002
		(0.185)	(0.182)	(0.211)	(0.008)	(0.008)	(0.013)
Capital dependency	Cash−to−assets	2.726***	2.727***	2.290***	0.146***	0.131***	0.195***
		(0.650)	(0.647)	(0.612)	(0.029)	(0.029)	(0.040)
	Leverage	−0.005	−0.006	−0.002	0.000	0.000	0.000
		(0.005)	(0.005)	(0.004)	(0.000)	(0.000)	(0.000)
	Capex−to−assets	0.003	−0.000	−0.157	−0.003	−0.003	−0.010
		(0.113)	(0.115)	(0.121)	(0.006)	(0.006)	(0.009)
Risk and return	Return−on−assets	−0.016*	−0.017**	−0.010	−0.000	−0.000	−0.001
		(0.009)	(0.009)	(0.008)	(0.000)	(0.000)	(0.001)
	Earnings variability	−0.016	−0.005	0.033	0.009**	0.010**	0.014**
		(0.076)	(0.077)	(0.079)	(0.004)	(0.005)	(0.007)
	Price volatility	−0.022*	−0.026**	−0.024*	−0.001	−0.001	−0.002*
		(0.012)	(0.012)	(0.013)	(0.001)	(0.001)	(0.001)
	Market−to−book ratio	0.036	0.015	−0.008	−0.001	−0.001	0.002
		(0.133)	(0.132)	(0.131)	(0.008)	(0.008)	(0.012)
Other factors	Capital intensity	1.333***	1.274***	1.763***	0.089***	0.090***	0.148***
		(0.417)	(0.424)	(0.434)	(0.029)	(0.029)	(0.044)
	Owner concentration	−0.009	−0.014	0.008	−0.001	−0.001	−0.002
		(0.060)	(0.059)	(0.058)	(0.004)	(0.004)	(0.005)
	Foreign sales	−0.007	−0.014	−0.025	0.000	−0.000	0.000
		(0.059)	(0.059)	(0.053)	(0.002)	(0.002)	(0.004)
	Constant	−5.885***	−6.560***	−5.764***	−0.051	−0.125	−0.133
		(1.366)	(1.176)	(1.157)	(0.094)	(0.094)	(0.117)
	Year	Yes	Yes	Yes	Yes	Yes	Yes
	Industry	Yes	Yes	Yes	Yes	Yes	Yes
	Country	Yes	Yes	Yes	Yes	Yes	Yes
	N	5701	5701	2980	5701	5701	2980
	Pseudo R^2 / Adj. R^2	0.338	0.340	0.344	0.167	0.165	0.213

Notes: This table presents results of Tobit and OLS regression models with one-year lagged explanatory variables, and where the dependent variable is the greenwashing severity score. All continuous variables are winsorized at the 0.5 % level at both ends. Standard errors are clustered at the company level and reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table B.5
OLS regression results with binary GW score.

		Full sample		Year > 2016
Category	Variable	(1)	(2)	(3)
Green reputation	ESG score × ESG score	0.573***		0.719***
		(0.116)		(0.187)
	ESG score	−0.711***		−0.956***
		(0.126)		(0.218)
	E score × E score		0.349***	
			(0.075)	
	E score		−0.390***	
			(0.071)	
	ESG disclosure score	0.117**	0.088	0.201**
		(0.059)	(0.063)	(0.091)
	GHG scope 1	0.002	0.002	0.005***
		(0.001)	(0.001)	(0.002)
	GHG scope 2	−0.007	−0.005	−0.014**
		(0.005)	(0.005)	(0.007)
	GHG scope 3 up	−0.000	−0.000	
		(0.003)	(0.003)	
	GHG scope 3 up + down			0.000
				(0.000)
Size and visibility	Size	0.045***	0.045***	0.054***
		(0.007)	(0.007)	(0.007)
	Analyst coverage	0.005	0.004	0.006
		(0.009)	(0.009)	(0.012)
Capital dependency	Cash−to−assets	0.142***	0.125***	0.167***
		(0.034)	(0.034)	(0.045)
	Leverage	−0.000	−0.000	0.000
		(0.000)	(0.000)	(0.000)
	Capex−to−assets	−0.006	−0.005	−0.013
		(0.007)	(0.007)	(0.011)
Risk and return	Return−on−assets	0.000	0.000	0.000
		(0.000)	(0.000)	(0.001)
	Earnings variability	0.007	0.009*	0.005
		(0.005)	(0.005)	(0.008)
	Price volatility	−0.001	−0.001	−0.001
		(0.001)	(0.001)	(0.001)
	Market−to−book ratio	−0.001	−0.001	−0.004
		(0.010)	(0.010)	(0.013)
Other factors	Capital intensity	0.090***	0.088***	0.142***
		(0.032)	(0.032)	(0.046)
	Owner concentration	−0.003	−0.003	−0.005
		(0.004)	(0.004)	(0.006)
	Foreign sales	0.000	−0.000	0.001
		(0.003)	(0.003)	(0.004)
	Constant	−0.042	−0.117	−0.035
		(0.097)	(0.097)	(0.119)
	Year	Yes	Yes	Yes
	Industry	Yes	Yes	Yes
	Country	Yes	Yes	Yes
	N	6654	6654	3711
	Adjusted R^2	0.158	0.157	0.197

Notes: This table presents results of OLS regression models, where the dependent variable is the binarized greenwashing (GW) severity score. All continuous variables are winsorized at the 0.5 % level at both ends. Standard errors are clustered at the company level and reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table B.6
Definitions of corporate misconduct features.

Feature	Measurement	Source
Controversial marketing	Number of controversies published in the media linked to the company's marketing practices, such as over marketing of unhealthy food to vulnerable consumers.	LSEG
Energy management issues	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
Environmental controversies	Is the company under the spotlight of the media because of a controversy linked to the environmental impact of its operations on natural resources or local communities?	LSEG
ESG controversies score	ESG controversies category score measure a company's exposure to environmental, social, and governance controversies and negative events reflected in global media.	LSEG
Greenwashing severity score	Mean severity of individual greenwashing accusation assessments.	Own collection
Land and ecosystems issues	Refers to criticism of a company or a project as it relates to the destruction of land-based ecosystems.	RepRisk
Misleading communication	This issue refers to instances where a company distorts the truth to present itself in a positive light, while simultaneously contradicting this constructed image through its actions.	RepRisk
Overuse and wasting	This issue refers to a company's overuse, inefficient use of waste of renewable and non-renewable resources, such as energy, water, and commodities.	RepRisk
Product issues on health and environment	This issue refers to providing a product or service which poses an unnecessary risk to the consumer's health or the environment.	RepRisk
Supply chain issues	This issue refers to companies being held accountable for the actions of their suppliers. Both vendors and subcontractors are considered part of the supply chain.	RepRisk

Notes: This table provides the definitions of the corporate misconduct variables, which are used as features alongside the determinant variables in the forecasting models.

Table B.7
Descriptive statistics for features.

Category	Feature	Obs.	Mean	Std.	Min	Median	Max
Determinant	ESG score	5906	0.62	0.18	0.02	0.64	0.96
Determinant	E score	5906	0.60	0.24	0.00	0.64	0.99
Determinant	ESG disclosure score	5906	0.49	0.13	0.03	0.49	0.84
Determinant	GHG scope 1	5906	1.66	5.74	0.00	0.13	80.95
Determinant	GHG scope 2	5906	0.48	1.10	0.00	0.16	19.57
Determinant	GHG scope 3 up	5906	1.85	1.97	0.15	1.25	21.95
Determinant	Size	5906	8.42	1.53	3.27	8.37	13.10
Determinant	Analyst coverage	5906	17.25	8.00	0.00	17.00	51.00
Determinant	Cash-to-assets	5906	0.12	0.11	0.00	0.09	0.99
Determinant	Leverage	5906	25.91	16.48	0.00	25.08	230.61
Determinant	Capex-to-assets	5906	4.21	3.83	0.00	3.24	53.12
Determinant	Return-on-assets	5906	6.93	12.52	−70.08	5.70	269.11
Determinant	Earnings variability	5906	41.37	83.82	0.17	26.51	3880.72
Determinant	Price volatility	5906	24.08	7.74	8.52	22.78	64.46
Determinant	Market-to-book ratio	5906	3.89	18.32	−0.94	2.30	1070.46
Determinant	Capital intensity	5906	0.29	0.25	0.00	0.22	0.99
Determinant	Owner concentration	5906	23.85	23.09	0.00	16.55	97.48
Determinant	Foreign sales	5906	61.24	36.20	0.00	71.21	421.10
Misconduct	Controversial marketing	5906	0.97	0.16	0.00	1.00	1.00
Misconduct	Energy management issues	5906	0.56	0.50	−1.00	1.00	1.00
Misconduct	Environmental controversies	5906	0.03	0.16	0.00	0.00	1.00
Misconduct	ESG controversies score	5906	52.49	8.86	0.00	53.78	55.71
Misconduct	Greenwashing severity score	5906	0.04	0.18	0.00	0.00	1.00
Misconduct	Land and ecosystems issues	5906	−0.34	3.55	−51.00	0.00	1.00
Misconduct	Misleading communication	5906	−0.05	2.30	−44.00	0.00	1.00
Misconduct	Overuse and wasting	5906	0.37	0.99	−23.00	0.00	1.00
Misconduct	Product issues on health and environment	5906	−0.27	5.08	−125.00	0.00	1.00
Misconduct	Supply chain issues	5906	−0.44	4.26	−89.00	0.00	1.00
Dummy	Year	5906					
Dummy	Industry	5906					
Dummy	Country	5906					

Notes: This table provides the descriptive statistics for all features used in the forecasting models. The corporate misconduct variables (*Controversial marketing*, *Misleading communication*, *Overuse and wasting*, *Product issues on health and environment*, *Supply chain issues*, *Energy management issues*, and *Land and ecosystems issues*) are defined as 1 minus the total number of incidences of each variable within a year.

Appendix C. Description of forecasting models

Our analysis considers the following models. For each model, we additionally summarize which imbalance handling strategy performed best and explain the underlying rationale, conditional on the cost parameter c.

Logistic Regression. Chosen for its simplicity and interpretability, logistic regression estimates the log odds of an event and is well suited to binary classification tasks such as forecasting greenwashing. Imbalance strategy: Logistic Regression performs best with (i) default settings and hyperparameter tuning for $c = 0.99$, (ii) Up-sampling with HT for $c = 0.90$, and (iii) k-fold CV without imbalance strategy for $c = 0.50$. The shift reflects that strong cost asymmetry can tolerate the class imbalance, while moderate asymmetry benefits from balance correction.

Random Forest. This ensemble method aggregates multiple decision trees–each built on different subsamples of the data–to capture non-linear relationships and interactions between features. Its design helps reduce overfitting and improves generalization (Breiman, 2001). Imbalance strategy: For all cost settings ($c = 0.99$, 0.90, 0.50), the Random Forest model performs best with default settings and k-fold cross-validation. This highlights the model's inherent robustness to class imbalance when using ensemble averaging and internal sampling.

K-Nearest Neighbors (KNN). KNN classifies observations based on their proximity in the feature space. Its intuitive approach is useful for identifying companies with similar characteristics (Cover and Hart, 1967). Imbalance strategy: KNN performs best with default parameters and k-fold CV at $c = 0.99$ and $c = 0.90$, while ClassWeights with HT yield superior results at $c = 0.50$. This reflects the model's tendency to overfit the rare class at high asymmetry, with balance correction becoming more important as cost asymmetry declines.

Support Vector Machines (SVM). SVMs are included because of their strong performance in high-dimensional settings. By identifying the hyperplane that maximally separates classes, they can effectively handle cases where there is a clear margin between greenwashing and non-greenwashing observations (Cortes and Vapnik, 1995). Imbalance strategy: At $c = 0.99$ and $c = 0.50$, Up-sampling combined with HT performs best, while at $c = 0.90$ only HT is required. These results show that at extreme cost asymmetries, data manipulation (Up-sampling) becomes essential to enhance rare-event recall, whereas at intermediate settings, model tuning alone suffices.

Decision Trees. Valued for their interpretability, decision trees partition data based on feature thresholds. Although they can capture non-linear patterns, they are prone to overfitting without proper regularization or pruning (Breiman et al., 1984). Imbalance strategy: Default settings with CV work best at $c = 0.99$, while ClassWeights with HT are optimal at $c = 0.90$ and $c = 0.50$. The results indicate that reweighting the class distribution is more effective than data resampling when the emphasis shifts from extreme recall toward a more balanced trade-off.

Gradient Boosting. This method builds an ensemble of trees sequentially, with each successive tree attempting to correct the errors of its predecessor. Although less interpretable than simpler models, gradient boosting is known for its high predictive accuracy in modeling both linear and non-linear relationships (Friedman, 2001). Imbalance strategy: The model performs best with default settings and k-fold CV at $c = 0.99$, and with Up-sampling or ClassWeights and HT for $c = 0.90$ and $c = 0.50$. While Gradient Boosting handles class imbalance naturally, at moderate cost asymmetry levels, additional balancing techniques improve precision and specificity.

Feedforward Neural Networks. Using a fully connected architecture and binary cross-entropy as the loss function, these networks are designed to model intricate nonlinear interactions. While they operate as "black boxes" and offer limited interpretability, they provide a robust benchmark for capturing complex patterns in data (LeCun et al., 2015). Imbalance strategy: The Feedforward Neural Network performs best with Up-sampling and HT for $c = 0.99$ and $c = 0.50$, while ROSE and HT are most effective for $c = 0.90$. These strategies help increase the presence and weight of rare greenwashing events during training, improving recall under cost asymmetry.

Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) Networks. To capture temporal dependencies and sequential patterns in greenwashing behavior, we extend our analysis to sequence-based models. RNNs provide a basis for modeling short-term dependencies, while LSTM networks, through their gating mechanisms, address issues such as the vanishing gradient problem, making them well suited for longer sequences (Goodfellow et al., 2016; Hochreiter and Schmidhuber, 1997). Imbalance strategy: The RNN performs best with ROSE and HT for $c = 0.99$, with Up-sampling (without HT) for $c = 0.90$, and with Up-sampling for $c = 0.50$. LSTM follows a similar pattern, though ROSE is optimal at both $c = 0.99$ and $c = 0.50$. This suggests that synthetic oversampling (ROSE) is particularly effective under extreme asymmetry, while simple Up-sampling remains useful for more balanced conditions.

By integrating these diverse models and carefully selecting imbalance strategies based on cost-sensitive performance, our approach balances predictive power with interpretability across different evaluation scenarios.

Appendix D. Performance metrics of forecasting models

The performance metrics of the forecasting models are defined as follows, where TP determines true positives (correctly predicted positive cases), TN true negatives (correctly predicted negative cases), FP false positives (negative cases incorrectly predicted as positive), and FN false negatives (positive cases incorrectly predicted as negative).

Recall (Sensitivity, True Positive Rate): Recall measures the proportion of actual positives that are correctly identified by the model.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Specificity (True Negative Rate): Specificity measures the proportion of actual negatives that are correctly identified by the model.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Target Function (Cost-weighted Accuracy): Incorporates the relative cost c of false negatives versus false positives. Let q be the positive prevalence, then

$$w = \frac{q\,c}{1 - q - c + 2\,q\,c} \quad \text{and} \quad \text{TF} = w \cdot \text{Recall} + (1 - w) \cdot \text{Specificity}$$

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