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Sustainable Development Goals omission and environmental sentiment metric for greenwashing and ESG controversies alert in green bonds

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Omissione degli Obiettivi di Sviluppo Sostenibile e metrica del *sentiment* ambientale nell'analisi della *disclosure* dei *green bonds*

Un sistema di alert per il *greenwashing* e le controversie ESG

A. Nicolodi, S. Paterlini, M. Gentile, V. Foglia Manzillo, G. Vittorioso(*)

Sintesi del lavoro

I *green bond* rappresentano uno strumento centrale della finanza sostenibile, indirizzando i capitali verso progetti che supportano gli obiettivi ambientali e la transizione verso un'economia a basse emissioni di carbonio. Le crescenti preoccupazioni legate ai rischi di *greenwashing* evidenziano la necessità di disporre di strumenti in grado di valutare le informazioni di sostenibilità diffuse dagli emittenti. Lo studio risponde a questa esigenza applicando tecniche di Intelligenza Artificiale - dizionari tematici e *domain-specific transformer models* costruiti sull'architettura BERT – per esaminare in che modo l'omissione di contenuti relativi agli Obiettivi di Sviluppo Sostenibile (*Sustainable Development Goals*, SDGs) è collegata al tono del linguaggio ambientale e specifico sugli SDG nelle rendicontazioni di sostenibilità.

Analizzando emittenti europei di *green bond* nel periodo 2019–2023, è stato costruito lo SDG *Omission Index* (SDGOI), un indicatore innovativo che misura il divario tra gli SDG dichiarati per l'allocazione dei proventi e quelli successivamente rendicontati nelle *disclosure* di sostenibilità. I risultati mostrano che gli emittenti che utilizzano una terminologia più specifica, tendono a rendicontare un numero maggiore di SDGs, mentre il ricorso a un linguaggio ambientale generico non risulta significativamente associato all'ampiezza della

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copertura degli SDGs. Lo studio, inoltre, rileva che un'eccessiva enfasi *opportunity-oriented* nel linguaggio ambientale è positivamente correlata all'indicatore SDGOI e, quindi, al rischio di *greenwashing*. Inoltre, è stata definita l'*Environmental Sentiment Metric* (ESM), una nuova metrica che quantifica il *sentiment* ambientale *opportunity-oriented.* Tale indicatore è positivamente associato alle controversie ESG e alle accuse di *greenwashing*, anche dopo aver controllato per gli *score* ESG e per la dimensione aziendale.

Integrare queste metriche nell'infrastruttura della finanza sostenibile offre a investitori, regolatori e *assurance providers* strumenti utili per valutare le informazioni sulla sostenibilità, incentivando al tempo stesso gli emittenti a riportare dati in modo trasparente e responsabile.

Sustainable Development Goals omission and environmental sentiment metric for greenwashing and ESG controversies alerts in green bonds

A. Nicolodi, S. Paterlini, M. Gentile, V. Foglia Manzillo, G. Vittorioso(*)

Abstract

Green bonds are a cornerstone of sustainable finance, directing investment toward projects that support environmental objectives and the transition to a low-carbon economy. Yet, the growing risk of greenwashing threatens to undermine the credibility of such instruments. Greenwashing refers to situations where sustainability-related statements do not clearly and fairly reflect, (i.e., through the omission of material information), the underlying sustainability profile of an entity or financial product. The development of robust analytical tools to assess the credibility of issuers' sustainability claims plays a key role in ensuring that green bond financing genuinely contributes to measurable environmental outcomes, rather than serving merely as a vehicle for reputational enhancement. These tools also support more effective supervision thereby helping to prevent the risk of misleading investors and weakening market trust. Leveraging a combination of dictionary-based techniques and domain specific BERT transformer models, we explore how the omission of Sustainable Development Goals (SDGs) content in corporate disclosure relates to the volume and tone of environmental and SDGs specific language in the sustainability reports of green bonds issuers. To this purpose, we developed two new metrics that allow to systematically assess the link between the disclosure and the risk of misleading sustainability claims and information omission. The first indicator, the Sustainable Development Goals Omission Index (SDGOI), shows that an opportunity-oriented tone in general environmental sentences is positively associated with SDGs omission, potentially representing a distinctive trait of greenwashing risk. Therefore, we introduced the Environmental Sentiment Metric (ESM), a novel indicator that quantifies opportunity-oriented environmental sentiment and connects it to greenwashing accusations and ESG controversies. We found that elevated ESM scores are significantly associated with higher ESG controversy levels and with greenwashing accusations, demonstrating its potential as an alert signal of disclosure credibility risks in the green bond market. Integrating these indicators into the infrastructure of sustainable finance can provide investors and regulators with analytical tools for assessing sustainability disclosures, while encouraging issuers to report transparently and accountably – thereby enhancing the effectiveness and integrity of capital markets.

JEL Classifications: G34, G38, J33, K22, M52.
Keywords: greenwashing, green bond, AI, NPL, greenwashing alert metric, SDG omission, sentiment analysis.

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Contents

1 Introduction

Green bonds are pivotal in financing the transition to a sustainable economy by channelling capital into environmentally beneficial projects. These instruments are specifically designed to fund initiatives such as renewable energy, clean transportation and climate resilience, aligning with the objectives of the 2015 Paris Agreement and the United Nations Sustainable Development Goals (SDGs).

To ensure transparency and impact, green bond proceeds must be allocated to well-defined eligible projects.

In 2024, green bonds emerged as the dominant category within the sustainable finance market, with issuances reaching USD 381 billion in the corporate sector and USD 257 billion in the public sector, according to the OECD's 2025 Global Debt Report[1].

Until the recent Regulation (EU) 2023/2631 on European green bonds, the European regulatory landscape lacked a unified standard for certifying green financial instruments. As a result, green bonds were typically issued under a variety of voluntary frameworks developed by international self-regulatory organisations.

These frameworks, adopted at the discretion of issuers, provided procedural guidance but did not enforce uniform compliance. Among the most widely recognised are the Green Bond Principles (GBP), published by the International Capital Market Association (ICMA), and the Climate Bonds Standard developed by the Climate Bonds Initiative (CBI).

Both have gained global acceptance and serve as foundational references for market participants seeking to align with best practices in sustainable finance.

However, concerns about greenwashing have grown, as some issuers might leverage the green label without clearly and fairly reflect the underlying sustainability profile of an entity and delivering meaningful environmental impact.

Common signs include selective disclosure, vague sustainability claims, opportunity-oriented statements, and weak alignment with recognised frameworks.

In the absence of robust verification mechanisms, companies may omit or make misleading claims about their alignment with the United Nations Sustainable Development Goals (SDGs), often through vague or non-binding references to sustainability frameworks. These claims lack intentional integration into the firm's ESG strategy and are instead presented retrospectively, without clear evidence of targeted action.

One common manifestation of such greenwashing is the selective disclosure of positive SDG alignment, while omitting goals that might reveal trade-offs, negative externalities, or insufficient ambition.

1 See: https://www.oecd.org/en/publications/global-debt-report-2025_8ee42b13-en.html.

Additionally, firms may overstate their contributions to the SDGs – whether through overarching strategies, specific projects, or financial commitments – without providing a transparent logic model that links outputs to measurable outcomes.

Therefore, corporate green bonds may carry some levels of uncertainty, particularly in relation to greenwashing risks and potential legal exposure. These concerns are especially pronounced for issuers who opt not to undergo independent verification or obtain third-party certification of their sustainability claims.

As climate and environmental risks intensify, scrutiny around potentially misleading claims is likely to increase, particularly when disclosures fail to demonstrate how corporate actions substantively contribute to global sustainability objectives. Moreover, underestimating environmental impacts through optimistic or ambiguous reporting may lead to a misjudgement of transition risks, potentially affecting both investor confidence and regulatory compliance.

This study addresses a gap in the literature concerning the development of alert mechanisms for greenwashing in the context of green bond issuance, an area of growing importance given the rapid expansion of sustainable finance instruments. Despite the increasing volume of green bonds, there remains, indeed, limited empirical research on tools capable of systematically identifying misleading sustainability claims and selective disclosure.

Moreover, the research aligns with the need to promote the adoption of supervisory technologies (SupTech), which increasingly rely on AI-driven models to enhance regulatory efficiency, risk detection, and compliance monitoring. SupTech tools – such as machine learning models for anomaly detection, natural language processing for regulatory reporting, and predictive analytics for systemic risk assessment – must now align with the AI Act's provisions on transparency, human oversight, and data governance. This convergence of regulatory innovation and technological advancement underscores the need for supervisory authorities to develop robust AI governance frameworks that not only comply with legal standards but also foster trust and resilience in the financial system.

Responding to the previously underlined needs, the paper builds upon the prototype developed by CONSOB and the University of Trento - Greenwashing alert system for EU green bonds. The CONSOB–University of Trento prototype[2], which leverages advanced natural language processing techniques and integrates domain specific BERT transformer models, such as ClimateBERT and ESGBERT with a proprietary SDG-aligned dictionary that maps targeted keywords to specific SDGs, based on the alignment between the Green Bond Principles (GBP) and the SDGs framework.

Specifically, the study seeks to answer the following research questions. Firstly, it introduces the SDGs Omission Index (SDGOI) and analyses how the omission of SDGs in sustainability disclosures can be systematically examined and linked to factors such as type of sentence, sentiment, and other relevant variables to develop further potential greenwashing alerts in green bond issuances. Secondly, the research

2 https://www.consob.it/documents/d/area-pubblica/fintech14.

tests if the tone and sentiment of sustainability-related disclosures, quantified through domain specific BERT transformer models, can be leveraged to develop alert metrics for greenwashing risk, independently of SDGs-related disclosure content. Departing from studies that operationalise greenwashing as a 'talk' versus 'walk' discrepancy (i.e., Kim *et al.*, 2015; Lagasio, 2024; Kathan *et al.*, 2025), our work investigates whether greenwashing alert indicators can be constructed from the 'talk' alone.

We fill a gap by hypothesizing that specific linguistic patterns, in particular opportunity-oriented sentiment in environmentally themed sentences combined with the omission of relevant SDGs, can serve as proxies for greenwashing risk. This novel approach enables a more targeted identification of opportunity-oriented communication within the specific context of green bonds, addressing a critical gap in trying to capture greenwashing risk.

This paper, therefore, makes key contributions to the literature. Indeed, it introduces the SDGOI, a metric designed to help assess whether issuers effectively integrate their stated SDGs commitments into communications and sustainability reports. In particular, the empirical analysis reveals a positive association between opportunity-oriented sentiment in environmental content and SDGOI, suggesting that tone can serve as a foundation for developing additional greenwashing alert metrics. Moreover, the study develops and empirically tests the Environmental Sentiment Metric (ESM), a novel tool that quantifies opportunity-oriented language in sustainability narratives. Through empirical analysis, we show that the ESM scores are positively associated with ESG controversies and greenwashing accusations, underscoring its potential as an alert indicator of greenwashing risk in the green bond market.

2 Literature review

The increasing prevalence of sustainability-oriented corporate communication has intensified concerns regarding the authenticity of environmental claims, a phenomenon widely known as greenwashing (Delmas *et al.*, 2011). Despite the growing relevance of sustainability reporting, the empirical identification and quantification of greenwashing through text analysis remain methodologically challenging and conceptually fragmented.

The absence of a universally accepted definition, coupled with its multifaceted nature, has led to a proliferation of measurement approaches. Existing methods range from ESG disclosure–performance comparisons (i.e., Cho *et al.*, 2012) to perception-driven proxies (i.e., Testa *et al.*, 2018) and sentiment-based evaluations (i.e., Arena *et al.*, 2015), highlighting the complexity of assessing the gap between symbolic and substantive sustainability actions (Lublóy *et al.*, 2025).

Greenwashing is a relevant phenomenon not only in equity markets but also in corporate debt, given its implications for financing costs and investor trust (Peng *et al.*, 2024; Roggi *et al.,* 2024). A key research stream investigates the so-called green premium or greenium – that is, the additional cost (or discount) associated with environmentally friendly financial instruments. Empirical studies consistently document heterogeneity in the presence and magnitude of this phenomenon, showing that investors may price both genuine sustainability and reputational risk (Schmittmann *et al.*, 2022; Baldi *et al.*, 2022; Xu *et al.,* 2022).

Within this debate, green bonds have attracted significant attention as emblematic instruments of sustainable finance. Ge *et al.* (2025) examine the impact of green bond issuance on the ESG performance of Chinese listed firms, finding improvements in environmental and social dimensions. Issuance is thus interpreted as both a financing tool for sustainable projects and a reputational signal of corporate commitment. However, the study also uncovers evidence suggestive of greenwashing, given that improvements do not differ significantly across firms with varying pollution intensity or political ties, raising concerns about the authenticity of ESG enhancements.

These findings highlight that disclosures and voluntary statements, above all if self-reported, could be prone to strategic manipulation (i.e., Cho *et al.,* 2015; Dyck *et al.,* 2019; Christensen *et al.,* 2021). Walker *et al.* (2012) show that firms often engage in symbolic sustainability communication to protect legitimacy without substantive environmental change, ultimately undermining stakeholder trust and financial performance. Similarly, Yu *et al.* (2020) develop a peer-relative greenwashing score based on discrepancies between ESG disclosure and actual performance. Their findings reveal that large firms, despite extensive reporting, are particularly exposed to accusations of symbolic disclosure due to visibility and stakeholder pressure. Importantly, the study also shows that governance mechanisms, such as board independence and institutional ownership, can mitigate these risks, while external scrutiny, including foreign listings, reduces greenwashing incidence.

Recent conceptual contributions expand the scope from "greenwashing" to "ESG-washing". Todaro *et al.* (2024), for example, highlight how firms strategically appropriate ESG and circular economy terminology to construct reputational legitimacy in the absence of substantive alignment. This reinforces the argument that greenwashing is multidimensional, spanning environmental, social, and governance dimensions. At the same time, systematic reviews confirm both the conceptual fragmentation and the methodological diversity in this field.

Lublóy *et al.* (2025) underline the reliance on perception-based measures and hypothetical cases, while Sneideriene *et al.* (2025) use bibliometric mapping to document an increasing demand for rigorous, standardised metrics. Similarly, Zioło *et al.* (2024) stress that reliance on theoretical frameworks such as stakeholder theory, legitimacy theory, and institutional theory is frequent but inconsistent, which complicates generalisation and comparability.

Another important strand of literature critiques the reliability of ESG ratings. Drempetic *et al.* (2020) show that firm size inflates ESG scores due to better disclosure capabilities, rather than superior sustainability. This concern is reinforced by Kathan *et al.* (2025), who disentangle apparent from real environmental performance in European listed firms. While ESG scores correlate with narrative disclosure (apparent performance), they negatively associate with objective ecological outcomes, particularly among large firms.

Treepongkaruna *et al.* (2024) reach similar conclusions in the U.S. context, showing that high ESG scores are not associated with lower carbon emissions, suggesting that ratings often function as reputational tools rather than performance indicators.

The integration of artificial intelligence (AI) into public sector governance has sparked a rich and evolving academic debate across legal, administrative, and technological disciplines. IMF (2025) explores how financial supervisory authorities can enhance their oversight capabilities by integrating Artificial Intelligence (AI) into their operations. It emphasises the need for a tailored project management methodology to guide the safe and effective implementation of AI, considering the unique risks and strategic goals of these institutions. Ensuring explainability mitigates bias and fosters stakeholder collaboration; moreover, strong governance frameworks and sufficient resources enhance the results of tool's deployment. BIS (2025) describes a comprehensive framework for managing the integration of artificial intelligence into central banking operations. It emphasises that while AI offers significant benefits, such as improved data analysis, forecasting, and operational efficiency, it also introduces complex and interconnected risks, including cybersecurity threats, reputational damage, and challenges related to model reliability and interpretability.

Veale *et al.* (2019), examine the transformative yet conservative nature of machine learning adoption in public management, stressing the political and value-laden consequences of algorithmic systems. Hillo *et al.* (2025) provide empirical evidence on legitimacy perceptions of automated decision-making among citizens and administrators, reinforcing the importance of transparency in maintaining trust. AI offers unprecedented opportunities for efficiency and predictive governance, but its deployment must be guided by robust legal frameworks, institutional safeguards, and a commitment to democratic accountability. In the context of financial supervision, Deriu *et al.* (2025) contributes by framing SupTech not merely as a technological upgrade, but as a cultural and institutional shift requiring multidisciplinary engagement and ethical oversight. AI based Suptech solutions provide potential benefits and risks including enhanced speed and efficiency in market anomaly detection, the necessity of maintaining human oversight, ensuring traceability, explainability, and respect for fundamental rights. The role of AI is comparable as a digital assistant, supporting but not replacing human decision-making.

To address the limitations related to ESG performance scores, research studies increasingly turn to natural language processing (NLP) and sentiment-based approaches. These methods allow systematic analysis of unstructured textual data such as sustainability reports, press releases, earnings calls, and risk factor disclosures.

By leveraging sentiment analysis, topic modelling, and semantic similarity, researchers can identify discrepancies between corporate narratives and operational outcomes. Early work on financial disclosure tone already highlighted the informativeness of sentiment measures. For instance, Koelbl (2019) document that the tone of MD&A disclosures conveys significant information for U.S. REIT performance, while Tsang *et al.* (2023) show that different sentiment types in risk factor disclosures matter for investors, particularly in the context of cybersecurity breaches. These insights from mainstream finance feed directly into sustainability studies, where textual sentiment is now applied to detect ESG-related misrepresentation.

Building on Loughran *et al.* (2016), recent sustainability literature uses sentiment dictionaries and machine learning tools to measure the tone, polarity, and readability of ESG communication. Studies such as Luccioni *et al.* (2020), Bingler *et al.* (2022), Bingler *et al.* (2024), and Moodaley *et al.* (2023) apply NLP-based metrics to detect divergences between corporate claims and actual performance, demonstrating their value as early warning signals.

Conceptual frameworks such as that of Dorfleitner *et al.,* (2023) explicitly operationalise greenwashing as the gap between "green talk" and "green walk", while Lagasio (2024) propose the ESG-Washing Severity Index (ESGSI), which combines sentiment metrics with third-party ESG ratings to detect symbolic disclosure. Empirical evidence suggests that larger firms exhibit higher ESGSI scores, consistent with reputational incentives.

Methodologically, our work is most closely aligned with and builds upon the work of Bingler *et al.* (2022), Bingler *et al.* (2024) and Lagasio (2024) in using advanced NLP techniques to scrutinise sustainability reports.

Recent applications further highlight the strategic use of textual tone. Gorovaia *et al.* (2024) show that U.S. firms subject to environmental penalties expand the length and positivity of CSR reports while reducing transparency. Similarly, bibliometric studies (i.e., Sneideriene *et al.,* 2025) confirm that AI-based approaches are becoming a dominant frontier in detecting reputational manipulation.

Importantly, these tools align with the broader academic effort to move from perception-based to verifiable, impact-oriented metrics. Yet, the scarcity of confirmed greenwashing cases remains a key challenge in validating the proposed metrics.

3 Hypotheses development on SDGs omission

Sustainability disclosures are critical for evaluating companies' sustainability strategies and actions. Since the Paris Agreement in December 2015, corporate climate commitments have surged, increasing by nearly 25% between 2015 and 2020 (Bingler *et al.*, 2022).

Yet, questions remain about whether these commitments reflect genuine sustainability leadership or superficial responses to growing public scrutiny.

Prior studies highlight the need to scrutinise the authenticity of corporate disclosures, warning of greenwashing risks when claims lack substantiation or measurable impact (i.e., Bingler *et al.*, 2022; Schimanski *et al.*, 2024).

This study examines weaknesses in corporate sustainability communication in the European green bond market, focusing on two elements: selective omission of SDGs-related information and the tone of sustainability disclosures.

Therefore, we investigate whether textual sentiment and content characteristics are systematically linked to SDGs omission, a potential distinctive trait of greenwashing risk due to selective disclosure. Moreover, we try to disentangle what type of communication is associated with a greater lack of SDGs information.

In the context of financial instruments, best practices outlined by market guidelines and standards, such as the Green Bond Principles (GBPs), recommend that companies explicitly specify which SDGs they aim to support. ESMA reports on greenwashing point out that claims about contributions to the UN SDGs could be particularly prone to greenwashing risks. Therefore, when an analysis reveals notable inconsistencies between the SDGs mentioned by issuers, it may warrant specific attention.

As such, the absence of clear references to the stated SDGs in corporate reporting to shareholders can reasonably be associated with greenwashing alert, raising concerns about the transparency and authenticity of the company's sustainability claims. The issuer might obscure the omission of information related to SDGs by inflating the text with general environmental statements lacking specific references or by emphasizing sentences with opportunity-oriented sentiment, while avoiding any mention of the climate risks associated with the projects financed by the green bond issuance. Therefore, we formulate the following two hypotheses:

Hypothesis 1 (Target information): A greater use of SDGs-themed sentences is associated with broader coverage of the SDGs declared by issuers.

Hypothesis 2 (Dilution of information): A greater use of environmental sentences is associated with less coverage of the SDGs declared by issuers.

We want to test the effects on the omission of SDGs information, of the concentration of SDGs-themed phrases and environmental phrases. The interest of this analysis lies in the fact that companies with a high level of cheap talk prioritise maintaining a positive public perception over making meaningful changes to their business practices (Bingler *et al.*, 2024).

This research not only studies the content of the disclosure but also the way it is presented. In particular, the focus is given on the sentiment of SDGs and environmental-themed sentences. While previous studies, such as Tsang *et al.* (2023) and Koelbl (2019) have shown that positive and negative sentiment types carry meaningful information, they do not extend their analysis to the specific context of green bonds. Here, we aim to test if there is an association between coverage of SDGs information, and type of sentiment, distinguishing it as opportunity-oriented, risk or neutral.

Therefore, we test two additional hypotheses:

Hypothesis 3 (SDGs Sentiment importance): A higher presence of opportunity-oriented sentiment within SDGs-related statements is associated with more coverage of the SDGs declared by the issuers.

Hypothesis 4 (Environmental Sentiment importance): A higher presence of opportunity-oriented sentiment within environmental-related statements is associated with less coverage of the SDGs declared by the issuers.

With the aim of testing these hypotheses we propose a new indicator which measure the omission of SDGs-related information in sustainability reports, that is the SDGs Omission Index (SDGOI) as in Eq. (1), comparing the SDGs declared at the time of bond issuance with those explicitly referenced later in sustainability reports, such that:

$$SDGOI = 1 - \frac{SDGsFound}{SDGsDeclared} \quad (1)$$

where *SDGsFound* are the ones found by the NLP approach within the sustainability report (see Section 4.1), while *SDGsDeclared* are the ones reported by LSEG with respect to the use of proceeds of a green bond. The ratio indicates the proportion of declared SDGs that are identified in the reporting phase. Subtracting this ratio from one highlight the share of SDGs that remain unmentioned in the reports.

In the following analysis, only SDGs [1, 2, 3, 6, 7, 8, 9, 11, 12, 13, 14, 15][3] are considered as they map directly into the GBPs. In particular, we extract SDGs-related sentences from sustainability reports using a dictionary-based approach. To ensure accurate attribution, the system builds a custom dictionary that links keywords to each

3 SDG1: No Poverty, SDG2: Zero Hunger, SDG3: Good Health and Well-being, SDG6: Clean Water and Sanitation, SDG7: Affordable and Clean Energy, SDG8: Decent Work and Economic Growth, SDG9: Industry, Innovation and Infrastructure, SDG11: Sustainable Cities and Communities, SDG12: Responsible Consumption and Production, SDG13: Climate Action, SDG14: Life Below Water, SDG15: Life on Land.

SDG by mapping the GBPs to the SDGs, based on the reference table on page 3 of the ICMA SDG Mapping Report[4] (see Paterlini *et al.*, 2025 and Section 4.1 for further details).

4 Dataset

This study focuses on the green bond market in Europe. We begin by clarifying the operational definition of "green" bond. To ensure a robust classification we relied on two independent data providers: LSEG and FactSet.

LSEG applies the standards established by the International Capital Market Association (ICMA), whereas FactSet identifies green bonds by examining disclosures in the use-of-proceeds section of the bond prospectus or in the final terms and conditions of the issuance.

Based on this classification, issuers were ranked by the number of green bonds issued between 2013 and 2023. This starting point was chosen because prior to 2013 the issuance of green bonds was extremely limited. Once issuers were sorted according to their issuance activity, their sustainability reports were retrieved through LSEG and supplemented with targeted manual web-searches, restricted to the period 2019–2023. This temporal choice aligns with the evolution of the EU's regulatory framework following 2018 'Action Plan: Financing Sustainable Growth[5]. This initiative marked the beginning of a structured regulatory framework, making the subsequent period the most relevant for assessing disclosure practices and alignment with sustainability standards.

We exhaustively include all firms with seven or more green bond issuances. The remaining population was stratified into two groups (4–6 bonds and ≤3 bonds) and randomly sampled in proportion to their prevalence within the lower-issuance population. These proportions were applied exclusively during document retrieval; issuers without an accessible or English-language sustainability report were not replaced within their stratum.

Although this method departs from the original issuance distribution – due to the complete inclusion of high-frequency issuers – it ensures broad market coverage, capturing approximately 75% of the total issued green-bond volume (as defined by LSEG and FactSet) in the period. This approach prioritises representativeness in terms of issuance magnitude rather than firm count and follows standard stratified sampling principles for skewed distributions (Tillé *et al.*, 2017).

The final dataset consists of 898 reports from 195 unique issuers, comprising 396 Sustainability Reports, 310 Other Non-Financial Reports, 77 Annual and Sustainability Reports, and 115 Annual Reports which also include sustainability

4 See: https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/June-2020/Mapping-SDGs-to-Green-Social-and-Sustainability-Bonds-2020-June-2020-090620.pdf.

5 See: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52018DC0097.

information. For simplicity, the terminology of sustainability reports will be used henceforth to refer to the documents analysed.

The distribution of issuer's domicile and sector by year are shown in the Appendix (Tables a.1-a.2).

4.1 NLP methodology

The computation of SDGOI relies on the NLP methodology presented in Paterlini *et al.* (2025). The procedure involves multiple phases.

Firstly, by using ESGBert (Schimanski *et al.*, 2024), phrases related to the environment in the sustainability report are identified (label: environmental or none).

Secondly, ClimateBERT (Bingler *et al.*, 2022; Webersinke *et al.*, 2022 and Bingler *et al.*, 2024) enables the identification of environmental claims in the report (label: environmental claim or none). An environmental claim is defined as a statement that expresses an opinion, a judgment, or verifiable information regarding climate or the environment. It differs from an environmental sentence in that the latter is a mere mention of environmental issues without expressing an opinion or verifiable information.

Thirdly, sentiment labels are assigned to sentences from the sustainability reports using ClimateBERT, classifying them based on emphasis on risks (label: Risk), emphasis on opportunities (label: Opportunity), or a neutral tone (label: Neutral).

Finally, SDGs phrases are identified through a dictionary-based search for SDGs-related phrases in the sustainability reports (i.e., *SDGsFound*) and compared with the declared SDGs (i.e., *SDGsDeclared*) of active Green Bonds in the reference year. In particular, a list of keywords for each specific SDG was created by mapping GBPs into SDGs and using also a set of keywords from LSEG use of proceeds' description.

Once defined in the dictionary with keywords associated for each SDG, sustainability documents were searched to identify which SDG from the a priori declared could be found in the reports (see also Paterlini *et al.*, 2025). The SDGOI index is then computed as reported in Eq. (1).

4.2 Variables

Based on the NLP-based methodology, we construct a set of text-based variables to quantify both the presence and the tone of content related to environmental themes and the SDGs (see Appendix Tables a.3-a.4 for some descriptive sample statistics). Specifically, we compute the proportion of environmentally labelled sentences relative to the total number of sentences in each document (i.e., *EnvContent_Of_Total*), as well as the proportion of environmentally labeled claims (i.e., *EnvClaims_Of_Total*).

In parallel, we calculate analogous metrics for SDGs-related content, including the proportion of SDGs-themed sentences (i.e., *SDGContent_Of_Total*) and the proportion of SDGs-themed claims (i.e., *SDGClaims_Of_Total*).

To assess the tone of the content, we further compute the share of environmentally labelled sentences that are associated with opportunity-oriented or risky sentiment (i.e., *Sent_Opp_Of_EnvContent* and *Sent_Risk_Of_EnvContent*, respectively). Similarly, we derive the corresponding proportions for SDGs-related sentences (i.e., *Sent_Opp_Of_SDGContent* and *Sent_Risk_Of_SDGContent*).

In addition to these text-based indicators, we incorporate a structural variable: the number of Green Bonds actively outstanding as of December 31 of the reporting year (i.e., *ActiveBonds*). While the relationship between the volume of outstanding bonds and the quality of sustainability disclosure has received limited attention in prior research, it is reasonable to expect that firms with a larger presence in the green bond market are subject to greater scrutiny by both investors and regulators. This increased visibility may, in turn, create stronger incentives for issuers to enhance the comprehensiveness, transparency, and reliability of their sustainability reporting.

5 Empirical results on SDGs omission

To test the hypothesis described in Section 3, we use a fixed effect panel regression (Eq. (2)), with heteroskedasticity-robust standard errors clustered at the firm level.

$$SDGOI_{i,t} = \beta_0 + \beta_1 EnvContent\_Of\_Total_{i,t} + \beta_2 EnvClaims\_Of\_Total_{i,t} + \beta_3 SDGContent\_Of\_Total_{i,t} + \beta_4 SDGClaims\_Of\_Total_{i,t} + \beta_5 Sent\_Opp\_Of\_EnvContent_{i,t} + \beta_6 Sent\_Risk\_Of\_EnvContent_{i,t} + \beta_7 SDG\_Sent\_Opp\_Of\_SDGContent_{i,t} + \beta_8 SDG\_Sent\_Risk\_Of\_SDGContent_{i,t} + \beta_9 ActiveBonds_{i,t} + \epsilon_{i,t}$$

where we control for year and sector fixed effects. Including sector fixed effects accounts for unobserved heterogeneity across entities that may influence the dependent variable but remain time-invariant. These controls are essential to mitigate omitted variable bias, as they absorb systematic differences between sectors that could otherwise confound the estimates. Results are shown in Table 1.

The proportion of SDGs sentences (i.e., *SDGContent_Of_Total*), as well as the proportion of SDG claims (i.e., *SDGClaims_Of_Total*), display a strong and consistently negative relationship with the SDGOI across all models' specifications ($p < 0.01$). This indicates, as expected, that a greater proportion of SDG content within a report is associated with more complete coverage about the SDGs.

The negative coefficient suggests that integrating SDGs content might serve as a mechanism for mitigating environmental narratives and selective disclosure, which is consistent with our first hypothesis.

Conversely, the second hypothesis cannot be substantiated, as the quote of environmental sentences (i.e., *EnvContent_Of_Total*) and quote of environmental claims (i.e., *EnvClaims_Of_Total*) are not statistically significant.

Table 1 – Impacts of environmental and SDG-related content, claims and sentiment on SDGOI.

variable	SDGOI	SDGOI	SDGOI	SDGOI
EnvContent_Of_Total	0.040 (0.119)			
EnvClaims_Of_Total		0.199 (0.375)		
SDGContent_Of_Total			-4.672*** (1.008)	
SDGClaims_Of_Total				-6.250*** (2.163)
Sent_Opp_Of_EnvContent	0.302** (0.144)	0.282* (0.150)	0.325** (0.128)	0.328** (0.132)
Sent_Risk_Of_EnvContent	-0.176 (0.311)	-0.166 (0.311)	-0.235 (0.295)	-0.191 (0.242)
SDG_Sent_Opp_Of_SDGContent	-0.426*** (0.066)	-0.427*** (0.066)	-0.412*** (0.065)	-0.410*** (0.035)
SDG_Sent_Risk_Of_SDGContent	-0.130 (0.132)	-0.125 (0.132)	-0.145 (0.133)	-0.148 (0.096)
active bonds	0.001* (0.000)	0.001** (0.000)	0.001 (0.000)	0.001 (0.000)
year FE	yes	yes	yes	Yes
sector FE	yes	yes	yes	Yes
observations	667	667	667	667
R-squared	0.287	0.288	0.320	0.300
F-statistic	19.079***	19.103***	22.308***	20.233***

Note: standard errors clustered at firm level in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Source: our computation. Standard errors are heteroskedasticity-robust and clustered at the firm level. Year and sector fixed effects are included in all specifications. The share of environmental content and environmental claims is not related to SDGOI while the share of both SDG Content and SDG Claims is negative related with the omission of SDG. Opportunity-oriented sentiment of environmental content is positively associated with SDGOI while opportunity-oriented sentiment of SDG content shows a negative relationship.

Hypotheses 3 and 4, instead, cannot be rejected. The proportion of environmental sentences with opportunity-oriented sentiment (i.e., *Sent_Opp_Of_EnvContent*) exhibits, indeed, a consistently significant positive relationship ($p < 0.1$ or $p < 0.05$) with the dependent variable across all models.

On the one hand, this finding aligns with the expectation that opportunity-oriented framing of environmental narratives is linked to SDGs omission and potentially selective disclosure, a typical characteristic of greenwashing.

Moreover, opportunity-oriented sentiment of SDG sentences (i.e., *SDG_Sent_Opp_Of_SDGContent*) demonstrates a consistent and highly significant negative relationship ($p < 0.01$) with the SDGs Omission Index across all models. This implies that an opportunity-oriented tone in SDGs-related communication is associated with broader disclosure.

Regarding risky sentiment, the coefficient of the proportion of SDGs-related sentences (i.e., *SDG_Sent_Risk_Of_SDGContent*) with risky sentiment as well as the coefficient of proportion of environmental sentence with risky sentiment (i.e., *Sent_Risk_Of_EnvContent*) are not significant.

Overall, the findings highlight the relationship between content, sentiment, and the strategic omission of SDGs-related information in sustainability reports. These observations could inform the development of a new metric that captures opportunity-oriented sentiment independently of SDGs statements and assess its association with ESG controversies and greenwashing accusations. A positive association would suggest its potential as an alert measure for greenwashing in a broader sense.

6 A sentiment-based metric

The analysis of the SDGOI revealed a positive association with opportunity-oriented tone in corporate environmental statements. This finding indicates that textual information may serve as a useful indicator of discrepancies between the SDGs companies declare and the ones they pursue, thereby pointing to selective disclosure practices as a potential form of greenwashing.

However, a limitation of this methodological approach is that it applies only to firms explicitly declaring commitment to the SDGs. While this approach yields valuable insights, it inherently limits the sample size and scope of applicability.

Building on previous findings that demonstrate a positive link between SDGOI and opportunity-oriented environmental sentiment, we address a critical gap in sustainable finance by proposing a novel metric based on opportunity-oriented environmental sentiment, which could provide broader insights into association with ESG Controversies (ESGCs) and Greenwashing Accusations (GWAs), without being constrained by SDGs disclosures. By focusing on opportunity-oriented environmental sentiment, we aim to develop a greenwashing alert measure for enhancing transparency and risk assessment across the green bond market in Europe.

6.1 The Environmental Sentiment Metric

We introduce the Environmental Sentiment Metric (ESM), which is calculated as the standardised count of environment-related sentences exhibiting opportunity-oriented sentiment:

$$ESM_{i,t} = (Env\_Sent\_Opp_{i,t} - \overline{Env\_Sent\_Opp_t}) \, / \, \sigma_{Env\_Sent\_Opp_t} \qquad (2)$$

where $Env\_Sent\_Opp_{i,t}$ is the number of environmental labelled sentences with opportunity-oriented sentiment for the *i*-th issuer in year *t* after min-max normalisation, $\overline{Env\_Sent\_Opp_t}$ is the mean of the number of environmental labeled sentences with opportunity-oriented sentiment across all issuers in year t and $\sigma_{Env\_Sent\_Oppt}$ is the corresponding standard deviation of the number of environmental labelled sentences with opportunity-oriented sentiment in year t.

The ESM addresses critical challenges in textual analysis of sustainability disclosures by integrating min-max normalisation and annual standardisation. Min-max normalisation accounts for stylistic differences (Sebastiani, 2002) and verbosity while preserving ordinality, avoiding the instability inherent in ratio-based metrics that conflate sentiment intensity with textual volume (Loughran *et al.*, 2011; Gentzkow *et al.*, 2010).

Standardisation within each year ensures cross-sectional and temporal comparability, anchoring scores to evolving reporting norms (i.e., post-2015 SDGs adoption trends) and isolating firm-level deviations from industry-wide baselines (Hoberg *et al.*, 2016). By retaining absolute counts rather than ratios, the metric preserves the magnitude of opportunity-oriented sentences, distinguishing firms with substantively different disclosure scales – critical for greenwashing alerts. This methodology aligns with NLP best practices, mirroring Term Frequency–Inverse Document Frequency (TF-IDF) weighting for corpus-adjusted relevance (Ramos, 2003) and Z-score standardisation for robust feature engineering in document classification (Sebastiani, 2002).

6.2 ESG controversies score and greenwashing accusations

In the absence of a significant number of actual greenwashing cases, our study relies on issuers' ESG Controversy scores (ESGCs) from LSEG and a self-developed Greenwashing Accusations (GWAs) metric (see below).

Furthermore, we also consider ESG scores from LSEG and the logarithm of market capitalisation as a proxy for issuer size. The ESG score, as defined by LSEG, represents an overall company score based on the information in the environmental, social and corporate governance pillars, with values from 0 (poorest ESG performance) to 100 (best grade). The ESGCs is defined, by LSEG, as a measure of company's exposure to environmental, social and governance controversies and negative events related to sustainable issues which are tracked by global media.

In the following analysis we construct a binary variable, still called ESGCs, which is equal to 0 if the firm had no controversies and 1 otherwise.

Figure 1 reports the relationship between ESG Scores and the presence of ESG controversies both provided by LSEG in the sample period. The boxplot suggests that firms facing controversies tend to exhibit higher ESG Scores. This result is in line with the literature (i.e., Kim *et al.*, 2015; Kathan *et al.*, 2025; Marquis *et al.*, 2016) and could be explained by considering that firms with better scores receive more media and stakeholder attention and, consequently, could be more likely subject to disputes.

Figure 2 shows the distribution of firm's size by ESGCs, suggesting a positive relationship between those variables. Those findings are consistent with prior literature which suggests that larger firms have broader operations and higher ESG values, and greater visibility and disclosure by large firms increases the probability of detection and reporting of controversies (i.e., Kathan *et al.*, 2025; Gregory, 2024; Lins *et al.*, 2017).

We also introduce the Greenwashing Accusations (GWAs) variable, defined as a binary indicator that identifies whether a firm was subject to formal legal allegations or public accusations of greenwashing between 2019 and 2023.

To account for potential late disclosures in sustainability reports, the coverage of 2023 accusations was extended through March 2024. Following established literature on corporate environmental misconduct (Lyon *et al.*, 2015; Delmas *et al.*, 2011), the variable includes both formal legal actions (i.e., regulatory sanctions or lawsuits) and non-legal but publicly documented allegations (i.e., NGO reports or media investigations), recognizing that reputational damage can arise even without litigation (Seele and Gatti, 2017).

We constructed the variable through a two-phase methodology, integrating AI-assisted data collection with manual verification. Initial data gathering employed large language models (i.e. DeepSeek and ChatGPT), which were systematically prompted to identify legal and non-legal allegations against each target company between January 2019 and March 2024.

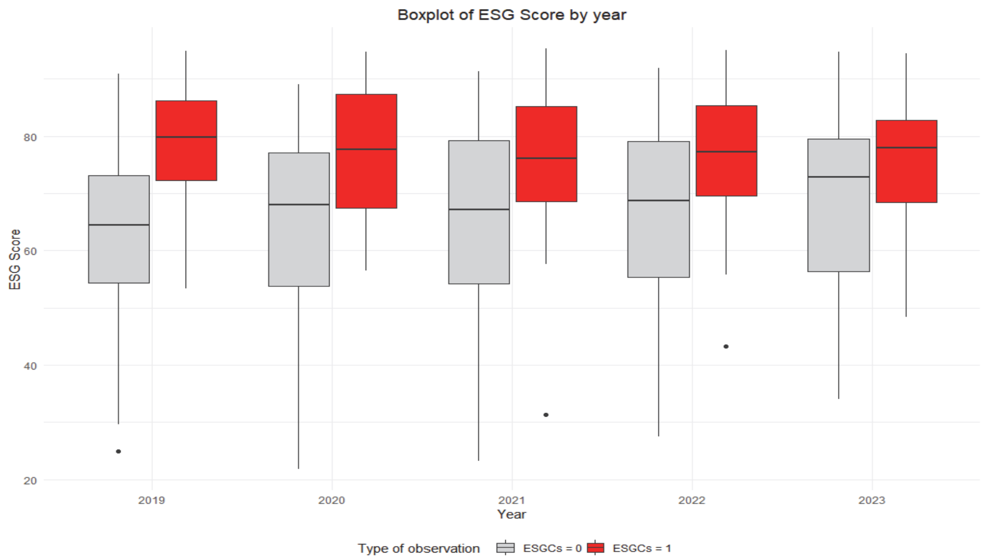
To ensure traceability, each query explicitly requested source citations and verifiable URLs. Subsequently, rigorous manual validation was conducted, involving both direct examination of the AI-provided sources and supplementary searches using identical parameters on Google. This dual approach, leveraging computational efficiency while maintaining human oversight was implemented to mitigate potential hallucinations or omissions inherent in automated retrieval systems, thereby enhancing the dataset's reliability.

While this approach provides a useful measure of greenwashing risk, it may underreport accusations against private firms (Kim *et al.*, 2015). Nevertheless, the variable aligns with reputational risk theory (Walker *et al.*, 2012), capturing both regulatory and societal dimensions of greenwashing, and is particularly relevant for green bond issuers given the region's stringent disclosure standards (EU Taxonomy Regulation, 2020).

The boxplots in Figure 3 highlights a positive relationship also between ESG scores and GWAs. Both ESGCs and GWAs, consequently, appears to be coherent indicators of reputational risk exposure, suggesting that they capture overlapping dimensions of ESG-related scrutiny, albeit with differing scope and intensity.

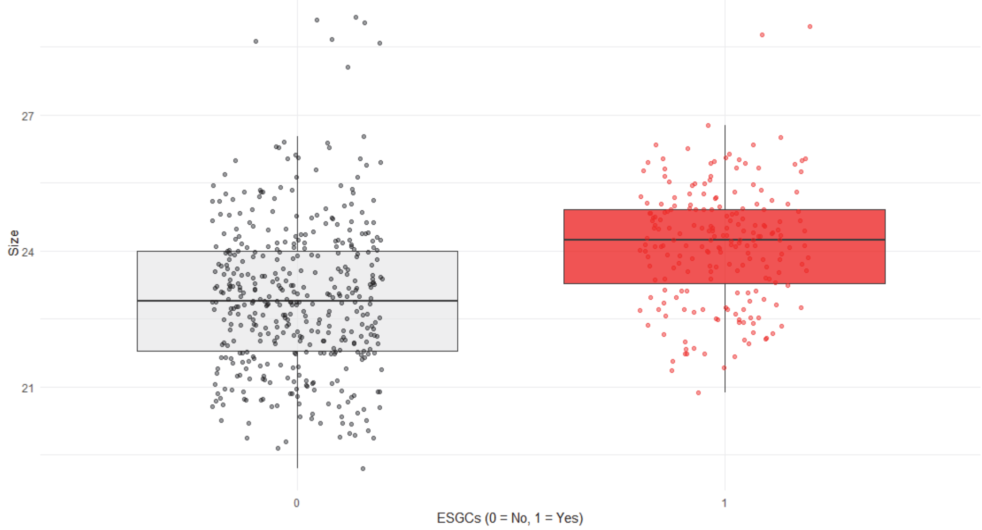
GWAs concentration among high ESG firms mirrors the broader controversy trend, reinforcing the idea that superior ESG performance attracts heightened attention by stakeholders that may uncover both generalised controversies and targeted allegations. Both ESGCs and GWAs serve as indicators of potential issues, related to greenwashing, among green bond issuers. ESGCs typically cover a broad range of incidents and apply to a larger set of companies, with 208 reported cases. In contrast, GWAs (coded as 1) are more narrowly defined and pertain to a smaller subset of issuers (50 in total), often highlighting specific cases in which firms are suspected of misleadingly portraying their sustainability efforts. As expected, there is strong overlapping between the two with 34 out of the 50 GWAs also captured within ESGCs (see Table a.5 in the Appendix for some sample descriptive statistics).

Figure 1 – ESG scores for issuers with and without ESG controversies



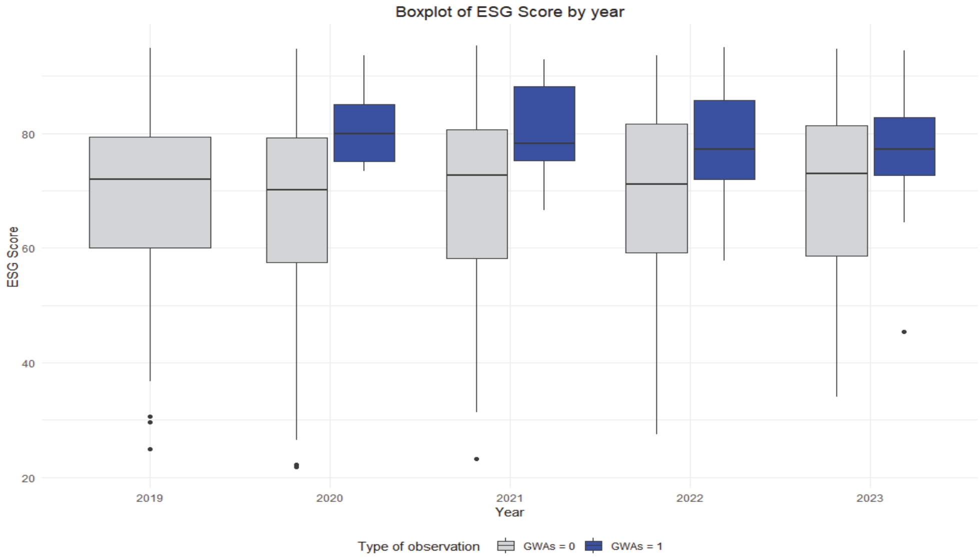
Source: our computations on the dataset.

Figure 2 – Size for issuers with and without ESG controversies



Source: our computations on the dataset.

Figure 3 – ESG scores for issuers with and without greenwashing accusations



Source: our computations on the dataset.

6.3 Empirical analysis

6.3.1 Univariate analysis

We begin with a univariate analysis to compare group means between firms with ESGCs or GWAs equal to one and those equal to zero, to test whether the two groups differ significantly across key variables. To assess statistical significance, we applied two tests: an independent samples t-test, which evaluates whether the means of each variable differ significantly between groups, and a Wilcoxon rank-sum test, which assesses differences in medians.

Table 2 reports main findings regarding ESM, ESG scores and size. Results of the test suggest that firms involved in controversies tend to place excessive emphasis on opportunities in their sustainability reports. Indeed, on average, ESM tends to be considerably higher among issuers involved in ESG controversies with respect to the other group; moreover, firms under dispute exhibit significantly higher ESG scores.

Several strands of academic research have sought to explain the counterintuitive finding that issuers with better ESG performance may also be more frequently associated with ESG-related controversies (i.e. Kim *et al.*, 2015, Kathan *et al.*, 2025). Academic literature highlights that firms with high ESG ratings are often large, publicly traded companies that actively showcase their sustainability credentials. This heightened visibility could make them more susceptible to scrutiny from stakeholders, media outlets, and regulatory bodies. Consequently, any deviation from stated ESG commitments is more likely to be detected and publicised, resulting in a greater incidence of reported controversies. Furthermore, firms with robust ESG programs often engage in multifaceted initiatives across diverse geographies and sectors. The complexity inherent in managing such programs could increase the likelihood of operational lapses or ethical breaches. Lastly, it is important to underline the temporal granularity of ESG scores provided by LSEG. Indeed, ESG performance is typically reported on an annual basis, reflecting year-end values across a range of environmental, social, and governance indicators. This annual frequency implies that ESG scores may not fully capture intra-year developments, including short-term controversies or corrective actions taken by firms in response to stakeholder pressure. The lagged nature of ESG data can contribute to a disconnect between a firm's current ESG performance and its most recently published ESG score. For instance, a firm may receive a high ESG rating based on the previous year's disclosures, while simultaneously facing reputational challenges or controversies that emerge in the current reporting period. This temporal misalignment may partially explain the observed positive correlation between ESG scores and ESG controversies in empirical studies. Companies with larger size tend to have larger ESG scores in LSEG and as they are subject to more scrutiny, they can exhibit positive association with ESG Controversies.

Indeed, the time-based improvement in ESG Score (i.e., ΔESG Score) is less pronounced for controversial firms (0.77) compared to non-controversial ones (2.07), suggesting that the score incorporates information regarding disputes only with some delay.

The same group comparison analysis was replicated using GWAs as the classification variable, yielding qualitatively consistent results, which are shown in Table 3. The direction and statistical significance of key findings, including higher opportunity-oriented sentiment, a higher size, elevated ESG scores, and attenuated post-event ESG improvement – closely mirrored those observed for ESGCs.

This coherence across the two related measures strengthens the inference that both variables capture underlying firm-level traits associated with reputational risk and strategic disclosure behaviour. Such consistency supports the use of either variable – ESGC or GWA – or both complementarily in analyses of ESG-related disclosure strategies.

Table 2 – Differences between issuers with and without ESG controversies

variable	mean (ESGCs = 0)	mean (ESGCs = 1)	mean diff.	t-test	Wilcoxon
ESM in t	-0.13	0.26	0.39	***	***
ESM in t+1	-0.13	0.32	0.45	***	***
ESG Score in t	65.88	76.90	11.02	***	***
ESG Score in t+1	67.28	77.82	10.54	***	***
ΔESG Score	2.07	0.77	-1.30	**	**
size in t	23.00	24.10	1.10	***	***

Note: * p<0.1, ** p<0.05, *** p<0.01. Differences in means and medians for the ESM, ESG scores are evaluated using t-tests and Wilcoxon rank-sum tests adjusting for differences in sample size*; t* represents the current time period, whereas *t+1* denotes one period ahead; *ESGCs = 0* indicates that issuers are not involved in any ESG controversies; ESGCs = 1 indicates that issuers are involved in some ESG controversies. Source: our computations on the dataset.

Table 3 – Differences between issuers with and without greenwashing accusations

variable	mean (GWAs = 0)	mean (GWAs = 1)	mean diff.	t-test	Wilcoxon
ESM in t	-0.04	0.42	0.46	**	***
ESM in t+1	0.00	0.45	0.45	*	***
ESG Score in t	68.80	78.29	9.49	***	***
ESG Score in t+1	70.41	80.60	10.19	***	***
ΔESG Score	1.69	0.37	-1.32		
size in t	23.30	24.20	1.10	***	***

Note: * p<0.1, ** p<0.05, *** p<0.01. Differences in means and medians for the ESM, ESG scores are evaluated using t-tests and Wilcoxon rank-sum tests adjusting for differences in sample size; t represents the current time period, whereas t+1 denotes one period ahead; GWAs = 0 indicates that issuers are not involved in any greenwashing accusations; GWAs = 1 indicates that issuers are involved in some greenwashing accusations. Source: our computations on the dataset.

6.3.2 Multivariate analysis

Building on the univariate analysis, we estimate two separate logistic regression models to examine how key explanatory variables affect the likelihood of ESGCs and GWAs outcomes in a multivariate framework.

Each model includes fixed effects for year and sector to control for unobserved heterogeneity and to isolate the effect of the independent variables on the outcomes of interest.

In particular, we estimate through a logistic model the probability for an issuer to be involved in an ESG controversy or in a greenwashing accusation:

$$\text{logit}\left(Pr\left[Y_{i,t}\right]\right) = \beta_0 + \beta_1 ESM_{i,t} + \beta_2 ESGScore_{i,t} + \beta_3 Size_{i,t} + FE \quad (3)$$

$$\text{logit}\left(Pr\left[Y_{i,t+1}\right]\right) = \beta_0 + \beta_1 ESM_{i,t} + \beta_2 ESGScore_{i,t} + \beta_3 Size_{i,t} + FE \quad (4)$$

where variable *Y* is the ESGCs or the GWAs, and FE refers to year and sector fixed effects.

Estimates with current measure of variables ESGCs and GWAs (at time *t*) are reported in Table 4, while Table 5 shows the results when considering ESGCs and GWAs one period ahead (i.e. at *t*+1).

The analysis identifies that ESM is persistently linked with ESGCs both contemporaneously and with a one-period lag. The ESM is also positively linked with GWAs within the same year when the ESG Score is not explicitly accounted for. The positive association aligns with theoretical frameworks on opportunity-oriented environmental disclosure, where firms engage in symbolic sustainability practices to manipulate stakeholder perceptions while avoiding substantive environmental commitments (Lyon *et al*., 2015, Testa *et al.*, 2018).

When ESM and ESG Score are included jointly in the full models, the results confirm that both predictors maintain their statistical significance in explaining ESGCs. This suggests that ESM provides information not fully subsumed by ESG scores, consistent with prior research showing that sentiment-based indicators capture dimensions of market perception distinct from rating-based measures (Loughran *et al.*, 2016)[6].

Moreover, consistently with the previous analysis, higher ESG scores show a positive association both with ESGCs and GWAs, potentially reflecting "ESG overclaiming" (Lyon *et al.*, 2015)[7] or measurement limitations in capturing genuine sustainability efforts, as noted in critiques of ESG scores divergence (Berg *et al.,* 2022).

Firm size emerges as a positive and highly significant variable across nearly all specifications. A larger firm has a higher probability of facing both ESG controversies and greenwashing accusations, both in the current and subsequent year. This finding provides robust support for the "visibility hypothesis", which posits that larger firms attract greater scrutiny from media, activists, and regulators, making them more susceptible to public controversies (Brammer *et al.,* 2006; Clarkson *et al.,* 2008).

The results underscore the importance of distinguishing between authentic environmental stewardship and strategic posturing, as standardised sentiment metrics like the one proposed can act as alert indicators of latent legitimacy crises[8].

It is important to emphasize that the ESM is designed as a complementary analytical tool to support expert assessment rather than as a standalone predictive classifier. Its purpose is to provide additional textual-based evidence, not to mechanically discriminate firms or identify greenwashing events.[9]

6 The attenuation of ESM's significance in some full specifications is not related to multicollinearity issues, rather it is consistent with the partial conceptual overlap between sentiment-based and score-based ESG proxies. This dynamic has been documented in related work showing that alternative sustainability metrics often share explanatory content but contribute complementary information depending on the outcome of interest (Chatterji *et al.*, 2016; Dorfleitner *et al.*, 2015).

7 As reported in Lyon *et al.*, 2015 "ESG overclaiming" is "communication that misleads people into forming overly positive beliefs about an organisation's environmental performance, practices, or products".

8 Robustness checks confirm that results are qualitatively similar after including total sentence counts and their logarithmic transformation as control variables.

9 Since the ESM is not intended as a predictive model but as an explanatory metric embedded in a broader analytical framework, measures of model discrimination or predictive accuracy are not reported.

Table 4 – Contemporaneous logistic regression estimates

variable	ESGCs at time t			GWAs at time t		
ESM at time t	0.600*** (0.202)		0.347** (0.165)	0.327** (0.129)		0.179 (0.134)
ESG Score at time t		0.065*** (0.012)	0.059*** (0.012)		0.057*** (0.014)	0.053*** (0.014)
size	0.463*** (0.117)	0.368*** (0.112)	0.367*** (0.112)	0.309*** (0.113)	0.271** (0.116)	0.267** (0.118)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
sector FE	Yes	Yes	Yes	Yes	Yes	Yes
observations	623	623	623	502	502	502
squared correlations	0.228	0.277	0.289	0.110	0.127	0.129
Pseudo R-squared	0.156	0.203	0.211	0.069	0.103	0.100

Note: standard errors clustered at firm level in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Multicollinearity was assessed using the Pearson Correlation Matrix and the Variance Inflation Factor (VIF) test. All VIF values are well below the conservative threshold of 2.5 suggested by Allison (2012), indicating no serious multicollinearity concerns. Similarly, tolerance values exceed the 0.4 cut-off recommended by Menard (2001), further confirming the robustness of the model. Source: our computations on the sample dataset.

Table 5 – Logistic regression estimates one period ahead

variable	ESGCs at time t+1			GWAs at time t+1		
ESM at time t	0.604*** (0.192)		0.362** (0.154)	0.086 (0.201)		-0.135 (0.206)
ESG Score at time t		0.059*** (0.012)	0.053*** (0.012)		0.057*** (0.014)	0.063*** (0.015)
size	0.396*** (0.123)	0.300*** (0.114)	0.301*** (0.114)	0.262** (0.107)	0.271** (0.116)	0.203* (0.115)
year FE	Yes	Yes	Yes	Yes	Yes	Yes
sector FE	Yes	Yes	Yes	Yes	Yes	Yes
observations	482	482	482	464	464	464
squared correlations	0.205	0.258	0.270	0.092	0.128	0.130
Pseudo R-squared	0.126	0.167	0.176	0.037	0.093	0.088

Note: standard errors clustered at firm level in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Multicollinearity was assessed using the Pearson Correlation Matrix and the Variance Inflation Factor (VIF) test. All VIF values are well below the conservative threshold of 2.5 suggested by Allison (2012), indicating no serious multicollinearity concerns. Similarly, tolerance values exceed the 0.4 cut-off recommended by Menard (2001), further confirming the robustness of the model. Source: our computations on the dataset.

7 Conclusion

Green bonds have emerged as a cornerstone of sustainable finance, enabling companies and governments to raise capital for environmentally beneficial projects. However, the rapid growth of this market has raised concerns about the credibility and verifiability of environmental claims, making it essential to develop robust tools for issuing potential alert on greenwashing.

As sustainable finance continues to gain prominence, the need to address greenwashing – where firms misrepresent their environmental practices – has become increasingly urgent. Introducing alert metrics to assess greenwashing risk is essential for enhancing market transparency, protecting investors, and ensuring the credibility of ESG disclosures. However, the development of such metrics presents several challenges. First, greenwashing is inherently multidimensional, involving not only environmental claims but also social and governance aspects, which complicates standardisation. Second, the lack of universally accepted definitions and benchmarks makes it difficult to distinguish between genuine sustainability efforts and strategic misrepresentation. Third, data availability and quality remain uneven across firms and jurisdictions, limiting the effectiveness of automated detection tools. Moreover, there is a risk that overly rigid metrics may penalise firms engaged in legitimate transition efforts or discourage innovation in sustainability reporting. Therefore, designing greenwashing risk indicators requires a careful balance between analytical rigor, contextual sensitivity, and regulatory adaptability. It also calls for interdisciplinary collaboration among financial analysts, legal scholars, data scientists, and supervisory authorities to ensure that such tools are both technically sound and normatively grounded.

Our paper aims at introducing new greenwashing risk metrics based on the prototype developed in Paterlini *et al.* (2025). The study firstly defines the Sustainable Development Goals Omission Index (SDGOI), a novel metric that reveals a systematic association between the omission of SDG-related information in sustainability disclosure and an opportunity-oriented environmental tone.

Empirical evidence reveals that such omissions reflect consistent patterns of selective disclosure, a practice commonly linked to greenwashing, thus providing a transparent and interpretable signal of misalignment between declared and reported SDGs.

The SDGOI therefore emerges as a useful tool for detecting disclosure gaps that mirror opportunity-oriented behaviour, offering researchers and practitioners a new lens to understand, monitor, and potentially capture greenwashing practices in sustainability communication. Beyond its methodological relevance, SDGOI also clears up the broader dynamics of sustainability disclosure, where omission and selective emphasis serve strategic purposes in shaping perceptions of corporate commitment.

Building on this, we extend the analysis beyond issuers that explicitly declare SDGs and introduce the Environmental Sentiment Metric (ESM). This metric quantifies the extent to which environmental statements in corporate sustainability reports adopt an opportunity-oriented tone, thereby providing a broader perspective on rhetorical strategies associated with greenwashing risk. Univariate and multivariate analyses consistently show that high ESM values are positively associated with ESG controversies in both the current and subsequent year, as well as with greenwashing accusations in the same year. These results suggest that opportunity-oriented sentiment in environmental narratives is not merely a stylistic choice, but a potential marker of credibility risks in sustainability disclosure. In this sense, the ESM underscores how sentiment-driven rhetoric contributes to the construction of sustainability narratives that may overstate commitment and underplay challenges, reinforcing the role of language as a strategic tool in shaping stakeholder perceptions.

Looking ahead, this line of research offers several promising paths. First, refining SDGOI and ESM through AI and machine learning techniques could improve their contextual sensitivity and enhance the detection of omission patterns and sentiment-driven misrepresentation. Second, applying these metrics to a broader and more diverse pool of issuers would strengthen their generalisability and robustness. A wider availability of documented greenwashing cases would be especially valuable for validating the predictive power of these indicators. Consistent with the Fintech Working Paper No. 14, the underlying framework is inherently flexible and its analytical limitations stem from its modular construction: alternative dictionaries or LLM-based classifiers can be integrated, potentially enabling different applications but also yielding varying empirical outcomes. Future research should also examine the adaptability of the proposed model to evolving regulatory frameworks, assessing its ability to remain effective as sustainability disclosure requirements are revised and expanded. Finally, embedding SDGOI and ESM within the evolving infrastructure of sustainable finance, whether in disclosure standards, independent assurance practices or ESG data platforms, could significantly enhance their practical utility. Such integration would not only provide investors and regulators with reliable tools for evaluating the credibility of sustainability disclosures but also create stronger incentives for issuers to engage in truthful, transparent, and accountable reporting. In this way, SDGOI and ESM may serve not only as diagnostic instruments for greenwashing alerts but also as catalysts for a cultural shift toward greater accountability and integrity in sustainability communication.

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Appendix

Tables a.1 and a.2 show the descriptive statistics of the full sample.

Table a.1 – Issuer sectors by year

sector	2019	2020	2021	2022	2023
agency	1	1	1	1	1
banks	48	52	56	57	54
electric power	18	21	23	22	21
energy company	4	4	4	4	4
gas distribution	2	2	2	2	2
manufacturing	36	41	42	42	39
other financial	26	34	34	35	30
service company	15	18	19	19	19
communication	4	4	5	5	5
transportation	2	2	4	5	5
total	*156*	*179*	*190*	*192*	*180*

Note: green bonds, which belong to the 'Agency' sector based on LSEG, are classified as corporate bonds by FactSet and for this reason they are included. Source: our computations on the dataset.

Table a.2 – Issuer domicile by year

domicile	2019	2020	2021	2022	2023
AT	5	6	7	7	7
BE	3	4	5	5	4
CZ	0	0	0	1	1
DE	29	29	31	30	29
DK	8	8	8	8	8
ES	11	12	12	13	12
FI	7	7	7	7	7
FR	19	24	28	27	27
GR	5	5	5	5	3
HU	1	1	1	1	1
IE	2	5	5	5	4
IT	18	20	20	20	18
LU	3	4	4	4	4
NL	12	17	16	18	17
PL	3	4	4	4	3
PT	1	1	1	1	0
SE	29	31	35	35	34
SI	0	1	1	1	1
total	*156*	*179*	*190*	*192*	*180*

Source: our computations on the dataset.

Tables a.3 and a.4 show the descriptive statistics of the sample used in the SDGOI analysis.

Table a.3 – Descriptive statistics by year and environmental content

variable	2019	2020	2021	2022	2023
environmental content (%)					
mean	0.31	0.32	0.35	0.35	0.35
median	0.36	0.31	0.35	0.36	0.35
SD	0.16	0.14	0.13	0.13	0.13
min	0.03	0.04	0.06	0.04	0.06
max	0.63	0.72	0.70	0.69	0.71
environmental claims (%)					
mean	0.05	0.06	0.07	0.06	0.06
median	0.05	0.06	0.06	0.06	0.05
SD	0.04	0.04	0.04	0.04	0.04
min	0.00	0.00	0.00	0.00	0.00
max	0.25	0.21	0.24	0.23	0.22
opportunity environmental sentiment (%)					
mean	0.32	0.32	0.30	0.27	0.26
median	0.30	0.30	0.28	0.25	0.24
SD	0.15	0.15	0.16	0.13	0.13
min	0.06	0.04	0.06	0.08	0.04
max	0.70	0.85	0.74	0.75	0.71
risk environmental sentiment (%)					
mean	0.09	0.10	0.10	0.11	0.11
median	0.09	0.09	0.09	0.10	0.11
SD	0.05	0.05	0.05	0.06	0.05
min	0.00	0.00	0.00	0.00	0.00
max	0.25	0.57	0.29	0.30	0.33

Note: this table presents descriptive statistics for sustainability disclosure metrics incorporate reports. All percentage values represent proportions of total content. Environmental content measures reflect the relative emphasis on environmental topics. Sentiment metrics capture the tone of disclosure, with opportunity sentiment indicating positive forward-looking statements and risk sentiment indicating cautious or negative statements. The sample consists of firms that declared SDG commitments during the period 2019-2023. Source: our computations on the dataset.

Table a.4 – Descriptive statistics by year and by SDG content

variable	2019	2020	2021	2022	2023
SDGs content (%)					
mean	0.01	0.01	0.01	0.01	0.01
median	0.01	0.01	0.01	0.01	0.01
SD	0.01	0.02	0.02	0.02	0.01
min	0.00	0.00	0.00	0.00	0.00
max	0.06	0.08	0.14	0.13	0.09
SDGs claims (%)					
mean	0.00	0.00	0.01	0.01	0.01
median	0.00	0.00	0.00	0.00	0.00
SD	0.01	0.01	0.01	0.01	0.00
min	0.00	0.00	0.00	0.00	0.00
max	0.02	0.04	0.04	0.05	0.03
opportunity SDGs sentiment (%)					
mean	0.52	0.55	0.55	0.51	0.51
median	0.60	0.64	0.62	0.57	0.52
SD	0.35	0.32	0.29	0.27	0.27
min	0.00	0.00	0.00	0.00	0.00
max	1.00	1.00	1.00	1.00	1.00
risk SDGs sentiment (%)					
mean	0.03	0.03	0.04	0.03	0.04
median	0.00	0.00	0.00	0.00	0.00
SD	0.13	0.09	0.10	0.06	0.10
min	0.00	0.00	0.00	0.00	0.00
max	1.00	0.75	1.00	0.40	1.00
SDGs Omission Index					
mean	0.29	0.29	0.20	0.19	0.21
median	0.20	0.20	0.13	0.15	0.17
SD	0.31	0.32	0.27	0.24	0.26
min	0.00	0.00	0.00	0.00	0.00
max	1.00	1.00	1.00	1.00	1.00

Note: this table presents descriptive statistics for sustainability disclosure metrics incorporate reports. All percentage values represent proportions of total content. SDG content measures reflect the relative emphasis on SDG topics. Sentiment metrics capture the tone of disclosure, with opportunity sentiment indicating positive forward-looking statements and risk sentiment indicating cautious or negative statements. The sample consists of firms that declared SDG commitments during the period 2019-2023. Source: our computations on the dataset.

Table a.5 shows the descriptive statistics of the sample used in the ESM analysis.

Table a.5 – ESG score, ESG controversies, greenwashing accusations and size by year

variable	2019	2020	2021	2022	2023
ESG score					
mean	68.62	68.36	69.71	70.01	70.80
median	71.94	72.00	73.18	71.51	73.85
SD	15.27	16.05	15.15	14.62	13.81
min	24.98	21.82	23.29	27.47	33.96
max	94.86	94.69	95.27	95.00	94.68
ESGCs					
mean	0.33	0.35	0.40	0.27	0.32
median	0.00	0.00	0.00	0.00	0.00
SD	0.47	0.48	0.49	0.44	0.47
min	0.00	0.00	0.00	0.00	0.00
max	1.00	1.00	1.00	1.00	1.00
GWAs					
mean	0.00	0.05	0.08	0.08	0.17
median	0.00	0.00	0.00	0.00	0.00
SD	0.00	0.22	0.28	0.27	0.38
min	0.00	0.00	0.00	0.00	0.00
max	1.00	1.00	1.00	1.00	1.00
Size					
mean	23.35	23.40	23.31	23.44	23.30
median	23.34	23.30	23.25	23.47	23.30
SD	1.66	1.58	1.66	1.70	1.62
min	19.93	19.87	19.80	19.87	19.21
max	28.78	29.09	28.95	29.17	28.67

Note: this table presents descriptive statistics for the main variables used in the analysis. ESG Score represents environmental, social and governance performance. ESGCs is a binary variable indicating the presence of ESG controversies. GWAs represents governance and compliance indicators. Size is the natural logarithm of market capitalisation. The sample period spans from2019 to 2023. Source: our computations on the dataset.

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