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Sustainability performance and corporate greenwashing:

Empirical evidence on measurement, determinants, and financial implications

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Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

eingereicht an der Fakultät für Wirtschaftswissenschaften der Universität Regensburg

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Tag der Disputation: 18.12.2025

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A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
Doktor der Wirtschaftswissenschaft (Dr. rer. pol.)

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To Mona.

Acknowledgements

First and foremost, I would like to express my sincere gratitude to my advisor, Prof. Dr. Gregor Dorfleitner, for his continuous support, insightful guidance, and the opportunities he provided during my doctoral studies in the Department of Finance at the University of Regensburg.

I am also grateful to my second advisor, Prof. Dr. Sven Bienert, for his valuable insights and constructive feedback. Inspiring discussions with Prof. Dr. Bienert and Prof. Dr. Dorfleitner significantly enhanced the quality of my research.

I am thankful to my co-authors for their valuable collaboration throughout this dissertation. In particular, I thank Prof. Dr. Sebastian Utz, co-author of five of the six studies, for his guidance, support, and substantial contribution.

I would also like to thank my colleagues in the Department of Finance for their helpful discussions and suggestions, as well as for their friendship. I am also indebted to the German Academic Scholarship Foundation and the Stiftung Mercator for their financial support.

Finally, I would like to express my deepest appreciation to my family, friends, and fiancée for their endless encouragement, unconditional support, and boundless patience throughout this journey.

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Chapter 1

Introduction

1.1 Motivation and research context

"We must have zero tolerance for net-zero greenwashing," declared United Nations (UN) Secretary-General António Guterres at the 27th Conference of the Parties (COP27) to the UN Framework Convention on Climate Change (United Nations, 2022). His warning highlights a central paradox of sustainable finance: as markets direct substantial capital toward sustainability-labeled assets, concerns persist about the credibility and verifiability of the accompanying environmental and social performance claims (Christensen et al., 2022; Lyon and Montgomery, 2015; Marquis et al., 2016).

According to Bloomberg Intelligence (2024), environmental, social, and governance (ESG) assets under management surpassed USD 30 trillion in 2022 and are estimated to reach USD 40 trillion by 2030, representing over 25% of the projected USD 140 trillion in total assets under management (AUM). Europe is set to remain the largest market, with ESG assets expected to exceed USD 18 trillion by 2030. Over the past decade, sustainable finance has emerged as a central theme in both academic research and market practice, reflecting a growing consensus that ESG factors are integral to long-term value creation (Clark et al., 2015; Friede et al., 2015). This development has been driven by empirical evidence that companies with superior ESG ratings tend to exhibit lower cost of capital, reduced volatility, and enhanced operational resilience (Amel-Zadeh and Serafeim, 2018; Giese et al., 2019; Krüger, 2015; Lins et al., 2017).

This dissertation addresses a set of interrelated research questions with broad implications for sustainable finance: how can corporate sustainability performance and greenwashing behavior be empirically measured, what company-level and institutional factors determine their dynamics, and under what conditions do they have material financial consequences for companies and investors? Focusing on the environmental dimension, given its urgency in addressing climate change and biodiversity loss as emphasized by recent UN conferences such as COP16 to the Convention on Biological Diversity and COP29 to the UN Framework Convention on Climate Change, the dissertation examines these questions along three interconnected dimensions.

First, in the green bond market, the dissertation tests whether third-party greenness ratings reduce information asymmetry and are associated with higher secondary-market liquidity. Second, it measures greenwashing risk as the gap between apparent (disclosure-based) and real (outcome-based) environmental performance, examines how ESG scores relate to greenwashing risk, analyzes market reactions and the determinants of greenwashing, and develops an economics-based forecasting framework. Third, in an emerging market context, it analyzes how ownership structure and regulation, specifically an ESG disclosure mandate, are associated with ESG ratings and the ESG–profitability relation. Together, the findings suggest that stronger institutions, more stringent and transparent disclosure regulations, and improved verification mechanisms may reduce information frictions, enhance market signals, and encourage companies to shift from symbolic disclosure to demonstrable sustainability performance. Consequently, credible ESG information is essential not only for regulators and civil society but also for market participants such as sustainability-oriented investors, who incorporate such signals into their portfolio decisions.

According to the market efficiency hypothesis (Fama, 1970), asset prices should incorporate all available information, financial and nonfinancial, so that security valuations accurately reflect expected future cash flows. In efficient markets, investors would immediately price in any material ESG-related risks or opportunities, whether stemming from carbon transition policies, labor controversies, or greenwashing behavior. Financial markets also play an active informational role in shaping real economic decisions, as companies learn from market signals and investor reactions (Goldstein, 2022). This perspective highlights that credible ESG information affects not only asset pricing, but also companies' strategic and investment behavior through informational feedback channels. In practice, however, information asymmetries remain pervasive: companies hold private knowledge of their true sustainability performance, while investors depend on voluntary disclosures that may be incomplete, delayed, or strategically managed (Akerlof, 1970; Christensen et al., 2021; Healy and Palepu, 2001).

According to signaling theory (Spence, 1973), managers may selectively disclose favorable ESG information to differentiate themselves from peers, but such disclosures are not costlessly verifiable and may suffer from adverse selection. Such gaps in credible information hinder the efficient allocation of capital and can expose stakeholders to hidden regulatory, reputational, and operational risks (Christensen et al., 2021; Healy and Palepu, 2001; Krüger, 2015). Therefore, it may be sensible to extend standard asset-pricing models, which typically assume symmetric information, to account for potential mispricing induced by ESG disclosure noise. Recent advances in asset pricing show how ESG preferences and constraints can be incorporated into efficient frontier models (Pedersen et al., 2021). This is supported by evidence showing that mandatory disclosure reduces information asymmetries (Krueger et al., 2024) and that disagreement among ESG ratings contributes to return premia (Brandon et al., 2021).

Stakeholder theory (Freeman, 1984) further highlights the multifaceted pressures that compel companies to report nonfinancial information. Together with investors, a wide range of other stakeholders, e.g., employees, suppliers, customers, civil society groups, financial intermediaries, and policymakers have a legitimate interest in a company's environmental and social impact. For example, institutional investors with sustainable investment mandates demand robust climate-related information to guide their portfolio choices (Krueger et al., 2020), financial markets increasingly price carbon and related ESG factors into asset valuations (Bolton and Kacperczyk, 2021), and investor demand for green assets has been shown to drive both relative market performance and expected return premia (Pástor et al., 2022). Employees also value a company's sustainability performance: companies that treat their workforce responsibly and foster employee satisfaction tend to perform better in the long run (Edmans, 2011). Banks structuring sustainability-linked loans rely on transparent ESG performance metrics to determine contract terms and loan spreads (Kim et al., 2025). At the same time, regulatory bodies such as the Task Force on Climate-related Financial Disclosures (TCFD) and the European Union (EU) have introduced mandatory or quasi-mandatory reporting frameworks (e.g., the EU Taxonomy) that seek to standardize the measurement and communication of sustainability performance and environmental risks (European Parliament and the Council of the European Union, 2020; Task Force on Climate-related Financial Disclosures, 2017).

From the lens of institutional theory (DiMaggio and Powell, 1983), these regulatory and normative pressures generate coercive, normative, and mimetic forces that shape organizational behavior. Coercive pressures arise, e.g., when governments mandate sustainability disclosures or impose carbon pricing, while normative pressures can stem from professional networks and trade associations that establish voluntary ESG guidelines. Mimetic pressures, meanwhile, encourage companies to imitate industry leaders' sustainability practices to avoid being perceived as laggards. In this context, adopting ESG practices and disclosing sustainability metrics can, according to legitimacy theory (Aldrich and Fiol, 1994; Ashforth and Gibbs, 1990; Suchman, 1995), help organizations secure societal approval. In particular, social and environmental disclosures may signal that a company operates in accordance with evolving societal values (Deegan, 2002). Legitimacy emerges as a strategic resource: companies that align with stakeholder expectations can secure access to critical resources needed for growth and survival (Zimmerman and Zeitz, 2002), while legitimacy also enhances reputation and fosters a license to operate, both of which may strengthen long-term financial performance (Suchman, 1995). However, when companies' stated commitments diverge from their measurable outcomes, stakeholders cannot accurately assess risk, and capital markets may fail to reward genuinely sustainable enterprises (Delmas and Burbano, 2011; Krueger et al., 2024; Lyon and Montgomery, 2015; Walker and Wan, 2012).

One of the most visible manifestations of such divergence is greenwashing, broadly understood as the communication of environmental claims that exaggerate, misrepresent, or omit relevant information, thus inducing overly favorable perceptions of environmental performance (Delmas and Burbano, 2011; Lyon and Montgomery, 2015; Marquis et al., 2016). Greenwashing can take many forms. It can be as simple as a vague product label, such as “eco-friendly” or “carbon neutral,” or it can be more complex, such as the selective disclosure of favorable metrics while concealing unfavorable outcomes (de Freitas Netto et al., 2020). In relation to the phenomenon of greenwashing, empirical evidence demonstrates that ESG ratings often lack consistency and exhibit low inter-rater reliability, with correlations between major rating providers sometimes below 0.5 (Berg et al., 2022; Chatterji et al., 2016; Dorfleitner et al., 2015). According to Berg et al. (2022), much of this divergence comes from differences in the dimensions included (scope), in the underlying variables used to measure similar attributes (measurement), and to a lesser extent in how these attributes are weighted (weighting). Complementary evidence shows that markets price the uncertainty arising from disagreement over ESG ratings, as investors require compensation for holding assets exposed to such disagreement (Avramov et al., 2022). Consequently, investors may be misled into financing companies with overstated ESG disclosures, which impairs market efficiency and exacerbates adverse selection problems (Christensen et al., 2022; Lyon and Montgomery, 2015; Marquis et al., 2016).

Green bonds provide a complementary setting to study these dynamics, but with a structural distinction: unlike ESG ratings that evaluate companies holistically, green bond labels and external reviews operate at the financial instrument level. They certify that the proceeds are used for environmentally beneficial projects, thereby offering investors a basic level of transparency regarding the use of funds. In this context, the green bond market illustrates both the promise and pitfalls of sustainable finance. Conceived in 2007 to finance projects with positive environmental externalities (e.g., renewable energy, energy efficiency, clean transportation), green bonds have expanded rapidly. By the end of Q1 2024, lifetime issuance crossed USD 3 trillion (Chouhan and Harrison, 2024). In 2024 alone, aligned green issuance reached USD 671.7 billion, bringing cumulative aligned issuance to USD 3.5 trillion (Muldoon et al., 2025). For investors, however, a fundamental challenge remains: the environmental credibility of financed projects must be transparent and verifiable. Regulatory frameworks such as the Green Bond Principles and the EU Green Bond Standard, together with second-party opinions (SPOs), seek to reduce this information asymmetry and enhance market confidence.

In principle, the “greenium,” i.e., the yield discount associated with green bonds, embodies investor willingness to accept lower returns in exchange for measurable environmental impact, thereby lowering issuers’ cost of capital and aligning corporate incentives with global objectives (Flammer, 2021). Yet empirical evidence on the greenium is mixed: while some studies report significant yield spreads of 2–5 basis points in favor of green bonds, others find negligible or even negative spreads once issuance characteristics and credit risk are controlled (Dorfleitner et al., 2022; Hachenberg and Schiereck, 2018; Karpf and Mandel, 2017; Tang and Zhang, 2020; Zerbib, 2019). These inconsistencies emphasize the need to examine whether market mechanisms such as greenness ratings within SPOs help investors distinguish between credible and less credible green bonds.

In this regard, recent evidence suggests that better greenness ratings strengthen the greenium (Dorfleitner et al., 2022).

While the greenium has commanded considerable attention, a critical but underresearched driver of green bond pricing is liquidity. Secondary-market liquidity, encompassing bid–ask spreads, turnover ratios, and depth measures, directly influences bond valuations and investors' required liquidity premia (Chordia et al., 2001). Many green bonds suffer from pronounced illiquidity, which significantly contributes to their yield spreads relative to conventional bonds (Wulandari et al., 2018). Liquidity premia can even overshadow modest greenium effects, making liquidity risk particularly salient in fixed-income markets, where illiquidity can substantially increase required yields and obscure sustainability-related pricing effects (Zerbib, 2019). Furthermore, green bonds tend to trade less frequently than conventional bonds, rendering them especially sensitive to liquidity conditions and associated risk premia (Tang and Zhang, 2020; Zerbib, 2019). Against this backdrop, the first part of the dissertation (Chapter 2) examines the relationship between SPO-assigned greenness ratings and green bond liquidity, thereby addressing whether such third-party verifications reduce information asymmetries and are associated with higher secondary market liquidity. It further explores whether this greenness–liquidity relationship differs across issuer types. If label credibility matters for bonds, a similar issue arises at the issuer level. When disclosures diverge from actual outcomes, investors face the risk of greenwashing, which also constitutes a form of information asymmetry.

The second part of the dissertation (Chapters 3–6) turns to company-level greenwashing. Drawing on the theoretical framework of Dorfleitner and Utz (2024) and on the theoretical literature of greenwashing drivers (Delmas and Burbano, 2011; Lyon and Maxwell, 2011; Marquis et al., 2016), it first introduces a greenwashing measurement framework that systematically compares companies' voluntary ESG disclosures with objective environmental indicators such as official emissions, energy consumption, and controversy data to generate a company-level greenwashing risk indicator. By quantifying the discrepancy between reported and actual environmental performance, this framework aims to identify instances where companies may overstate their sustainability performance. In doing so, the greenwashing risk indicator not only captures the degree of misrepresentation but also serves as a proxy for information asymmetry and potential mispricing in capital markets, since investors may systematically misinterpret inflated ESG disclosures as genuine environmental performance. Building on these insights, the dissertation next evaluates whether higher ESG scores correlate with lower greenwashing risk or merely reflect more extensive disclosure practices, thereby providing further evidence to the literature on ESG rating validity (Berg et al., 2022; Chatterji et al., 2016; Christensen et al., 2022; Dorfleitner et al., 2015). To address the financial implications of greenwashing, the dissertation employs an event-study methodology and cumulative abnormal returns analysis to examine how the stock market reacts to allegations of greenwashing. Moreover, it identifies company-level and event-level characteristics that amplify or attenuate price reactions. To conclude the second part, the dissertation documents the prevalence of greenwashing across a large cross-section of companies, examines company-level determinants that are associated with greenwashing behavior, and constructs an economic-based forecasting model that estimates future greenwashing risk, thereby proposing a forward-looking tool for stakeholders such as investors and regulators. More broadly, the analysis of greenwashing suggests that information asymmetry regarding ESG issues may not be limited to the company level but could also be influenced by the broader institutional and governance environment. This perspective provides a conceptual link to differences between public and private ownership structures and to the weaker institutional settings of emerging markets.

While a large share of existing studies on sustainability performance focuses on publicly traded companies in developed markets, the third part of the dissertation (Chapter 7) examines Brazil as an emerging economy, where privately held enterprises play a significant role in economic activity, employment, and emissions. Small and medium enterprises, overwhelmingly privately held and often family-owned, account for more than 95% of registered companies worldwide, over half of jobs, and more than one-third of GDP in many emerging markets, highlighting the need to better understand their ESG behavior (Alibhai et al., 2017). Under agency theory, private companies face different principal–agent dynamics than public corporations: absent dispersed shareholders and under weaker disclosure mandates, managers may have fewer incentives to report ESG metrics transparently (Jensen and Meckling, 1976). At the same time, the socioemotional wealth (SEW) theory (Berrone et al., 2010) suggests that family-controlled companies, which are prevalent in emerging markets such as Brazil, may prioritize long-term stakeholder objectives and community relationships over short-term profits. Although this orientation can encourage greater substantive ESG investments, such companies typically have less extensive formal disclosure, reflecting lower external pressure and a preference for privacy. Conversely, private equity–backed companies are typically characterized by tightly aligned profit incentives and exit-oriented strategies, which may reduce the priority given to costly sustainability initiatives (Davis et al., 2014).

By contrasting public and private companies in Brazil, the dissertation addresses an important research gap: how ownership structures are associated with ESG performance and its relationship with financial outcomes. Beyond ownership considerations, Brazil provides a particularly compelling research setting. As one of the world's largest economies and top greenhouse gas emitters, corporate sustainability practices in Brazil have outsized implications for climate policy and financial markets (International Monetary Fund, 2025; International Energy Agency, 2023). More broadly, the Brazilian context can be viewed as part of the global shift towards a low-carbon economy. Alongside China and parts of Europe, Brazil is emerging as a key player in climate action and carbon pricing reforms (J.P. Morgan Chase & Co., 2023). This makes Brazil representative of broader trends in emerging markets. Moreover, Brazilian capital markets are characterized by strict requirements for listed companies and limited transparency for private companies (La Porta et al., 1999; Leal and Carvalhal-da-Silva, 2005). These institutional contrasts enable analysis of how ownership structure is related to companies' ESG performance and its relationship with financial outcomes. Finally, the introduction of an ESG disclosure mandate (CVM Resolution No. 59) in 2021 created a quasi-natural experiment to study how regulation shapes ESG behavior.

In integrating insights from sustainable finance, including the liquidity dynamics of green bonds, the economics of company-level greenwashing, the reliability of ESG ratings, and the role of ownership structure in corporate sustainability performance, the dissertation contributes to three interrelated strands of research. First, it enhances measurement and forecasting techniques for corporate sustainability performance and greenwashing behavior, providing investors, lenders, and policymakers with practical tools to improve capital-allocation decisions and regulatory oversight. Second, it deepens our understanding of green bond market dynamics by examining the interplay between third-party greenness ratings, issuance characteristics, and bond liquidity, thereby informing the design of more rigorous green bond standards. Third, it extends the analysis to privately held companies, which play a central role in emerging economies undergoing low-carbon transitions. In doing so, it provides targeted insights for regulators, multilateral development banks, and impact investors seeking to align private-sector behavior with sustainability objectives.

Ultimately, by quantifying the gap between reported and realized sustainability performance, the dissertation demonstrates that ESG disclosure on its own is often not a sufficient signal. Although sustainability performance spans environmental, social, and governance dimensions, the analysis primarily focuses on environmental performance as the most pressing area of systemic risk. As sustainable finance continues to evolve into mainstream practice, the ability to distinguish substantive environmental impact from cosmetic compliance will determine whether capital markets can effectively address the challenges of climate change, biodiversity loss, and resource depletion. Only then can sustainable finance fulfill its promise of aligning private profit motives with the broader public good.

1.2 Structure and contribution

Table 1.1 summarizes all studies included in the dissertation and shows their assignment to individual chapters, along with information on publication status and venue.

Table 1.1: Overview of dissertation studies

Chapter	Title	Publication	
		Status	Publication venue
2	Greenness ratings and green bond liquidity	Published	Finance Research Letters
3	Greenwashing in public European companies	Submitted	Contemporary Issues in Green Finance: Policies, Regulations, and Greenwashing
4	What you see is not what you get: ESG scores and greenwashing risk	Published Open access	Finance Research Letters
5	What drives stock market reactions to greenwashing? An event study of European companies	Major revision completed	Finance Research Letters
6	Determinants and forecasting of corporate greenwashing behavior	Major revision completed	Journal of Economic Behavior & Organization
7	ESG and financial performance in public and private companies: Evidence from Brazil	Submitted	Journal of Corporate Finance

Notes: This table summarizes the six dissertation studies, including their chapter assignment, title, and stage in the publication process. The column "Publication venue" reports the journal or edited volume in which each study has been published or is currently under review. The study *Greenwashing in public European companies* is intended to be published as a book chapter in the edited volume *Contemporary Issues in Green Finance: Policies, Regulations, and Greenwashing*, which is planned for publication by Springer Nature under the Palgrave Macmillan imprint as part of the *Palgrave Studies in Green Finance* series.

The remainder of the dissertation is organized as follows. Section 1.3 provides an executive summary of each study, highlighting the contribution of each chapter. The individual studies are then presented in Chapters 2–7, as outlined in Table 1.1. The dissertation concludes in Chapter 8 with a discussion of research limitations, avenues for future research, practical implications, and an outlook.

1.3 Summary of the chapters

Greenness ratings and green bond liquidity

This chapter examines how third-party greenness ratings are associated with secondary-market liquidity in the green bond market. Understanding liquidity is crucial because it represents a well-documented risk factor influencing bond valuation (e.g. Amihud et al., 2006; Chen et al., 2007; Dick-Nielsen et al., 2012; Elton and Green, 1998; Elton, 2001; Utz et al., 2015). Previous evidence shows that green bond liquidity can affect yield spreads (Wulandari et al., 2018), while financial market theory links liquidity to information asymmetry and adverse selection costs (e.g. Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985). This suggests that greenness ratings may enhance market transparency and liquidity.

The empirical analysis draws on a comprehensive global panel of 3,496 green bonds issued between 2008 and 2020. Each bond is rated by a second-party opinion (SPO) provider as either "dark green" or "medium green," labeled "no shade" when no "shade of green" rating is assigned, or issued without an SPO ("no SPO"). Liquidity is proxied by state-of-the-art measures of bid–ask spreads and the percentage of zero-trading days (Schestag et al., 2016), as well as by Lesmond's LOT estimates (Lesmond et al., 1999). Annual panel regressions control for bond characteristics (issued amount, maturity, seniority, currency, and whether the bond is straight (non-convertible)), issuer type (agency, corporate, financial, municipal, sovereign, and supranational), credit rating, and macroeconomic variables.

The results show a positive relationship between SPO greenness ratings and liquidity. Bonds with a greenness rating have narrower bid–ask spreads (by around 3.5 basis points), lower LOT-based transaction costs, and fewer zero-trading days compared to bonds without a greenness rating. The association is most pronounced for corporate and municipal issuers, while public-sector entities (agencies, sovereigns, and supranationals) and financial institutions show weaker or insignificant greenness–liquidity relationships.

When distinguishing between shades of green, there is no significant difference in the relationship with liquidity between bonds with "dark green" and "medium green" ratings. However, bonds with "no shade" ratings tend to have insignificant or weaker associations with liquidity. This suggests that the presence of a greenness rating, rather than its precise shade, is positively associated with liquidity.

The chapter's central insight is that external greenness ratings are associated with differences in market outcomes. SPO greenness ratings appear to reduce information asymmetry in the green bond market and are related to higher secondary-market liquidity. This may lower the cost of capital for issuers and strengthen overall market transparency.

Greenwashing in public European companies

In this chapter, we develop and calibrate a rigorous quantitative framework to distinguish between a company's apparent environmental disclosure and its real environmental impact, thereby generating a novel greenwashing risk indicator. Although greenwashing has received increasing attention from academics, most empirical studies still examine products, services, or isolated company cases (e.g., Delmas and Burbano, 2011; Torelli et al., 2020), leaving company-level analyses understudied. Initial attempts to quantify corporate greenwashing often rely on simplified proxies, such as gaps between ESG performance and disclosure, that fail to capture its multidimensional nature (e.g. Ioannou et al., 2022; Kim and Lyon, 2015; Marquis et al., 2016; Mateo-Márquez et al., 2022; Roulet and Touboul, 2015; Walker and Wan, 2012).

Our sample comprises 1,031 STOXX Europe 600 constituents from 2011–2023, of which 595 company-year observations with confirmed greenwashing incidents are identified through manual review of 1,254 information sources collected via web search engines, NGO reports, news articles, and social media platforms. Each case is evaluated by four independent raters who assign a human-coded severity score between 0 (no greenwashing) and 1 (greenwashing), with interpolation used when repeated offenses span nonconsecutive years. These human assessments serve as the foundation for calibrating the greenwashing risk model.

Building on the theoretical framework of Dorfleitner and Utz (2024), we distinguish between apparent indicators of environmental performance, such as emission-reduction targets, disclosure intensity, or energy-efficiency policies, and real indicators, including actual greenhouse gas intensities, controversy records, and supply-chain risks. The analysis shows that companies emphasizing apparent environmental performance while exhibiting a difference between apparent and real outcomes face a higher estimated risk of greenwashing.

The model demonstrates strong classification performance. Placing greater weight on detecting true cases of greenwashing, the approach correctly identifies nearly nine out of ten incidents, though at the cost of a moderate false-positive rate. Dimension-level decomposition shows that resource use drives most of the apparent–real gap, whereas environmental governance and resource use account for the largest share of real performance.

Overall, the chapter provides a novel, comprehensive, and human-collected dataset of severity-assessed greenwashing cases and develops a rigorous, multi–information-pillar framework for quantifying company-level greenwashing risk. Together, these contributions lay the groundwork for subsequent analyses of the relationship between greenwashing risk and ESG scores (Chapter 4), stock market reactions (Chapter 5), and company-level determinants (Chapter 6). The findings have practical implications for a variety of stakeholders, particularly investors and regulators. Investors can use the proposed measurement framework to identify and evaluate greenwashing risks associated with corporate environmental claims. In turn, regulators can use the insights to improve disclosure standards, promote transparency, and develop verification mechanisms to mitigate greenwashing behavior.

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

This chapter examines whether ESG scores reliably signal a company's true environmental performance or merely reflect its communicated efforts. While ESG ratings are widely used by investors and academics to guide decision-making, they are often inconsistent and prone to manipulation due to managerial incentives and opaque methodologies (Amiraslani et al., 2023; Benuzzi et al., 2023; Berg et al., 2022; Cohen et al., 2023; Chatterji et al., 2016; Dorfleitner et al., 2015; Galletta et al., 2023; Goyal et al., 2023).

Focusing on STOXX Europe 600 constituents from 2015–2023, we use 417 hand-collected greenwashing incidents with manual assessed severity scores. ESG scores (from LSEG and Bloomberg) are compared to two distinct measures, building on the theoretical framework of Dorfleitner and Utz (2024): apparent environmental performance, which reflects a company's stated commitments, environmental partnerships, product and policy disclosures, and other self-reported initiatives; and real environmental performance, which is based on verifiable outcomes such as greenhouse gas emission intensities, incident-based controversy records, and supply chain or resource use issues.

Our empirical analysis shows that companies with higher ESG scores tend to have stronger apparent environmental performance and weaker real environmental performance. This indicates that ESG ratings are more closely tied to what companies say than what they do. Portfolios sorted by ESG score and company size reveal that large companies with top-quartile ESG ratings account for the greatest number of greenwashing cases, suggesting that high ESG scores can mask actual misalignment between reported and realized environmental outcomes. We also find that increased analyst coverage reduces the gap between apparent and real environmental performance, particularly for smaller, carbon-intensive companies and those in industries we classify as "brown," namely energy, industrials, utilities, and basic materials. This suggests that more intensive scrutiny could align publicly reported ESG claims with measurable environmental results. This finding corroborates previous studies that have suggested analyst scrutiny can mitigate information asymmetry and greenwashing behavior (Chan and Chan, 2014; Lee and So, 2017; Li et al., 2019; Liu et al., 2023).

The chapter demonstrates that relying solely on ESG scores, particularly for companies with high scores, may lead investors and researchers to underestimate the true extent of greenwashing risk. By distinguishing between communicated efforts and measurable impact, the chapter highlights the need for more nuanced metrics when using ESG data for investment decisions or academic research.

What drives stock market reactions to greenwashing? An event study of European companies

In this event study, we examine how stock markets respond to company-level greenwashing allegations. While empirical evidence on the financial implications of greenwashing remains limited, the few existing studies show mixed results (Du, 2015; European Securities and Markets Authority, 2023; Li et al., 2024a; Lyon and Montgomery, 2015; Teti et al., 2024; Walker and Wan, 2012; Xu et al., 2025). To advance this research stream, we hand-collect 296 events for STOXX Europe 600 companies (2018–2023), classify cases into six categories (compliance, marketing, products, operations, investment, and social impact), and code both severity and financial materiality. The event date is defined as the earliest credible public disclosure of the allegation (e.g., through news outlets or NGO reports), ensuring that stock market reactions are tied to the first moment when investors could respond. Using an event-study design based on daily stock returns and the widely used Fama–French five-factor model, we first estimate expected returns for each company and compute abnormal returns (AR) as the difference between actual and expected returns. We then calculate cumulative abnormal returns (CAR) by summing the ARs over different event windows. Specifically, we focus on a ten-day window to capture the immediate market reaction to greenwashing allegations and a twenty-day window to examine whether this reaction persists or evolves over a longer horizon.

Average CARs are not significantly different from zero for the full sample, but cross-sectional heterogeneity is pronounced. Companies with the lowest total assets in the sample experience negative CARs, and compliance-related allegations are consistently associated with negative market reactions. In consumer industries, cases of social impact also trigger negative market reactions, especially immediately after disclosure. Allegations first reported by general media are linked to more negative immediate market reactions. Furthermore, financial materiality is associated with negative CARs, whereas severity scores do not explain returns. Higher ESG scores mitigate the impact of financially material allegations, supporting the reputational insurance hypothesis (Flammer, 2013; Godfrey et al., 2009). Prior exposure to greenwashing, measured as the number of past cases a company faced in the previous five years, reduces market reactions to new allegations in consumer industries, suggesting investor learning or desensitization.

Taken together, the chapter shows that market reactions to greenwashing are context-dependent, shaped by company size, industry, ESG scores, and the characteristics of the allegation. The results reconcile conflicting findings in the literature and establish a direct link between greenwashing and shareholder value. From a practical perspective, investors can incorporate greenwashing risk and the associated potential drawdown into their portfolio and risk-management processes, while companies may adapt their disclosure and communication strategies in light of their own exposure to adverse market reactions.

Determinants and forecasting of corporate greenwashing behavior

In this chapter, we first identify which companies are more prone to greenwashing and then show how to economically forecast greenwashing risk. Estimating such risk is crucial because greenwashing exposes investors to hidden financial and reputational risks through information asymmetry and potential litigation (Pizzetti et al., 2021; Seele and Gatti, 2017; Siano et al., 2017; Torelli et al., 2020; Walker and Wan, 2012). While theoretical research on greenwashing is well established (e.g., Delmas and Burbano, 2011; Lyon and Montgomery, 2015), empirical evidence on its company-level determinants remains limited.

The identification of explanatory variables builds on prior work on greenwashing drivers (Delmas and Burbano, 2011; Marquis et al., 2016; Zhang, 2022) and broader research on corporate environmental performance and misconduct (Chen and Chu, 2024; Clarkson et al., 2011; Cormier and Magnan, 1999; Dorfleitner et al., 2022; Ioannou and Serafeim, 2012; Peng et al., 2024). Using panel data for 746 STOXX Europe 600 companies (2011–2023) and manual assessed greenwashing severity scores (ranging from 0 to 1), we run regressions with year, industry, and country fixed effects.

We find a U-shaped relationship between greenwashing severity scores and both overall ESG scores and standalone environmental scores, i.e., companies at the bottom and top of these scales engage in more greenwashing than mid-range peers. ESG disclosure intensity is also associated with higher greenwashing severity scores, suggesting that extensive reporting can mask actual environmental performance. Among emissions measures, only direct (i.e., scope 1) greenhouse gas intensity is positively related to greenwashing behavior, in particular from 2017 onward. Larger companies, which have greater visibility and resources, tend to engage in greenwashing more often. The same is true for companies with abundant cash holdings, consistent with agency theory and the free cash flow hypothesis (Jensen, 1986). Excess liquidity can increase managerial discretion, encouraging symbolic rather than substantive sustainability actions.

Next, we estimate regression models with industry dummy variables and control for company characteristics to compare greenwashing behavior across industries. Consumer-facing industries, i.e., consumer discretionary and consumer staples, are associated with higher greenwashing severity scores, significantly above other industries. Additionally, greenwashing severity scores tend to be positively correlated with the basic materials and utilities industries. The real estate, technology, and telecommunications industries exhibit the lowest levels of greenwashing behavior.

Finally, we develop a machine-learning framework that incorporates economic considerations in order to predict whether a company is more likely to engage in greenwashing the following year. We compile features consisting of one-year-lagged versions of all determinants used, as well as historical indicators of environmental controversies (e.g., controversial marketing, energy management issues, and supply chain controversies), and the previous year's greenwashing severity score. We split the 2012–2022 data into a 70% training set and a 30% test set, and reserve 2023 for validation. To reflect the assumption that missing a true greenwashing case tends to be more costly than a false alarm, particularly for sustainability-oriented investors, we optimize each model's classification threshold to maximize a cost-weighted combination of recall (the share of correctly identified greenwashing cases) and specificity (the share of correctly identified non-greenwashing cases). The models clearly outperform a no-information benchmark on both the test and validation sets, as well as a naive "last-year greenwashing score" benchmark on the validation set in nearly all cases. Among nine classifiers, the recurrent neural network (RNN) consistently delivers the best balance of detecting greenwashing and avoiding overflagging. Specifically, out-of-sample tests using the 2023 validation set show that this model correctly identifies 70% to 100% of actual greenwashing cases and accurately classifies 46% to 89% of non-greenwashing cases across high and moderate false-negative cost settings.

Our findings reveal that companies with very low or very high ESG (and environmental) scores, high ESG disclosure scores, large size, substantial cash reserves, and high capital intensity are most likely to engage in greenwashing. Greenwashing behavior is most prevalent in consumer industries, followed by industries with high emissions and environmental impact. RNN models can accurately forecast next-year greenwashing behavior based on economic considerations, providing information that goes beyond environmental pillar scores of ESG ratings and helps stakeholders such as investors and regulators allocate scrutiny more effectively. The identified determinants and forecasting framework enable corporate stakeholders to assess and incorporate (future) greenwashing risk into their decision-making, while offering policymakers guidance to refine disclosure regulation, strengthen third-party verification, and evaluate the effectiveness of current regulatory initiatives.

ESG and financial performance in public and private companies: Evidence from Brazil

Using unique questionnaire-based ESG data on 156 publicly listed and 317 privately held Brazilian companies from 2017 to 2023, this chapter examines the relationship between ownership structure, financial performance, regulation, and sustainability performance. While the link between ESG scores and corporate financial performance has been extensively studied, results remain mixed and inconclusive (e.g., Avramov et al., 2022; Dixon-Fowler et al., 2013; Eccles et al., 2014; Friede et al., 2015; Pástor et al., 2022; Pedersen et al., 2021). At the same time, prior research has shown that ESG assessments tend to focus on large, publicly traded companies (Drempetic et al., 2020). In contrast, private companies have received considerably less attention (Shive and Forster, 2020). Evidence from emerging markets remains especially limited (e.g., Duque-Grisales and Aguilera-Caracuel, 2021; Ioannou and Serafeim, 2011).

ESG pillar scores (E, S, and G) are constructed using questionnaire-data, normalized by year, and benchmarked against available LSEG scores. This aligns them closely with the LSEG methodology, including industry benchmarking. The three pillars are combined into a normalized composite ESG score ranging from 0 to 1.

Using these ESG scores, panel regressions and propensity score matching reveal that public companies underperform their private counterparts by 0.06 points in composite ESG scores, which is driven by a 0.23-point deficit in the governance score. This underperformance appears most pronounced among large companies with low leverage, high liquidity, and low capital intensity. Both lagged and contemporaneous return on assets (ROA) are positively associated with ESG scores, consistent with the financial slack hypothesis (Lys et al., 2015; Seifert et al., 2004; Waddock and Graves, 1997). This is especially true for large companies, companies with low leverage, low liquidity, and low capital intensity, as well as for those operating in industries we classify as “brown”. In contrast, however, we find no relationship between lagged ESG scores and ROA. Regarding ownership structures, we find that companies that go private improve their ESG scores by 0.13 points. Furthermore, family ownership increases the profitability of private companies, as evidenced by higher ROA.

Exploiting Brazil’s 2021 CVM Resolution No. 59, which mandated ESG disclosure for listed companies, a difference-in-differences design shows that public companies improved ESG scores by 0.05 points (about one-quarter of a standard deviation) relative to private peers, with no evidence of diverging pre-trends. This suggests that the disclosure mandate increased transparency and improved the quality of reporting, consistent with prior research on the effects of mandatory ESG disclosure (Christensen et al., 2021; Grewal et al., 2019; Ioannou and Serafeim, 2011; Krueger et al., 2024).

In summary, public companies exhibit lower performance in governance and overall ESG compared to their private counterparts. However, stronger sustainability performance appears to be enabled by profitability and regulatory pressure. The findings emphasize the importance of ownership structure and regulatory enforcement as key drivers of ESG outcomes in emerging markets. For policymakers, extending disclosure requirements to large private companies could promote comparability across ownership types and enhance transparency. For investors and lenders, the evidence suggests that private companies may be undervalued in terms of ESG performance and that profitability is a prerequisite for meaningful sustainability performance.

Chapter 2

Greenness ratings and green bond liquidity

This research project is joint work with Gregor Dorfleitner (University of Regensburg) and Sebastian Utz (University of Augsburg). The paper has been published as:

Dorfleitner, G., Eckberg, J., Utz, S. (2023), Greenness ratings and green bond liquidity. *Finance Research Letters*, 55, 103869.

Abstract Using a global panel dataset of 3,496 green bonds and conducting regressions, we find a positive relationship between greenness ratings from second-party opinions (SPOs) and green bond liquidity. Green bonds from corporate and municipal issuers with a greenness rating show higher liquidity than green bonds without a greenness rating. For financial institutions and other public issuers besides municipalities, we find no effect of greenness ratings on green bond liquidity.

Keywords Green bonds, Liquidity, External review, Second-party opinion, Shade of green, Climate finance, Impact investing

2.1 Introduction

This study investigates the effect of greenness ratings for green bonds, assigned by second-party opinion (SPOs), on green bond liquidity. It is important to examine this relationship since liquidity, in addition to parameters such as credit rating, is a well-documented risk factor in the financial literature that has an impact on the value of bonds (e.g. Elton and Green, 1998; Elton, 2001; Amihud et al., 2006; Chen et al., 2007; Dick-Nielsen et al., 2012; Utz et al., 2015). Specifically, studies predominantly show that bonds with higher liquidity tend to have lower yields.

In the environment of green bond market, the analysis of bond liquidity and its determinants is not yet covered in the literature. However, there are numerous studies on the green bond premium, i.e., the difference between the yields of green bonds and similar conventional bonds (e.g. Hachenberg and Schiereck, 2018; Bachelet et al., 2019; Zerbib, 2019; Tang and Zhang, 2020; Dorfleitner et al., 2022; Koziol et al., 2022). These studies consider the liquidity of green bonds as an important control variable for a possible liquidity premium when examining the green bond premium. In this context, Wulandari et al. (2018) find that green bond liquidity has an effect on yield spreads. Therefore, and since the research question of which factors influence the liquidity of green bonds is still unanswered, we analyze the relationship between greenness ratings of green bonds and their liquidity.

Theory dictates that market liquidity is related to the level of information asymmetry and adverse selection costs in markets (e.g. Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985). As of today, green bonds lack an official and universally accepted framework which assures the environmental impact of the financed projects and the correct use of proceeds. The alignment of a green bond according to the Green Bond Principles (GBPs) is not mandatory and the issuer can decide if they assign an independent external review such as an SPO to the green bond. Also, post-issuance reporting on the use of proceeds is not standardized. However, SPOs may contain additional and relevant information, leading to information asymmetry when SPOs are not used. In particular, the use of a greenness rating by SPOs can reduce information asymmetry by providing a standardized and transparent assessment of the environmental impact of a green bond. This may result in higher liquidity and lower returns, as investors may be more willing to invest in bonds that have been independently verified as environmentally friendly. By reducing liquidity risk, green bond issuers could benefit from lower costs of capital and higher market valuations. Thus, liquidity effects have high capital-market implications, especially for green bonds.

We analyze a sample of 3,496 green bonds to examine the determinants of green bond liquidity. Firstly, we use three alternative liquidity measures over a period of 14 years: the bid-ask spread, the LOT liquidity estimate (Lesmond et al., 1999; Chen et al., 2007), and the measure of zero-trading days (Lesmond et al., 1999; Chen et al., 2007). Secondly, we analyze the effect of greenness ratings on green bond liquidity by estimating regressions in which we control for credit risk, bond-specific characteristics, macroeconomic variables, and year effects. We find clear evidence that green bonds with a good greenness rating awarded by an SPO show higher liquidity. When we split the greenness rating of green bonds into a dark green and medium green shade, we do not find a significant difference in liquidity between the green bonds of these two shades. Hence, while the color of green, awarded by a greenness rating in an SPO, versus no shade matters for the liquidity of a green bond, the particular shade of green does not have an effect on liquidity. In additional tests, we investigate whether the greenness-liquidity relation differs for specific issuer types. Green bonds issued by corporate entities and municipalities show a significant effect of greenness ratings on liquidity, while our findings do not provide significant evidence for green bonds issued by financial institutions and public issuers.

The contribution of this study is as follows. First, we extend the literature on green bonds and bond liquidity by providing evidence of the relationship between greenness ratings and green bond liquidity. Albeit most studies on green bonds (mostly with a focus on the green bond premium) suffer from small sample sizes due to the application of matching approaches, we provide evidence from a large sample of green bonds as no bond pairs are formed to analyze green bond liquidity. Second, the study contributes to the literature on environmental and climate finance by examining how the use of greenness ratings can increase transparency and standardization in the green bond market. Finally, the results are particularly important (1) for investors to know what liquidity they can expect when investing in a green bond and (2) for issuers to know how they can improve the liquidity of their green bonds to benefit from reduced capital costs.

2.2 Sample and data set

2.2.1 Data set

Our data set comprises a unique combination of information from different sources. The main data is extracted from the Environmental Finance (EF) bond database and contains green bonds issued from April 2008 until April 2020. It includes self-labeled green bonds with information on bond issuance and related documents, such as external review reports. The data set is supplemented by bonds which are labeled as green on Thomson Reuters Eikon. Further basic bond features are added from Eikon, such as credit rating[1] and seniority. As information on external reviews included in the EF database is comprehensive but not complete, the data set is augmented by external review reports from the International Capital Market Association (ICMA) and the Climate Bond Initiative (CBI). Still missing data is hand-collected from the issuers' official websites while existing data is validated through manual checks. Data on the shade of green ratings is also hand-collected via downloaded SPOs. We adapt the methodology of Dorfleitner et al. (2022) and classify the awarded shade of green by the different SPO providers into three unified categories: dark green, medium green, and no shade. Finally, daily time-series data on clean prices, bid and ask yields,

[1]Note that different credit rating regimes are converted into the same scale as that of S&P on Eikon.

and macroeconomic data from April 2008 to April 2021 are extracted from Bloomberg and Eikon. Following Bao et al. (2011), only bonds that have been active for at least one year are included in the data set, and quotes with bid-ask spreads that are negative or zero are eliminated. Additionally, as greenness ratings only appear in our sample from 2013 onwards, only observations from 2013 onwards are included in the analysis. After these corrections, the final data set consists of 3,496 green bonds.

2.2.2 Description of liquidity measures

We consider the three liquidity measures (1) bid-ask spread, (2) LOT liquidity estimate, and (3) zero-trading days. The bid-ask spread is defined as the amount by which the ask price exceeds the bid price of a security and can be interpreted as the round-trip transaction cost for an immediate transaction (e.g. Longstaff et al., 2005; Chen et al., 2007; Bao et al., 2011). The LOT liquidity estimate captures transaction cost of equity and is defined as the difference between the buy-side and sell-side transaction cost with respect to a marginal investor (Lesmond et al., 1999; Chen et al., 2007). The measure of zero-trading days is calculated as a percentage of zero-trading days relative to total trading days per bond per year and follows the rationale that zero-trading days are more likely for less liquid securities (Lesmond et al., 1999; Chen et al., 2007). We calculate liquidity measures on bond-year level and winsorize all liquidity measures at the 1% and 99% levels. Moreover, to reduce noise in the liquidity measures stemming from bond-year observations with only a few daily price observations to estimate liquidity measures, we remove 95 bond-year observations of green bonds from the original sample since their maturity is less than six months. Subsequently, we have a total of 17,679 bond-year observations in our panel dataset, whereas only 13,002 observations are available for the LOT liquidity estimate due to data limitations. The correlation between the bid-ask spread and the LOT liquidity estimate is 6.73%, while the correlation between the bid-ask spread and the zero-trading days measure is 16.43%. The correlation between the LOT liquidity estimate and the zero-trading days measure is not significantly different from zero. Comparable correlation levels between liquidity measures can be found, for example, in Dick-Nielsen et al. (2012). The liquidity measures are interpreted in the sense that the lower their value, the more liquid the security. A higher value of the measures means less liquidity or a higher level of illiquidity. We follow the majority of bond liquidity papers such as Longstaff et al. (2005), Goyenko et al. (2009) and Schestag et al. (2016) and use the term liquidity measures.

2.2.3 Descriptive analysis

Table 2.1 reports the descriptive statistics for the metric green bond characteristics. The average bid-ask spread of a green bond is 9.30 basis points (bp), the average LOT estimate is 22.57 bp, and an average green bond in our sample has 16.47% zero-trading days. The average time to maturity is 10 years yet with a notable standard deviation of 17.94 years. The sample includes green bonds with both low and high issued amounts, with a focus on low to medium issued amounts. The average coupon rate is 3.56%, with a standard deviation of 1.72%.

Table 2.1: Descriptive statistics for metric variables

Variable	Obs.	Mean	Std.	Min	Median	Max
A. Time-variant						
Bid-Ask (bp)	17,679	9.30	13.38	1.60	4.99	101.20
LOT (bp)	13,002	22.57	11.46	2.30	20.64	66.55
%ZTD (%)	17,679	16.47	29.28	1.15	4.65	100.00
maturity (years)	17,679	10.00	17.94	0.25	8.37	1,000.61
B. Time-invariant						
issued_amount (m USD)	3,496	121.36	328.19	0.01	5.43	6,693.70
coupon (%)	2,518	3.56	1.72	0.00	4.00	10.18

Notes: This table summarizes the descriptive statistics on metric time-variant and time-invariant variables. The sample consists of a total of 3,496 green bonds with 17,679 annual observations.

Table 2.2 shows descriptive statistics for categorical explanatory variables. The sample includes the following types of external reviews for third-party validation of the green credentials of a green bond: SPOs, CBI certifications, verifications, and green ratings[2]. One-third of green bonds in the sample is assigned to an SPO, while CBI certifications, verifications and green ratings are used less frequently. Over 85% of green bonds have no shade of green. Of those green bonds that have a shade of green, about two-thirds have a dark green shade (349) and one-third have a medium green shade (158). Nearly three-quarters of green bonds are denominated in USD, while the currencies EUR (9.75%) and SEK (5.64%) have a lower share and the remaining currencies account for less than 5% each. Regarding the issuer types, the largest share of green bonds comes from municipal issuers (63.44%) and corporates (19.05%). The remaining green bonds are issued by financial issuers such as banks or originate from the public issuers agency, sovereign, and supranational. In addition, over one-third of green bonds have an AAA credit rating, while those with a credit rating of less than A− have a share of 8.20%. Only a small number of green bonds (68) are non-investment grade.

2.3 Empirical results

2.3.1 Main results

We analyze the relation between the greenness of SPOs and the liquidity of green bonds in a regression model with double-clustered (issuer and bond) standard errors and year fixed effects. The main advantage of this model is that it allows us to estimate coefficients of time-invariant variables (such as the greenness rating of the green bonds) and at the same time make use of the

[2]CBI provides a detailed description of existing external review types: www.climatebonds.net/market/second-opinion

Table 2.2: Descriptive statistics for categorical variables

Variable	Obs.	Relative	Variable	Obs.	Relative
SPO			*CBI_certification*		
Yes	1,165	33.32	Yes	565	16.16
No	2,331	66.68	No	2,931	83.84
shade			*verification*		
dark green	349	9.98	Yes	113	3.23
medium green	158	4.52	No	3,383	96.77
no shade	658	18.82			
no SPO	2,331	66.68	*green_rating*		
			Yes	84	2.40
SPO_provider			No	3,412	97.60
CICERO	444	12.70			
DNV GL	47	1.34	*issuer_type*		
ISS ESG	82	2.35	agency	170	4.86
Sustainalytics	416	11.90	corporate	666	19.05
Vigeo Eiris	108	3.09	financial	252	7.21
Other	68	1.95	municipal	2,218	63.44
No SPO	2,331	66.68	sovereign	19	0.54
			supranational	171	4.89
credit_rating			*currency*		
AAA	1,192	34.10	AUD	40	1.14
AA+	369	10.55	BRL	11	0.31
AA	596	17.05	CAD	35	1.00
AA−	199	5.69	CHF	19	0.54
A+	157	4.49	CNY	100	2.86
A	188	5.38	COP	1	0.03
A−	131	3.75	DKK	2	0.06
BBB+	106	3.03	EUR	341	9.75
BBB−	37	1.06	GBP	21	0.60
BBB	76	2.17	HUF	2	0.06
BB+	21	0.60	IDR	6	0.17
BB	19	0.54	INR	31	0.89
BB−	8	0.23	JPY	66	1.89
B+	5	0.14	MXN	8	0.23
B	5	0.14	MYR	40	1.14
B−	8	0.23	NGN	1	0.03
D	2	0.06	NOK	23	0.66
NR[a]	377	10.78	NZD	8	0.23
			PLN	2	0.06
seniority[b]			RUB	3	0.09
MTG	14	0.40	SEK	197	5.64
SEC	6	0.17	SGD	3	0.09
SR	966	27.63	TRY	2	0.06
SRBN	12	0.34	USD	2,527	72.28
SRP	18	0.51	ZAR	7	0.20
SRSEC	68	1.95			
UN	190	5.43	*straight*		
OTHER	31	0.89	Yes	1,708	48.86
NULL	2,191	62.67	No	1,788	51.14

Notes: This table reports descriptive statistics of categorical variables for the sample which consists of 3,496 green bonds.
[a]NR means that a credit rating is not available on Eikon.
[b]*seniority* indicates the combined information on bond seniority and collateral status on Eikon. MTG: senior secured and mortgage backed; SEC: secured; SR: senior secured; SRBN: senior non-preferred; SRP: senior preferred; SRSEC: senior secured; UN: unsecured; OTHER: other seniority and collateral status; NULL: no information available.

panel structure of the data with year fixed effects and double-clustered standard errors. To this extent, we specify our regression model respectively with the bid-ask spread, the LOT liquidity estimate, and the percentage of zero-trading days as the dependent variable. The macroeconomic variables *government_bond* and *term_slope* are assigned to green bonds according to their denominated currency and are integrated into the regression model as control variables for general economic growth. The bond-specific variable *issued_amount* (in USD) is logarithmized. *no_SPO* is set as the reference category for the shade of green variables. *municipal* is set as the reference category for the issuer types.

The two specific regression models are set up as follows: In the first specification, the main variables of interest are the dummy variables *dark_green*, *medium_green*, and *no_shade*, indicating whether a specific shade of green rating is available. We integrate these dummy variables besides control variables (see Models (1), (3), and (5) in Table 2.3). In the second specification, we integrate the dummy variables *green* and *no_shade* besides control variables (see Models (2), (4), and (6) in Table 2.3). *green* indicates that a green bond has a dark green or a medium green shade but does not differentiate between these shades.

Table 2.3 presents the results. The coefficients of *dark_green* and *medium_green* are both significantly negative in each model when *no_SPO* is set as the reference category, except for *medium_green* in Model (3) in which the LOT liquidity measure is the dependent variable. Moreover, the coefficient of *no_shade* is either not significant (Models (1) and (5)) or the coefficient of *dark_green* has a higher negative value than *no_shade* (Model (3)), indicating a higher liquidity effect for green bonds with a specific shade of green compared to green bonds without a shade of green. To this extent, also Models (2), (4), and (6) show consistent and significant negative coefficients for the variable *green*. Since a lower value of the liquidity measures indicates higher liquidity, green bonds with a shade of green rating are associated with better liquidity than green bonds without such a rating. Specifically, green bonds with a shade of green rating, on average, have a lower bid-ask spread of 3.90 bp and 4.47% fewer zero-trading days, which is significant at the 1% and 5% levels, respectively. At the same time, the negative coefficient of 0.94 bp for the LOT estimate at the 10% level also indicates higher liquidity. Hence, a greenness rating on green bonds is actually related to higher liquidity. However, comparing the coefficients of the two shade of green variables *dark_green* and *medium_green* in Models (1), (3), and (5), we cannot find a consistent difference in the impact on liquidity. As such, a better shade of green in the greenness rating of green bonds shows no relation to liquidity.

2.3.2 Differences between issuer types

To examine the differences in the impact of greenness ratings on green bond liquidity by issuer type, we set up four additional regression models. We combine the public issuer types agency, sovereign, and supranational into the category “other”. Then, we use the bid-ask spread as the dependent

Table 2.3: Liquidity of green bonds according to the shade of green rating

	Bid-Ask		LOT		%ZTD	
	(1)	(2)	(3)	(4)	(5)	(6)
dark_green	−3.666***		−1.148*		−3.372*	
	(1.157)		(0.588)		(1.989)	
medium_green	−4.409***		−0.322		−6.863***	
	(1.089)		(0.801)		(2.053)	
green		−3.900***		−0.941*		−4.471**
		(1.054)		(0.512)		(1.924)
no_shade	0.180	0.185	−0.648**	−0.655**	0.008	0.034
	(0.708)	(0.709)	(0.259)	(0.258)	(1.964)	(1.967)
CBI_certification	−0.238	−0.246	−0.569**	−0.566**	1.573	1.535
	(0.553)	(0.554)	(0.278)	(0.278)	(1.616)	(1.619)
verification	−2.762**	−2.734**	0.248	0.224	−5.175**	−5.041**
	(1.240)	(1.235)	(0.699)	(0.697)	(2.564)	(2.559)
green_rating	−1.051	−1.134	0.492	0.700	0.657	0.269
	(1.287)	(1.292)	(1.432)	(1.484)	(2.213)	(2.174)
issued_amount	0.333*	0.330*	0.160**	0.162**	4.906***	4.892***
	(0.194)	(0.194)	(0.073)	(0.073)	(0.509)	(0.510)
maturity	−0.024*	−0.024*	−0.001	−0.001	−0.050	−0.050
	(0.014)	(0.014)	(0.003)	(0.003)	(0.034)	(0.034)
straight	−0.778*	−0.790*	0.231**	0.237**	4.426***	4.371***
	(0.441)	(0.439)	(0.104)	(0.103)	(1.466)	(1.466)
government_bond	0.678	0.677	5.048***	5.049***	0.129	0.126
	(0.498)	(0.498)	(1.884)	(1.884)	(1.058)	(1.058)
term_slope	−0.153	−0.156	−3.183	−3.172	−1.784	−1.795
	(0.861)	(0.860)	(4.496)	(4.496)	(1.533)	(1.529)
agency	1.091	1.032	1.553**	1.588**	−1.856	−2.132
	(1.091)	(1.077)	(0.691)	(0.685)	(2.111)	(2.099)
corporate	4.222***	4.211***	0.596	0.587	4.542*	4.494*
	(1.631)	(1.624)	(0.916)	(0.912)	(2.416)	(2.413)
financial	1.842	1.784	−0.445	−0.405	−0.082	−0.353
	(1.585)	(1.570)	(0.912)	(0.921)	(2.993)	(2.990)
sovereign	3.111	3.045	−6.013**	−6.112**	−5.928	−6.241*
	(2.257)	(2.188)	(2.568)	(2.565)	(3.716)	(3.657)
supranational	2.722*	2.633*	−0.868	−0.793	−2.559	−2.977
	(1.412)	(1.397)	(0.805)	(0.805)	(2.558)	(2.606)
year	Yes	Yes	Yes	Yes	Yes	Yes
credit_rating	Yes	Yes	Yes	Yes	Yes	Yes
seniority	Yes	Yes	Yes	Yes	Yes	Yes
currency	Yes	Yes	Yes	Yes	Yes	Yes
_cons	25.756**	25.874**	87.224***	86.939***	19.827	20.385
	(10.260)	(10.301)	(12.488)	(12.487)	(18.875)	(19.252)
N	17,679	17,679	13,002	13,002	17,679	17,679
R^2	0.327	0.327	0.840	0.840	0.116	0.116
Adjusted R^2	0.324	0.324	0.839	0.839	0.112	0.112

Notes: This table reports the results of the regression models with *Bid-Ask*, *LOT* or *%ZTD* as the dependent variable. The reference category for the shade of green variables is *no_SPO*. The reference category for the issuer type variables is *municipal*. Standard errors are double-clustered at the issuer and bond levels. The full sample includes 17,679 annual observations from 3,496 green bonds. The subsample in Models (3) and (4) only includes 13,002 annual observations from 2,486 green bonds.
*** p<0.01, ** p<0.05, * p<0.10.

variable for each model and add *green* as an explanatory dummy variable for the subsamples of the four different issuer groups (corporate, financial, municipal, and other). The results are presented in Table 2.4. The coefficients of *green* show that corporate entities have the highest negative value (-6.81 bp) which is significant at the 1% level. A green shade also has a significant impact on the bid-ask spread for municipal issuers (-1.75 bp). For financial institutions and the category 'other', we find no effect of a greenness rating on the bid-ask spread. Accordingly, corporate issuers appear to have significant excess liquidity when they assign greenness ratings to their green bonds. This effect can also be found for municipal green bonds, but not for green bonds from financial institutions and other public entities besides municipalities. A possible explanation for this pattern is that financial institutions only act as intermediaries for green bonds and do not implement their own green projects. However, it should also be noted that the categories 'financial' and 'other' have the smallest sample sizes of the issuer types.

For a robustness check, we examine the differences in the effects found by inserting the variables *no_shade* or *medium_green* instead of *no_SPO* as the reference category for the shade of green variables in the regression models from Tables 2.3 and 2.4. For these variations of the model specifications, we can confirm the main results and likewise find no significant difference between the variables *dark_green* and *medium_green*. Additionally, a split in the observation period in two subperiods spanning from 2013-2016 and from 2017-2021 confirms the findings regarding the relationship between the greenness of the green bonds and their liquidity for both subperiods.

2.4 Conclusion

In this paper, we investigate the relationship between greenness ratings and the liquidity of green bonds in a large and comprehensive world-wide sample. The results of the study indicate that green bonds with a greenness rating by an SPO have higher liquidity. We find this effect for corporate and municipal issuers, but not for financial and other public issuers besides municipalities.

These findings have important implications for investors, issuers, and policymakers. Investors who value high liquidity, low transaction cost, and a verified green impact of the projects financed by the green bond should integrate the presence of greenness ratings in green bonds into their investment decision. Issuers may benefit from increased liquidity by obtaining a greenness rating pre-issuance, which can make the green bond more attractive to investors and lower the cost of capital to finance environmentally-friendly projects. For policymakers, these findings suggest that promoting greenness ratings for green bonds may help improve the liquidity of these bonds, which can help to raise trust in the green bond market, increase market efficiency, and support the development of a low-carbon and climate-resilient economy.

The study is subject to some limitations: although we have one of the largest samples of green bonds that has ever been studied, the market is young and still developing. In particular, the comparability

Table 2.4: Differences in the liquidity effect of shade of green ratings by issuer type

	Corporate	Financial	Municipal	Other
	(1)	(2)	(3)	(4)
green	−6.807***	0.418	−1.745***	−2.328
	(2.577)	(2.808)	(0.421)	(1.698)
no_shade	−3.615	3.768	−0.395	1.146
	(2.858)	(3.150)	(0.429)	(1.625)
CBI_certification	−1.897	2.608	−0.071	8.492***
	(2.481)	(2.595)	(0.455)	(3.119)
verification	−5.872**	−0.309	0.789	−0.765
	(2.834)	(2.474)	(1.982)	(1.749)
green_rating	−1.492	−3.997*	59.931***	1.791
	(1.842)	(2.228)	(2.163)	(1.778)
issued_amount	0.143	1.462*	0.907***	−0.320
	(0.628)	(0.750)	(0.088)	(0.505)
maturity	−0.020**	−1.351***	−0.023	−0.339***
	(0.010)	(0.353)	(0.049)	(0.063)
straight	−4.738**	−1.457	0.081	−3.394**
	(1.857)	(1.826)	(0.554)	(1.609)
government_bond	4.291***	1.220	−3.228***	2.307**
	(1.197)	(1.635)	(1.107)	(0.878)
term_slope	4.844***	2.870	−3.084**	5.241**
	(1.764)	(2.668)	(1.471)	(2.486)
year	Yes	Yes	Yes	Yes
credit_rating	Yes	Yes	Yes	Yes
seniority	Yes	Yes	Yes	Yes
currency	Yes	Yes	Yes	Yes
_cons	21.963*	−20.662**	23.614***	−5.352
	(11.501)	(10.267)	(5.493)	(6.407)
N	2,776	973	12,243	1,687
R^2	0.403	0.462	0.102	0.641
Adjusted R^2	0.390	0.432	0.099	0.629

Notes: This table reports the results of the regression models with *Bid-Ask* as the dependent variable and the subsamples of green bonds issued by the types corporate, financial, municipal, and other. The reference category for the shade of green variables is *no_SPO*. Standard errors are double-clustered at the issuer and bond levels.
*** p<0.01, ** p<0.05, * p<0.10.

of the LOT liquidity estimate with the other liquidity measures is slightly limited due to a lower number of observations. Moreover, we did not investigate intra-day liquidity using high-frequency liquidity measures. We encourage further research on green bond liquidity, including investigating the persistence of the found effect over future time periods, examining the impact of events on green bond liquidity, and exploring other factors that may affect green bond liquidity.

Chapter 3

Greenwashing in public European companies

This research project is joint work with Gregor Dorfleitner (University of Regensburg), Manuel C. Kathan (University of Augsburg), and Sebastian Utz (University of Augsburg).

Abstract In this paper, we empirically calibrate a measurement model for corporate greenwashing based on a sample of 1,031 European publicly-listed companies included in the STOXX Europe 600 during the period 2011–2023. We manually identify and assess greenwashing cases using a standardized framework, and assign a greenwashing severity score to each company-year observation that shows indications of greenwashing. We construct our greenwashing measurement model using a novel theoretical approach that distinguishes between the apparent (i.e., communication of a company's environmental efforts) and real (i.e., actual environmental impact) green performance. The calibration of our model is based on our sample and incorporates variables that capture company-level information across "soft ESG," "textual self-representation," "green virtue," and "hard ESG" over three different environmental categories: emissions, environmental governance, and resource use. Applying our model, which compares apparent and real green performance, yields a score for each company-year that reflects the risk of the company engaging in greenwashing. In this regard, our specification of the model is able to measure 89% of the greenwashing observations correctly (sensitivity), while it also correctly specifies 59% of the non-greenwashing observations (specificity). Moreover, the paper explores potential future developments in greenwashing behavior across Europe, particularly in response to recently enacted regulatory measures.

Keywords Greenwashing, Greenwashing indicator, Corporate misconduct, CSRD, Regulation, STOXX Europe 600, ESG scores, Environmental performance, Misleading environmental claims

3.1 Introduction

Greenwashing has garnered increasing attention in recent years, particularly in the academic literature. However, most empirical studies still focus on specific products, services, or isolated case studies of companies (e.g., Delmas and Burbano, 2011; Torelli et al., 2020), leaving the phenomenon at the company level underexplored. While several initial attempts have been made to quantify company-level greenwashing (e.g., Walker and Wan, 2012; Roulet and Touboul, 2015; Kim and Lyon, 2015; Marquis et al., 2016; Ioannou et al., 2022; Mateo-Márquez et al., 2022), existing approaches tend to rely on simplified indicators, such as the gap between ESG performance and ESG disclosure. These models are often limited in scope and fail to adequately capture the complex and multidimensional nature of greenwashing. Moreover, ESG scores that are often used as proxies for ESG performance are inconsistent across rating agencies (Berg et al., 2022) and rather tend to measure ESG disclosure than ESG performance (Kathan et al., 2025). Furthermore, these models lack the ability to distinguish between "real" and "apparent" sustainability, and do not account for potential non-linearities in company behavior.

To address these limitations, we build on the holistic framework of Dorfleitner and Utz (2024) and construct a novel indicator that captures the risk of greenwashing behavior on a continuous scale. Our approach combines multiple sustainability dimensions and is applied to a longitudinal sample of publicly listed European companies. This enables us to systematically examine greenwashing patterns at the company level and their underlying company characteristics in a robust and comprehensive way.

In our empirical approach, we first hand-collect greenwashing cases for a sample of 1,031 European publicly-listed companies included in the STOXX Europe 600 during the period from 2011 to 2023 and assess their severity based on a self-developed rating scheme. Second, we also collect environmental data in different dimensions of sustainability and pillars of information, and classify them into apparent or real green performance. Third, we calibrate the measurement model using the mean of the greenwashing severity score per company-year as the dependent variable and the environmental data as independent variables. The model achieves a sensitivity of 89% and a specificity of 59%, indicating that it identifies the majority of severe greenwashing cases while accepting a moderate rate of false positives. In addition, we quantify the gap between average apparent and real green performance across our three environmental dimensions, illustrating the extent to which they diverge.

To complement these empirical findings, we conducted semi-structured interviews with key stakeholders—including representatives from academia, the financial industry, the real economy, and NGOs—as well as a survey of decision-makers in the financial industry. These qualitative insights reveal that defining greenwashing and accessing reliable data remain significant challenges. Nonetheless, there is broad agreement on the practical importance of a company-level greenwashing risk measurement framework. Experts emphasize that companies face substantial reputational risks, and that effective greenwashing assessment requires not only robust measurement of both apparent and real green performance but also a clear categorization system to enable meaningful benchmarking comparisons. The respondents emphasize the value of a robust greenwashing risk indicator for assessing corporate risk in investment decisions and guiding regulatory efforts, while also warning of the potential pitfalls of false signals if the measurement approach lacks rigor. Thus, the greenwashing risk indicator provides company stakeholders, such as investors and consumers, with the benefit that they can calculate greenwashing risk indicators to use them for their decision-making processes and get a better assessment of the actual environmental performance and the environmental and reputational risks of companies.

Our primary contribution lies in demonstrating the feasibility of the theoretical measurement model proposed by Dorfleitner and Utz (2024, henceforth, DU Model) through a comprehensive empirical study based on a relevant sample of European companies. Our paper suggests a selection of significant company characteristics that are associated with the apparent and real green performance in particular, and with the greenwashing risk indicator in general. Moreover, we discuss challenges of implementing and assessing greenwashing within the environment of future regulation.

The remainder of this paper is structured as follows. In Section 3.2, we describe in detail how we collected and constructed the dataset of greenwashing cases using a systematic search and human judgment. In Section 3.3, we explain our approach to estimating the measurement model that captures the difference between apparent and real green performance, which provides an objective indicator of company-level greenwashing risk. In Section 3.4, we discuss further empirical research conducted based on our dataset and show its value for analyzing various research questions. Section 3.5 presents the results of expert interviews and a survey of the financial industry on the utility of a model for measuring greenwashing. Next, Section 3.6 reviews the impact of current and future European sustainability regulations, focusing on their potential to reduce greenwashing. Finally, Section 3.7 contains a discussion of the empirical and practical implications of the findings.

3.2 Establishing the greenwashing data set

3.2.1 Sample selection

This paper focuses on analyzing greenwashing behavior among European companies. The sample consists of 1,031 companies that were constituents of the STOXX Europe 600 index at least at one point in time between 2011 and 2023. We retrieve company-level data from Compustat Global, allowing us to track all company-years regardless of whether the companies remained in the index, thus mitigating potential survivorship bias. Since the STOXX Europe 600 covers approximately 90% of the free-float market capitalization across European equity markets, the sample provides broad and representative coverage of large European companies.

We focus on Europe for both conceptual and practical reasons. Conceptually, greenwashing is a subjective and context-dependent phenomenon that requires ex-post validation by multiple stakeholders to establish credible cases (Seele and Gatti, 2017). A European setting—with its active media landscape, engaged NGOs, and increasing regulatory scrutiny—offers favorable conditions for the public exposure and documentation of greenwashing cases, which are crucial for calibrating our measurement model.

Practically, the use of a broad and consistent reference index combined with a comprehensive data source allows us to construct a longitudinal panel that captures company-level developments over time. This approach enables a robust empirical investigation of greenwashing patterns and their determinants at the company level.

A worldwide search on Google Trends[1] for the term *Greenwashing* from 2011 to 2023 reveals that eight out of the top ten countries with the highest search volume are European. In addition, European policymakers are actively working to enhance scrutiny of greenwashing practices, for example with initiatives such as the EU Taxonomy, the Corporate Sustainability Reporting Directive (CSRD), and the Sustainable Finance Disclosure Regulation (SFDR), which are embedded in the EU Sustainable Finance Framework. In particular, the Green Claims Directive (GCD) aims to prevent greenwashing at the company level (European Commission, 2023).

3.2.2 Collecting greenwashing cases

We hand-collect a dataset of greenwashing cases at the company level to calibrate the DU Model. To compile these cases, we gather information from various sources of greenwashing accusations, including web search engines, NGO reports, news articles, and social media platforms such as X (formerly known as Twitter), by searching for the term *Greenwashing* and related keywords. Given the heterogeneous nature of these sources and the varying quality of accusations, we apply the standardized evaluation framework originally published by Kathan et al. (2025) to ensure consistent classification, as detailed in Table 3.1. Wherever possible, our assessment follows the definition by Delmas and Burbano (2011), which states that "a greenwashing company engages in two behaviors simultaneously: poor environmental performance and positive communication about its environmental performance." However, we acknowledge that not all sources provide explicit evidence for both components. In such cases, classification decisions are made conservatively and transparently based on the available information and contextual cues, as specified in our coding criteria.

We collect a total of 1,254 information sources (specified by links). After classifying the sources according to the framework (see Table 3.1), we remove 356 links. These deleted links lack new information (139) about a case or have other issues (217), such as technically unusable information

[1] Data retrieved from Google Trends: https://trends.google.de/trends/explore?date=2011-01-01%202023-12-31&q=greenwashing&hl=de.

and cases that do not meet our definition of greenwashing. Greenwashing cases are evaluated based on the year of the earliest observed published source reporting on the respective case.

Table 3.1: 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 cases. It is used to construct a dataset of independent cases that follow our definition of greenwashing and can be clearly assigned to a specific company year. The framework was initially published in Kathan et al. (2025).

3.2.3 Greenwashing severity score

In addition to providing information on whether a company has a genuine greenwashing case in a given year, we also assess the severity of the greenwashing case using a human judgment method. Therefore, four research assistants independently classify the severity within a range from 0 (no greenwashing) to 1 (greenwashing) following the classification scheme described in Table 3.2. As the final proxy, we calculate the mean of all four assessments and obtain a greenwashing severity score for each case.

Table 3.2: Assessment of greenwashing severity

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

Notes: This table describes the framework for assessing the severity of greenwashing cases. It is developed based on previous greenwashing cases and ensures a granular and comparable assessment of severity between 0 (no greenwashing) and 1 (greenwashing). The framework was initially published in Kathan et al. (2025).

The design of the greenwashing severity scores is described below using several examples. An example of *light greenwashing* is the case of a company from the utilities industry with a mean severity score of 0.19. The respective company sold its coal-fired power plants to a private equity company to decarbonize its balance sheet, even though the power plants continued to operate and pollute under the new ownership. Hence, the company appears environmentally responsible by removing the plants from its portfolio, but the actual environmental impact remains unchanged, highlighting a superficial shift rather than genuine environmental improvement. However, as the company does not directly use the transaction to showcase its own environmental credentials and thus does not significantly increase its apparent green performance, the case was categorized as *light greenwashing*.

An exemplary *medium greenwashing* case with a mean severity of 0.50 comes from the energy industry, where a company publicly emphasizes its commitment to energy transition and sustainability, yet continues to expand fossil fuel exploration and production in various regions. Although the company emits a significant amount of greenhouse gases and has been publicly criticized by environmental organizations for inconsistencies between its climate commitments and its operational practices, it avoids making explicit false claims or inventing metrics. Since the company's green claims are broad and not linked to specific, verifiably false statements—and because it simultaneously reports its emissions transparently—this case is classified as *medium greenwashing*.

An exemplary clear *greenwashing* case with a mean severity of 0.88 hails from the industrial industry. The related company faces two accusations: On the one hand, the company advertises the use of green methanol, which, according to experts, can produce even more emissions with its production. On the other hand, the company is fighting the accusation of not showing transparency regarding plastic waste exports. Since these accusations can be found repeatedly in various sources and the company in question also describes itself as carbon neutral on its website, this case is classified as clear *greenwashing*.

Moreover, we apply the following approaches to assign greenwashing severity scores in the specific cases. For instance, if greenwashing indications for a company appear to document persistent greenwashing behavior over several years but are not documented by sources in each subsequent year, we use interpolation to fill gaps in the data set. If, for example, a 2020 article reports a company's misleading climate commitments and a 2022 article confirms continued misconduct (but no article is found for 2021), the 2021 value is generated through interpolation. In more detail, our interpolation rule states that if at least two sources from different years indicate consistent behavior, we assign the maximum recorded greenwashing score from the surrounding years to the intermediate years without direct observations, i.e., we impute the highest greenwashing score from 2020 and 2022 and assign it to 2021. This method applies to 30 greenwashing cases and 43 company-years.

Next, we construct a panel dataset with a company-year structure by keeping the maximum composite severity score across all cases within each company-year. Finally, we obtain 595 company-years with mean greenwashing severity scores greater than zero. Table 3.3 summarizes the data processing steps and the severity assessment of greenwashing cases.

Table 3.3: Collection and processing of greenwashing cases

Step	Obs.
Panel A: Identifying greenwashing cases (2011-2023)	
Initial sample of STOXX 600 companies containing 1,031 unique companies	
Information sources	1,254
− Sources without new information	139
− Other cleaning steps	217
= Cleaned information sources	898
+ Interpolations (company-years)	43
= Total GW cases (*GW score* > 0)	941
− Non-maximal severity cases within company-year	346
= Total GW cases (panel aggregated)	595
Panel B: Matching to company characteristics (2015-2023)	
Total GW cases (panel aggregated)	595
− Cases before 2015 or with missing company characteristic observations	311
= GW cases for measurement model estimation	284
Final sample of GW and non-GW cases containing 883 unique companies	

Notes: This table summarizes the identification and preparation of greenwashing (GW) cases. We report GW observations ("Obs.") and the corresponding number of unique companies. Panel A documents the case collection process, following the framework in Table 3.1. "*GW score*" denotes the severity of greenwashing on a continuous scale in the range from 0 to 1. In the panel structure, only the most severe case per company-year (i.e., the maximum "*GW score*") is retained. Panel B reports the final sample used to estimate the measurement model. Due to missing company-level data, the sample is restricted to 2015 to 2023, comprising 284 GW cases across 883 companies.

3.2.4 Descriptive statistics on the greenwashing cases

Figure 3.1 visualizes the evolution of greenwashing cases collected over the sample years 2011 to 2023. A clear upward trend in the number of greenwashing cases (company-year observations with mean greenwashing severity scores greater than zero) can be seen, with the peak in 2021 and a slight decline in cases since then. In contrast, the mean severity score has only risen slightly over the years and has remained relatively constant in the corridor between 0.6 and 0.8. A comparison of the Google search trends for the keywords "ESG" and "Greenwashing" with the number of observed greenwashing cases reveals a similar pattern in the upward trend, which has risen sharply since 2018 in particular. This is an indication of greater interest in the topic of greenwashing and the associated increased scrutiny of companies, which may have led to more cases being detected. We assume that attention to the topic of sustainability and greenwashing increased with the adoption of the Paris Agreement in 2015, which also increased the comparability of the cases.

Since data availability on company-level characteristics is more comprehensive from 2015 onwards, we restrict our sample to the period 2015 to 2023 for the remainder of the analysis. As shown in

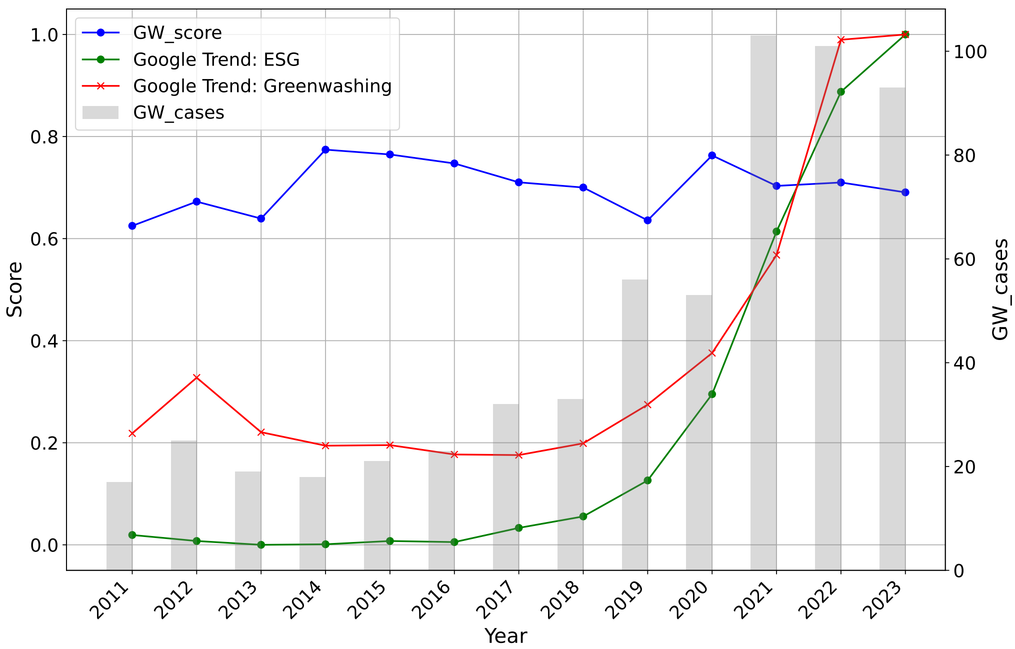


Figure 3.1: Greenwashing cases and related Google search trends over time. The "GW_score" is the annual average of the severity scores of the 595 collected greenwashing cases (see the severity classification scheme in Table 3.2 for definitions). The Google trend data is normalized. "GW_cases" is the number of annual observations with mean greenwashing severity scores greater than zero.

Table 3.3, this results in a subsample of 284 greenwashing cases with complete company-level data, matched across 883 companies.

Table 3.4 shows the descriptive statistics of the categorical variables for the sample from 2015 to 2023. With the United Kingdom (219 companies), Germany (104 companies), and France (102 companies), the countries with the highest gross domestic products in Europe account for around 50% of the sample. Switzerland, Spain, Italy, and the Scandinavian and Benelux countries also account for a significant share. The distribution of companies across the individual industries is fairly balanced, with most companies operating in the Industrial (19.48%), Financial (17.67%), and Consumer Discretionary (15.97%) industries. Regarding greenwashing occurrences, most company-year observations with mean greenwashing severity scores greater than zero can be observed in the countries United Kingdom (85), Germany (58), and France (38). We measure the highest mean severity of greenwashing (1.00) in Finnish companies, although it should be noted that we only observe two cases. In addition, Norway (0.85) and Switzerland (0.82) also have high average severity levels for their cases. In terms of the distribution of greenwashing cases across industries, most cases were observed in the Consumer Discretionary (63), Financial (44), and Basic Materials (39) industries. Greenwashing cases with the highest severity occur in the emissions-intensive industries of Basic Materials (0.82), Utilities (0.78), and Energy (0.76). The descriptive statistics across countries and industries reveal that the higher the mean greenwashing severity scores are, the lower the standard deviations measured across the four individual assessments. This means that the assessments converge particularly for the clear greenwashing indications. We assume that this is related to the increased media attention and information transparency of greenwashing cases with a higher greenwashing severity scores, which leads to a lower divergence of ratings.

Table 3.4: Descriptive statistics of categorical variables

Category	#firms	Rel.	firm-year obs. GW	firm-year obs. no GW	GW_ score	Std.
Country						
Belgium	25	2.83	1	117	0.19	–
Denmark	31	3.51	7	167	0.78	0.19
Finland	26	2.94	2	159	1.00	0.00
France	102	11.55	38	578	0.56	0.27
Germany	104	11.78	58	514	0.78	0.24
Italy	42	4.76	6	206	0.81	0.23
Netherlands	49	5.55	10	250	0.74	0.29
Norway	24	2.72	5	126	0.85	0.06
Spain	39	4.42	13	235	0.56	0.31
Sweden	76	8.61	10	373	0.72	0.31
Switzerland	62	7.02	18	334	0.82	0.22
United Kingdom	219	24.80	85	1,151	0.74	0.25
Rest	84	9.51	31	435	0.73	0.26
Industry						
Basic materials	66	7.47	39	369	0.82	0.25
Consumer discretionary	141	15.97	63	729	0.74	0.26
Consumer staples	66	7.47	32	342	0.70	0.30
Energy	44	4.98	28	210	0.76	0.27
Financials	156	17.67	44	822	0.62	0.26
Health care	57	6.46	9	322	0.67	0.24
Industrials	172	19.48	34	959	0.69	0.27
Real estate	56	6.34	0	302	–	–
Technology	53	6.00	2	240	0.63	0.09
Telecommunications	36	4.08	3	173	0.60	0.31
Utilies	36	4.08	30	177	0.78	0.20

Notes: This table reports the descriptive statistics of the categorical, time-invariant variables for the 2015–2023 sample of 883 public European companies and 284 greenwashing cases. "GW" ("no GW") includes all observations with mean greenwashing severity scores greater than (equal to) zero. "GW_score" indicates the mean severity score of the greenwashing cases (see the severity classification scheme in Table 3.2 for definitions).

3.3 Empirical estimation of a greenwashing measurement model

3.3.1 Data and measurement framework

We adapt the DU Model to measure corporate greenwashing behavior. The approach combines the apparent green performance of a company, measured by the information pillars soft ESG data, textual self-representation, and green virtues (e.g., signaled by memberships in green initiatives), with its real green performance based on hard ESG data (see Figure 3.2). In general, the theoretical idea of the framework is that if the apparent green performance exceeds the real green performance, greenwashing risk arises. In this context, apparent green performance reflects a company's reported environmental performance, while real green performance captures the true environmental impact based on objectively measurable factors.

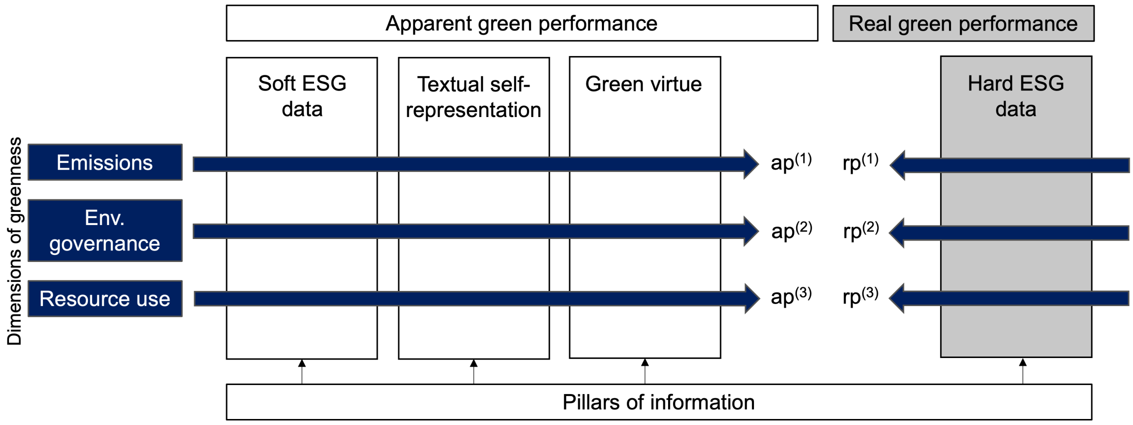


Figure 3.2: Greenwashing measurement framework. *ap* refers to apparent green performance, *rp* to real green performance. Greenwashing risk arises when *ap* exceeds *rp* using multiple information pillars across emissions, environmental governance, and resource use dimensions.

The information pillars are determined based on existing literature, which documents them to be crucial drivers of greenwashing (Bauckloh et al., 2023; Papoutsi and Sodhi, 2020; Szabo and Webster, 2021). As a normative basis for assessing environmental performance, we classify the variables into the three dimensions "emissions," "environmental governance," and "resource use," respectively denoted with $i = 1, 2, 3$. For every information pillar and every dimension, we collect appropriate variables, motivated by an extensive literature review, from the data providers RepRisk, LSEG, Trucost environmental, CDP, and Bloomberg. We classify the variables into apparent or real green performance and winsorize the continuous variables at the 1% level at both ends. Moreover, without loss of generality, we normalize all variables to a scale of 0 to 1 for ease of interpretation. Table 3.5 reports the description and Table 3.6 the summary statistics of the variables used for greenwashing measuring in our framework.

Table 3.5: Description and labeling of measurement variables

Variable	Description	Information pillar	Dimension	Apparent/Real
Emissions reduction target	Percentage of emission reduction target set by the company.	Soft ESG	Emissions	Apparent
Env. partnerships	Does the company report on partnerships or initiatives with specialized NGOs, industry organizations, governmental or supra-governmental organizations, which are focused on improving environmental issues?	Green virtue	Emissions	Apparent
GHG scope 1 intensity	Greenhouse gas (GHG) emissions from sources that are owned or controlled by the company (categorised by the Greenhouse Gas Protocol) divided by the company's revenue.	Hard ESG	Emissions	Real
GHG scope 2 intensity	Greenhouse gas (GHG) emissions from consumption of purchased electricity, heat or steam by the company (categorised by the Greenhouse Gas Protocol) divided by the company's revenue.	Hard ESG	Emissions	Real
ESG disclosure score	Proprietary Bloomberg score based on the extent of a company's environmental, social and governance (ESG) disclosure.	Soft ESG	Env. governance	Apparent
CSR strategy score	CSR strategy category score reflects a company's practices to communicate that it integrates the economic (financial), social and environmental dimensions into its day-to-day decision-making processes.	Soft ESG	Env. governance	Apparent
Ecological products	Does the company report on specific products which are designed for reuse, recycling or the reduction of environmental impacts?	Textual self-representation	Env. governance	Apparent
ESG reporting scope	The percentage of the company's activities covered in its environmental and social reporting.	Hard ESG	Env. governance	Real
Misleading communication	This issue refers to when a company manipulates the truth in an effort to present itself in a positive light, and in the meantime contradicts this self-created image through its actions.	Hard ESG	Env. governance	Real

Controv. marketing	Is the company under the spotlight of the media because of a controversy linked to the company's marketing practices, such as over marketing of unhealthy food to vulnerable consumers?	Hard ESG	Env. governance	Real
Env. controversy score	Company's exposure to environmental controversies and negative events reflected in global media.	Hard ESG	Env. governance	Real
Env. innovation score	Environmental innovation category score reflects a company's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.	Hard ESG	Env. governance	Real
Sustainable packaging policy	Does the company have a policy to improve its use of sustainable packaging?	Soft ESG	Resource use	Apparent
Energy efficiency policy	Does the company have a policy to improve its energy efficiency?	Soft ESG	Resource use	Apparent
Biodiversity impact reduction	Does the company report on its impact on biodiversity or on activities to reduce its impact on the native ecosystems and species, as well as the biodiversity of protected and sensitive areas?	Textual self-representation	Resource use	Apparent
Consumer health and environmental issues	This issue refers to providing a product or service which poses an unnecessary risk to the consumer's health or the environment.	Hard ESG	Resource use	Real
Supply chain issues	This issue refers to companies who are held accountable for the actions of their suppliers. Both vendors and subcontractors are considered part of the supply chain.	Hard ESG	Resource use	Real
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, commodities, etc.	Hard ESG	Resource use	Real
Waste intensity	Direct and indirect waste quantity relative to revenue.	Hard ESG	Resource use	Real
Energy management	Involves the management of energy consumption during operations, including energy efficiency and intensity. Energy consumption from the product use is outside of the scope.	Hard ESG	Resource use	Real

Land ecosystem issues	Refers to criticism of a company or a project as it relates to the destruction of land-based ecosystems (land-based community of organisms and their physical environment on a particular piece of land).	Hard ESG	Resource use	Real

Notes: This table reports the description of variables including their labels assigned according to the measurement framework illustrated in Figure 3.2.

Table 3.6: Summary statistics for greenwashing measurement variables

Variable	Mean	Std.	Min.	Median	Max.	Obs.
Emission reduction target	0.68	0.47	0.00	1.00	1.00	4,929
Env. partnerships	48.55	41.17	0.00	75.56	93.55	4,929
GHG scope 1 intensity	125.41	384.91	0.05	9.14	2,800.56	4,929
GHG scope 2 intensity	39.22	79.64	0.19	12.33	522.63	4,929
ESG disclosure score	51.16	10.93	16.40	51.40	74.83	4,929
CSR strategy score	63.42	25.49	0.00	70.36	98.85	4,929
Ecological products	0.18	0.39	0.00	0.00	1.00	4,929
ESG reporting scope	92.28	18.16	11.70	100.00	100.00	4,929
Misleading communication	−0.10	1.86	−11.00	0.00	1.00	4,929
Controversial marketing	0.98	0.13	0.00	1.00	1.00	4,929
Env. contr. score	52.65	9.43	0.00	53.96	55.71	4,929
Env. innov. score	42.86	33.63	0.00	47.73	98.59	4,929
Sust. pack. policy	0.27	0.44	0.00	0.00	1.00	4,929
Energy effic. policy	0.94	0.24	0.00	1.00	1.00	4,929
Biodiv. impact red.	0.36	0.48	0.00	0.00	1.00	4,929
Consum. health and env. iss.	−0.02	2.31	−18.00	0.00	1.00	4,929
Supply chain issues	−0.27	2.46	−16.00	0.00	1.00	4,929
Overuse and wasting	0.44	0.62	−2.00	0.00	1.00	4,929
Waste intensity	104.77	751.56	0.01	6.89	7,356.92	4,929
Energy management	0.58	0.49	0.00	1.00	1.00	4,929
Land ecosystem issues	−0.30	2.64	−16.00	0.00	1.00	4,929

Notes: This table presents summary statistics of the variables used to measure greenwashing for 883 European public companies observed over the period 2015–2023. The company misconduct variables collected from RepRisk are coded as 1 minus the sum of a company's incidences within a year for each variable, respectively. Note that all variables are normalized to the [0, 1] range using min–max normalization prior to the regression analysis.

We measure greenwashing behavior by calibrating the measurement model as follows. For every dimension $i \in \{1,2,3\}$, we denote the different company characteristics to measure the apparent green performance by xa

$$xa_1^{(i)}, \ldots, xa_{N_i}^{(i)}$$

and different company characteristics to measure the real green performance xr by

$$xr_1^{(i)}, \ldots, xr_{M_i}^{(i)}.$$

The functions to be calibrated are

$$ap^{(i)} = \sum_{j=1}^{N_i} wa_j^{(i)} xa_j^{(i)}$$

and

$$rp^{(i)} = \sum_{j=1}^{M_i} wr_j^{(i)} xr_j^{(i)},$$

with ap denoting the apparent green performance, rp the real green performance, and w_j the weight of variable j.

To obtain the estimate of the greenwashing risk indicator variable, we have in total $N_1 + N_2 + N_3 + M_1 + M_2 + M_3$ input variables and weights to be chosen so that the function

$$GW = 1 - \prod_{i=1}^{3} \left(1 - \max\left(\sum_{j=1}^{N_i} wa_j^{(i)} xa_j^{(i)} + \sum_{j=1}^{M_i} wr_j^{(i)} xr_j^{(i)}, 0\right)\right) \tag{3.1}$$

is best fit to n real company observations of GW as well as the $N_1 + N_2 + N_3 + M_1 + M_2 + M_3$ variables. We achieve this via performing a nonlinear least squares regression. GW can be interpreted as the probability that there is greenwashing in at least one of the three dimensions.

3.3.2 Results of the greenwashing measurement model

We estimate the measurement model for the selected sample using the mean greenwashing severity score as dependent variable and the classified environmental variables as independent variables in Equation 3.1.[2] We obtain a greenwashing score that can be interpreted as a risk indicator that a company is engaging in greenwashing. Accordingly, Table 3.7 provides the regression results of the model.

[2] As a robustness check, we also conduct out-of-sample tests with different specifications (randomized distribution of 70% of the company-years to the training data set and 30% to the test data set, balanced and unbalanced) and 10,000 model runs each, respectively. On average, the model performances and the statistical significance of variables are essentially comparable with the selected model, which is validated in-sample.

Table 3.7: Regression results for the greenwashing measurement model

Variable	Apparent/Real	Coefficient
Emissions		
Emission reduction target	Apparent	0.009**
Environmental partnerships		0.008
GHG scope 1 intensity	Real	−0.136***
GHG scope 2 intensity		−0.173***
Environmental governance		
ESG disclosure score		0.282***
CSR strategy score	Apparent	0.336***
Ecological products		0.026**
ESG reporting scope		−0.051**
Misleading communication		−0.266***
Controversial marketing	Real	0.037*
Env. controv. score		−0.163***
Env. innov. score		−0.024
Resource use		
Sust. packag. policy		−0.174***
Energy effic. policy	Apparent	0.738***
Biodiv. impact red.		0.013
Consumer health and env. issues		0.188***
Supply chain issues		−0.393***
Overuse and wasting		−0.180***
Waste intensity	Real	0.044
Energy management		0.026
Land ecosystem issues		−0.130***
N		4,929
Adjusted R^2		0.346
RMSE		0.149

Notes: This table reports the results of the non-linear regression model run on the 2015–2023 sample according to Equation 3.1, with *GW score* as the dependent variable. *GW score* is the mean greenwashing severity score. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Overall, an adjusted R^2 of 0.35 together with an $RMSE$ of 0.15 indicates a reasonable goodness of fit of the measurement model. To analyze the effects of the variables on the greenwashing risk indicator, we can interpret the model coefficients according to the classification of the variables as apparent or real green performance. In general, as high apparent and low real green performance increase greenwashing risk, we expect positive coefficients for the variables measuring apparent green performance when explaining the variation of the greenwashing severity scores, and negative ones for the variables measuring real green performance.

In the emissions dimension, the variable emission reduction target—which belongs to the apparent performance pillar and indicates whether a company has disclosed a formal target to reduce emissions—is positively and significantly associated with greenwashing risk. This suggests that companies publicly committing to emission reduction goals may, on average, exhibit higher apparent than real environmental performance. On the real green performance pillar, both GHG scope 1 and scope 2 intensities are negatively and significantly associated with greenwashing, implying that companies with lower actual emission intensities are less likely to engage in greenwashing behavior. These results align with our expectations: signaling intentions without corresponding performance increases the risk of greenwashing, while measurable reductions in emissions reduce it.

In the environmental governance dimension, all variables in the apparent pillar are positive and significantly different from zero, i.e., they have explanatory power to estimate greenwashing risk. The positive signs are also aligned with our expected influence on the greenwashing estimate. The reporting-intensive variables ESG disclosure score and CSR strategy score show statistical significance at the 1% level. The real green performance variables misleading communication and environmental controversy score from LSEG, measuring the actual negative performances, are statistically significantly different from zero with negative coefficients. Also, the ESG reporting scope variable contributes to the real green performance in this dimension. The environmental innovation score is not significant in this model.

In the resource use dimension, energy efficiency policy has a positive effect on the greenwashing estimate, while the sustainable packaging policy influences the greenwashing estimate negatively. Biodiversity impact reduction has no explanatory power. The estimates of the variables associated with the real green performance pillar of the RepRisk variables supply chain issues, overuse and wasting, and land ecosystem issues document a negative and statistically significant relationship with the greenwashing severity score. However, the variable consumer health and environmental issues has a positive and significant coefficient, meaning that it has a decreasing effect on the greenwashing estimate value. Lastly, the variables waste intensity and energy management are not significant in the model.

Neither the coefficient of the sustainable packaging policy nor that of the consumer health and environmental issues variable has the sign that we expected in terms of both apparent and real green performance classifications. However, it should be noted that this measurement framework represents only an exemplary implementation. It is possible to implement target function optimized models with an individual selection of appropriate variables and variable labels according to the apparent and real green performance.

To assess the performance of the model, we examine the Receiver Operating Characteristic (ROC) curve shown in Figure 3.3 with a total Area Under the Curve (AUC) value of 0.86 documents that the measurement model has a good accuracy, considering that a value of 0.5 would indicate that the model is no better than a random estimate. In addition, the curve shows the trade-off between the values for sensitivity (the ability to correctly identify true positives) and specificity (the ability to correctly identify true negatives). Depending on the intended use of the greenwashing risk indicator

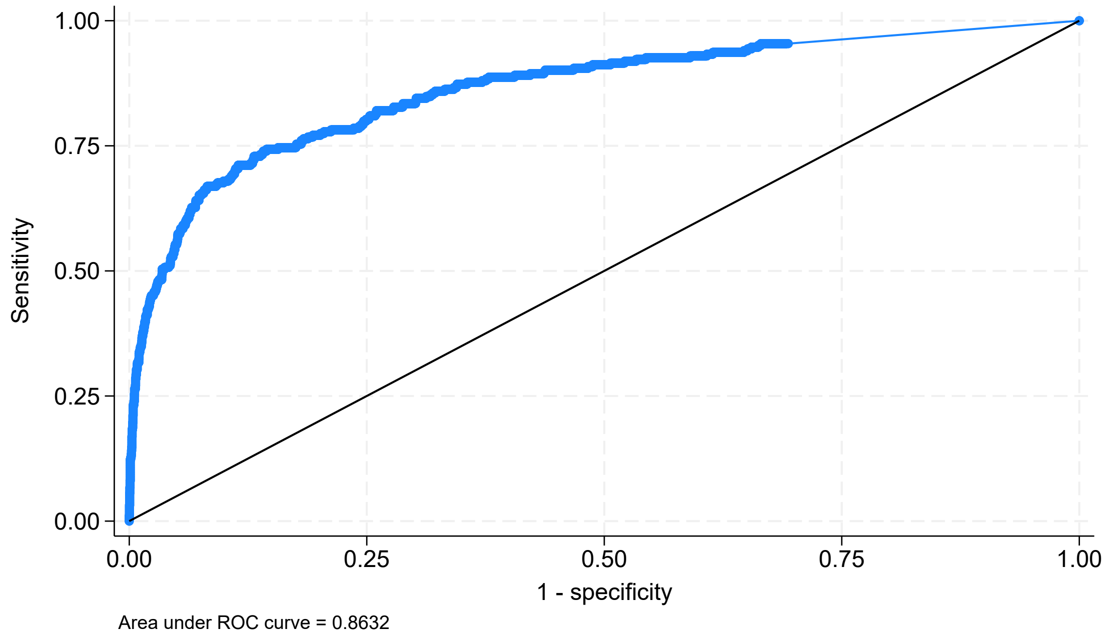


Figure 3.3: Receiver Operating Characteristic (ROC) curve illustrating the classification performance of the greenwashing measurement model. The curve plots the true positive rate (sensitivity) against the false positive rate (1 − specificity) across different classification thresholds.

and the user's preferences, one can choose a threshold value. We assume that an investor will incur higher costs for overseeing an actual case of greenwashing than for mistakenly accusing a company of greenwashing. This is due to the costs that should be priced in as a result of the greenwashing risk, especially reputational and litigation risks. In this scenario, the greenwashing risk indicator can be seen as a monitoring tool that serves as an indication of greenwashing behavior that needs to be further investigated in the decision-making process. Therefore, we put more emphasis on maximizing model sensitivity while achieving a tolerable false positive rate, as measured by specificity. To achieve this, we select a classification threshold of 1% as the best-fit model. Accordingly, we receive the following performance metrics. 253 of 284 cases of greenwashing are detected, while 31 cases are not detected, resulting in a sensitivity of 89.1%. In terms of non-greenwashing company-years, 2,758 are correctly identified, while 1,887 are incorrectly classified as greenwashing. This leads to a specificity value of 59.4%. In other words, greenwashing cases are correctly identified in 89% of the greenwashing observations. In addition, for 59% of the non-greenwashing observations, it is correctly estimated that there is no greenwashing.

In order to have a better understanding of the composition of apparent and real green performance and the respective distribution of performance across the measurement dimensions, we use the estimated regression coefficients and the average values of the statistically significant variables to calculate the average values of apparent and real green performance for the measurement dimensions. The dimensions are weighted equally when calculating the difference between apparent and real green performance, which reflects the greenwashing estimate of our model. The results are illustrated in Figure 3.4. It can be seen that the emissions dimension contributes relatively little to the calculation of the greenwashing estimate. In this respect, the resource use dimension can be seen as the most important driver of apparent green performance, while the environmental governance dimension, together with the resource use dimension, contribute significantly to the calculation of real green performance. As reported in Table 4.4, the variables energy efficiency policy (apparent) and supply chain issues (real) can be seen as the main drivers in the resource use dimension. For the environmental governance dimension, the RepRisk variable misleading communication has a high explanatory power for the real green performance. The average greenwashing risk indicator across all company-years is 6%.

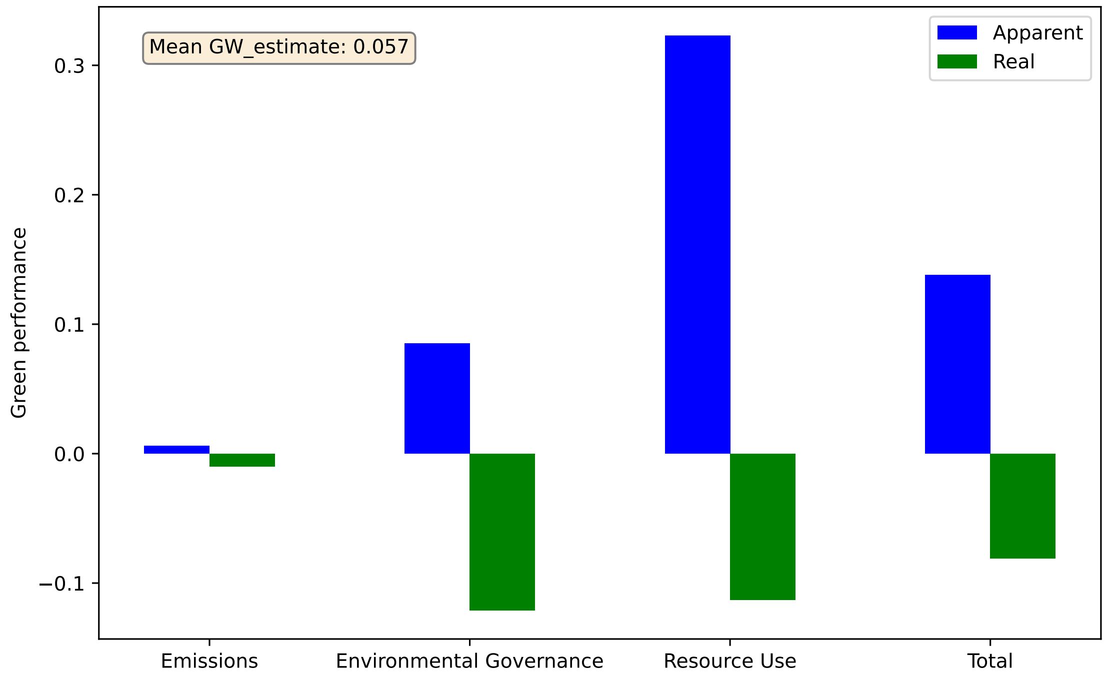


Figure 3.4: This figure illustrates the distribution of apparent and real green performance across the greenness dimensions. Using the estimated regression coefficients and the means of the significant variables, average green performance scores are calculated for each dimension. The dimensions are equally-weighted for the calculation of the difference between apparent green performance and real green performance.

3.4 Further research

Our greenwashing data has already been applied to three empirical research questions, which we briefly outline in the following section. Note that each of the three empirical set-ups uses a different subset of the original greenwashing dataset, due to the empirical methodology employed and varying degrees of missing data (on variables other than the greenwashing indicator).

Kathan et al. (2025) utilize 417 cases of greenwashing from 2015 to 2023 to construct apparent and real green performance, employing measurement variables similar to those demonstrated above. The findings of the analysis show a positive correlation between ESG scores and instances of greenwashing, as the former primarily reflect a company's apparent green performance rather than its actual environmental impact. A further finding of the study is that increased analyst coverage is associated with a reduced extent of exaggeration of environmental claims.

Eckberg et al. (2025) investigate the determinants and predictability of corporate greenwashing using 365 greenwashing cases from 2011 to 2023. They find that both ESG low- and ESG high-rated companies exhibit higher greenwashing risk—particularly in consumer-facing industries. The results comprise further key drivers of greenwashing, such as company size, cash-to-assets ratios, and capital intensity. Additionally, Eckberg et al. (2025) apply machine learning models—most notably a Recurrent Neural Network (RNN)—capable of forecasting greenwashing cases by one year, achieving strong predictive performance by incorporating economic cost asymmetries and identifying key predictive features such as lagged greenwashing, ESG disclosure, and company-level characteristics.

Dorfleitner et al. (2025) use 297 greenwashing events from 2018 to 2023 and analyze how stock markets react to greenwashing allegations in an event study setting. The findings reveal that small companies in consumer-related industries suffer the most significant negative cumulative abnormal returns, particularly when allegations are of high materiality. Within consumer-facing industries, the market response weakens if companies have previously faced multiple greenwashing incidents, suggesting a potential desensitization effect. In non-consumer industries, higher ESG scores help mitigate negative stock price impacts, while compliance-related and investment-focused allegations—especially in consumer industries—trigger the strongest market penalties.

In summary, our greenwashing case sample provides a valuable empirical basis for research and helps to generate insights into corporate sustainability behavior. Specific company-level characteristics can be identified as significant determinants of greenwashing incidents. While greenwashing scandals cannot be predicted with complete accuracy, it is possible to develop economically meaningful predictive models that help to anticipate and potentially avoid such cases. Moreover, although share prices do not always fall in response to greenwashing allegations, certain constellations, such as small company size, certain industries, and compliance-related greenwashing can trigger significant negative market reactions.

3.5 Implications for practice

To assess the practical relevance of a greenwashing risk indicator (i.e., measuring the risk that a company engages in greenwashing), we conduct (1) semi-structured interviews with relevant experts from the practice and (2) a survey with decision makers from the financial industry.

3.5.1 Expert interviews

Interviewees are selected based on their expertise and professional intersections on the topic of greenwashing. Furthermore, a heterogeneity between academia, the financial industry, and the real economy is ensured. Based on the selection criteria, the interviews are conducted with the following persons: one person from academia, one person from the financial industry, two persons from the real economy, and one person from an NGO.

From the multiple interviews conducted, several vital implications emerge. The experts stress that defining greenwashing and accessing pertinent data pose substantial challenges. Moreover, the interviews highlight the reputation risk faced by companies as a significant concern and emphasize the importance of assessing a company's ambition for improvement when evaluating greenwashing. Additionally, there is a unanimous endorsement of the need for an objective greenwashing indicator at the company level. For measurement and communication, interviewees recommend categorizing companies, facilitating benchmark comparisons, and ensuring clear and comprehensible communication of the measurement methodology. For the latter, it is considered useful for users that, along with the apparent green performance and the real green performance, the subcategories of the greenwashing risk indicator calculation are also published.

Complementing these findings, the interview with the NGO provides additional valuable insights. For the NGO, greenwashing is classified as a form of consumer deception and fraud. The NGO employs a variety of strategies to combat greenwashing, which encompass media accusations, peer group comparisons using the best-in-class approach, and consumer pressure. The importance of accurate measurement, considering industry-specific nuances, and recognizing the role of marketing in masking environmental underperformance are underscored. Furthermore, the interview sheds light on the significance of clear legal frameworks and enforcement in regulatory efforts to combat greenwashing.

In summary, the amalgamation of insights from the interviews enriches our understanding of greenwashing, substantiates the need for a robust and objective greenwashing indicator, and advocates for transparent communication and industry-specific considerations in its development.

3.5.2 Survey in the financial industry

In addition to interviews, an online survey was conducted with eleven decision-makers from the financial industry. The survey consisted of nine questions and was answered by the respondents between October and November 2023. Seven of the respondents work at a bank, two in asset management, one at an organization for ESG services & solutions, while one person indicated "association/club/network" as their affiliation. Six respondents stated that they have at least partial decision-making authority for the strategic direction of their company or organization. The companies represent a heterogeneous group in terms of managed assets, so no bias in the results regarding a specific group of investors is expected. The assets under management were divided into ranges of 1-50 billion USD (four responses), 200-300 billion USD (one response), and 400-500 billion USD (two responses). The remaining respondents did not provide information on managed assets. While there are significant differences in the use of sustainability criteria in investment decisions, there is consensus that the risk of greenwashing at the corporate level is relevant to the work of the respondents. Five individuals answered this question as “very important,” another five as “important,” and one person as “neutral.” Similarly, when asked about the relevance of a greenwashing indicator for assessing the risk of greenwashing at the corporate level, over 70% of respondents indicated that such an indicator would be relevant to them (responses “strongly agree” and “agree”), while only three respondents answered “neutral.” In this context, it was noted that the risk of false signals from the greenwashing indicator should be considered and that the measurement and estimation methodology should be consistent and well-founded. Additionally, one person pointed out that in the future, the risk of greenwashing could be evaluated through the increased data quality provided by the CSRD in conjunction with personal discussions with companies.

3.6 The effect of recent and future sustainability regulation

The observation period of our European sample ends roughly at the point where the more recent EU regulatory frameworks, namely the CSRD, the SFDR, and the GCD, have begun or are beginning to take effect.

First and most importantly, the CSRD needs to be mentioned, which came into force in 2023. The CSRD is an EU directive that obliges companies to report on sustainability in a comprehensive and standardized manner, i.e., no longer just voluntarily or superficially. A central component of the CSRD is the European Sustainability Reporting Standards (ESRS) framework. The ESRS specify exactly what and how companies must report, for instance on environmental issues (e.g., CO_2 emissions), social issues, and governance.

Under the validity of the CSRD, greenwashing can be expected to become more difficult for the following reasons (Papathanassiou and Nieto, 2025):

- Mandatory, comparable data: Companies must provide verifiable key figures (e.g., emissions in CO_2 equivalents), not just fine words. This makes deceptions more easily visible.
- External audit obligation: Sustainability reports must be audited by external auditors, similar to financial reports. This prevents embellished statements.
- Double materiality: Companies must report on how their actions affect the environment and society, as well as how sustainability risks affect their business. This renders empty public relations promises impossible.

- Standardized disclosure requirements: Through the ESRS, there are uniform standards, making greenwashing through creative interpretations of sustainability more difficult.

In summary, the CSRD promotes transparency and traceability in sustainability reporting, thereby making corporate greenwashing both riskier and more easily detectable.

Other EU-related regulations that may help reduce greenwashing are the SFDR and the future GCD. The SFDR has been in effect since March 2021. It aims to increase transparency in the financial industry by requiring financial market participants and financial advisers to disclose how they integrate sustainability risks and impacts into their investment decisions and advisory processes. The GCD, which must be implemented into national law by 2026, aims to combat greenwashing by establishing clear, evidence-based requirements for companies that make environmental claims about their products or services. Specifically, the directive mandates that companies substantiate their environmental claims using standardized assessment methods, such as the Product Environmental Footprint (PEF) method, which calculates a product's environmental impact throughout its life cycle. While the PEF method has limitations, the GCD reflects a genuine effort to combat greenwashing in the European market.

While we expect all three legal frameworks to have a mitigating effect on company-level greenwashing behavior, this cannot be proven today. However, our methodology may help analyze the potential progress with respect to greenwashing in the near future. Moreover, it needs to be mentioned that the costs for companies to comply with the regulation are also a subject of discussion. Outside the EU, there are also sustainability-related regulations. They appear to be generally less stringent. As a result, it remains difficult to make a reliable global prediction about the future prevalence of greenwashing.

3.7 Conclusion

The current market and regulatory structure allows companies to exploit loopholes and inaccurately report their environmental impacts. However, current efforts to combat greenwashing appear to be insufficient, as regulations cannot completely eliminate information asymmetries.

In this paper, we empirically measure greenwashing at the company level using a rigorous framework that includes several information pillars and dimensions of sustainability. We aggregate the data by calculating the difference between the company's apparent and real green performance, which is consistent with the definitions of company-level greenwashing in the literature. Using this framework, we measure company-level greenwashing for a comprehensive sample of European public companies and shed light on the functioning and evolution of this phenomenon over several years. The measurement model has a sensitivity of 89% and a specificity of 59%.

Our proposed framework for measuring greenwashing complements the literature on measuring corporate misconduct and environmental business risks. In addition, the greenwashing risk indicator has high practical relevance. It can be of value to climate-conscious stakeholders, such as asset managers managing their green investments or financial service providers in terms of risk management, and increase information transparency, leading to more efficient markets and encouraging companies to change their behavior. In addition, other stakeholders such as lenders and consumers can use the greenwashing risk indicator to make more informed decisions.

Future research can extend the measurement of greenwashing at the company level to a global sample. In addition, the greenwashing risk indicator offers the opportunity to analyze the asset pricing implications of greenwashing, as well as stakeholder and corporate reactions on the reported greenwashing cases.

Chapter 4

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

This research project is joint work with Manuel C. Kathan (University of Augsburg), Sebastian Utz (University of Augsburg), Gregor Dorfleitner (University of Regensburg), and Lea Chmel (University of Augsburg). The paper has been published as:

Kathan, M. C., Utz, S., Dorfleitner, G., Eckberg, J., Chmel, L. (2025), What you see is not what you get: ESG scores and greenwashing risk. *Finance Research Letters*, 74, 106710.

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

Keywords ESG scores, Greenwashing, Greenwashing indicator, Information asymmetry, Analysts coverage

4.1 Introduction

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

Investors are willing to sacrifice returns to prevent greenwashing risk (Kleffel and Muck, 2023) and aim to avoid greenwashing companies in the long term (Li et al., 2024b). In this regard, we investigate whether investing in companies with high ESG scores helps mitigate greenwashing risk. To achieve this, we hand-collect greenwashing cases of the STOXX Europe 600 constituents from 2015 to 2023 and relate them to ESG scores from the data providers LSEG (formerly Refinitiv) and Bloomberg. Portfolios double-clustered by ESG score and company size quartiles reveal that companies with high ESG scores and large sizes contain the highest numbers of greenwashing cases. Tests, based on greenwashing risk estimated following the theoretical model of Dorfleitner and Utz (2024) show that ESG scores primarily reflect the apparent environmental performance that refers to the perceived strengths of a company's ecological efforts, reflecting the claims made in its reports. In contrast, the real environmental performance, i.e., a company's actual ecological effectiveness and impact based on quantifiable outcomes, correlates negatively with ESG scores.

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

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

4.2 Sample and methodology

4.2.1 Greenwashing cases and sample

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

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

Table 4.1 shows the summary statistics of our sample. *United Kingdom*, *Germany*, and *France* account for almost 50% observations of the sample, but only for nearly 30% of the greenwashing cases. The distribution of companies across individual sectors is balanced. The highest relative occurrences of greenwashing cases are in the *Utilities* (15.91%) and *Energy* (12.32%) sectors.

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

Table 4.1 (last two columns) shows the country and industry averages for the mean and standard deviation of the greenwashing severity scores for the sample of greenwashing cases. Emissions-intensive sectors (*Basic Materials, Utilities, Energy*) and customer-related industries (*Consumer*

Discretionary, Consumer Staples) show the highest greenwashing severity scores. Across countries and industries, higher average greenwashing severity scores tend to come with lower standard deviations across the four assessments.

Table 4.1: Summary statistics of greenwashing cases per country and industry

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

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

4.2.2 ESG scores and greenwashing cases

Table 4.2 presents the number of greenwashing cases across double-sorted portfolios. Panel A shows portfolios sorted first by LSEG ESG scores and then by company size (log sales), both in ascending order from the lowest ("1 (low)") to the highest ("4 (high)") quartile. For example, portfolio "1-LSEG ESG scores" and portfolio "1-company size" represent 6.25% of company-years, containing the smallest companies within the lowest ESG scores company-years in our sample. Panels B–E follow the same logic but are sorted first by the variable mentioned at each panel's heading.

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

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

Moreover, as a benchmark, we determine greenwashing risk following the approach of recent studies (e.g., Jin et al., 2024; Li et al., 2024c; Lin et al., 2023; Liu et al., 2023; Liu and Li, 2024; Peng et al., 2024; Sun, 2024; Yu et al., 2020; Zhang, 2023b) and classify portfolios accordingly. The high greenwashing portfolio in Panel D (E) accounts for only 98 (119) of the 391 (376) total greenwashing cases.[1] Thus, these greenwashing risk measures do not reflect the actual greenwashing cases properly, highlighting the need for more reliable estimation approaches.

[1] In Panels D and E of Table 4.2, we standardize the ESG Disclosure scores and ESG scores across the entire sample, following the widely adopted standardization method (e.g., Jin et al., 2024; Lin et al., 2023; Liu and Li, 2024; Peng et al., 2024) to calculate greenwashing behavior. For robustness, we also perform standardization by year (see Table A.5) and by industry-year (see Table A.6). The results remain similar across these alternative standardization approaches.

Table 4.2: Portfolio double sorting of company-year greenwashing cases based on ESG-related variables and company size

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

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

Table 4.3 shows the development of greenwashing and ESG-related variables over our sample period, separately for the greenwashing (GW) and non-greenwashing (non-GW) samples. The number of greenwashing cases increases over time. Moreover, the values of ESG variables in company-years with greenwashing accusations are, on average, higher than those in company-years without greenwashing accusations (Columns (4)–(9)).[2]

Table 4.3: Number of greenwashing cases, severity scores, and ESG scores per year

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

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

4.3 Greenwashing risk and estimation

4.3.1 Theoretical foundation

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

From a theoretical perspective, the observed relationship can be explained through signaling theory (Spence, 1973), institutional theory (DiMaggio and Powell, 1983), and moral licensing theory (Merritt et al., 2010). Market pressure and reputational concerns can drive companies to greenwash

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

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

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

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

To capture the mismatch between a company's sustainable claims and its actual environmental impact, which determines its greenwashing risk, we empirically implement and calibrate the theoretical model proposed by Dorfleitner and Utz (2024). This approach distinguishes between a company's apparent and real environmental performance to assess its greenwashing risk. Apparent environmental performance (AP) refers to the perceived environmental actions of a company as reflected in its environmental claims. For example, an oil company might pledge to reduce CO_2-emissions by 50% by 2040 in its sustainability report. These targets are challenging to quantify because they are forward-looking, with the actual business impact remaining uncertain. Real environmental performance (RP) refers to a company's actual, quantifiable environmental impact. It primarily relies on measurable quantities such as the number of environmental incidents involving a company as reported by the media and current CO_2-emissions.

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

[3]A detailed description of the theoretical model can be found in Dorfleitner and Utz (2024).

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

4.3.2 Greenwashing risk estimation

We calibrate the model by identifying variables related to a company's greenwashing risk and then estimating a non-linear model using least squares regressions, as proposed by Dorfleitner and Utz (2024). The process for selecting variables included in our model estimation is as follows. First, we choose variables recognized in the literature as drivers of greenwashing behavior (e.g., Papoutsi and Sodhi, 2020, and references therein). This step provides a broad set of variables obtained from the four databases introduced in Section 4.2.1. Second, we ensure that the variables have sufficient coverage across our sample. Third, we address multi-collinearity by selecting variables with relatively low pairwise correlations. Finally, we categorize our selected variables into our predefined dimensions and distinguish between AP and RP.

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

Table 4.4 presents the estimated coefficients and model statistics, along with categorizing whether a variable corresponds to AP or RP. Almost all variables (except for *Scope 2 intensity*) contribute to explaining the greenwashing severity scores. Variables linked to AP are associated with increased greenwashing risk, while RP-related variables are associated with a reduced risk.

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

Table 4.4: Regression results

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

Notes: This table presents non-linear regression results with the mean greenwashing severity scores as the dependent variable and the selected independent variables to calculate the greenwashing risk ($[0,1]$), following the model approach by Dorfleitner and Utz (2024). The sample covers companies of the STOXX Europe 600 from 2015 to 2023. Variables are classified into distinct environmental dimensions and categorized based on whether they contribute to a company's real or apparent environmental performance. All continuous variables are winsorized at the 0.5% level. Independent variables are normalized to a scale ranging from 0 to 1 using the Min-Max normalization. For variable descriptions, see Table A.3. Standard errors are clustered at the company level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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

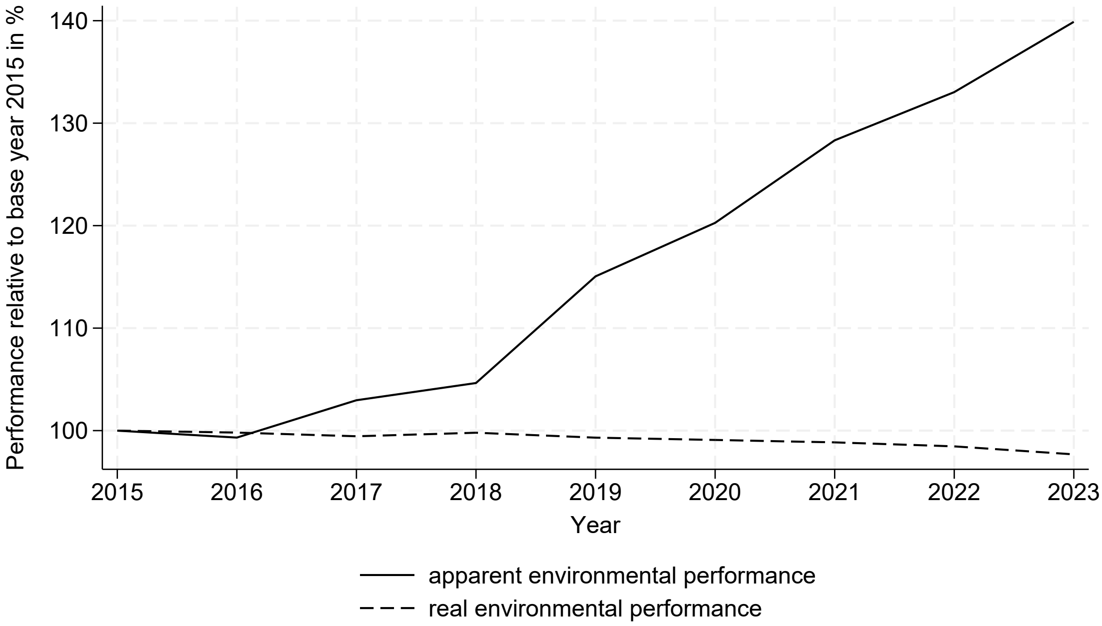


Figure 4.1: This figure displays the development of sample companies' average apparent and real environmental performance over time. The *y*-axis measures environmental performance, either apparent (solid) or real (dashed line), expressed relative to the baseline year 2015. The *x*-axis shows the years.

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

Figure 4.1 shows the development of the cross-sectional annual average AP and RP from 2015 to 2023, relative to 2015. While the average RP remains stable throughout the period, the apparent one shows a significant increase of roughly 40% by 2023 compared to 2015. Thus, while real environmental impact has been rather constant, the communication on companies' environmental strategies has substantially increased.

4.4 Greenwashing risk and ESG scores

Table 4.5 contains pair-wise Pearson correlations between ESG scores and (1) apparent environmental performance, (2) real environmental performance, and (3) greenwashing risk. Pearson correlations between E(SG) (i.e., E individually and ESG) scores and AP range from 0.48 to 0.63 for LSEG ESG (Panel A). Consequently, ESG scores tend to be high when a company's AP is perceived as strong. In contrast, the correlations with the RP are negative and close to -0.25. Therefore, ESG scores are higher for companies with low RP. The correlations between greenwashing risk and E(SG) scores are positive and range between 0.32 and 0.41. Almost all correlations of the pair-wise combinations are statistically significantly different from zero and display a relatively consistent pattern over time.

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

To rule out potential biases from using LSEG ESG scores, given provider discrepancies (e.g., Berg et al., 2022), we repeat the analysis with Bloomberg ESG scores. Panel B shows smaller, but still significant correlations, confirming the robustness of our results. We also use Bloomberg's ESG Disclosure scores (Panel C), demonstrating that increased disclosure of ESG-related information correlates with a company's AP and risk of greenwashing.

Table 4.5: Pearson correlation between E(SG) scores and environmental performance of companies

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

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

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

Table 4.6 presents the results for the relationship between *Diff-AP-to-RP* and *Log(1 + No. of analysts)* for the entire sample (Column (1)), and for subsamples based on "company size" (Columns (2)–(3)) and "scope 1 intensity" (Columns (4)–(5)), which are split at the median values of the respective variable. Columns (6) and (7) show the results for brown (Energy, Industrials, Utilities, and Basic Materials) and non-brown industries.

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

Table 4.6: Regression results

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

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

4.5 Conclusion

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

Appendix

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

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

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

Table A.2: Assessment of greenwashing severity

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

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

Table A.3: Definition of Variables

Variable	Description	Source
	Dimension: Emissions (apparent performance)	
Emissions target (binary)	Has the company set targets or objectives to be achieved on emissions reduction? In scope are the short-term or long-term reduction target to be achieved on emissions to land, air or water from business operations.	Refinitiv
Environmental partnerships (score)	Does the company report on partnerships or initiatives with specialized NGOs, industry organizations, governmental or supra-governmental organizations, which are focused on improving environmental issues?	Refinitiv
	Dimension: Emissions (real performance)	
Scope 1 intensity	Greenhouse gas (GHG) emissions from sources that are owned or controlled by the company (categorised by the Greenhouse Gas Protocol) divided by the company's revenue	Trucost
Scope 2 intensity	Greenhouse gas (GHG) emissions from consumption of purchased electricity, heat or steam by the company (categorised by the Greenhouse Gas Protocol) divided by the company's revenue	Trucost
	Dimension: Environmental governance (apparent performance)	
Eco-friendly products (binary)	Does the company report on specific products which are designed for reuse, recycling or the reduction of environmental impacts?	Refinitiv
Environmental restore initiatives (score)	Does the company report or provide information on company-generated initiatives to restore the environment?	LSEG

(continued)

Variable	Description	Source
Dimension: Environmental governance (real performance)		
Misleading communications	This issue refers to when a company manipulates the truth in an effort to present itself in a positive light, and in the meantime contradicts this self-created image through its actions.	RepRisk
Supply-chain-issues	This issue refers to companies who are held accountable for the actions of their suppliers. Both vendors and subcontractors are considered part of the supply chain.	RepRisk
Dimension: Resource use (apparent performance)		
Water efficiency policy (binary)	Does the company have a policy to improve its water efficiency? In scope are the various forms of processes/mechanisms/procedures to improve water use in operation efficiently	LSEG
Energy efficiency policy (binary)	Does the company have a policy to improve its energy efficiency? In scope are the various forms of processes/mechanisms/procedures to improve energy use in operation efficiency	LSEG
Dimension: Resource use (real performance)		
Energy management (Overuse and wasting resources)	Involves the management of energy consumption during operations, including energy efficiency and intensity. Energy consumption from the product use is outside of the scope.	RepRisk
Landscape impact (Impacts on landscapes, ecosystems and biodiversity)	This issue covers impacts of company activities on ecosystems or landscapes such as forests, rivers, seas, etc., contamination of groundwater and water systems, deforestation, impacts on wildlife, etc.	RepRisk

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

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

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

Notes: This table presents summary statistics of the variables used to calculate greenwashing risk, following the theoretical model approach by Dorfleitner and Utz (2024). The sample covers companies of the STOXX 600 Europe from 2015 to 2023. All continuous variables are winsorized at the 0.5% level. The variables taken from RepRisk (*Misleading communications*, *Supply-chain-issues*, *Energy management*, and *Landscape impact*) are defined as 1 minus the sum of a company's incidences within a year for each variable, respectively, to capture a company's environmental performance. For variable descriptions, see Table A.3.

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

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

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

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

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

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

Chapter 5

What drives stock market reactions to greenwashing? An event study of European companies

This research project is joint work with Gregor Dorfleitner (University of Regensburg), Sebastian Utz (University of Augsburg), and Teresa Brehm (University of Regensburg).

Abstract This study examines stock market reactions in response to 296 greenwashing events involving STOXX Europe 600 companies. The results indicate that companies with the lowest total assets in our sample experience negative cumulative abnormal returns. Financially material cases, which are likely to affect company performance through legal and investor-related consequences, also lead to negative market reactions. Compliance-related allegations trigger the most consistent negative market reactions compared to other types of allegations. We also find evidence of moderating effects, with ESG reputation shaping the extent of market reactions. The findings highlight that market reactions to greenwashing are highly context-dependent, reflecting company size, industry, ESG scores, and the characteristics of the allegation.

Keywords Greenwashing, Stock market, Event study, Financial performance, Cumulative average abnormal returns

5.1 Introduction

In 2022, the German asset management company DWS Group faced widespread allegations of greenwashing after the claiming of overstating the use of sustainable investment criteria by the former head of sustainability, triggering regulatory investigations in Germany and the United States (Reuters, 2022). These allegations contributed to a significant decline in DWS's share price and raised serious investor concerns about the credibility of companies' environmental claims. Such high-profile cases highlight investors' growing sensitivity to environmental misconduct and raise important questions about its broader financial impact on publicly traded companies.

While empirical evidence on the financial implications of greenwashing remains limited, the few existing studies show mixed results (Lyon and Montgomery, 2015; Walker and Wan, 2012; Du, 2015; European Securities and Markets Authority, 2023; Li et al., 2024a; Teti et al., 2024; Xu et al., 2025). Related research highlights that negative CSR events, including environmental controversies, can reduce company value (Krüger, 2015), while companies with stronger CSR reputations are better protected in crises (Lins et al., 2017; Utz, 2018).

This study investigates stock market reactions to greenwashing allegations using an event study approach. We hand-collect 296 greenwashing allegations in the period 2018–2023 for public European companies included in the STOXX Europe 600 index. In addition, we classify cases by type, severity, and financial materiality to account for the heterogeneity of greenwashing practices. Our approach builds on recent efforts to empirically identify greenwashing using publicly available sources and ESG signals (Yuan et al., 2024), but extends them through manual screening, severity scoring, and financial materiality classification.

Our analysis builds on two key theoretical channels: information asymmetry and legitimacy theory. First, greenwashing increases information asymmetry between companies and investors by obscuring the true sustainability performance of a company. Investors rely on ESG disclosures to assess risk and future cash flows. Greenwashing allegations undermine this trust, which may result in a price reaction when the truth is revealed (Healy and Palepu, 2001; Krüger, 2015; Walker and Wan, 2012). Second, drawing on legitimacy theory, companies are seen as socially embedded actors whose legitimacy depends on alignment with stakeholder expectations and social norms. Greenwashing accusations may erode this legitimacy, resulting in reputational damage and negative valuation effects (Suchman, 1995; Lyon and Montgomery, 2015; Flammer, 2013).

Our results show that cumulative abnormal returns following greenwashing allegations are not significantly different from zero on average for the full sample. However, there is substantial variation across company, event, and industry characteristics. We observe significant negative market reactions to greenwashing allegations for the companies with the lowest total assets, for compliance-related allegations, and for financially material cases in consumer industries. Social-impact allegations also lead to negative market reactions in consumer industries, especially immediately after disclosure. Market reactions are amplified when allegations are reported by general media outlets, although the effect dissipates quickly. Furthermore, we find that ESG reputation buffers negative reactions in financially material cases. This moderating effect is observed for EU-based consumer companies and in the post-2021 period, i.e., 2022–2023, consistent with the documented increase in greenwashing cases over time (Kathan et al., 2025) and growing investor scrutiny.

Our study makes three key contributions to the growing literature on corporate environmental misconduct and financial performance. First, we build on the dataset of greenwashing allegations introduced by Kathan et al. (2025) and extend it by adding precise event dates and aligning cases with stock return data. The manual case identification combined with a structured severity rating system offers more granularity than previous studies that rely on binary ESG controversy flags or automated news classification (e.g., Du, 2015; Xu et al., 2025). Second, while earlier research often reports mixed or insignificant average valuation effects of greenwashing allegations (e.g., Lyon and Montgomery, 2015; Walker and Wan, 2012; Li et al., 2024a; Teti et al., 2024), our findings reveal that stock market reactions are highly conditional on company and event characteristics such as company size, industry, ESG reputation, and the financial materiality of the allegation. Third, we document market reaction heterogeneity, which has received limited attention thus far. We demonstrate that, in certain contexts, ESG scores and prior greenwashing exposure mitigate reputational penalties. Furthermore, we show that compliance-related cases lead to consistent negative market reactions across the full sample, while social impact-related cases trigger particularly negative market reactions in consumer-facing industries. Overall, our results reconcile some of the conflicting findings in the literature by emphasizing the importance of contextual factors in explaining stock price reactions to greenwashing allegations.

5.2 Sample, data, and methodology

We construct a novel dataset of greenwashing allegations involving companies listed in the STOXX Europe 600 index, covering the period from 2018 to 2023.[1] Greenwashing cases are identified through a structured manual screening of multiple information channels, including web-based news platforms, NGO reports, and social media content (e.g., Twitter/X). To ensure reliability and mitigate source bias, the data collection process was conducted by a trained team of research assistants and guided by a standardized decision protocol (see Table A.1).

Each collected information source is reviewed according to predefined inclusion and exclusion criteria. We retain sources that provide original or materially new allegations of greenwashing tied to identifiable companies. Redundant sources (e.g., syndicated news articles repeating the

[1] An earlier version of this dataset was used in Kathan et al. (2025) to examine the relationship between ESG scores and greenwashing risk. Their findings show that the number of greenwashing allegations in Europe increased substantially in 2021 and 2022, consistent with heightened ESG scrutiny and media attention in recent years.

same allegation without added content), unverifiable accusations, and materials that do not directly reference the target company (e.g., fund-level accusations or sector-wide critiques) are excluded. When sources provide new insights on previously identified cases, they are treated as valid entries for the corresponding publication year.

Each greenwashing case that meets our inclusion criteria is then evaluated by four independent researchers who assign a severity score between 0 (no greenwashing) and 1 (greenwashing). The evaluation follows a structured rating framework that considers factors such as the specificity and credibility of the allegation, its alignment with environmental claims made by the company, and whether the behavior represents deception, omission, or exaggeration (see Table A.2). The final severity score for each case is computed as the average of the four ratings.

To avoid overweighting companies with multiple cases in a given year, we retain only the most severe case per company-year. In total, after applying further filters for data availability and removing cases with confounding events (e.g., earnings or M&A announcements) to isolate company-specific effects in the estimation or event window, our final sample comprises 296 greenwashing events from 128 unique companies. For each event, we define the event date as the earliest credible public disclosure of the allegation.[2]

Our approach differs from prior studies that rely on binary ESG controversy flags or proprietary incident tagging. By combining manual case identification, human-coded severity scores, and rigorous filtering criteria, we construct a greenwashing dataset with greater transparency and granularity. This enables a more precise analysis of how investors respond to greenwashing events of varying severity and financial materiality.

We apply an event study methodology commonly used in the financial literature (Flammer, 2013; Krüger, 2015; MacKinlay, 1997). We use daily adjusted stock prices from LSEG for companies and the STOXX Europe 600 index to calculate returns. We estimate expected returns based on the Fama-French five-factor model over the 100 trading days preceding the event. Using these expected returns, we calculate abnormal returns (AR) for each company by subtracting the expected returns from the actual returns. We then obtain cumulative abnormal returns (CAR) by summing the ARs over different event windows. We calculate CARs for event windows of up to 61 trading days following the initial disclosure of a greenwashing allegation. For detailed analysis, we focus on shorter windows commonly used in ESG-related event studies. Specifically, we use a [0,10] day window (11 trading days) to capture immediate stock price reactions, while allowing for potential delayed market reactions (e.g., Krüger, 2015). Additionally, we follow Flammer (2013) and use a [0,20] day window (21 trading days) to test whether the market reaction persists or evolves over a longer period.

We collect control variables primarily following Krüger (2015), with data sourced from LSEG.

[2] Company responses (e.g., clarifications) are not consistently observable or immediate, making this date the most reliable benchmark. The use of daily data and dispersion of events over multiple years helps minimize macroeconomic confounding.

Table A.3 reports the definitions of the variables. *Market value* and *current ratio* are log-transformed to mitigate skewness. *Smaller size (bottom 5%)* is a binary indicator equal to 1 if a company's total assets are below 5 billion EUR (approximately equal to the 5% percentile of total assets), and 0 otherwise. For greenwashing (GW) allegations, we distinguish between two dimensions: the *GW severity score*, a continuous measure (0 to 1) based on human assessments of case severity, and *GW materiality*, a binary variable that captures financial materiality using keyword-based text analysis as a proxy.

Table 5.1 reports the descriptive statistics for the 296 company-event observations. The mean CAR is slightly positive over the 11- and 21-day event windows, while the 41-day window yields an average close to zero. Extending the horizon to 61 trading days produces a slightly negative but still small average CAR. Across all windows, the substantial variation in CARs indicates that, on average, greenwashing allegations do not lead to systematic negative stock market reactions for the full sample. The sample companies exhibit a wide range of market values. Based on total assets, in about 7% of the observations companies are classified as *smaller size (bottom 5%)*, as multiple cases per company are included in the sample. *ESG scores* are relatively high on average (0.76), but the sample also includes companies with comparatively low *ESG scores*, ensuring variation in sustainability ratings. Industries are broadly distributed, with consumer-related sectors (*Consumer staples* and *Consumer discretionary*) prominently represented. In terms of event characteristics, compliance-related and operations-related greenwashing allegations are the most common. Companies faced on average 1.8 different greenwashing cases in the five years prior to the event. The average *GW severity score* is 0.66, indicating moderate to high severity cases overall, while financial materiality (*GW materiality*) is identified in approximately 7% of the observations.

Figure 5.1 illustrates the average market reactions to greenwashing allegations by plotting cumulative average abnormal returns (CAAR) over a 40-day event window. The CAARs are disaggregated across the most significant company-, industry-, and event-level characteristics associated with greenwashing allegations. Smaller companies show negative market reactions peaking around day 25, while companies operating within the industries *Industrials*, *Health care*, and *Communication services* exhibit consistently negative trajectories. Compliance-related cases face negative market reactions, particularly within the first 20 days, whereas *GW materiality* does not exhibit systematically more negative CAARs compared to non-material cases.

Table 5.1: Descriptive statistics

Variable	Mean	Std.	Min	Median	Max
Cumulative abnormal returns					
CAR [0,10]	0.007	0.106	−0.202	−0.006	1.225
CAR [0,20]	0.005	0.121	−0.395	0.004	1.323
CAR [0,40]	0.000	0.171	−0.744	−0.008	1.689
CAR [0,60]	−0.007	0.215	−1.039	−0.016	1.689
Company characteristics					
Market value	10.198	1.358	6.036	10.183	13.487
Smaller size (bottom 5%)	0.071	0.257			
ESG score	0.762	0.124	0.269	0.786	0.954
Current ratio	0.175	0.391	−0.838	0.151	1.823
Leverage	0.638	0.156	0.214	0.654	1.124
Industries					
Communication services	0.034	0.181			
Consumer discretionary	0.172	0.378			
Consumer staples	0.182	0.387			
Energy	0.095	0.293			
Health care	0.034	0.181			
Industrials	0.172	0.378			
Materials	0.166	0.372			
Utilities	0.139	0.346			
Financials & Real estate	0.007	0.082			
Greenwashing categories					
Compliance	0.074	0.263			
Investment	0.014	0.116			
Marketing	0.358	0.480			
Operations	0.368	0.483			
Products	0.132	0.339			
Social impact	0.054	0.227			
Event characteristics					
Source general media	0.122	0.327			
Cases last 5 years	1.764	1.650	0.000	1.000	5.000
GW severity score	0.657	0.277	0.063	0.750	1.000
GW materiality	0.071	0.257			

Notes: This table reports summary statistics on the variables for the full sample. The data is based on 296 company-event observations. CAR denotes cumulative abnormal returns, while $[0,10]$, $[0,20]$, $[0,40]$ and $[0,60]$ define the event windows, i.e., 11, 21, 41, and 61 trading days after a greenwashing allegation, respectively. The *GW severity score* determines the severity of greenwashing cases based on human judgment, while *GW materiality* captures financial materiality (see Table A.3 for variable definitions). Min, Median, and Max are omitted for binary variables.

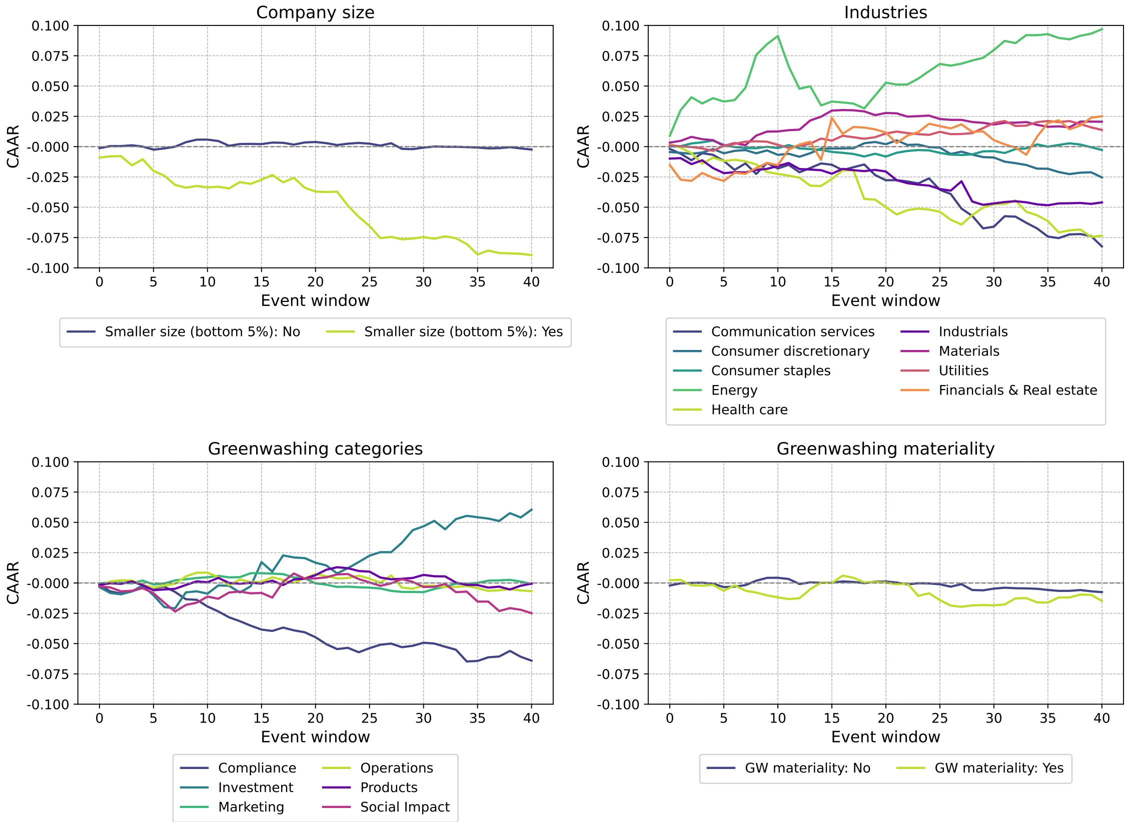


Figure 5.1: Cumulative average abnormal returns (CAAR) over the [0,40] event window by company size, industries, greenwashing categories, and greenwashing materiality, based on 296 greenwashing events. *Smaller size (bottom 5%)* is a binary variable equal to 1 if the company's total assets are below 5 billion EUR, and *GW materiality* captures financial materiality (see Table A.3 for variable definitions).

5.3 Results

To examine heterogeneity in stock market reactions to greenwashing allegations, we estimate OLS regression models using CAR as the dependent variable and including company- and event-specific characteristics as explanatory variables, following the approach of Flammer (2013) and Krüger (2015).

Table 5.2 presents results for the [0,10] event window, while Table 5.3 presents the results for the [0,20] event window. In both tables, Models 1–3 are estimated on the full sample with industry fixed effects, while Models 4–7 focus on the consumer and non-consumer industry subsamples. This distinction allows us to capture industry-level differences, which is relevant because industries with stricter regulatory oversight and greater consumer environmental awareness tend to exhibit different market sensitivities to greenwashing (Bottega et al., 2024; Ruiz-Blanco et al., 2022). Model 1 in each table serves as the baseline, excluding the greenwashing assessment variables. Models 2 and 3 include *GW severity score* and *GW materiality* to assess their incremental effects. Models 3, 5, and 7 also introduce interaction terms between *GW materiality* and *ESG score* to capture conditional effects. Both linear and quadratic terms of *ESG score* are included in all models to account for potential nonlinear relationships.

5.3.1 Impact of company size and visibility

Across both event windows, the binary variable *smaller size (bottom 5%)* is consistently and significantly negatively associated with CARs. Specifically, companies classified as small experience average losses of about 5–6 percentage points relative to larger companies across all full-sample models (Models 1–3). In contrast, the continuous measure *market value* (log market capitalization) shows no significant relationship with CARs, suggesting that stock market reactions are not primarily driven by company visibility or investor attention. Subsample results indicate that the negative association between *smaller size (bottom 5%)* and CARs holds in consumer-facing industries (Table 5.2, Models 4–5).

5.3.2 Event characteristics and moderating factors

Compliance-related allegations are consistently linked to negative market reactions over both event windows, indicating investor sensitivity to cases involving breaches of formal rules or legal standards. In consumer industries, *social impact* cases trigger negative market reactions.

Media visibility also plays a role. Allegations reported by the *general media* are associated with significantly more negative CARs in the full sample. This effect is concentrated in non-consumer industries and in the immediate aftermath of disclosure (Table 5.2, Models 1–3 and 6–7).

The *GW severity score* shows no systematic association with CARs. By contrast, *GW materiality* emerges as a central determinant. It is significantly negatively related to CARs in consumer industries in the [0,10] window (Table 5.2, Models 4–5). In the [0,20] window (Table 5.3), the relation is significantly negative in the full sample (Model 3) and the non-consumer subsample (Model 7). Moreover, the interaction term *GW materiality* $\times$ *ESG score* shows a positive and significant relation to CARs in consumer industries over the [0,10] window, which extends to the full sample in the [0,20] window. This pattern is consistent with a buffering role of ESG reputation. In addition, a U-shaped effect of *ESG score* emerges in non-consumer industries in the [0,20] window, where moderate ESG levels are associated with the mitigation of negative market reactions (Table 5.3, Models 6–7).

Finally, the variable *cases last 5 years* shows a positive association with CARs in consumer industries, with marginal effects in the [0,10] window and slightly stronger effects in the [0,20] window. This suggests that repeated exposure to greenwashing reduces informational surprise and weakens market reactions over time.

Table 5.2: CAR regressions on company and event characteristics – event window [0,10]

	Full sample			Subsample: Industry			
				Consumer		Non-consumer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Company characteristics							
Market value	−0.008	−0.009	−0.008	−0.008	−0.007	−0.013	−0.013
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.013)	(0.013)
Smaller size (bottom 5%)	−0.048**	−0.048**	−0.048**	−0.053**	−0.056**	−0.037	−0.037
	(0.022)	(0.022)	(0.023)	(0.023)	(0.022)	(0.031)	(0.032)
ESG score	0.299	0.256	0.264	−0.124	0.019	0.284	0.285
	(0.297)	(0.329)	(0.332)	(0.503)	(0.489)	(0.446)	(0.440)
ESG score × ESG score	−0.231	−0.200	−0.210	0.093	−0.018	−0.162	−0.162
	(0.212)	(0.237)	(0.241)	(0.321)	(0.311)	(0.368)	(0.367)
Current ratio	0.012	0.011	0.010	0.022*	0.021	0.008	0.008
	(0.017)	(0.017)	(0.017)	(0.013)	(0.013)	(0.025)	(0.026)
Leverage	0.101	0.101	0.099	0.005	−0.003	0.030	0.031
	(0.105)	(0.108)	(0.109)	(0.077)	(0.078)	(0.089)	(0.090)
Greenwashing categories							
Compliance	−0.040**	−0.037**	−0.038**	−0.002	0.001	−0.047*	−0.047*
	(0.018)	(0.018)	(0.018)	(0.014)	(0.014)	(0.025)	(0.025)
Investment	−0.013	−0.012	−0.012	−0.026*	−0.027*	−0.041	−0.041
	(0.017)	(0.016)	(0.016)	(0.014)	(0.014)	(0.039)	(0.039)
Marketing	−0.009	−0.008	−0.008	0.017	0.015	−0.021	−0.021
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.021)	(0.021)
Products	0.001	0.000	0.001	0.006	0.007	−0.022	−0.022
	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.024)	(0.024)
Social impact	−0.011	−0.012	−0.009	−0.061***	−0.059***	−0.036	−0.036
	(0.015)	(0.015)	(0.016)	(0.017)	(0.018)	(0.026)	(0.029)
Event characteristics							
Source general media	−0.026**	−0.027**	−0.028**	−0.006	−0.006	−0.029*	−0.029*
	(0.013)	(0.013)	(0.013)	(0.011)	(0.012)	(0.016)	(0.016)
Cases last 5 years	−0.000	0.000	0.000	0.007*	0.006	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
GW severity score		−0.022	−0.021	0.010	0.016	−0.028	−0.028
		(0.032)	(0.033)	(0.020)	(0.020)	(0.046)	(0.046)
GW materiality		−0.004	−0.092	−0.042**	−0.295***	−0.009	−0.002
		(0.013)	(0.092)	(0.016)	(0.109)	(0.018)	(0.119)
GW materiality × ESG score			0.113		0.311**		−0.008
			(0.115)		(0.130)		(0.158)
Constant	−0.072	−0.042	−0.043	0.099	0.048	0.043	0.043
	(0.099)	(0.110)	(0.111)	(0.160)	(0.153)	(0.192)	(0.188)
Industry	Yes	Yes	Yes	No	No	No	No
N	296	296	296	105	105	191	191
R^2	0.128	0.132	0.132	0.242	0.268	0.054	0.054

Notes: This table presents the results of OLS regressions where the dependent variable is the cumulative abnormal return (CAR), calculated over the [0,10] event window. Models 1–3 use the full sample, while Models 4–5 and 6–7 are estimated separately for consumer and non-consumer industry subsamples, respectively. Consumer industries include Consumer discretionary and Consumer staples. Event-specific variables determine the type of the greenwashing cases, with Operations as the reference category. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5.3: CAR regressions on company and event characteristics – event window [0,20]

	Full sample			Subsample: Industry			
				Consumer		Non-consumer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Company characteristics							
Market value	−0.002	−0.002	−0.001	−0.007	−0.005	−0.004	−0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.015)	(0.015)
Smaller size (bottom 5%)	−0.064*	−0.063*	−0.065*	−0.067	−0.070	−0.026	−0.030
	(0.035)	(0.036)	(0.037)	(0.042)	(0.043)	(0.044)	(0.045)
ESG score	0.632*	0.609	0.634*	−0.144	0.034	1.174***	1.146***
	(0.364)	(0.377)	(0.376)	(0.799)	(0.758)	(0.407)	(0.409)
ESG score × ESG score	−0.507**	−0.492*	−0.528*	0.096	−0.042	−0.874***	−0.866***
	(0.258)	(0.270)	(0.270)	(0.521)	(0.492)	(0.296)	(0.296)
Current ratio	−0.001	−0.001	−0.004	0.028	0.028	0.009	0.004
	(0.021)	(0.021)	(0.021)	(0.024)	(0.024)	(0.032)	(0.032)
Leverage	0.035	0.038	0.032	0.021	0.010	−0.042	−0.046
	(0.096)	(0.096)	(0.096)	(0.112)	(0.116)	(0.069)	(0.070)
Greenwashing categories							
Compliance	−0.062**	−0.063**	−0.064**	−0.057*	−0.053*	−0.049	−0.051
	(0.028)	(0.027)	(0.027)	(0.030)	(0.030)	(0.037)	(0.038)
Investment	0.021	0.022	0.023	−0.034	−0.035	0.015	0.016
	(0.033)	(0.033)	(0.034)	(0.025)	(0.025)	(0.047)	(0.048)
Marketing	−0.012	−0.012	−0.013	0.001	−0.001	−0.019	−0.020
	(0.016)	(0.016)	(0.016)	(0.020)	(0.020)	(0.022)	(0.022)
Products	0.008	0.008	0.008	0.003	0.005	−0.012	−0.012
	(0.016)	(0.016)	(0.016)	(0.022)	(0.022)	(0.022)	(0.022)
Social impact	0.004	0.004	0.013	−0.038**	−0.036**	−0.022	−0.014
	(0.025)	(0.025)	(0.025)	(0.017)	(0.017)	(0.034)	(0.034)
Event characteristics							
Source general media	−0.014	−0.015	−0.017	−0.003	−0.004	−0.023	−0.024
	(0.014)	(0.014)	(0.014)	(0.017)	(0.017)	(0.019)	(0.019)
Cases last 5 years	−0.001	−0.001	−0.001	0.011*	0.010*	−0.003	−0.003
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
GW severity score		−0.009	−0.006	0.007	0.015	−0.005	−0.005
		(0.029)	(0.029)	(0.037)	(0.036)	(0.041)	(0.041)
GW materiality		0.007	−0.283**	−0.008	−0.323	0.002	−0.214*
		(0.022)	(0.119)	(0.038)	(0.284)	(0.026)	(0.126)
GW materiality × ESG score			0.372**		0.388		0.284
			(0.152)		(0.335)		(0.175)
Constant	−0.188	−0.177	−0.181	0.092	0.029	−0.279	−0.265
	(0.131)	(0.134)	(0.133)	(0.275)	(0.260)	(0.174)	(0.175)
Industry	Yes	Yes	Yes	No	No	No	No
N	296	296	296	105	105	191	191
R^2	0.087	0.087	0.094	0.126	0.139	0.055	0.058

Notes: This table presents the results of OLS regressions where the dependent variable is the cumulative abnormal return (CAR), calculated over the [0,20] event window. Models 1–3 use the full sample, while Models 4–5 and 6–7 are estimated separately for consumer and non-consumer industry subsamples, respectively. Consumer industries include Consumer discretionary and Consumer staples. Event-specific variables determine the type of the greenwashing cases, with Operations as the reference category. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.3.3 Robustness checks

We first conduct a placebo test by randomly reassigning event dates within the 2018–2023 sample period, while ensuring valid estimation and event windows for each observation. The resulting CAAR trajectories (Figure A.1) fluctuate around zero or are slightly positive, confirming that our findings are not driven by random market fluctuations or methodological artifacts. Using the placebo dataset, we also re-estimate the same regression models as in our main analysis. The untabulated results show no systematic relationships between company or event characteristics and abnormal returns, further supporting the robustness of our findings.

Second, we examine whether temporal and institutional contexts shape market reactions to greenwashing. Using the [0,10] event window[3], we interact our main explanatory variables with a dummy variable for *EU* headquarters and with a dummy for the *pre-2022* period. The EU interaction models (Table A.5) indicate limited heterogeneity overall, but two patterns emerge. The buffering effect of *ESG scores* in financially material cases on CARs is observed for EU-based companies, particularly in consumer-facing industries. Conversely, the negative effect of *smaller size (bottom 5%)* on CARs is observed among non-EU companies in the non-consumer subsample. The temporal heterogeneity test (Table A.4) shows that the *pre-2022* dummy has a negative and statistically significant coefficient at the 10% level in full-sample models. This indicates that negative market reactions were stronger in earlier years. More importantly, the interaction of *ESG scores* with *pre-2022* yields a positive coefficient and its squared term a negative coefficient, both statistically significant at the 10% level. This suggests that the buffering effect of ESG performance has strengthened after 2021. The effect is particularly visible in the consumer subsample.

Finally, we test the sensitivity of our results to alternative event windows. While our main analysis focuses on [0,10] and [0,20], we extend the horizon to [0,40] and [0,60]. The untabulated results suggest that the significance of the effects on CARs diminishes over longer windows, which supports the interpretation that market reactions to greenwashing allegations are concentrated in the short term.

5.4 Discussion

Our results are consistent with two main theoretical mechanisms: (1) a financial channel rooted in information asymmetry, where investors update expectations about future cash flows in light of greenwashing allegations (Akerlof, 1970; Healy and Palepu, 2001; Krüger, 2015; Walker and Wan, 2012), and (2) an ethical/reputational channel linked to legitimacy theory, where perceived hypocrisy or deception leads to reputational damage and stakeholder sanctioning (Suchman, 1995; Ashforth and Gibbs, 1990; Lyon and Montgomery, 2015; Cho et al., 2012; Flammer, 2013).

[3]The results for the [0,20] window are consistent and do not reveal any noteworthy additional effects.

Evidence for the financial channel is visible in several findings. The consistent negative effect of *smaller size (bottom 5%)* suggests that small companies face greater valuation losses due to limited financial and organizational resources to absorb ESG crises. This aligns with the view that reputational slack buffers larger companies against investor backlash (Flammer, 2013). The absence of a significant effect for the continuous variable, *market value*, indicates that investor attention alone cannot explain market reactions. Rather, the structural vulnerability of small companies is what drives the observed effect.

The negative market reaction to *compliance*-related cases also fits the information asymmetry channel. Investors appear to price in heightened expectations of litigation, fines, or regulatory sanctions when allegations involve legal or regulatory breaches. Similarly, the more negative CARs observed for financially material cases reflect investor concern over ESG misconduct that has direct implications for future cash flows. These patterns align with the view that greenwashing is perceived by investors as a financial risk.

Several results highlight the importance of the legitimacy channel. Negative CARs in consumer-facing industries suggest that reputational risks are significant in highly visible sectors, where stakeholder scrutiny and moral outrage tend to be intense (Jo and Na, 2012; Lyon and Montgomery, 2015). Within these industries, allegations related to *social impact* activities trigger legitimacy shocks. This is consistent with evidence that negative CSR events touching core stakeholder concerns such as human rights violations, labor exploitation, and environmental harm elicit reputational penalties and negative stock market reactions (e.g., Krüger, 2015).

Moreover, we find that companies with higher ESG reputations are partially insulated from legitimacy shocks in financially material cases, as shown by the positive and significant interaction term *GW materiality* $\times$ *ESG score*. This supports the "reputational insurance" hypothesis, where strong ESG performance preserves stakeholder trust during controversies (Godfrey et al., 2009; Flammer, 2013). Furthermore, the buffering effect of *ESG scores* strengthens after 2021, which is consistent with the rising awareness of ESG performance, as well as the increased scrutiny of greenwashing by investors and stakeholders. We also find that the moderating role of *ESG scores* is observed for EU-based companies, particularly those in consumer-facing industries. This reflects the influence of stricter regulatory environments and higher normative expectations.

Finally, the positive effect of *cases last 5 years* in consumer industries may reflect legitimacy dynamics. Repeated allegations reduce informational surprise, gradually desensitizing investors and lowering the shock value of new events.

5.5 Conclusion

This study provides novel evidence on stock market reactions to greenwashing allegations for a comprehensive sample of European companies. While average CARs are close to zero, we find strong heterogeneity: smaller companies and financially material cases are associated with significant negative market reactions. However, ESG reputation can mitigate these reactions under certain conditions. Overall, market reactions to greenwashing appear highly context-dependent, shaped by company characteristics, case features, and the broader institutional environment.

At the same time, our analysis has limitations. Despite a structured rubric and multiple independent raters, our severity variable is based on human coding and may entail some degree of subjectivity. Future work could complement this approach with automated text analysis (e.g., NLP models) and cross-validation using third-party ESG controversy scores. Furthermore, we do not empirically disentangle the theoretical mechanisms underlying investor reactions. Additionally, we do not incorporate company responses to allegations, which can vary considerably in terms of timing and form. Addressing these aspects in future studies would further enhance the understanding of how financial markets respond to greenwashing.

Appendix

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 cases. The framework was initially developed 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 presents the classification framework used to assess the severity of greenwashing cases. Each case is independently rated by four researchers based on standardized criteria. The final *GW severity score* is computed as the average of these four human assessments. The framework was initially developed in Kathan et al. (2025).

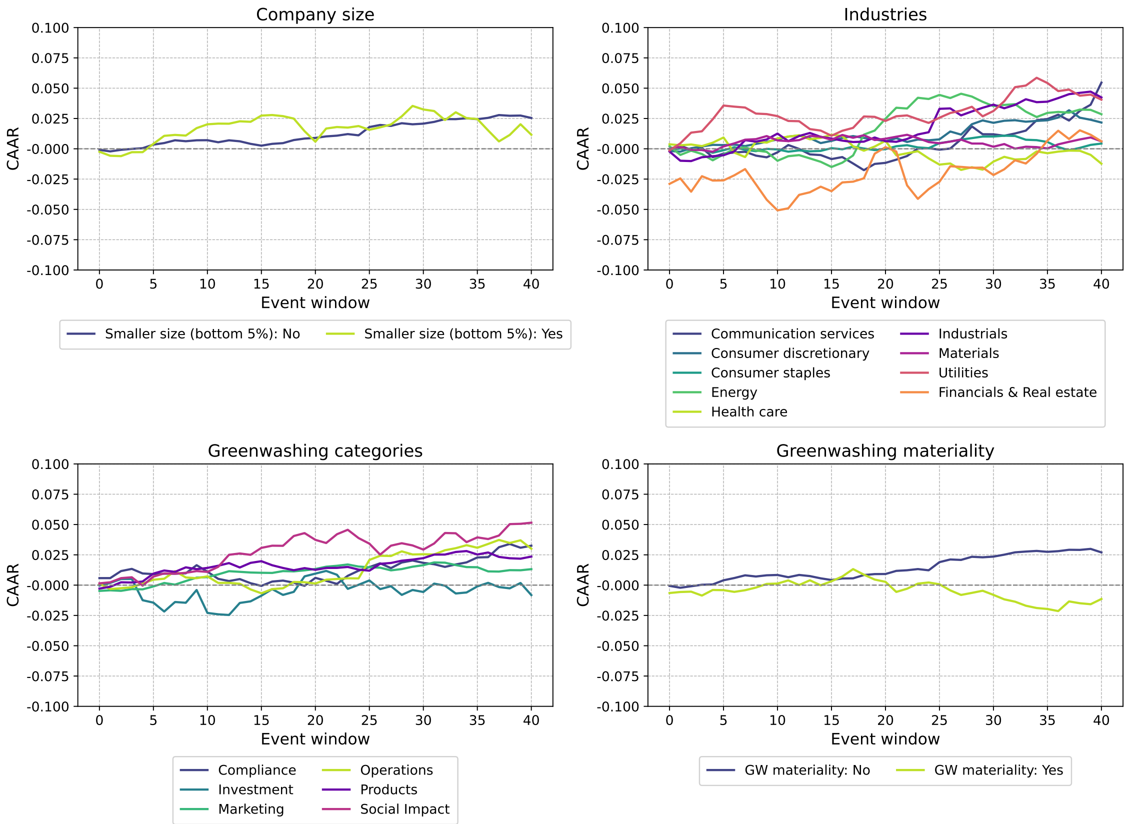


Figure A.1: Placebo test: Cumulative average abnormal returns (CAAR) over the [0,40] event window by company size, industries, greenwashing categories, and greenwashing materiality. For each greenwashing case, the actual disclosure date is replaced with a randomly assigned trading day within the 2018–2023 sample period, ensuring valid estimation and event windows. *Smaller size (bottom 5%)* is a binary variable equal to 1 if the company's total assets are below 5 billion EUR, and *GW materiality* captures financial materiality (see Table A.3 for variable definitions).

Table A.3: Description of variables

Category	Variable	Description
Company characteristics	Market value	Logarithmic market value of a company's stock expressed in millions of EUR, calculated by multiplying the number of shares by the stock price.
	Smaller size (bottom 5%)	Binary variable equal to 1 if the company's total assets are below 5 billion EUR; 0 otherwise.
	ESG score	LSEG's environmental, social and governance score divided by 100.
	Current ratio	Logarithmic liquidity ratio indicating short-term solvency using current assets vs. liabilities.
	Leverage	Total liabilities of the company divided by total assets.
Industries	Consumer discretionary	Companies offering non-essential goods and services like retail, travel, and entertainment.
	Consumer staples	Companies producing essential goods such as food, beverages, and household products.
	Energy	Companies involved in oil, gas, and renewable energy production and distribution.
	Industrials	Companies in manufacturing, aerospace, transportation, and infrastructure.
	Materials	Companies engaged in mining, chemicals, construction materials, and packaging.
	Utilities	Companies providing essential services like electricity, water, and natural gas.
	Others	Companies in the communications services, healthcare, financial, and real estate industries.
Greenwashing categories	Compliance	Greenwashing cases related to legal compliance and regulatory issues, including misleading claims about meeting environmental standards.
	Investment	Greenwashing cases related to financial investments, green bonds, and ESG funds that mislead on their sustainability impact.
	Marketing	Greenwashing cases related to misleading advertisements or branding with false environmental claims.
	Operations	Greenwashing cases related to production processes, supply chains, or business practices.
	Products	Greenwashing cases related to product sustainability, including misleading claims about environmental benefits and material sourcing.
	Social impact	Greenwashing cases related to corporate social responsibility, the effects on local communities, including human rights violations, labor exploitation, and environmental harm.
Event characteristics	Source general media	Binary variable equal to 1 if the greenwashing case was first reported by a general news media outlet (e.g., Reuters, BBC, The Guardian, Handelsblatt); 0 otherwise.
	Cases last 5 years	Count variable measuring the number of distinct years in which the company faced at least one greenwashing allegation in the five years prior to the focal event.
	GW severity score	Mean severity score of individual human assessments of greenwashing cases, measured on a continuous scale from 0 (no greenwashing) to 1 (most severe greenwashing).
	GW materiality	Binary variable equal to 1 if the case description contains keywords related to financial materiality (deceptive, fined, harmful, lawsuit, sued); 0 otherwise.

Notes: This table provides definitions and measurements of variables.

Table A.4: Temporal heterogeneity test for CAR regressions on company and event characteristics – event window [0,10]

	Full sample			Subsample: Industry			
				Consumer		Non-consumer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temporal characteristics							
Pre-2022	−0.322*	−0.318*	−0.299*	−0.411	−0.331	−0.272	−0.274
	(0.167)	(0.170)	(0.172)	(0.373)	(0.384)	(0.214)	(0.216)
Company characteristics							
Smaller size (bottom 5%)	−0.054*	−0.053*	−0.054*	−0.058*	−0.064**	−0.014	−0.014
	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)	(0.062)	(0.062)
Smaller size (bottom 5%) × pre-2022	0.024	0.020	0.020	0.019	0.022	−0.026	−0.025
	(0.042)	(0.042)	(0.042)	(0.047)	(0.046)	(0.074)	(0.074)
ESG score	−0.282	−0.330	−0.259	−0.790	−0.503	−0.240	−0.234
	(0.392)	(0.427)	(0.458)	(0.879)	(0.885)	(0.568)	(0.572)
ESG score × ESG score	0.195	0.227	0.171	0.520	0.292	0.225	0.219
	(0.289)	(0.315)	(0.343)	(0.555)	(0.555)	(0.477)	(0.481)
ESG score × pre-2022	0.952*	0.946*	0.884*	1.036	0.751	0.844	0.843
	(0.501)	(0.510)	(0.521)	(0.976)	(0.996)	(0.691)	(0.695)
ESG score × ESG score × pre-2022	−0.711*	−0.706*	−0.659*	−0.677	−0.447	−0.641	−0.637
	(0.377)	(0.381)	(0.395)	(0.626)	(0.635)	(0.536)	(0.540)
Greenwashing categories							
Compliance	−0.046**	−0.047**	−0.044**	−0.005	0.005	−0.065**	−0.065**
	(0.021)	(0.022)	(0.022)	(0.021)	(0.020)	(0.029)	(0.029)
Compliance × pre-2022	0.023	0.025	0.023	0.007	−0.001	0.052	0.052
	(0.026)	(0.028)	(0.028)	(0.023)	(0.022)	(0.049)	(0.050)
Investment	−0.010	−0.009	−0.009	−0.022	−0.025	−0.034	−0.034
	(0.017)	(0.016)	(0.016)	(0.015)	(0.016)	(0.035)	(0.036)
Marketing	−0.008	−0.007	−0.008	0.018	0.017	−0.019	−0.019
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.021)	(0.021)
Products	−0.001	−0.000	−0.000	0.008	0.007	−0.023	−0.023
	(0.014)	(0.014)	(0.014)	(0.017)	(0.017)	(0.027)	(0.027)
Social impact	−0.009	−0.010	−0.008	−0.058***	−0.059***	−0.035	−0.034
	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)	(0.026)	(0.030)
Event characteristics							
Source general media	−0.027**	−0.028**	−0.028**	−0.005	−0.004	−0.036**	−0.036**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)	(0.018)
Cases last 5 years	−0.004	−0.003	−0.003	0.004	0.004	−0.002	−0.002
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Cases last 5 years × pre-2022	0.005	0.004	0.005	0.007	0.007	0.002	0.002
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.012)	(0.012)
GW severity score		−0.019	−0.017	0.005	0.013	−0.021	−0.021
		(0.031)	(0.032)	(0.021)	(0.022)	(0.044)	(0.044)
GW materiality		0.010	−0.221	−0.041	−0.444***	0.020	−0.291
		(0.019)	(0.181)	(0.030)	(0.166)	(0.030)	(0.433)
GW materiality × pre-2022		−0.020	0.181	0.006	0.405*	−0.041	0.299
		(0.029)	(0.186)	(0.031)	(0.211)	(0.046)	(0.395)
GW materiality × ESG score			0.292		0.498**		0.395
			(0.225)		(0.190)		(0.562)
GW materiality × ESG score × pre-2022			−0.253		−0.493**		−0.435
			(0.240)		(0.247)		(0.520)
Constant	0.119	0.146	0.125	0.365	0.295	0.213	0.212
	(0.124)	(0.139)	(0.144)	(0.343)	(0.351)	(0.236)	(0.237)
Other company characteristic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	No	No	No	No
N	296	296	296	105	105	191	191
R^2	0.138	0.141	0.142	0.261	0.296	0.061	0.061

Notes: This table presents the results of temporal heterogeneity test OLS regressions where the dependent variable is the cumulative abnormal return (CAR), calculated over the [0,10] event window. To analyze temporal heterogeneity, we include interaction terms for our main variables of interest, as well as a binary variable labelled *pre-2022*, which takes the value of 1 if a greenwashing case was observed between 2018 and 2021, and 0 for later events. Models 1–3 use the full sample, while Models 4–5 and 6–7 are estimated separately for consumer and non-consumer industry subsamples, respectively. Consumer industries include Consumer discretionary and Consumer staples. Event-specific variables determine the type of the greenwashing cases, with Operations as the reference category. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.5: Institutional heterogeneity analysis: CAR regressions on company and event characteristics – event window [0,10]

	Full sample			Subsample: Industry			
				Consumer		Non-consumer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Company characteristics							
EU	0.287	0.328	0.341*	0.345	0.173	0.358	0.366
	(0.190)	(0.204)	(0.204)	(0.540)	(0.484)	(0.292)	(0.283)
Smaller size (bottom 5%)	−0.080***	−0.082***	−0.082***	−0.085***	−0.088***	−0.107***	−0.108***
	(0.025)	(0.027)	(0.027)	(0.031)	(0.031)	(0.034)	(0.034)
Smaller size (bottom 5%) × EU	0.058	0.063	0.062	0.040	0.038	0.153***	0.152**
	(0.040)	(0.041)	(0.041)	(0.055)	(0.053)	(0.059)	(0.060)
ESG score	0.564*	0.579*	0.592*	−0.405	−0.418	0.484	0.481
	(0.338)	(0.333)	(0.339)	(0.382)	(0.398)	(0.391)	(0.393)
ESG score × ESG score	−0.412	−0.423*	−0.434*	0.317	0.331	−0.336	−0.334
	(0.255)	(0.251)	(0.258)	(0.266)	(0.279)	(0.318)	(0.321)
ESG score × EU	−0.843	−0.981*	−1.007*	−0.751	−0.227	−1.069	−1.086
	(0.557)	(0.592)	(0.596)	(1.409)	(1.259)	(0.881)	(0.865)
ESG score × ESG score × EU	0.580	0.682	0.693	0.392	0.012	0.763	0.772
	(0.403)	(0.429)	(0.434)	(0.909)	(0.810)	(0.653)	(0.647)
Greenwashing categories							
Compliance	−0.058*	−0.063*	−0.063*	−0.017	−0.016	−0.070	−0.070
	(0.030)	(0.033)	(0.033)	(0.027)	(0.027)	(0.046)	(0.047)
Compliance × EU	0.018	0.028	0.026	0.013	0.022	0.017	0.016
	(0.032)	(0.033)	(0.034)	(0.032)	(0.030)	(0.052)	(0.053)
Investment	−0.015	−0.014	−0.013	−0.029*	−0.033**	−0.048	−0.047
	(0.020)	(0.018)	(0.019)	(0.016)	(0.016)	(0.046)	(0.047)
Marketing	−0.007	−0.006	−0.006	0.014	0.011	−0.017	−0.017
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.020)	(0.020)
Products	−0.000	−0.000	0.000	0.003	0.001	−0.024	−0.024
	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.024)	(0.025)
Social impact	−0.011	−0.012	−0.008	−0.062***	−0.063***	−0.035	−0.033
	(0.015)	(0.015)	(0.016)	(0.014)	(0.013)	(0.025)	(0.028)
Event characteristics							
Source general media	−0.028**	−0.029**	−0.030**	−0.005	−0.001	−0.027	−0.028
	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.018)	(0.018)
Cases last 5 years	−0.001	−0.000	−0.000	0.009*	0.009*	0.007	0.007
	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)	(0.009)	(0.009)
Cases last 5 years × EU	0.000	−0.000	−0.000	−0.003	−0.004	−0.016	−0.016
	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)	(0.013)	(0.013)
GW severity score		−0.029	−0.028	0.010	0.019	−0.043	−0.043
		(0.032)	(0.032)	(0.022)	(0.022)	(0.048)	(0.049)
GW materiality		−0.018	−0.057	−0.062***	0.006	−0.019	−0.011
		(0.024)	(0.144)	(0.020)	(0.084)	(0.026)	(0.156)
GW materiality × EU		0.018	−0.064	0.022	−0.502***	0.021	−0.032
		(0.030)	(0.162)	(0.027)	(0.173)	(0.037)	(0.185)
GW materiality × ESG score			0.050		−0.086		−0.009
			(0.178)		(0.104)		(0.194)
GW materiality × ESG score × EU			0.105		0.639***		0.070
			(0.206)		(0.208)		(0.249)
Constant	−0.151	−0.133	−0.135	0.195	0.217	−0.034	−0.033
	(0.104)	(0.105)	(0.106)	(0.134)	(0.142)	(0.137)	(0.136)
Other company characteristic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	No	No	No	No
N	296	296	296	105	105	191	191
R^2	0.138	0.143	0.145	0.280	0.332	0.085	0.085

Notes: This table presents the results of OLS regressions where the dependent variable is the cumulative abnormal return (CAR), calculated over the [0,10] event window. To analyze institutional heterogeneity, we include interaction terms for our main variables of interest, as well as a binary variable, *EU*, which takes the value of 1 if the company is headquartered in the EU and 0 otherwise. Models 1–3 use the full sample, while Models 4–5 and 6–7 are estimated separately for consumer and non-consumer industry subsamples, respectively. Consumer industries include Consumer discretionary and Consumer staples. Event-specific variables determine the type of the greenwashing cases, with Operations as the reference category. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Chapter 6

Determinants and forecasting of corporate greenwashing behavior

This research project is joint work with Gregor Dorfleitner (University of Regensburg), Manuel C. Kathan (University of Augsburg), and Sebastian Utz (University of Augsburg).

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

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

6.1 Introduction

Growing concerns about corporate greenwashing have intensified among investors and stakeholders. According to the Ernst & Young 2024 Institutional Investor Survey, 85% of investors believe that greenwashing is a greater challenge today than it was five years ago (Ernst & Young, 2024). Greenwashing, defined as the misrepresentation of an organization's environmental performance, creates a situation of asymmetric information, where companies have private knowledge of their true environmental performance until misconduct is revealed. This information asymmetry exposes stakeholders such as investors to hidden financial and reputational risks, as greenwashing undermines corporate legitimacy (Seele and Gatti, 2017) and can lead to costly litigation and reputational damage (Pizzetti et al., 2021; Siano et al., 2017; Torelli et al., 2020; Walker and Wan, 2012).

This study investigates the company-level determinants of greenwashing behavior and develops a forecasting framework to support sustainability-oriented stakeholders in integrating greenwashing risk into their decision-making processes. Stakeholders may include (corporate) customers, employees, suppliers, and investors, all of whom have a strong interest in identifying greenwashing risks in companies as early as possible. For investors in particular, early detection of increased greenwashing risk can enable more effective management of idiosyncratic risk, can reduce the likelihood of share price declines following greenwashing revelations, and can help mitigate reputational damage, especially for ESG-focused mutual funds.

In this paper, we examine the relationship between company characteristics and greenwashing cases. Prior research has identified various company characteristics linked to greenwashing, which can be considered greenwashing determinants. These characteristics are mostly based on theoretical arguments (e.g., Delmas and Burbano, 2011; Lyon and Montgomery, 2015). However, a comprehensive empirical investigation of greenwashing 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. Moreover, we organize these variables into categories that reflect different channels of influence on greenwashing behavior. Both the categories and variables are grounded in economic theory, providing a robust theoretical foundation for our analysis.

Our measure of greenwashing is a score based on hand-collected greenwashing cases. It measures the severity of greenwashing cases observed in a company-year as a discrete variable between 0% (no greenwashing) and 100% (greenwashing) based on human judgment. We analyze the contemporary relationship between company characteristics and greenwashing using a panel data set of STOXX Europe 600 constituents between 2011 and 2023. To capture the significance of greenwashing determinants, we estimate regression models that include year, industry, and country fixed effects.

We find that greenwashing is most prevalent among companies with both poor and excellent ESG ratings. This relationship persists when focusing specifically on environmental scores. Even companies perceived as environmental leaders may engage in greenwashing, posing risks that investors may not fully consider in their decision-making. In addition to sustainability ratings, other key factors associated with greenwashing include company size, the ratio of cash and short-term investments to total assets, the ratio of fixed assets to total assets, and the extent of ESG disclosure. We further conduct a refined analysis using industry dummies instead of industry fixed effects and show that greenwashing is more prevalent in industries that directly interact with consumers. In contrast, the Telecommunications, Real estate, and Technology industries exhibit a lower propensity for greenwashing.

After identifying the determinants of greenwashing, we use machine learning models to forecast greenwashing behavior, drawing on these determinants and environmental corporate misconduct variables that reflect a company's real environmental performance in terms of its environmental standards and practices. Machine learning models excel at handling complex, non-linear relationships and often outperform traditional regression approaches. We optimize the models based on an economic framework that specifically accounts for sustainable-oriented stakeholders, and evaluate the out-of-sample predictive accuracy with performance metrics on a validation dataset. This setting allows us to examine the greenwashing forecasting in a real-world scenario.

With respect to greenwashing forecasting, we show that more costs can be saved by correctly identifying greenwashing cases (i.e., avoiding false negatives) than by reducing false positives, as the assumed consequences of undetected greenwashing—such as reputational damage or stock price crashes—are substantially higher than the opportunity or review costs associated with falsely flagged companies. By optimizing our machine learning models using an economic framework that accounts for this cost imbalance, we show that the larger the gap between these two types of costs, the greater the potential for cost savings. The Recurrent Neural Network (RNN) model delivers the best and most robust out-of-sample forecasting performance, achieving true positive rates between 70% and 100% and true negative rates between 46% and 89% across high and moderate false-negative cost settings. Furthermore, the SHapley Additive exPlanations (SHAP)-based feature importance analysis reveals that the ESG disclosure score, energy management issues, the one-year lagged greenwashing severity score, and company size are the most influential predictors.

Our findings contribute to the academic literature as well as to practical applications. First, we extend the literature on the determinants of (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) by empirically analyzing the relationships between company-specific characteristics and greenwashing behavior. Second, we build on the literature on corporate misconduct forecasting (e.g., Antulov-Fantulin et al., 2021; Liu et al., 2015; Wang et al., 2020) and show how greenwashing risk can be estimated so that sustainability-oriented stakeholders such as investors can incorporate this exposure of a company to greenwashing behavior into their decision-making processes. Finally, policymakers can use our findings to identify greenwashing companies and strengthen regulations to mitigate greenwashing behavior.

The remainder of the paper is structured as follows. Section 6.2 presents the theoretical basis for the investigation of company-specific greenwashing determinants, industry-level variation, and the forecasting of greenwashing. Section 6.3 provides the description of greenwashing cases and the construction of the sample. Section 6.4 shows the results of the empirical analyses of greenwashing determinants, while Section 6.5 covers the analysis of greenwashing forecasting. Section 6.6 discusses the practical implications of the findings and concludes the paper.

6.2 Theoretical foundation

Estimating corporate greenwashing risk is important to a wide range of stakeholders because greenwashing poses significant financial risks related to litigation and reputational damage (Pizzetti et al., 2021; Siano et al., 2017; Torelli et al., 2020; Walker and Wan, 2012). To address different needs, it is valuable to (1) identify the determinants of greenwashing and (2) develop methods to forecast greenwashing behavior. While some stakeholders may focus on assessing contemporary greenwashing risk using empirically identified determinants, others, such as investors, may prioritize forecasting future greenwashing risk using advanced forecasting models. Stakeholders interested in assessing contemporary greenwashing risk may include (corporate) customers, employees, and suppliers. For example, a supplier may seek to reduce greenwashing risk within its supply chain by analyzing company-level determinants as part of its due diligence process. In order to establish a robust theoretical foundation, the subsequent section will address the theory on (1) the determinants of greenwashing behavior, (2) industry-level variation, and (3) the forecasting of greenwashing.

6.2.1 Company-level greenwashing determinants

Companies operate in a complex and evolving environment defined by intensifying pressure and rising expectations from regulators, stakeholders, and broader society to implement sustainable practices. Drawing on multiple theoretical frameworks—institutional theory, legitimacy theory, signaling theory, and stakeholder theory—greenwashing emerges as a strategic response by companies aiming to reconcile these pressures, expectations, and information asymmetries within the growing demands for sustainability (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 like greenwashing offer a lower-effort means of appearing 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). In this framework, companies may engage in greenwashing to protect or restore their legitimacy in the eyes of stakeholders. Environmental performance has become a critical dimension of organizational legitimacy (Cho and Patten, 2007). When a gap exists between a company's real environmental performance and stakeholder expectations, greenwashing functions as a legitimacy management tool, enabling companies to misrepresent or exaggerate their environmental efforts in order to reassure stakeholders and preserve social acceptance amid growing scrutiny and potential controversies (Bansal and Clelland, 2004).

Stakeholder theory highlights that companies must manage the competing interests and expectations of diverse stakeholder groups, including investors, (corporate) customers, employees, suppliers, regulators, and Non-governmental organizations (NGOs) (Freeman, 2010). Greenwashing, thus, operates 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 knowledge about their real environmental performance, while external stakeholders must rely on observable signals to make assessments (Spence, 1973). In this context, greenwashing enables companies to send 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 when meaningful environmental improvements are absent (Lyon and Montgomery, 2015).

Taken together, these perspectives position greenwashing as a deliberate and strategic company behavior 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 significantly across companies, influenced by internal characteristics and contextual factors that affect the costs and benefits of such behavior.

Accordingly, we identify several key categories from the different theoretical perspectives that may affect a company's engagement in greenwashing. A company with a strong *green reputation* often faces intensified scrutiny, which can both pressure them to maintain their image and incentivize defensive exaggeration of environmental efforts, particularly when discrepancies between real and apparent performance are difficult to verify (Delmas and Burbano, 2011; Marquis et al., 2016; Kathan et al., 2025). Similarly, *size and visibility* increase exposure to stakeholders and public attention, thereby raising both the risk of detection and the motivation to engage in symbolic environmental claims to preserve a responsible image (Drempetic et al., 2020; Fiss and Zajac, 2006;

Aouadi and Marsat, 2018). *Capital dependency* further affects greenwashing incentives, as companies reliant on ESG-sensitive investors may overstate sustainability credentials to secure financing, while companies with abundant financial resources might prioritize symbolic actions based on managerial incentives and external expectations (Cheng et al., 2014; Schreck and Raithel, 2018; Freeman, 2010). Financial considerations related to *risk and return* factors may also play a crucial role, as companies facing financial pressure may potentially use greenwashing to signal stability and long-term commitment, while balancing 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). For example, 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 if dominant shareholders seek reputational benefits or access to ESG-sensitive capital (Burkart et al., 1997; Ioannou and Serafeim, 2012). Similarly, foreign operations may expose companies to more stringent or heterogeneous environmental expectations, influencing both behavior and disclosure (Ioannou and Serafeim, 2019). Table 6.1 provides an overview of the theoretical foundations corresponding to each category, specifying the theories that underpin our conceptualization of greenwashing determinants at the company level.

Table 6.1: Theoretical foundations of greenwashing determinants

Category	Related theories	Rationale
Green reputation	legitimacy, stakeholder	Company with strong green reputations face increased stakeholder scrutiny. Greenwashing helps to manage expectations and preserve legitimacy when real 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 influences corporate greenwashing behavior.

The identification of empirical variables within these categories draws from the existing literature, including foundational work on greenwashing drivers (Delmas and Burbano, 2011; Marquis et al., 2016; Zhang, 2022), as well as broader research on corporate environmental and social performance and corporate misconduct (Chen and Chu, 2024; Clarkson et al., 2011; Cormier and Magnan, 1999; 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, thereby structuring the operationalization of our empirical analysis. While the specific variables are not detailed here, they are introduced and discussed in the empirical framework in Section 6.4.1.

6.2.2 Industry-level greenwashing variation

Beyond company-specific characteristics, greenwashing can also vary systematically across industries. These variations stem from differences in regulatory scrutiny, consumer awareness, and the environmental impact of each industry, all of which are related to the theoretical framework discussed in the previous section.

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 stringent regulations and high levels of consumer environmental awareness tend to show more uncovering of greenwashing practices (Ruiz-Blanco et al., 2022). In a similar vein, companies in clean production industries and those based in regions with highly developed green financial instruments tend to exhibit great restraint in greenwashing behaviors (Zhang, 2023a).

Based on these observations, we argue that greenwashing is more prevalent in (1) consumer-related industries and (2) industries with high environmental impact. Companies in consumer-related industries face increased scrutiny, which increases their exposure to accusations and detection of greenwashing. Media outlets and NGOs such as Greenpeace, which prioritize consumer protection, play a crucial role in amplifying the identification of greenwashing as frequent accusers. Additionally, business-to-consumer (B2C) companies often invest in green marketing communications to enhance corporate legitimacy and cultivate perceptions of being environmentally and socially responsible (Nyilasy et al., 2014; Prakash, 2002). Through these efforts, they aim to improve brand attitudes and influence purchasing intentions. However, exaggerating environmental claims carries the risk of being perceived as a greenwasher. Conversely, companies with significant environmental impacts may resort to greenwashing as a cost-effective strategy to manage public perception of their environmental performance. True transformational initiatives tend to be costly, leading short-sighted managers to opt for selective disclosure and exaggerated green claims as an affordable and fast-to-implement alternative.

6.2.3 Greenwashing forecasting

Given the significant financial risks posed by greenwashing, including reputational risk and litigation risk (Pizzetti et al., 2021; Siano et al., 2017; Torelli et al., 2020; Walker and Wan, 2012), sustainability-oriented stakeholders, particularly investors, have a critical interest in accurately forecasting a company's likelihood of engaging in greenwashing.

To build a framework for assessing the economic significance of a greenwashing forecasting method, we consider the expected loss function

$$EL = FN \cdot c + FP \cdot (1-c), \tag{6.1}$$

where FN is the number of false negatives, FP is the number of false positives, and c and $(1-c)$ represent the associated expected costs of a false negative or false positive classification, respectively (note that without loss of generality, we assume both costs to add up 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 $FP = (1-S) \cdot N \cdot (1-q)$. Plugging this into Equation (6.1), we obtain:

$$EL = (1-R) \cdot N \cdot q \cdot c + (1-S) \cdot N \cdot (1-q) \cdot (1-c) \tag{6.2}$$

for our expected loss function to be 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

$$w \cdot R + (1-w) \cdot S \rightarrow \max! \tag{6.3}$$

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.

In general, it can be assumed that $c > 1-c$, reflecting the fact that a false negative, i.e., an undetected case of greenwashing, causes much more damage than a false positive, i.e., a company falsely accused of greenwashing (e.g., Gatti et al., 2019; Walker and Wan, 2012).[2] If we consider an

[1] See the appendix, "Performance metrics of forecasting models," on page 133 for the definitions of recall and specificity.

[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 approach.

investment case, the cost of an undetected greenwashing case could be, for example, a significant loss due to reputational damage or a stock price crash. The lower cost of a false positive may be seen as an opportunity cost—such as the lost diversification contribution or the inability to realize returns from falsely excluded companies—as well as the cost of additional manual review of the case. As an illustration, if $c = 0.99$ and $(1-c) = 0.01$ (i.e., a cost ratio of $99:1$) and $q = 0.05$, then the weight on recall is $w = 0.8390$, while for a cost ratio of $9:1$ the weight is $w = 0.3214$.

Using this framework, we allow the trade-off between recall and specificity to be balanced on the basis of economic considerations from the perspective of a sustainability-oriented stakeholder. Note that a perfect forecast (recall and specificity of 1) is generally not achievable due to the complexity of greenwashing behavior and the inherent situation that not all cases are detected.

6.3 Greenwashing cases and sample construction

We analyze greenwashing cases based on a sample of STOXX Europe 600 constituents from 2011 to 2023. Europe's leadership in global sustainable finance[3] makes it a particularly relevant context for examining corporate greenwashing, especially from the perspective of stakeholders and investors aiming to mitigate associated reputational and financial risks.

Our initial sample comprises 1,031 companies included in the index 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 a total of 1,254 information sources containing greenwashing accusations. Following a structured quality review based on a predefined classification framework (see Table A.1), we excluded 356 sources. In particular, we removed redundant entries, such as those referencing already-documented cases without providing additional information, to ensure the dataset reflects only unique informational content. This approach aims to mitigate the risk of overrepresenting certain companies and inflating the number of accusations.

In the next step, four trained researchers independently assessed the 898 information sources concerning the severity of the greenwashing accusations, as the sources varied in the extent and clarity with which they indicated potential greenwashing. This procedure was implemented to ensure a consistent and balanced classification across heterogeneous sources. To this end, the researchers applied a predefined classification scheme with scores ranging from 0 (no greenwashing) to 1 (greenwashing). For a comprehensive description of the greenwashing severity score categories, along with illustrative examples for each greenwashing category, see Table A.2. We then calculated the mean of the four individual assessments to derive a composite greenwashing severity score for each information source.

We construct a panel dataset with a company-year structure by retaining the highest composite

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

severity score within each company-year in cases where multiple greenwashing accusations existed for the same company in a given year. Furthermore, in cases where a company exhibited repeated greenwashing behavior across multiple years, and where evidence was available for two non-consecutive years with a gap in between, we applied interpolation. Specifically, we added 43 interpolated company-year observations to account for the likely continuation of greenwashing behavior during the undocumented years. This yielded 595 company-year observations with greenwashing cases and 8,864 company-year observations without, represented by a greenwashing severity score of zero. In the final step, we merged this dataset with a set of control variables, which substantially reduced the sample size due to missing observations.[4] The final sample comprises 6,654 company-year observations across 746 unique companies, of which 377 company-years are associated with greenwashing accusations.

Table 6.2 presents descriptive statistics for the final sample. In the Columns of "Full sample," we report the overall industry distribution, which is relatively well-balanced. The largest share of companies comes from the *Industrial* and *Consumer discretionary* industries. The Column "GW obs. (%)" in the Columns of "Subsample of GW cases" indicates the proportion of greenwashing (GW) cases in each industry relative to the total number of greenwashing cases across all industries. Most greenwashing cases occur in the consumer-related industries *Consumer discretionary* (29.4%) and *Consumer staples* (16.2%) as well as in the emission- and resource-intensive industries *Basic materials*, *Industrials*, *Utilities*, and *Energy* (accounting for approximately 50% in total). The highest mean greenwashing severity scores (Column "Mean GW sev. (%)") are observed in the industries *Basic materials* (79.0%), *Energy* (76.8%), and *Utilities* (75.6%). The standard deviation of the mean greenwashing severity scores (Column "Std. GW sev. (%)") tends to decrease as the mean greenwashing severity scores increase, suggesting greater assessment consistency for more severe cases.

Figure 6.1 shows the distribution of greenwashing cases over the sample period from 2011 to 2023. We observe an upward trend in annual greenwashing cases, rising from 14 in 2011 to 72 in 2021, with a slight decline to 68 in 2022, and a renewed increase to 93 in 2023. The increase in cases is particularly noticeable from 2015 onwards. Reasons for the increase in greenwashing behavior may be attributed to (1) increased institutional pressure and (2) intensified scrutiny by the media and NGOs (e.g., Delmas and Burbano, 2011). This may be related to the increased interest in corporate environmental performance, especially since the signing of the Paris Agreement in 2015. In contrast to the number of greenwashing cases, the mean greenwashing severity scores remain similar across years, fluctuating within a range of 60% to 87%.

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

Table 6.2: Descriptive statistics of greenwashing cases across industries

	Full sample		Subsample GW cases			
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	1,182	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	1,515	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**	**6,654**	**377**			

Notes: This table presents summary statistics of greenwashing (GW) cases and GW severity scores, categorized by industry, for companies in the STOXX Europe 600 index from 2011 to 2023. “Full sample” includes all companies in our sample, “Subsample GW cases” includes only the greenwashing company-year observations. Column “N” denotes the number of companies, and column “GW obs. (%)” shows the proportion of greenwashing cases in each industry relative to the total number of greenwashing cases across all industries. Column “Mean GW severity (%)” (“Std. GW severity (%)”) shows the mean (standard deviation) of the GW severity scores in percentage values based on the sample of greenwashing cases.

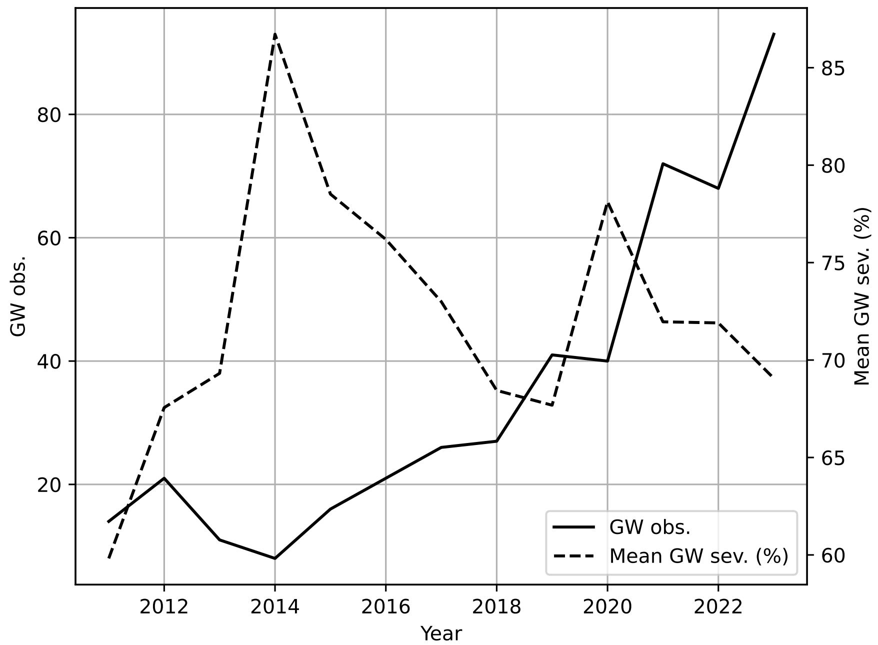


Figure 6.1: Annual development from 2011–2023 of greenwashing cases within our sample (GW obs.) and mean greenwashing severity scores (%) (Mean GW sev.) for the subsample of greenwashing cases.

6.4 Greenwashing determinants

6.4.1 Company-level characteristics

In this section, we present our determinant analysis, using our greenwashing severity score as the dependent variable and various company characteristics as independent variables, alongside year, industry, and country fixed effects. Since the severity score is bounded between 0 and 1 and exhibits a substantial mass at zero (i.e., left-censoring), we apply Tobit model regressions that appropriately account for this censoring and avoid bias from truncation at the lower bound. We also use OLS regressions that do not correct for censoring but allow for straightforward interpretation of marginal effects.[5]

The set of variables included in the models consists of variables unrelated to corporate misconduct to capture only contemporary company characteristics and to avoid problems of multicollinearity with respect to our measure of greenwashing. Thereby, we avoid explaining greenwashing behavior with contemporary company misconduct variables that (partly) measure greenwashing risk. Table A.6 reports the pairwise Pearson correlation coefficients of the used variables in our models. To assess for multicollinearity, we calculate the Variance Inflation Factor (VIF) values based on an OLS regression model. The analysis reveals that there are no significant concerns regarding linear dependencies among the determinant variables. To capture the nonlinear associations of the *ESG score* as well as the *E score*, we include both the quadratic and linear terms in all models. In our regression models, we also account for temporal variation in greenwashing behavior and the limited data availability of certain variables. First, we assume that public awareness and scrutiny of sustainability and greenwashing increased following the adoption of the Paris Agreement in 2015. This heightened interest may have increased pressure on companies to demonstrate stronger environmental performance, which may have contributed to an increase in greenwashing behavior, as well as to improvements in the detection and comparability of such cases over time. Second, the variable *GHG Scope 3 up+down* is only available from 2017 onwards. Since downstream emissions are typically harder to control and more difficult to disclose transparently, they may be an important factor in explaining greenwashing behavior. Accordingly, we include additional regression models based on the subsample starting in 2017.

Table 6.3 presents the main regression results for six different models. We report Tobit regression estimations in Models 1–3 and OLS regression estimations in Models 4–6. In addition, the first two models in each set of estimations use the full sample from 2011–2023 (Models 1, 2, 4, and 5), while the final model in each set uses the subsample from 2017 (Models 3 and 6), as indicated at the top of the table. Models 1 and 4 yield similar results to Models 3 and 6 when re-estimated on the 2017–2023 sample period using the same set of control variables, suggesting that our

[5] As a robustness check, we run equivalent OLS regression models with the binarized greenwashing severity score as the dependent variable, which further supports our findings. The results are reported in Table A.7.

findings are robust to the sample period and not driven by changes in data availability or regulatory developments over time. Moreover, to reduce simultaneity concerns, we re-estimate our main Tobit and OLS models using one-year-lagged explanatory variables. The untabulated results show that coefficient signs, magnitudes, and significance remain essentially unchanged, further supporting the robustness of our findings.

The results show that the squared *ESG score* has a positive coefficient, while the linear *ESG score* has a negative coefficient, with both coefficients being highly statistically significant. This suggests a U-shaped relationship between the greenwashing severity score and the *ESG score*. Specifically, greenwashing behavior tends to be high for companies with both high and low ESG scores. Thus, companies perceived as either brown or green may employ greenwashing as a strategy to manage environmental expectations in response to increased scrutiny. These findings complement the evidence provided by Kathan et al. (2025), who show that ESG scores predominantly capture apparent environmental performance rather than actual environmental impact, and that accusations of greenwashing are particularly prevalent among companies with high ESG scores. While Kathan et al. (2025) focus on the discrepancy between real and apparent environmental performance at the upper end of ESG scores, our results additionally highlight that companies with low ESG scores may also engage in greenwashing behavior, likely as a strategy to improve their reputational standing.

In order to examine the ESG relationship related to environmental factors more granularly, we integrate the quadratic and linear environmental score (*E score*) into Models 2 and 5 instead of the aggregated *ESG score*. Analogous to the *ESG score*, we also find a U-shaped relationship between the greenwashing severity score and the *E score*. This means that companies with a low and a high *E score* show a statistically significant, positive relationship with the greenwashing score. These results suggest that the *E score* may be an important factor associated with the ESG-greenwashing relationship, and companies that are perceived as brown (low *E score*) and green (high *E score*) exhibit higher greenwashing behavior. When we calculate the vertex points of the U-shaped relationships between E(SG) scores and the greenwashing severity score using the estimated coefficients of the quadratic and linear E(SG) variables in the regression models, we find that they are all above 0.5, indicating that low E(SG) rated companies are associated with higher greenwashing risk than high E(SG) rated companies.

In addition to the ESG scores, the coefficient for the *ESG disclosure score* is positive in all models at the 5% (Models 1, 3, 4, and 6) and 10% levels (Models 2 and 5), respectively. Thus, we find evidence that higher ESG-related disclosure is associated with higher greenwashing behavior. The rationale behind this relationship is that ESG-related disclosure, through subjective reporting, increases apparent environmental performance as perceived by stakeholders. Therefore, the results indicate that controlling for company characteristics, the ESG disclosure score appears to have a positive relationship with greenwashing. This may be because increased disclosure may widen the gap between apparent and real environmental performance.

The results for the GHG scope intensity variables are mixed. The coefficients for *GHG scope 1* in Models 3 and 6, which are constructed using the subsample from 2017 onward, are statistically significant positive at the 1% and 5% levels, respectively. These findings suggest that the relationship between *GHG scope 1* and companies' greenwashing behavior has evolved over time. This may be attributed to increased awareness and public scrutiny of GHG emissions following the signing of the Paris Agreement in 2015. Since reducing GHG emissions is costly and time-consuming, scrutinized companies with high levels of *GHG scope 1* may have resorted to greenwashing as a cost-effective marketing strategy to improve their short-term environmental reputation. Interestingly, in the same subsample *GHG scope 2* carries a negative and significant coefficient, which may indicate that companies with heavy indirect emissions face more scrutiny and thus report more cautiously.

In the *size and visibility* category, company *size*, has a positive relationship with observed greenwashing incidents, whereas *analyst coverage* does not contribute to greenwashing. To further explore the insignificant results for *analyst coverage*, we investigate its correlation with company *size*, which is positive (0.39, see Table A.6). When we re-estimate the regression models excluding *size*, the untabulated results show that *analyst coverage* becomes highly statistically significant with a positive coefficient. This suggests that company *size* may subsume part of the explanatory power of *analyst coverage* due to their overlapping visibility dimensions. Together with our findings on the relationship between greenwashing and ESG, these results show that larger (and more visible) companies are more likely to be associated with greenwashing than smaller companies. This provides further evidence of the size effect on ESG scores found in previous studies (Dobrick et al., 2023; Drempetic et al., 2020).

Moreover, the statistically positive coefficient of *cash-to-assets*, which is an indicator of low dependence on the capital markets in the case that higher cash balances were achieved through profits, indicates that financially unconstrained companies suffer from agency costs, as suggested by the free cash flow hypothesis (e.g., Jensen, 1986). According to this theory, managers may prioritize the use of free cash flow for private benefits over substantial environmental improvements. Following this view, greenwashing can serve as a strategy to enhance reputation, while managers may be less concerned about the potential risks associated with exposing greenwashing. This finding aligns with the evidence provided by Zhang (2023a), who shows that financially constrained companies are less likely to engage in greenwashing. Conversely, companies with greater financial flexibility may have more leeway to pursue symbolic ESG strategies that contribute to greenwashing behavior.

None of the variables in the category *risk and return* show consistently statistically significant coefficients across all models. Thus, greenwashing behavior appears to be unrelated to corporate financial performance in contemporary analyses. Finally, we observe a statistically significant coefficient for *capital intensity*, supporting the findings of Marquis et al. (2016) that *capital intensity* is related to environmental damage and selective disclosure as a subcategory of greenwashing.

Table 6.3: 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	6,654	6,654	3,711	6,654	6,654	3,711
	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.

6.4.2 Industry-level greenwashing variation

Besides investigating company-level determinants of greenwashing, we analyze how greenwashing behavior varies across industries, controlling for company characteristics as well as year and country fixed effects. Therefore, we vary Model 1 reported in Table 6.3 by rerunning the model, creating a dummy variable for each industry, and integrating these individually into the model as regressors. In addition, we iteratively exclude one dummy variable that represents the reference category in each model specification. This allows us to examine differences in greenwashing occurrence across industries. The coefficients of the industry dummies are presented in Table 6.4.

In Model 2 of Table 6.4, where *Consumer discretionary* is the reference category, we find negative and statistically significant coefficients in all other industries except for *Basic materials*, *Consumer staples*, *Energy*, and *Utilities*. We find similar results when *Consumer staples* is used as the reference category (Model 3). These findings suggest that, conditional on company-level controls, companies in consumer-facing industries exhibit higher levels of greenwashing compared to companies in most other industries. This supports our hypothesis, which posits that companies in consumer-oriented industries are more prone to greenwashing due to greater exposure to public scrutiny and reputational risk.

In contrast, companies in the *Telecommunications* industry exhibit the lowest relative levels of greenwashing behavior, followed by those in the *Real estate* and *Technology* industries, as shown in Models 8, 9, and 10. This is indicated by positive and statistically significant coefficients relative to other industries. However, it is important to interpret these findings with caution: as reported in Table 6.2, the number of greenwashing observations is extremely limited in the *Real estate* and *Technology* (1 company-year) and *Telecommunications* (3 company-years) industries, which may limit the reliability of these estimates.

Furthermore, as shown in Models 1 and 11, the industries *Basic materials* and *Utilities* which tend to have high environmental externalities, exhibit a higher likelihood of greenwashing compared to *Telecommunications*, *Technology*, *Real estate*, and *Health care*. At the same time, the coefficients of all other industries are insignificant in these models. Moreover, we find mixed results when the industries *Energy* and *Industrials* are set as reference categories (Models 4 and 7). Thus, the available evidence offers limited support for our hypothesis, which posits that greenwashing is more prevalent among industries that have a high degree of environmental impact because the true transformational projects entail greater costs and longer periods of time for these companies compared to other industries.

Overall, the cross-industry results highlight the importance of visibility and stakeholder proximity in explaining greenwashing behavior, above and beyond environmental impact alone.

Table 6.4: 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)
10Telecommunications	−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)
11Utilities	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	6,654	6,654	6,654	6,654	6,654	6,654	6,654	6,654	6,654	6,654	6,654

Notes: This table reports the industry coefficients from the Tobit regression Model 1 reported in Table 6.3, including year and country fixed effects and alternating industry dummies, each of which is set as a reference category. All regressions include a constant. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.5 Greenwashing forecasting

Having identified greenwashing determinants based on the full sample from 2011 to 2023, we now turn to the development of our greenwashing forecasting framework. To ensure a realistic out-of-sample forecasting scenario, we use greenwashing cases from 2023 to validate the predictive performance of our models. In line with common terminology in the forecasting literature, we refer to the explanatory variables as “features,” which correspond to the company characteristics and control variables analyzed in Section 6.4. We also distinguish between “positive” and “negative” observations, where positive observations are defined as cases with a greenwashing severity score greater than 0, while negative observations correspond to cases with a severity score equal to 0.

We employ a suite of machine learning models that capture a wide range of relationships, from simple linear patterns to complex non-linear and sequential dynamics. Previous research has demonstrated the effectiveness of these approaches in forecasting tasks in economics, such as predicting stock prices (Chong et al., 2017; Fischer and Krauss, 2018; Ghosh et al., 2022; Hoseinzade and Haratizadeh, 2019), organizational defaults (Antulov-Fantulin et al., 2021; Jones, 2023), and portfolio optimization (Lopez de Prado, 2018; Ghosh et al., 2022; Yun et al., 2020). Similarly, studies forecasting corporate misconduct and environmental disclosure have successfully applied these techniques (Frost et al., 2023; Liu et al., 2015; Serafeim and Caicedo, 2022; Wang et al., 2020). The appendix “Description of forecasting models” on page 131 provides a description of the considered models.

While the regression models focus only on company characteristics unrelated to corporate misconduct to avoid multicollinearity with the greenwashing measure, the forecasting models take a broader approach. For forecasting purposes, variables related to corporate misconduct are included, as past environmental controversies can serve as valuable predictors of future greenwashing behavior.[6] Specifically, we expand the forecasting dataset to include corporate environmental issue indicators from LSEG and RepRisk, which capture past patterns of misconduct. Furthermore, we integrate the lagged greenwashing severity score to account for temporal dependencies, as past greenwashing behavior is likely to persist and signal increased future greenwashing risk. This expanded set of variables allows the forecasting models to utilize both static company characteristics and dynamic, historically driven risk factors.

The definitions of the corporate misconduct features are provided in Table A.8. Moreover, the descriptive statistics for the complete set of features used in the forecasting models, including determinant and corporate misconduct variables, are shown in Table A.9. Note that the company misconduct variables collected from RepRisk are coded as 1 minus the sum of a company’s incidences within a year for each variable, respectively. This transformation aligns the variables with environmental performance, such that higher values indicate better (i.e., less harmful) behavior.

[6] We include all features, including the corporate misconduct features, in a lagged version in our forecasting models to avoid a look-ahead bias.

To construct the forecasting models, we start with preprocessing steps to obtain a high-quality dataset and to ensure the models' comparability and performance. First, to be able to construct performance metrics for the classification tests, we binarize our target variable with an initial threshold of 0. Second, we encode categorical variables using one-hot encoding. By applying one-hot encoding, categorical features are encoded as binary vectors by mapping the features to integer values and encoding each integer as a binary vector. Third, for appropriate scaling of features, we generate a normal quantile-quantile (Q-Q) plot for each feature, which visualizes the relationship with randomly generated, independent standard normal distributed data. The magnitude of linearity indicates that of all features, the *ESG disclosure score* follows a normal distribution. Therefore, we apply a standard scaling or Z-score normalization to this feature, which is appropriate for normally distributed features and scales features to unit variance with a mean of zero. All other continuous features are scaled using a minimum-maximum normalization. This preprocessing step ensures that all models are trained on normalized data, facilitating fair comparisons (Chawla et al., 2004). Fourth, we create one-year lagged versions for all features to create a forecasting setting and avoid data leakage from future information (look-ahead bias). Fifth, we randomly and stratified split the 2012–2022 dataset into a training dataset (70%) and a test dataset (30%), thereby ensuring an equal distribution between positive and negative classes in both datasets.[7] Sixth, we define the 2023 greenwashing cases as our validation set, which we use to validate our forecasting models on unseen data. This setting enables us to examine the forecasting of greenwashing in a real-world scenario.

Using the preprocessed data set, 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 the models, we choose the classification threshold where our economically motivated target function (TF), defined in Equation 6.3 and developed for sustainability-oriented stakeholders, is maximized on the test set. The selected threshold is then used to compute performance metrics on the validation set and compared to a naive forecast that takes the greenwashing severity score of 2022 as the forecasting value for 2023. Additionally, we include a no-information benchmark that generates "positive" or "negative" predictions 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. We run the models in different specifications for optimization purposes. We employ models with k-fold cross-validation (k-fold CV) to improve forecasting accuracy and generalization. In addition, we vary optimizers and loss functions for neural network models and apply commonly used methods to deal with our unbalanced data with few greenwashing observations and many non-greenwashing observations. These include 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). In addition, we run all models with default parameters as well as with hyperparameter-tuned (HT) specifications.

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

The training set contains a total of 3,864 observations, of which 235 are positive class observations, and 3,629 are negative class observations. The test data set consists of 1,656 observations, including 101 from the positive class and 1,555 from the negative class. Thus, in both data sets, 6% of all company-year observations contain greenwashing severity scores greater than 0. The validation set for the subsample of 2023 contains 386 total observations, with 43 observations classified as positive, and 343 observations classified as negative.

Following the assumption that, for a sustainability-oriented stakeholder, the cost of a false negative is significantly higher than the cost of a false positive in a real-world forecasting scenario, we optimize the classification threshold of our models by setting both cost parameters $c = 0.99$ and $c = 0.90$ in our TF. This implies a cost ratio of 99 : 1 and 9 : 1, respectively, and demonstrates representative specifications. 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 such as ours because greenwashing cases are rare. To address this issue, we adapt our imbalance handling strategy to each cost setting. For example, methods such as ROSE and Up-sampling are superior when c is high, such as 0.99, because these methods are known to improve sensitivity. For lower c values (i.e., 0.90), we allow the models to maintain a more balanced trade-off. According to this economic cost function, strategies that handle imbalance more moderately, such as Up-sampling and ClassWeights, tend to perform better at balancing recall and specificity. In these cases, Up-sampling remains effective, but for different reasons: it avoids excessively favoring the minority class and helps maintain overall model balance.

Table 6.5 presents the forecasting performance of all models on the test set. Panel A shows the results of models with optimized classification thresholds using a high cost weight of $c = 0.99$ in the target function (TF), while Panel B corresponds to a moderate cost setting of $c = 0.90$, and Panel C presents results for a low-cost scenario with $c = 0.50$. The models shown in each panel are the ones that achieve the highest TF values given the respective cost specifications. Details on model configurations, including imbalance handling strategies, tuning approach, and holdout treatment, are provided 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 $c = 0.50$. This performance gap is statistically significant for all models, as indicated by the paired t-test results (*P-diff* column). The improvements are particularly pronounced in recall and specificity, highlighting the models' ability to detect greenwashing cases while maintaining a low false positive rate.

Logistic Regression consistently performs 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. However, the best-performing model at each cost level varies: at $c = 0.99$ and $c = 0.90$, the Recurrent Neural Network (RNN) achieves the highest TF values (0.929 and 0.869, respectively), while at $c = 0.50$, Random Forest performs best with a TF of 0.952.

In the high-cost setting ($c = 0.99$), the RNN achieves a recall of 0.98 and specificity of 0.58, i.e., it correctly identifies 98% of all greenwashing cases (i.e., greenwashing severity score > 0) and 58% of non-greenwashing cases (i.e., greenwashing severity score $= 0$). At $c = 0.90$, it maintains strong performance with a recall of 0.79 and specificity of 0.92. These results demonstrate that the model can prioritize greenwashing detection according to the cost function. Imbalance handling strategies such as Up-sampling and ROSE are particularly beneficial for neural networks, substantially boosting recall. The impact of other models is more variable and depends on their interaction with the model architecture and cost setting.

To validate the out-of-sample predictive ability of the models, we re-run them using the 2023 validation set. Therefore, we use the models that have the highest TF fit on the test set. In addition, for benchmarking purposes, we consider a naive forecasting model that takes the greenwashing severity score of 2022 as the forecast for 2023. The performance metrics are shown in Table 6.6.

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, with $c = 0.99$, the no-information benchmark achieves a TF of only 0.12, while the naive forecast reaches 0.61. In comparison, all machine learning models exceed 0.87, with the RNN achieving the highest TF of 0.93. This corresponds to a cost reduction of approximately 92% relative to the no-information benchmark and over 82% compared to the naive forecast, as measured by the TF complement ($1 - \text{TF}$).

In Panel B ($c = 0.90$), the no-information benchmark reaches a TF score of 0.58, while the naive forecast reaches 0.80. The best model, Random Forest, achieves a TF score of 0.85. In Panel C ($c = 0.50$), the naive forecast achieves a TF of 0.92, marginally outperforming the no-information benchmark at 0.87, yet all learning models perform better, with the RNN again providing the highest TF of 0.94.

The naive forecast maintains strong specificity (up to 0.95) but moderate recall (0.56), reflecting a bias toward predicting the majority class. In contrast, machine learning models achieve much higher recall, up to 1.00 in several cases at $c = 0.99$. This is particularly valuable when the cost of false negatives is high. This demonstrates the practical advantage of data-driven classification methods—both traditional and learning-based—in capturing greenwashing behavior, especially when tailored to stakeholder-specific cost considerations.

Panel A confirms that the RNN is most effective when the cost of missing a greenwashing case is high ($c = 0.99$), reaching a recall of 1.00 and specificity of 0.46. In Panel B, Random Forest performs best under moderate cost sensitivity ($c = 0.90$), with a recall of 0.77 and specificity of 0.90. In Panel C ($c = 0.50$), where false positives and negatives are weighted more equally, the RNN again delivers the strongest performance. These findings underscore the economic importance of selecting a model that aligns with stakeholder cost preferences and sustainability priorities.

Table 6.5: 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. For each panel (cost = 0.99, 0.90, 0.50), the best-performing model is highlighted in bold.

Table 6.6: 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 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. For each panel (cost = 0.99, 0.90, 0.50), the best-performing model is highlighted in bold.

As a robustness check, we re-estimate the models without including the lagged greenwashing severity score. The untabulated results show that model performance remains stable and only slightly declines in terms of target function values. Importantly, even without the lagged score, our models continue to outperform the benchmark classifiers across all cost-sensitive evaluation scenarios. This confirms that the predictive power of our approach is not solely driven by past greenwashing behavior but also captures relevant company-level characteristics and performance indicators.

Finally, we analyze which features contribute most to the predictions of the RNN model under the high-cost setting ($c = 0.99$). To this end, we generate a SHAP (SHapley Additive exPlanations) summary plot based on the validation set, as shown in Figure 6.2. The plot displays both the magnitude and direction of each feature's impact on the model output, allowing for a detailed interpretation of feature relevance and behavior. To improve interpretability, all dummy variables, including year, industry, and country indicators, are excluded from the SHAP illustration.

The top predictor is the *ESG disclosure score*, followed by *energy management issues*, the one-year lagged *greenwashing severity score*, *size*, *analyst coverage*, and *environmental controversies*. This ordering implies that large companies with extensive ESG disclosures, notable energy management challenges, and prior greenwashing behavior are most influential in the model's greenwashing predictions. Additionally, variables identified as greenwashing determinants in Section 6.4 also exhibit substantial SHAP contributions, with *ESG disclosure score*, *size*, and *ESG score* emerging as the most relevant among that group.

6.6 Concluding remarks and discussion

This study investigates corporate greenwashing behavior by (1) identifying company-level determinants of greenwashing, (2) examining how greenwashing varies across industries, and (3) forecasting greenwashing risk using machine learning models within an economic-theoretical framework. The results contribute to both academic research and practical applications.

From an academic perspective, this study provides a comprehensive empirical analysis of company characteristics associated with greenwashing behavior. It extends the literature on corporate misconduct by integrating greenwashing as a critical factor of organizational behavior and by demonstrating that greenwashing can be forecasted with high accuracy. Specifically, the results show that companies with low and high overall ESG scores, as well as environmentally "brown" (low E score) and "green" (high E score) companies, 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 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 initial literature evidence that machine learning models

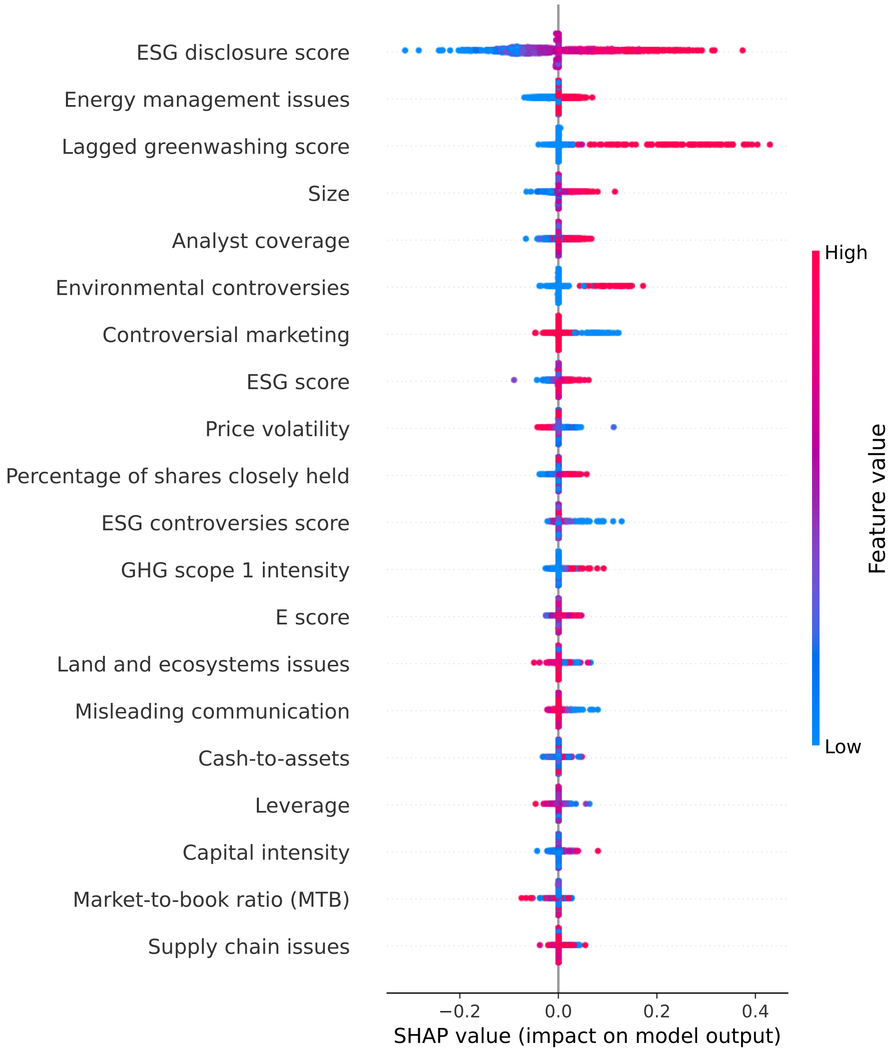


Figure 6.2: Feature importance for the RNN model at $c = 0.99$. This figure shows the SHAP values for the best-performing RNN model that was trained in a high-cost setting. Each point represents a SHAP value for one observation and one feature. It shows the direction and magnitude of the feature's contribution 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). To enhance interpretability, all dummy variables (e.g., year, industry, and country dummies) are excluded from the illustration.

exhibit high accuracy in forecasting corporate misconduct behavior (Antulov-Fantulin et al., 2021; Liu et al., 2015; Wang et al., 2020). Specifically, we achieve similar levels of recall-specificity pairs compared to 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.

Beyond academic insights, the study has significant practical implications. Predictive results show that several machine learning models, particularly sequential neural networks such as RNNs, achieve strong performance in forecasting future greenwashing behavior and outperform simple benchmarks such as a naive forecast that extrapolates recent greenwashing incidents into the future in predicting future greenwashing behavior or a stratified no-information benchmark. At the same time, we observe that logistic regression—despite its simplicity and interpretability—consistently delivers competitive results and in some scenarios comes close to or even exceeds the performance of more complex models. This highlights that both traditional and modern forecasting approaches can add value, depending on the cost preferences and transparency requirements of the stakeholder. Feature importance analyses reveal that the most influential drivers of predictive performance are ESG disclosure score, energy management issues, recent greenwashing behavior, and company size. The results highlight that when the cost of false negatives (i.e., failing to detect greenwashing) is high, optimized machine learning models can generate significant 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.

The proposed economic forecasting framework allows investors to tailor model weightings based on their specific cost structure, adjusting forecasts to reflect the severity of false negatives. For example, an ESG-branded mutual fund manager may face high false-negative costs due to potential capital outflows and reputational damage if a greenwashing constituent company is later discovered. In contrast, impact investors such as retailers or private equity investors may still face moderately high false negative costs due to reputational concerns and alignment with sustainability goals. However, capital providers such as banks and pension funds may face lower false negative costs, as their exposure to reputational or stakeholder-driven sustainability risks is often less direct and immediate. Thus, the choice of the optimal machine learning model and specification depends on the cost of false negatives and can be selected using historical data. Once identified, this model can be applied to forecast greenwashing behavior, tailored to specific stakeholder needs.

On a broader level, the findings provide valuable insights for stakeholders such as (corporate) customers, employees, suppliers, NGOs, and media organizations by identifying contemporary determinants that can serve as red flags in monitoring companies with elevated greenwashing risk. These determinants include large companies with extreme ESG (disclosure) scores, companies with large cash reserves, and high capital intensity. This knowledge can allow for more targeted scrutiny and can influence stakeholder decisions, such as consumer purchasing behavior. A key advantage of determinant analysis in this context is its low data requirements, which makes it fast and practical to use.

Finally, the study provides actionable insights for policymakers seeking to refine regulatory frameworks aimed at curbing greenwashing. Strengthening environmental oversight and improving corporate governance have been shown to reduce greenwashing tendencies (Driss et al., 2024; Zhang et al., 2024; Zhang, 2023a). Policymakers can use these results both 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 has the potential to inform a range of stakeholders, from investors and regulators to civil society, and ultimately support more transparent and sustainable corporate behavior.

Appendix

Greenwashing sample

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

We provide concrete examples for each greenwashing category in the following. In the case of *Light greenwashing*, our researchers rated an instance 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," recent data from a study within the information source revealed that these products have an increased water footprint compared to 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 delivering on its environmental claims. Therefore, the case exemplifies light greenwashing, with a mean greenwashing severity score of 0.25 based on independent assessments by four researchers, reflecting minor sustainability claims accompanied by shortcomings in real environmental performance.

A case reflecting *Medium greenwashing* involves Barclays' $10 billion sustainability-linked revolving credit facility provided to Shell. Barclays, a British multinational universal bank headquartered in London, operates across retail banking, credit cards, corporate and investment banking, and wealth management. It 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. Shell, officially known as Shell plc, is a British multinational oil and gas company and one of the largest energy companies in the world. While it has made public commitments to reduce its carbon footprint, Shell 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. Reflecting the general nature of the accusations and the lack of clarity around how Shell is utilizing the sustainability-linked revolving credit facility, our researchers rated this case with an average 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, 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. While Glencore asserts that it is committed to reducing its carbon footprint, its lobbying behavior suggests a reluctance to support binding regulatory measures necessary to achieve such 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 in order 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.

In case of a company engaging in *Greenwashing*, our researchers rated Volkswagen as an example. Volkswagen, a major German automotive manufacturer known for producing a wide range of passenger vehicles, 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.

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	1,096
	GHG scope 2	1,096
	GHG scope 3 up	1,096
	GHG scope 3 up+down	6,069
Size and visibility	Size	153
	Analyst coverage	443
Capital dependency	Cash-to-assets	1,406
	Leverage	206
	Capex-to-assets	734
Risk & return	Return-on-assets	256
	Earnings variability	239
	Price volatility	206
	Market-to-book ratio	320
Others	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. Note that the variable *GHG scope 3 up+down* is only available from 2017 to 2023.

Additional tables

Table A.4: Variable definitions, measures, and data sources

Category	Variable	Measurement	Source
Dependent variable	Greenwashing severity score	Mean severity of individual greenwashing case 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
Others	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 A.5: Descriptive statistics of determinant variables

Category	Variable	Obs.	Mean	Std.	Min	Median	Max
Dependent variable	Greenwashing severity score	6,654	0.04	0.18	0.00	0.00	1.00
Green reputation	ESG score	6,654	0.62	0.18	0.02	0.64	0.96
	E score	6,654	0.60	0.24	0.00	0.64	0.99
	ESG disclosure score	6,654	0.49	0.13	0.03	0.49	0.84
	GHG scope 1	6,654	1.61	5.68	0.00	0.13	80.95
	GHG scope 2	6,654	0.46	1.09	0.00	0.15	19.57
	GHG scope 3 up	6,654	1.81	1.97	0.15	1.19	22.75
	GHG scope 3 up+down	3,711	10.50	34.51	0.15	2.64	826.52
Size and visibility	Size	6,654	14,032.37	31,365.01	26.40	4,246.46	487,275.10
	Analyst coverage	6,654	17.05	8.00	0.00	17.00	51.00
Capital dependency	Cash-to-assets	6,654	0.12	0.11	0.00	0.09	0.99
	Leverage	6,654	26.05	16.01	0.00	25.30	154.04
	Capex-to-assets	6,654	4.20	4.62	0.00	3.22	210.84
Risk and return	Return-on-assets	6,654	6.83	12.40	−70.08	5.65	269.11
	Earnings variability	6,654	42.80	88.14	0.18	27.15	3,871.60
	Price volatility	6,654	24.19	7.77	8.52	22.95	64.46
	Market-to-book ratio	6,654	3.96	18.83	−0.92	2.28	1,070.46
Other factors	Capital intensity	6,654	0.29	0.25	0.00	0.22	0.99
	Owner concentration	6,654	23.92	23.30	0.00	16.67	99.00
	Foreign sales	6,654	60.99	36.47	0.00	71.23	421.10

Notes: This table reports summary statistics on the determinant variables for the full sample before data manipulation steps such as log-transforming and winsorizing.

Table A.6: 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 based on an OLS regression model, is 1.78. The highest VIF value is 3.73.

Table A.7: 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	6,654	6,654	3,711
	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 A.8: 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 case 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 reflect a company's real environmental performance and are used as features alongside the determinant variables in the forecasting models.

Table A.9: Descriptive statistics for features

Category	Feature	Obs.	Mean	Std.	Min	Median	Max
Determinant	ESG score	5,906	0.62	0.18	0.02	0.64	0.96
Determinant	E score	5,906	0.60	0.24	0.00	0.64	0.99
Determinant	ESG disclosure score	5,906	0.49	0.13	0.03	0.49	0.84
Determinant	GHG scope 1	5,906	1.66	5.74	0.00	0.13	80.95
Determinant	GHG scope 2	5,906	0.48	1.10	0.00	0.16	19.57
Determinant	GHG scope 3 up	5,906	1.85	1.97	0.15	1.25	21.95
Determinant	Size	5,906	8.42	1.53	3.27	8.37	13.10
Determinant	Analyst coverage	5,906	17.25	8.00	0.00	17.00	51.00
Determinant	Cash-to-assets	5,906	0.12	0.11	0.00	0.09	0.99
Determinant	Leverage	5,906	25.91	16.48	0.00	25.08	230.61
Determinant	Capex-to-assets	5,906	4.21	3.83	0.00	3.24	53.12
Determinant	Return-on-assets	5,906	6.93	12.52	−70.08	5.70	269.11
Determinant	Earnings variability	5,906	41.37	83.82	0.17	26.51	3,880.72
Determinant	Price volatility	5,906	24.08	7.74	8.52	22.78	64.46
Determinant	Market-to-book ratio	5,906	3.89	18.32	−0.94	2.30	1,070.46
Determinant	Capital intensity	5,906	0.29	0.25	0.00	0.22	0.99
Determinant	Owner concentration	5,906	23.85	23.09	0.00	16.55	97.48
Determinant	Foreign sales	5,906	61.24	36.20	0.00	71.21	421.10
Misconduct	Controversial marketing	5,906	0.97	0.16	0.00	1.00	1.00
Misconduct	Energy management issues	5,906	0.56	0.50	−1.00	1.00	1.00
Misconduct	Environmental controversies	5,906	0.03	0.16	0.00	0.00	1.00
Misconduct	ESG controversies score	5,906	52.49	8.86	0.00	53.78	55.71
Misconduct	Greenwashing severity score	5,906	0.04	0.18	0.00	0.00	1.00
Misconduct	Land and ecosystems issues	5,906	−0.34	3.55	−51.00	0.00	1.00
Misconduct	Misleading communication	5,906	−0.05	2.30	−44.00	0.00	1.00
Misconduct	Overuse and wasting	5,906	0.37	0.99	−23.00	0.00	1.00
Misconduct	Product issues on health and environment	5,906	−0.27	5.08	−125.00	0.00	1.00
Misconduct	Supply chain issues	5,906	−0.44	4.26	−89.00	0.00	1.00
Dummy	Year	5,906					
Dummy	Industry	5,906					
Dummy	Country	5,906					

Notes: This table provides the descriptive statistics of 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 sum of a company's incidences within a year for each variable, respectively, to capture a company's environmental performance.

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 (HT) 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.

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

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

Chapter 7

ESG and financial performance in public and private companies: Evidence from Brazil

This research project is joint work with Gregor Dorfleitner (University of Regensburg) and Heiko Spitzeck (Fundação Dom Cabral).

Abstract Using detailed, questionnaire-based ESG data for 156 public and 317 private Brazilian companies from 2017 to 2023, we examine the relationship between ownership structure, financial performance, and ESG performance. Panel regressions and propensity score matching reveal that public companies have lower ESG scores than private companies due to weaker governance. The gap is most pronounced among large companies with low leverage, high liquidity, and low capital intensity. Transitions from public to private ownership are associated with improved ESG scores. Prior profitability is positively linked to ESG scores, particularly in brown industries and among companies with weaker financial constraints, consistent with financial slack theory. Family ownership is positively associated with profitability, especially in private companies. A difference-in-differences design around an ESG disclosure regulation shows that ESG scores of public companies significantly increased after implementation. Our findings highlight the pivotal roles of ownership structure, financial slack, and disclosure mandates in shaping ESG performance in emerging markets.

Keywords ESG scores, Corporate ownership, Private companies, Financial performance, Disclosure regulation, Corporate governance, Emerging markets

7.1 Introduction

Empirical environmental, social, governance (ESG) studies tend to rely on large, publicly traded companies, reflecting the greater accessibility of ratings and disclosures for these companies (Drempetic et al., 2020). Yet small and medium enterprises (SMEs), overwhelmingly privately held and often family-owned, account for more than 95% of registered companies worldwide, over half of jobs, and more than one-third of GDP in many emerging markets (Alibhai et al., 2017). Despite this centrality, the ESG behavior of private companies remains under-examined, even though public and private companies have been shown to differ materially in their emissions (Shive and Forster, 2020). Meanwhile, Brazil offers a particularly compelling setting to study ESG behavior for at least three reasons. First, Brazil is one of the world's largest economies and the largest in Latin America, while also ranking among the top greenhouse gas emitters globally (International Monetary Fund, 2025; International Energy Agency, 2023). As the region's top greenhouse gas (GHG) emitter, the company's sustainability practices have outsized implications for climate change, regulation, and financial markets. Second, Brazilian capital markets are marked by a duality of formal regulation for public companies and limited transparency requirements for private companies, allowing for sharp ownership-based comparisons (La Porta et al., 1999; Leal and Carvalhal-da-Silva, 2005). Third, the 2021 introduction of CVM Resolution No. 59, i.e., a mandatory ESG disclosure requirement for listed companies, creates a rare opportunity to observe how regulation affects ESG behavior in an emerging market context. To address these gaps, we assemble a novel dataset of 473 Brazilian companies (317 private and 156 public) spanning 2017 through 2023. Companies are drawn from a large business journal survey and constitute the top-revenue companies in Brazil with balanced coverage across industries and company sizes.

Our methodological approach is fourfold. First, we construct E, S, and G pillar scores using survey subcomponents aligned to LSEG methodology, followed by normalization within each year. We then aggregate the three pillar scores to form a composite ESG score, which is normalized again. Second, we estimate panel regressions of ESG scores on ownership, performance, and company-level control variables while also considering subsample analyses to capture relevant between-company variation. To validate the robustness of the observed ownership–ESG relationship, we additionally apply a propensity score matching (PSM) approach that compares public and private companies with similar observable characteristics. Third, we analyze profitability proxied by return on assets (ROA) as a function of ESG to assess whether ESG enhances financial performance and whether this varies by ownership. Fourth, to identify the causal effect of regulatory pressure, we exploit Brazil's 2021 CVM 59 mandate (which compels all listed companies to disclose ESG data) via a difference-in-differences specification.

Our results reveal four main findings. First, public companies exhibit significantly lower ESG scores than private companies, a gap related heavily to underperformance in the governance dimension. This gap is most pronounced among large companies with low leverage, high liquidity, and low capital intensity. Propensity score matching confirms that even after controlling for observable company characteristics, public companies consistently score lower on ESG. Second, lagged ROA is positively associated with current ESG scores, consistent with the financial slack theory, while we find no evidence that ESG performance improves future profitability. The profitability–ESG link is particularly strong among companies in brown industries with low asset intensity, suggesting that financially constrained, high-impact sectors are especially responsive to performance-driven ESG investments. Third, the CVM 59 disclosure mandate led to a significant 0.05-point increase in ESG scores among listed companies relative to private peers (approximately one-quarter of a standard deviation) with no evidence of pre-2021 divergence in ESG trends. Fourth, among private companies, family ownership is associated with significantly higher financial returns, indicating that concentrated control may facilitate strategic alignment between long-term profitability and stakeholder priorities. Together, these findings highlight the central role of ownership structure and regulatory enforcement in shaping company-level ESG performance and their financial implications.

This paper contributes to the growing literature on ESG and corporate behavior in several ways. First, to the best of our knowledge, we are the first to conduct a large-scale panel data study at the intersection of ESG performance, financial performance, and corporate ownership, using a unique dataset covering over 470 public and private companies in Brazil from 2017 to 2023. Second, we provide rare empirical evidence on ESG behavior among private companies, an often-overlooked segment in ESG research despite its economic importance. Third, by leveraging the staggered implementation of a mandatory ESG disclosure rule for public companies, we offer causal insights into how regulatory enforcement can improve sustainability outcomes. Finally, we add to the debate on the direction of the ESG–performance link by showing that financial performance precedes ESG improvements, but not the other way around, highlighting the importance of financial slack in enabling sustainability investments.

The remainder of the paper proceeds as follows. Section 7.2 reviews the literature on ESG performance, ownership heterogeneity, and disclosure mandates, and develops our four hypotheses. Section 7.3 describes the composition of the sample and data, as well as the procedures for constructing and calibrating the ESG scores. Section 7.4 presents the empirical findings on ESG-ownership differences, the ESG–ROA nexus, and the causal impact of mandated ESG disclosure. Section 7.5 offers concluding remarks and discussion, highlighting implications for policymakers and investors.

7.2 Literature review, theoretical foundation, and hypotheses development

The relationship between ESG scores and corporate financial performance (CFP) has been extensively examined yet remains contentious (e.g., Dixon-Fowler et al., 2013; Eccles et al., 2014;

Pedersen et al., 2021; Avramov et al., 2022; Pástor et al., 2022; Friede et al., 2015). A recent review of the ESG–corporate finance literature highlights that companies' ESG profiles are systematically shaped by their market environment, leadership, and ownership characteristics, while also being closely linked to company risk, performance, and value (Gillan et al., 2021). At the same time, the review emphasizes that competing hypotheses and conflicting empirical results remain unresolved, underscoring the need for further research. Meta-analyses show that the ESG–performance link varies by context: industry, region, and whether a market is developed or emerging (e.g., Friede et al., 2015). However, existing studies overwhelmingly focus on publicly listed companies in North America and Europe, leaving the role of ownership structure (public versus private) an underexplored dimension. This gap motivates our analysis of how different ownership structures shape ESG performance in Brazil, a large emerging market.

Ownership matters because corporate owners influence managerial appointments and strategic investment decisions (Trostel and Nichols, 1982; Capron and Shen, 2007; Asker et al., 2013; Gilje and Taillard, 2016). In public companies, institutional investors and activist shareholders can exert pressure on innovation and competitive strategy (David et al., 2001; Hoskisson et al., 2002; Connelly et al., 2009). Over recent decades, public-company governance has shifted further toward concentrated institutional ownership and common-ownership concerns (Gillan and Starks, 2000; Goranova and Ryan, 2014; Kahan and Rock, 2007; Azar et al., 2018; Backus et al., 2021; Dennis et al., 2022). Meanwhile, the total number of publicly listed companies has declined, and companies are staying private longer (Kahle and Stulz, 2017; Doidge et al., 2017).

7.2.1 ESG and ownership incentives

From a theoretical standpoint, Friedman (1970b) argued that managers should prioritize shareholder profits above all else and avoid unprofitable "social" activities. Yet subsequent work shows that companies may improve social outcomes, such as workplace safety, even when such actions do not yield immediate financial gains (e.g., Cohn et al., 2021). One line of theory suggests that public companies are especially prone to "amoral drift" because diffuse ownership and quarterly earnings pressures incentivize short-termism and deter long-term ESG investments (Hart and Zingales, 2017). In contrast, private (and especially family-owned) companies may more easily integrate non-financial objectives when owners directly value employee, community, or environmental welfare (Hart and Zingales, 2017).

A complementary strand highlights that private equity owners pursue unequivocal profit-maximization, given their tightly aligned incentive structures and exit valuations (Davis et al., 2014). Limited disclosure requirements for private companies may also reduce pressure to engage in costly ESG initiatives. Hence, theory offers two competing hypotheses for private companies: (i) they may underinvest in ESG due to tighter profit incentives and lower reporting obligations, or (ii) they may invest more in ESG, especially when family ownership generates long-term, stakeholder-oriented priorities.

7.2.2 Theoretical ESG–CFP mechanisms

The relationship between ESG and financial performance can be understood through at least four conceptual mechanisms, each representing a distinct causal direction and set of assumptions (Preston and O'Bannon, 1997):

1. **Financial slack hypothesis (ROA $\xrightarrow{+}$ ESG).** Originating from the resource-based view and the broader corporate slack literature (Cyert and March, 1963; Bourgeois, 1981), the financial slack hypothesis posits that companies with higher profitability accumulate excess resources that can be deployed beyond core operational needs. Such "slack" enables managers to invest in activities with longer payback horizons, including ESG initiatives, without threatening short-term survival. In this sense, slack acts as a buffer that reduces the opportunity cost of engaging in sustainability. Empirical evidence supports this view: lagged profitability and cash flow, as indicators of organizational slack, have been shown to predict subsequent ESG engagement, consistent with the idea that companies require sufficient earnings to finance costly environmental or social projects (Waddock and Graves, 1997; Seifert et al., 2004). More recent evidence indicates that companies anticipating strong future performance invest more in CSR (Lys et al., 2015), while financial slack enables broader CSR diversification (Bouslah et al., 2023).

2. **Managerial opportunism hypothesis (ROA $\xrightarrow{-}$ ESG).** From an agency theory perspective, managers may strategically adjust ESG activities to serve their private interests rather than shareholder value (Jensen and Meckling, 1976; Preston and O'Bannon, 1997). When profitability is weak, managers face incentives to divert stakeholders' attention from poor financial results by emphasizing ESG engagement or disclosure, thereby using social and environmental initiatives as an impression management tool (Wartick and Cochran, 1985; Patten, 1991). Conversely, when financial performance is strong, managers may "cash in" by reducing ESG-related expenditures to boost short-term profitability and personal compensation. Empirical evidence supports this view, showing that ESG engagement can be employed opportunistically to mask weak financial performance or earnings manipulation arising from managerial agency conflicts (Prior et al., 2008; Kao et al., 2018). However, such evidence is relatively scarce and context-dependent. This suggests that, while this mechanism may operate in certain settings, it is unlikely to be a general pattern across companies or industries. In this sense, ESG activities can also reflect managerial opportunism rather than a credible commitment to sustainability, implying a negative association between company profitability and ESG performance.

3. **Trade-off hypothesis (ESG $\xrightarrow{-}$ ROA).** Early work in the economics of CSR emphasized

that engaging in social or environmental initiatives requires diverting resources away from profit-maximizing activities (Friedman, 1970a; Vance, 1975). From this perspective, ESG investments represent non-core expenditures such as upgrading production facilities, sourcing sustainable inputs, or expanding compliance systems that may not yield immediate financial returns. The costs associated with these actions can depress short-term profitability, particularly when reputational or efficiency gains are uncertain or delayed. This logic supports the trade-off hypothesis, which states that companies incur an opportunity cost through ESG engagement because it restricts managerial focus and reduces resources available for operational efficiency (McWilliams and Siegel, 2001). Empirical research echoes this concern, showing that ESG can act as a financial drag under certain conditions, consistent with the view that social responsibility may conflict with shareholder wealth maximization (Brammer et al., 2006; Makni et al., 2009; Li et al., 2020).

4. **Good management hypothesis (ESG $\xrightarrow{+}$ ROA).** The good management perspective originates in early corporate social performance research, which argued that companies attentive to stakeholder demands and social legitimacy are more likely to cultivate effective management practices and build long-term competitive advantage (Carroll, 1979; Wartick and Cochran, 1985). By systematically integrating ESG into core strategy, such companies strengthen governance systems, improve risk management, and foster stronger relationships with employees, customers, and regulators. ESG performance thereby serves as an indicator of superior managerial capability and strategic foresight, which enhance innovation, operational efficiency, and ultimately financial outcomes. In this view, ESG is not a cost center but a reflection of managerial quality and organizational effectiveness. Theoretically, proactive ESG engagement can enhance competitiveness and efficiency (Porter and van der Linde, 1995), and empirically, studies have documented a positive association between ESG engagement and profitability, suggesting that responsible management and financial success are mutually reinforcing rather than contradictory (Orlitzky et al., 2003; Kang et al., 2016; Lins et al., 2017; Li et al., 2018).

It is important to note that these mechanisms are not mutually exclusive. In practice, companies may display both profitability-driven ESG engagement and ESG-driven financial outcomes simultaneously. However, not all hypotheses can hold at the same time: either (1) financial slack or (2) managerial opportunism may explain the profitability–to–ESG link (or there is no link at all), while either (3) trade-off or (4) good management may explain the ESG–to–profitability link (or there is no link). The resolution of this apparent paradox lies in the temporal dimension: (1) and (2) describe how the financial situation precedes and shapes subsequent ESG performance, whereas (3) and (4) describe the financial effects that follow from particular ESG efforts. Thus, one mechanism from each pair can coexist, but not both from the same pair.

7.2.3 Empirical evidence on the ESG–CFP relationship

Empirical findings on the ESG–CFP relationship remain mixed. A comprehensive meta-analysis concludes that most studies report a non-negative association, with many finding positive results (Friede et al., 2015). At the same time, evidence highlights that the relationship is mediated by company-specific resources and contextual factors, which helps explain variation across settings (Surroca et al., 2010). Empirical work also shows that companies with strong sustainability practices tend to outperform over longer horizons, suggesting that ESG engagement can translate into durable financial benefits when embedded in organizational strategy (Eccles et al., 2014). Prior research further suggests that financially stronger companies are better able to invest in ESG activities, consistent with the idea that companies require sufficient earnings to finance costly environmental or social projects (Waddock and Graves, 1997). Moreover, the impact of ESG on financial performance depends on the type of activity undertaken: environmental, social, and governance dimensions may contribute differently to value creation (Dorfleitner et al., 2018). Meta-analyses focusing on emerging markets confirm that institutional and regional factors condition the ESG–CFP relationship, reinforcing the need for disaggregated analysis beyond developed economies (Duque-Grisales and Aguilera-Caracuel, 2021). Overall, the strength and direction of this relationship vary by industry, ownership structure, and regulatory environment, underscoring the importance of contextualizing results by both ownership structure and institutional setting.

7.2.4 Empirical evidence of ESG by ownership type

There is relatively little comparative evidence on ownership heterogeneity in ESG, particularly outside high-income countries. Shive and Forster (2020) examine emissions performance in the U.S. and find that publicly listed companies often underperform private companies, attributing this gap partly to market pressures and disclosure incentives. Studies on emerging markets are still scarce, despite the high prevalence of family and state ownership in these contexts. Empirical studies confirm that many family-controlled companies operationalize these theoretical motivations by allocating more resources to social and community-oriented ESG dimensions (La Porta et al., 1998; Berrone et al., 2010; Campopiano and De Massis, 2015). Block and Wagner (2015) further show that family companies are more likely to adopt CSR practices when privately held rather than publicly listed, supporting the notion that ownership concentration enables stronger alignment with non-financial goals. At the same time, more recent cross-country evidence demonstrates that ownership identity systematically shapes ESG performance: companies with founding families or individual blockholders underperform on ESG dimensions, unless family members occupy top management positions, in which case companies outperform all others (Villalonga et al., 2025). Relatedly, government involvement has also been found to matter. Using a global sample of privatized companies, Boubakri et al. (2019) document that residual state ownership is positively associated with CSR intensity, although the effect is nonlinear and depends on the trade-off between political and profit objectives. Experimental evidence also suggests that private equity investors value ESG disclosures: Crifo et al. (2015), using a framed field experiment with French private equity professionals, find that bad ESG disclosures significantly reduce valuation, indicating that private markets respond to reported ESG performance. However, whether these patterns extend to overall ESG performance, including environmental and governance pillars, and whether ESG investments generate different financial payoffs across ownership types remains largely unresolved in the literature. This gap is particularly salient in large emerging economies like Brazil, where family and private ownership dominate the corporate landscape but remain underexplored in ESG research. Notably, while some studies associate private ownership with stronger ESG engagement, particularly in family-controlled companies that prioritize long-term stakeholder value (Berrone et al., 2010; Campopiano and De Massis, 2015), other research emphasizes that public listing and the associated regulatory requirements and investor scrutiny foster more standardized ESG disclosure and formal governance practices (Ioannou and Serafeim, 2012; Cheng et al., 2014; OECD, 2022). These conflicting perspectives highlight the importance of empirical evidence from institutional contexts such as Brazil, where ownership forms are influenced by unique regulatory, informational, and enforcement environments.

7.2.5 ESG and CFP performance in Brazil

Empirical evidence on how ESG engagement relates to financial performance in Brazil remains limited and fragmented. Possebon et al. (2024) find that higher ESG scores among B3 stock exchange listed companies correlate with lower cost of capital and improved ROA—especially driven by environmental performance—highlighting the financial importance of ESG in Brazil's public market. Audit-related research (Del Giudice and Rigamonti, 2020) also links ESG practices to governance improvements through better audit quality, while emerging-market studies like Martins (2022) demonstrate how increased competition can depress ESG efforts in Brazil, indicating context-specific risks to ESG adoption. Moreover, the OECD highlights notable transparency and governance weaknesses among Brazilian listed companies, emphasizing deficits in board independence, ESG-linked incentives, and stakeholder transparency (OECD, 2022).

7.2.6 Regulatory shocks and ESG disclosure

A growing body of work examines the consequences of mandatory ESG disclosure regulations. The evidence highlights different dimensions of impact. One strand of research finds that disclosure mandates can lead to substantive improvements in corporate sustainability practices (Ioannou and Serafeim, 2011). Others emphasize that the main effect is to enhance transparency and reporting quality, while real-economy consequences remain less certain (Christensen et al., 2021). Additional research points to capital-market outcomes. For example, Grewal et al. (2019) shows that the EU's nonfinancial reporting directive triggered heterogeneous stock market reactions depending on companies' pre-existing ESG practices. Krueger et al. (2024) documents improvements in liquidity and information environments when disclosure mandates are strongly enforced. Overall, the literature indicates that mandatory disclosure effectively increases transparency and investor confidence. However, its impact on corporate behavior varies depending on the institutional context. To date, no study has leveraged a mandatory disclosure reform in Brazil to estimate its causal effect on company-level ESG performance.

7.2.7 Hypotheses development

Drawing on these theoretical strands and empirical gaps, we formulate four hypotheses. First, ownership structure may influence ESG behavior through competing mechanisms. On one hand, public companies are subject to stricter disclosure rules, financial oversight, and capital market pressure, which may incentivize more robust ESG governance and transparency. On the other hand, private companies, particularly those with long-term, concentrated ownership, may be better positioned to pursue stakeholder-oriented strategies and engage in ESG investments without short-term performance constraints (Hart and Zingales, 2017; Berrone et al., 2010). Existing empirical evidence is mixed and largely focused on developed markets (Duque-Grisales and Aguilera-Caracuel, 2021), while the Brazilian context introduces additional regulatory and institutional uncertainties.

H1. ESG performance differs systematically between public and private companies.

Second, the relationship between ESG performance and profitability has been explained through several competing mechanisms. The financial slack hypothesis suggests that companies with stronger financial performance possess excess resources that can be allocated to ESG initiatives without threatening core operations (Waddock and Graves, 1997; Seifert et al., 2004; Lys et al., 2015). In Brazil's emerging market context, characterized by heterogeneous capital access, fragmented ESG regulation, and voluntary sustainability practices, profitability is therefore a key enabler of ESG engagement. At the same time, the weak and evolving ESG disclosure landscape, particularly before CVM Resolution No. 59, created scope for managerial opportunism. Managers facing performance pressures may emphasize or exaggerate ESG engagement to protect legitimacy and deflect stakeholder scrutiny, consistent with agency theory and the managerial opportunism hypothesis (Preston and O'Bannon, 1997; Prior et al., 2008; Kao et al., 2018). By contrast, the trade-off and good management hypotheses highlight different mechanisms: the trade-off perspective emphasizes that ESG can divert resources from profit-maximizing activities (McWilliams and Siegel, 2001; Brammer et al., 2006; Makni et al., 2009), whereas the good management view stresses ESG as an outcome of superior governance and stakeholder relations (Porter and van der Linde, 1995; Orlitzky et al., 2003; Lins et al., 2017). Both hypotheses require more mature ESG integration, sustained governance alignment, and institutionalized stakeholder accountability—conditions only partially present in our setting. Taken together, we expect that profitability increases ESG performance, reflecting both genuine slack-based investment and, in some cases, opportunistic reporting.

H2. Higher profitability (ROA) is positively associated with stronger ESG performance.

Third, ownership concentration and family control shape how companies balance ESG engagement with financial performance. In private companies, concentrated family ownership tends to align management and ownership interests, supporting long-term strategies that emphasize stakeholder relationships and sustainability. Family-controlled companies often invest in ESG as part of preserving socioemotional wealth, prioritizing legacy, community reputation, and intergenerational continuity (Berrone et al., 2010). This alignment typically strengthens the ESG–performance link. Recent cross-country evidence further shows that family and individual blockholders are generally associated with weaker ESG performance, unless family members themselves occupy top management positions, in which case companies outperform peers (Villalonga et al., 2025). In contrast, when family ownership persists in publicly listed companies, it may lead to entrenchment and conflicts with minority shareholders, particularly in Brazil, where dual-class shares and pyramidal structures are prevalent (La Porta et al., 1999; Leal and Carvalhal-da-Silva, 2005). These agency problems can discourage substantive ESG investment, as controlling families may perceive ESG initiatives as generating diffuse stakeholder benefits with uncertain returns. Moreover, the presence of external shareholders in public companies may pressure families to emphasize short-term earnings, further weakening the ESG–ROA relationship.

H3. Family ownership amplifies the positive ESG–ROA relationship among private companies but weakens it among public companies.

Fourth, ESG disclosure regulations are designed to enhance transparency, reduce information asymmetries, and strengthen accountability by requiring companies to systematically report sustainability-related information. Such interventions constrain selective reporting and increase external scrutiny, which may incentivize companies to improve not only disclosure practices but also underlying ESG performance. Prior research suggests that mandatory disclosure regimes can generate diverse effects, ranging from substantive improvements in corporate sustainability practices to enhanced transparency and capital-market outcomes, particularly in settings where preexisting standards were weak or voluntary (Ioannou and Serafeim, 2011; Krueger et al., 2024; Christensen et al., 2021). In the Brazilian context, the introduction of ESG disclosure requirements for publicly listed companies represents a major institutional shift that should widen the ESG performance gap between public and private companies.

H4. ESG disclosure regulation leads to a significant increase in ESG scores.

7.3 Sample, data, and construction of ESG scores

7.3.1 Sample and data set

Our dataset comprises company-level survey responses and financial information for companies operating in Brazil between 2017 and 2023. Companies were selected based on annual revenue thresholds and their appearance in prominent industry rankings, including the Época Negócios "360 Best Companies" list. The initial contact database comprised approximately 3,000 companies. From this pool, we applied a cutoff of BRL 250 million (approx. USD 45–50 million) in annual revenues to restrict the target population to large companies with substantial economic relevance. The resulting population includes both publicly listed companies on the B3 (formerly Bovespa) Stock Exchange and large unlisted companies across a wide range of industries.

Data collection was conducted annually via a structured online questionnaire. Formal email invitations were sent to each company, followed by a minimum of two follow-up calls to encourage participation and clarify questions. Between 2017 and 2023, a total of 715 unique companies provided valid survey responses, each completing at least three modules with at least 70% valid information. This yielded 2,582 company-year observations in the database. Annual response rates averaged about 15–16% of all companies contacted through the mailing list, and around 90–95% of those that started the questionnaire completed the minimum required to participate, with both rates remaining stable across survey waves.

Financial and ESG information were self-reported by companies and, where applicable, verified using audited balance sheets and external documentation. A random subset of companies was asked to provide supporting financial statements, which were reviewed by the data validation partner Integratum. The panel is unbalanced, as participation varied from year to year: nearly half of the companies (330) participated only once, while 85 companies provided responses in all seven years.[1]

Overall, the dataset captures a broad cross-section of Brazilian companies in terms of size, ownership status, and industry affiliation. It provides a rare opportunity to compare ESG behavior and financial performance across public and private companies in an emerging market over a multi-year horizon.

7.3.2 Construction of the ESG scores

We construct harmonized ESG pillar scores (E, S, and G) and an aggregate ESG score using company responses to the structured questionnaire. These responses are coded into ESG variables that align with the LSEG methodology, such that higher values indicate better performance.[2]

[1] Participation distribution: 330 (1 year), 163 (2 years), 170 (3 years), 76 (4 years), 58 (5 years), 38 (6 years), 85 (7 years).

[2] LSEG's methodology can be accessed here (as of October 2024): https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf

Each ESG pillar is composed of several underlying *categories*, which represent groups of related survey indicators. For example, the environmental pillar aggregates emissions, innovation, and resource use. Tables A.1 and A.2 in the appendix provide the definitions and measurements as well as the descriptive statistics of the ESG variables, respectively.

To ensure consistency across pillars and comparability with the composite ESG score, we restrict the sample to company-year observations that have non-missing values for all three pillar measures. This requirement results in the removal of 214 observations because incomplete responses would otherwise distort the construction and benchmarking of the scores.

To construct our scores, we consider two complementary approaches:

(i) Equal-weighting approach. Each category is normalized to the unit interval $[0,1]$ by year and then averaged with equal weights to obtain pillar scores. The three pillar scores are in turn equally weighted to construct the composite ESG score. This method requires no regression and serves as a transparent benchmark.

(ii) Weight-calibration approach. For the subsample of 60 publicly listed companies with 226 collected company-year observations from LSEG, we regress LSEG scores (E, S, G, and aggregate ESG) on the corresponding normalized categories. This yields estimated coefficients that reflect the relative importance of each category in LSEG's methodology. In line with LSEG's benchmarking practice, we include industry fixed effects to ensure that resulting scores capture within-industry variation rather than structural cross-industry differences. The fitted values from these regressions are then normalized to the unit interval. The general regression structure for the weight-calibration approach is given as follows.

For observation i, let Score_i denote the observed LSEG (E, S, G, or ESG) benchmark (where available), and let Cat_{ij} denote the j-th normalized category belonging to that pillar. The weight-calibration regression is specified as:

$$\text{Score}_i = \beta_0 + \sum_{j=1}^{J} \beta_j \text{Cat}_{ij} + \sum_{k=1}^{K} \gamma_k D_{i,k} + \varepsilon_i, \tag{7.1}$$

where $D_{i,k}$ are industry dummies. The fitted values are obtained as

$$\widehat{\text{Score}}_i = \hat{\beta}_0 + \sum_{j=1}^{J} \hat{\beta}_j \text{Cat}_{ij} + \sum_{k=1}^{K} \hat{\gamma}_k D_{i,k}. \tag{7.2}$$

All regression-based fitted values are rescaled to the unit interval by year:

$$\text{Score}_i^* = \frac{\widehat{\text{Score}}_i - \min_j \widehat{\text{Score}}_j}{\max_j \widehat{\text{Score}}_j - \min_j \widehat{\text{Score}}_j}, \quad \text{Score}_i^* \in [0,1], \tag{7.3}$$

with Score_i^* denoting the calibrated and normalized ESG score for observation i.

For each (E, S, and G) pillar and for the composite ESG score, we compute results using both approaches and retain the specification that yields the higher correlation with the available LSEG benchmark.

The environmental pillar is designed to capture how companies manage ecological impacts and innovation. It combines three questionnaire-generated categories: (i) *emissions*, reflecting the integration of climate considerations into investment decisions, (ii) *innovation*, capturing environmental investments and cost reductions, and (iii) *resource use*, measuring monitoring practices across the supply chain. Applying our weight-calibration framework, the resulting normalized environmental score E_i^* achieves a correlation of 0.313 with the LSEG environmental benchmark, which is higher than under the equal-weighting approach. We therefore adopt the calibrated score as our final environmental measure.

The social pillar reflects how companies manage stakeholder relationships and labor practices. It builds on four categories: (i) *community* engagement, (ii) *human rights*, proxied by the absence of labor lawsuits, (iii) *product responsibility*, measured through the share of sustainable products, and (iv) *workforce* practices such as training, evaluation systems, and participation. In this case, the calibrated score performs poorly against the LSEG benchmark (correlation of 0.072), whereas the uncalibrated weighted score reaches 0.160. A reason is that our human rights proxy relies on negative indicators (number of lawsuits), which does not align directly with the LSEG methodology that emphasizes policies, practices, and controversy screening. Moreover, product responsibility is captured by a single variable (percentage of revenue from sustainable products) with only 196 non-missing observations, resulting in limited coverage. Consequently, our social score places slightly more weight on community and workforce categories, which have higher data availability. We therefore adopt the equal-weighted specification as our final S_i^*.[3]

The governance pillar measures the institutional framework that underpins ESG engagement. It aggregates two categories: (i) *CSR strategy*, such as the use of reporting standards and stakeholder inclusion, and (ii) *management practices*, including compliance systems and board structures. After calibration, the normalized governance score G_i^* reaches a correlation of 0.139 with the LSEG governance score, which is higher than under the equal-weighting approach. We therefore adopt the calibrated score as our final governance measure.

The composite ESG score is first formed as the equally weighted average of the three normalized pillar scores. Calibrating this aggregate to the LSEG ESG score yields a correlation of 0.693, which represents a statistically strong alignment. We therefore adopt the calibrated score as our final composite ESG measure.

As a robustness check of the score construction, we also form an alternative composite ESG score by aggregating the three equal-weighted pillar scores before calibration. Calibrating this alternative

[3]Note that ESG ratings from different providers often diverge due to variations in indicator selection, weighting, and underlying assumptions (Berg et al., 2022).

aggregate to the LSEG ESG score and normalizing it yields a correlation of 0.681, only slightly below that of the calibrated pillar–composite approach. The correlation between this alternative measure and our chosen calibrated composite ESG score is 0.778. These close correlations suggest that our results are not sensitive to the specific calibration order. We rely on the our approach of selecting pillar scores with the highest LSEG correlation (calibrated or equal-weighted) and calibrating the composite ESG score with LSEG ESG scores as our main specification. This best aligns with the widely used LSEG methodology, including its industry benchmarking.

7.3.3 Data cleaning and matching to company characteristics

We apply the following data cleaning steps to ensure the validity and comparability of the ESG measures. Due to structural differences in business models, financial reporting, and ESG disclosure requirements, we exclude companies from the financial industry, including banks, insurance companies, and other financial service providers (248 observations), as well as nonprofit organizations (152 observations). This exclusion is consistent with prior ESG literature, as financial institutions differ fundamentally in how their ESG performance is assessed, making comparisons with non-financial companies difficult (e.g., Scholtens, 2009).

Next, we match our ESG scores with company-level data used in the empirical analysis. Following standard practice in the ESG–CFP literature (e.g., Flammer, 2015; Benlemlih and Bitar, 2017), we include control variables grouped into four categories: company size and financial structure (log total assets, leverage, liquidity), operational complexity (capital intensity, R&D intensity, foreign sales share), profitability (return on assets), and ownership structure (e.g., family ownership, public listing status).[4] This matching process results in the removal of an additional 482 observations. Our final sample includes 317 private companies (939 company-year observations) and 156 public companies (547 company-year observations). Finally, to mitigate the influence of outliers, we winsorize all continuous financial variables at the 1st and 99th percentiles.

7.4 Empirical results

7.4.1 Descriptive statistics

Table 7.1 provides descriptive statistics for the full sample (Panel A) and separately by ownership type (Panel B). Panel A summarizes ESG scores, financial variables, and ownership characteristics across 1,486 company-year observations. Panel B compares public and private companies, reporting t-tests for mean differences. While the mean combined ESG scores do not differ significantly between ownership types, private companies exhibit lower environmental and social scores but significantly higher governance scores, with governance showing the largest gap (0.14 difference).

[4] The definitions of all variables used in the empirical analysis are reported in Table A.3 in the appendix.

E and G scores display greater variability than S scores, which remain relatively stable across ownership categories. The share of family-owned companies is broadly similar across groups, with private companies slightly more likely to be family-owned. Despite having smaller average asset bases, private companies achieve significantly higher returns on assets (2.38 difference) and are more concentrated in B2B sectors, whereas public companies tend to have higher leverage, liquidity, and R&D intensity.

Table 7.1: Descriptive statistics for company-level variables and ownership differences

Panel A. Descriptive statistics for company-level variables

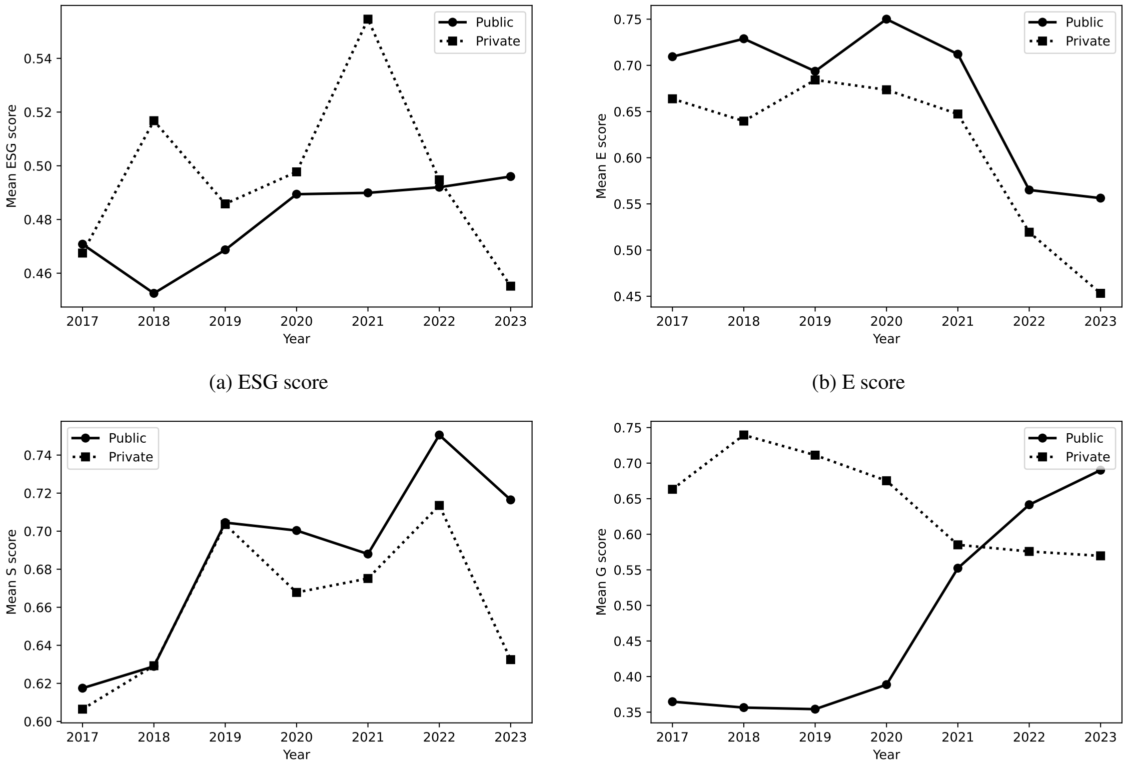
Variable	Obs.	Mean	Std.	Min	Median	Max
ESG score	1,486	0.49	0.21	0.00	0.51	1.00
E score	1,486	0.63	0.32	0.00	0.60	1.00
S score	1,486	0.67	0.18	0.00	0.70	1.00
G score	1,486	0.58	0.33	0.00	0.62	1.00
LSEG ESG score	191	0.56	0.20	0.03	0.58	0.89
LSEG E score	191	0.56	0.24	0.00	0.61	0.96
LSEG S score	191	0.59	0.23	0.01	0.61	0.95
LSEG G score	191	0.54	0.22	0.01	0.58	0.96
Public	1,486	0.37	0.48	0.00	0.00	1.00
Family	672	0.46	0.50	0.00	0.00	1.00
ROA	1,486	5.92	7.59	−14.83	4.65	33.21
Size	1,486	8.06	1.62	4.81	7.94	11.80
Leverage	1,486	0.29	0.19	0.00	0.28	0.80
Liquidity	1,486	0.43	0.49	−1.01	0.41	1.73
Capital intensity	1,486	0.03	0.03	0.00	0.02	0.13
B2B	1,486	0.51	0.50	0.00	1.00	1.00
R&D operations	1,486	0.83	0.38	0.00	1.00	1.00
Foreign operations	1,486	0.37	0.48	0.00	0.00	1.00
Go private	1,486	0.07	0.08	0.00	0.00	1.00
Go public	1,486	0.01	0.12	0.00	0.00	1.00

Panel B. Descriptive statistics by ownership type

	Public			Private			
Variable	Obs.	Mean	Std.	Obs.	Mean	Std.	Diff.
ESG score	547	0.482	0.186	939	0.509	0.217	0.015
E score	547	0.666	0.310	939	0.602	0.325	−0.064***
S score	547	0.693	0.161	939	0.663	0.184	−0.030***
G score	547	0.496	0.338	939	0.636	0.307	0.140***
Family	262	0.405	0.492	410	0.490	0.501	0.086**
ROA	547	4.416	6.631	939	6.792	7.966	2.376***
Total assets	547	9.160	1.390	939	7.412	1.384	−1.747***
Leverage	547	0.339	0.191	939	0.260	0.182	−0.079***
Liquidity	547	0.491	0.495	939	0.401	0.485	−0.090***
Capital intensity	547	0.031	0.023	939	0.031	0.026	−0.000
B2B	547	0.417	0.493	939	0.560	0.497	0.143***
R&D operations	547	0.887	0.317	939	0.794	0.404	−0.092***
Foreign operations	547	0.375	0.485	939	0.368	0.483	−0.006

Notes: Panel A reports summary statistics on company-level variables for the full sample of 1,486 company-year observations. Panel B reports descriptive statistics with t-tests across 156 public and 317 private companies. "Diff." is the mean difference between public and private companies. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 7.1 complements these descriptive statistics by illustrating how ESG scores evolve over the sample period for public and private companies. The overall ESG score indicates a modest improvement for public companies beginning in 2018. In contrast, private companies exhibit greater volatility, showing an upward trend from 2017 to 2021, followed by a decline between 2022 and 2023. E scores have declined for both company types, especially since 2021. In contrast, S scores have increased over the sample period. Governance scores show heterogeneous patterns: private companies experience a gradual decline, while public companies demonstrate a pronounced increase in governance performance, especially since 2020.



(a) ESG score

(b) E score

(c) S score

(d) G score

Figure 7.1: Evolution of ESG and pillar scores by ownership. Each panel plots year-by-year averages for public companies (solid line) vs. private companies (dashed line).

7.4.2 Differences in ESG performance across ownership types

To assess how ESG performance varies across ownership structures, we estimate OLS regressions of ESG scores on a *public*-company indicator and a comprehensive set of control variables. These include financial structure (*leverage*, *liquidity*), company *size*, operational complexity (*capital intensity*, *R&D intensity*, *foreign operations*), and year fixed effects to account for unobserved temporal heterogeneity. Over the observation period, 24 company-year observations capture companies going public (*go public*), and 12 company-year observations capture companies going private (*go private*). Pearson correlations for all variables are provided in Table A.4 in the appendix.

The results, shown in Table 7.2, reveal a clear pattern: public companies exhibit significantly lower ESG scores than private companies, even after controlling for company characteristics. The *public*-company coefficient is negative and highly significant across Models 1–3, providing empirical support for hypothesis H1. When decomposing ESG into its three pillars (Models 4–6), this gap is found to be related heavily to the governance dimension. In Model 6, the coefficient on the *public*-company indicator is -0.23, indicating that public companies score on average 0.23 lower on governance than comparable private companies, i.e., a difference of 23 percentage points on the 0–1 scale. By contrast, environmental and social scores are statistically indistinguishable between public and private companies.

Turning to financial performance, Models 1 and 2 include contemporaneous and lagged return on assets (*ROA*). In both cases, *ROA* is positively associated with ESG scores, consistent with the financial slack hypothesis: more profitable companies appear more capable of allocating resources toward ESG improvements. Specifically, a one percentage point increase in *ROA* is associated with a 0.2 percentage point increase in the *ESG score*. This relationship does not hold at the pillar level, where coefficients are small and insignificant.

Model 3 focuses on ownership transitions. Companies that move from public to private status (*lagged go private*) exhibit a statistically significant *ESG score* increase of 0.13 points. This reinforces the finding that private ownership correlates with stronger ESG performance. By contrast, transitioning from private to public (*lagged go public*) is not significantly related to ESG.

Company *size* consistently shows a strong positive relationship with ESG scores, in line with the size effect reported in the literature (Dobrick et al., 2023; Drempetic et al., 2020). Additionally, companies operating in business-to-business (*B2B*) sectors tend to score higher on ESG, with the advantage primarily related to stronger environmental performance (Model 4). *Capital intensity* also shows a positive association with environmental and governance scores, though estimates are imprecise. *R&D operations* and *foreign operations* yield mixed results.

Overall, the evidence supports hypotheses H1 and H2: we observe that private companies outperform public companies in overall ESG performance, an empirical pattern that emerges despite theoretical expectations of stronger governance among listed companies. In line with hypothesis H2, we also find that higher profitability and a transition to private ownership are positively associated with ESG scores.

7.4.3 Subsample heterogeneity by company characteristics

Table 7.3 presents company- and year-fixed-effects regressions of ESG scores on *public*-ownership status and *lagged ROA* across ten subsamples defined by size, leverage, liquidity, capital intensity, and industry. "Green" industries comprise agribusiness; food and beverage; wholesale and retail trade; information technology and telecommunications; software and services; professional services; education; healthcare; water and sanitation; pharmaceuticals and cosmetics; hygiene and beauty; electronics; and paper and pulp. All other industries, i.e., civil construction; infrastructure; construction materials and decoration; mechanical engineering and metallurgy; mining and steelmaking; chemicals and petrochemicals; energy (oil & gas); transportation; textiles, leather and apparel; and vehicles and auto parts, are classified as "brown."

Table 7.2: Determinants of ESG scores

	ESG			E	S	G
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership variables						
Public	−0.060**	−0.069**		−0.035	−0.014	−0.225***
	(0.024)	(0.029)		(0.029)	(0.014)	(0.027)
Performance variables						
ROA	0.002**		0.002	0.000	0.001	−0.000
	(0.001)		(0.002)	(0.001)	(0.001)	(0.001)
Lagged ROA		0.002*				
		(0.001)				
Transition variables						
Lagged go public			0.022			
			(0.057)			
Lagged go private			0.131***			
			(0.030)			
Company controls						
Size	0.030***	0.034***	0.022***	0.055***	0.023***	0.038***
	(0.007)	(0.009)	(0.008)	(0.008)	(0.005)	(0.008)
Leverage	0.065	0.056	0.019	0.045	−0.002	0.092
	(0.052)	(0.057)	(0.057)	(0.068)	(0.034)	(0.062)
Liquidity	−0.017	0.006	−0.005	−0.030	−0.014	−0.009
	(0.021)	(0.024)	(0.024)	(0.023)	(0.012)	(0.023)
Capital intensity	0.431	0.522	0.433	0.746*	0.485**	1.257***
	(0.364)	(0.396)	(0.401)	(0.438)	(0.227)	(0.410)
B2B	0.067***	0.068***	0.070***	0.054**	0.008	−0.019
	(0.019)	(0.022)	(0.023)	(0.024)	(0.014)	(0.022)
R&D operations	0.040*	0.030	0.033	0.088***	0.063***	0.094***
	(0.024)	(0.032)	(0.033)	(0.032)	(0.017)	(0.025)
Foreign operations	−0.012	−0.017	−0.012	0.014	0.034**	0.016
	(0.020)	(0.022)	(0.022)	(0.022)	(0.015)	(0.024)
Constant	0.159***	0.164**	0.246***	0.145**	0.369***	0.218***
	(0.059)	(0.074)	(0.070)	(0.072)	(0.044)	(0.072)
N	1,486	985	998	1,486	1,486	1,486
Adjusted R^2	0.075	0.070	0.049	0.155	0.121	0.102

Notes: This table reports regression coefficients where the dependent variable is the ESG score (Models 1–3) or the pillar scores (Models 4–6). Clustered standard errors at the company level are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The *public*-ownership coefficient is uniformly negative and statistically significant in the large-company (–0.08), low-leverage (–0.11), high-liquidity (–0.10) and low-capital-intensity (–0.08) subsamples, indicating that public ownership is associated with a 8–11-point reduction in *ESG score* relative to matched private peers precisely in contexts where companies have ample cash, light debt burdens, or few tangible assets to fund ESG investments. This finding emphasizes that listing-related pressures such as short-term shareholder demands, more stringent disclosure requirements, and rigorous governance norms can outweigh resource availability and systematically crowd out non-financial performance.

Lagged ROA is positively related to the *ESG score*, but only under specific conditions. In the large-company (0.003), low-leverage (0.004), low-liquidity (0.004), low-capital-intensity (0.005) and brown-industry (0.005) groups, prior-period profitability exerts a significant slack effect, consistent with financial-slack theory (Waddock and Graves, 1997).

Viewed together, these patterns highlight two consistent findings. First, publicly listed companies have lower ESG scores than comparable private companies. This “ESG discount” is strongest in subsamples where profitability faces fewer competing claims, such as large companies or those with low leverage, liquidity, or capital intensity. This suggests that market discipline suppresses ESG engagement precisely when slack resources could support it. Second, *lagged ROA* is only positively associated with ESG under conditions of weaker financial pressures or in brown industries, which is consistent with the financial slack hypothesis. Furthermore, the similar magnitudes of the *public* coefficient and the *lagged ROA* effect across all ten subsamples, relative to our full-sample OLS benchmarks, confirm the robustness of our core insight that market discipline costs and slack resources jointly determine cross-company differences in ESG performance.

Our subsample analysis reveals that the positive effect of lagged profitability on ESG performance materializes only under specific financial conditions: when companies face low liquidity, low leverage, and low capital intensity. These results align with financial slack theory, which holds that internal resources such as retained earnings are more likely to be channeled into discretionary, non-financial initiatives like ESG when external financing is constrained and fixed investment demands are limited. The absence of such an effect under high-leverage or high-capital-intensity conditions suggests that debt obligations and tangible asset investments crowd out ESG activity, even among otherwise profitable companies.

7.4.4 The financial performance–ESG–ownership nexus

Next, we examine how ESG performance and ownership structure relate to companies’ financial outcomes. We estimate *ROA* as the dependent variable and include industry and year fixed effects in all specifications to control for sector-specific and time-varying influences. Table 7.4 reports the results.

Model 1 begins with the *lagged ESG score* as the main explanatory variable, but the coefficient is

Table 7.3: Determinants of ESG scores: Subsample analysis

	Size		Leverage		Liquidity		Capital intensity		Industry	
	Large	Small	High	Low	High	Low	High	Low	Brown	Green
Ownership variables										
Public	−0.077**	−0.055	−0.035	−0.109***	−0.090***	−0.038	−0.062	−0.082**	−0.071	−0.044
	(0.034)	(0.041)	(0.039)	(0.039)	(0.035)	(0.037)	(0.040)	(0.034)	(0.048)	(0.033)
Performance variables										
ROA	0.003*	0.002	0.000	0.004**	0.001	0.004**	−0.002	0.005***	0.005**	−0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Company controls										
Size	0.059***	−0.032	0.021	0.048***	0.041***	0.022**	0.036***	0.030***	0.054***	0.021*
	(0.014)	(0.026)	(0.013)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.013)	(0.012)
Leverage	0.013	0.082	0.113	−0.025	0.071	0.037	0.020	0.071	0.099	−0.006
	(0.064)	(0.090)	(0.087)	(0.173)	(0.075)	(0.073)	(0.074)	(0.072)	(0.099)	(0.069)
Liquidity	0.027	0.019	−0.016	0.018	0.022	0.023	0.052	−0.029	0.002	0.026
	(0.026)	(0.041)	(0.034)	(0.030)	(0.045)	(0.038)	(0.033)	(0.027)	(0.035)	(0.032)
Capital intensity	1.667***	−0.497	0.150	0.857	0.750	0.389	−0.158	2.802	1.861***	−0.284
	(0.485)	(0.536)	(0.506)	(0.545)	(0.595)	(0.473)	(0.505)	(2.021)	(0.559)	(0.510)
B2B	0.070**	0.066**	0.061**	0.085***	0.097***	0.031	0.024	0.100***	0.023	0.109***
	(0.027)	(0.033)	(0.027)	(0.032)	(0.028)	(0.031)	(0.027)	(0.030)	(0.033)	(0.028)
R&D operations	0.010	0.049	0.074	−0.013	0.052	0.010	−0.040	0.071*	−0.001	0.030
	(0.044)	(0.040)	(0.048)	(0.037)	(0.046)	(0.034)	(0.037)	(0.042)	(0.039)	(0.045)
Foreign operations	−0.008	−0.051	0.003	−0.039	−0.032	0.006	−0.013	−0.039	−0.031	−0.012
	(0.026)	(0.039)	(0.029)	(0.030)	(0.030)	(0.029)	(0.027)	(0.031)	(0.032)	(0.029)
Constant	−0.106	0.641***	0.225**	0.077	0.059	0.290***	0.287***	0.108	−0.059	0.326***
	(0.130)	(0.170)	(0.109)	(0.098)	(0.103)	(0.092)	(0.094)	(0.096)	(0.108)	(0.100)
N	580	405	516	469	506	479	517	468	394	591
Adjusted R^2	0.159	0.050	0.058	0.098	0.107	0.033	0.048	0.142	0.175	0.066

Notes: Each column reports a subsample regression of ESG score on public dummy, lagged ROA, and controls. Splits are defined at median values. “Green” industries comprise agribusiness; food and beverage; wholesale and retail trade; information technology and telecommunications; software and services; professional services; education; healthcare; water and sanitation; pharmaceuticals and cosmetics; hygiene and beauty; electronics; and paper and pulp. “Brown” industries comprise civil construction; infrastructure; construction materials and decoration; mechanical engineering and metallurgy; mining and steelmaking; chemicals and petrochemicals; energy (oil & gas); transportation; textiles, leather and apparel; and vehicles and auto parts. Company-level clustered standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

statistically insignificant. This suggests that past ESG performance does not systematically predict current profitability once company characteristics and fixed effects are taken into account.

Model 2 introduces *family* ownership as a key explanatory variable. The results show that *family*-controlled companies report significantly higher *ROA*, with an estimated effect of 3.18 percentage points. This relationship remains robust and even strengthens in Model 3, which includes an interaction term between public status and family ownership. The interaction coefficient is negative and significant, indicating that the *ROA* premium for *family* ownership is concentrated in private companies. Specifically, *family*-owned public companies do not enjoy the same financial advantage as their private counterparts. This pattern supports hypothesis H3, which posits that the benefits of family control for financial performance are conditional on company ownership status.

In addition, Model 3 reveals a statistically significant positive effect of public status itself on *ROA*, conditional on the interaction terms, suggesting that publicly listed companies without *family* control may perform better financially than their private peers. Regarding company-level controls, the results are consistent with expectations. Larger companies report lower *ROA*, while greater *liquidity* is positively associated with profitability. *Leverage* is strongly negatively related to *ROA*, as anticipated. Other company characteristics, including *capital intensity*, *B2B* orientation, *foreign operations*, and *R&D operations*, are not consistently significant across models.

Overall, we find robust evidence that family ownership enhances profitability, particularly in private companies, while ESG performance does not significantly predict ROA in the presence of detailed controls. These results highlight the importance of ownership structure for financial outcomes in the Brazilian corporate context.

7.4.5 Policy-driven changes in ESG performance over time

In 2021, the Brazilian Securities and Exchange Commission (CVM) issued Resolution No. 59 (CVM 59), significantly restructuring the ESG disclosure framework for publicly listed companies. The regulation requires all listed companies to include detailed ESG information in their annual Reference Form, or to explain any omissions using a "comply or explain" model. CVM 59 aligns Brazil's disclosure practices with international standards such as the Global Reporting Initiative (GRI), the Sustainability Accounting Standards Board (SASB), and the Task Force on Climate-Related Financial Disclosures (TCFD). This promotes more standardized, transparent, and useful ESG reporting for decision-making purposes. We treat the implementation of CVM 59 as a quasi-natural experiment and an exogenous regulatory shock to the ESG disclosure environment in order to assess its causal impact on the ESG performance of public companies. To estimate this effect, we use a difference-in-differences (DiD) design and employ private companies as a control group for publicly listed companies subject to the regulation.

The DiD specification interacts a post-2021 indicator (*Year* $\geq$ *2021)* with a dummy variable for *public* companies and includes controls for company-level characteristics, year fixed effects,

Table 7.4: Determinants of ROA

	(1)	(2)	(3)
ESG variables			
Lagged ESG score	−1.932	0.299	0.272
	(2.174)	(2.679)	(2.664)
Ownership variables			
Public	0.247	0.724	2.321**
	(0.647)	(0.870)	(1.110)
Family		3.182***	4.492***
		(0.726)	(0.918)
Public × Family			−3.260**
			(1.264)
Company controls			
Size	−0.830***	−1.052***	−1.120***
	(0.258)	(0.334)	(0.335)
Leverage	−11.097***	−11.985***	−11.660***
	(1.761)	(2.046)	(2.045)
Liquidity	3.289***	3.246***	3.243***
	(0.644)	(0.821)	(0.815)
Capital intensity	6.824	−8.119	−9.473
	(12.511)	(14.736)	(14.067)
B2B	0.563	0.801	0.816
	(0.619)	(0.716)	(0.710)
R&D operations	0.857	1.859*	1.640
	(0.851)	(1.042)	(1.046)
Foreign operations	0.047	0.659	0.793
	(0.626)	(0.678)	(0.664)
Constant	13.040***	13.413***	13.677***
	(2.326)	(2.866)	(2.861)
N	998	514	514
Adjusted R^2	0.293	0.409	0.417

Notes: This table reports the results of regression models where the dependent variable is ROA. Company-level clustered standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

industry fixed effects, and company fixed effects. To explore dynamic treatment effects and relax the common trends assumption, we estimate an event-study model that interacts the *public* company indicator with year dummies from 2017 to 2023, using 2020 as the reference year. Standard errors are clustered at the company level throughout to account for serial correlation.

As shown in Table 7.5, the results indicate that the ESG scores of *public* companies increased significantly after the disclosure mandate took effect. In the DiD model (Column 1), the interaction term *Public* $\times$ *Year* $\geq$ *2021* is positive and statistically significant at the 1% level, with a coefficient of 0.045. This suggests that, conditional on the controls, the ESG scores of *public* companies rose by 4.5 percentage points relative to those of private companies following the implementation of CVM 59. The model also shows that, prior to the policy, *public* companies had lower ESG scores overall (–0.058). The post-2021 period is associated with a modest overall decline in ESG scores (–0.013), likely driven by control group dynamics.

The event-study model (Column 2) corroborates and extends these findings. The coefficients for *Public* $\times$ *Year* $\geq$ *2021 (cutoff)*, *Public* $\times$ *Year* $\geq$ *2022*, and *Public* $\times$ *Year* $\geq$ *2023* are positive and statistically significant at the 1% level. The estimated treatment effects increase in magnitude over time: 0.036, 0.047, and 0.061, respectively. In contrast, the interaction terms for 2017 through 2019 are small and statistically insignificant, which supports the parallel trends assumption and enhances the credibility of the causal interpretation. Both models demonstrate strong explanatory power, with adjusted R^2 values of 0.96 for the DiD and event-study models, respectively. This indicates that the model specifications capture a substantial share of the variation in ESG scores.

Figure 7.2 supplements these results with a graphical depiction of the estimated differences in ESG performance between public and private companies over time. The figure plots the average predicted *ESG score* differential based on an OLS regression with public-by-year interactions, full control variables, and fixed effects. The vertical axis reflects the difference in ESG scores, and the horizontal axis represents years relative to the baseline year of 2020, marked by a red dashed line. Before 2021, the differences between public and private companies are statistically insignificant, with confidence intervals overlapping zero. Starting in 2021, however, a distinct upward shift emerges, with the ESG performance of public companies steadily improving relative to private companies. By 2023, the gap closes and turns significantly positive, suggesting that, conditional on observables, public companies began outperforming their private counterparts in ESG terms as a result of the regulation.

Taken together, we find clear evidence supporting hypothesis H4: the conclusion of CVM 59 substantially and sustainably improved the ESG performance of listed companies. These results demonstrate that mandatory ESG disclosure, especially when implemented through a "comply or explain" mechanism, can drive meaningful behavioral change in corporate sustainability practices. The findings also highlight the importance of regulation in promoting transparency and accountability in ESG reporting, particularly in emerging markets where voluntary adoption may be inconsistent.

Table 7.5: ESG disclosure mandate impact on ESG scores of public companies

	DiD	Event-study
	(1)	(2)
Public × Year ≥ 2021 (DiD term)	0.045^{***}	
	(0.008)	
Public	-0.058^{***}	-0.053^{***}
	(0.013)	(0.013)
Year ≥ 2021	-0.013^{*}	
	(0.008)	
Public × Year 2017		−0.008
		(0.012)
Public × Year 2018		−0.011
		(0.011)
Public × Year 2019		−0.014
		(0.010)
Public × Year 2021 (cutoff)		0.036^{***}
		(0.011)
Public × Year 2022		0.047^{***}
		(0.011)
Public × Year 2023		0.061^{***}
		(0.011)
Constant	0.288^{***}	0.254^{***}
	(0.016)	(0.063)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Company	Yes	Yes
N	1,380	1,380
Adjusted R^2	0.955	0.955

Notes: This table reports the results of a difference-in-differences (DiD) regression model (Model 1) and an event-study regression model (Model 2), where the dependent variable is the ESG score. In Model 1, the coefficient on Public × Year ≥ 2021 equals the average change in ESG for public companies attributable to CVM 59. In Model 2, Year 2020 is the omitted category in all Public × Year interactions. Company-level clustered standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

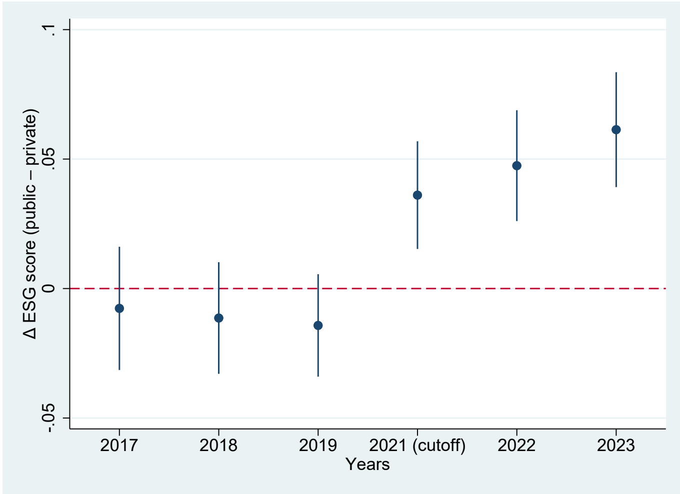


Figure 7.2: This illustration plots the average difference in predicted ESG scores between public and private companies in each calendar year from 2017 through 2023. The predictions are generated from an OLS regression that includes a public-by-year interaction term, control variables, and company- and industry-level fixed effects. Standard errors are clustered at the company level. The horizontal axis represents year (with 2020 as base year), and the vertical axis represents the average predicted ESG score with other covariates at their observed values and company fixed effects at 0. The difference between the public and private lines for a given year represents the impact of public ownership on ESG compared to 2020. A dashed red line at zero marks the 2020 baseline. Dots indicate point estimates of Public × Year from the lead-lag specification. Vertical lines show 95% confidence intervals.

7.4.6 Robustness checks

To ensure the robustness of our results, we implement two complementary checks.

(i) Propensity-score matching. To robustify our finding of inferior average ESG performance for publicly listed companies, we employ a propensity-matching approach (PSM). First, we reclassify industries into their corresponding GICS industry group, which is a standardized, globally recognized taxonomy that substantially reduces the number of industry classes, thereby increasing degrees of freedom and cross-industry variation to form high-quality matching pairs. We then estimate a logit propensity-score model predicting public listing status using control variables (company *size*, *leverage*, *liquidity*, *capital intensity*, *B2B* orientation, *R&D operations*, and *foreign operations*), alongside year and GICS-industry fixed effects. Using these scores, we implement 1 : 1 nearest-neighbour matching without replacement and a caliper of 0.05. Out of 547 treated observations (public companies), all 547 find suitable matches among the 939 private-company pool.

Table 7.6 reports the results. Post-matching balance diagnostics indicate excellent covariate balance: standardized mean differences in propensity scores fall from 1.7273 pre-matching to 0.0001 post-matching, and the variance ratio from 1.4475 to 0.9996. These metrics confirm that matching has effectively equated the treatment and control groups on observables. The average treatment effect on the treated (ATET) is –0.0534 ($p = 0.002$), indicating that public listing is associated with a 0.053-point lower ESG score compared to privately held counterparts. By balancing observable characteristics and holding constant year and GICS-industry effects, PSM isolates the impact of ownership form, addressing selection bias and enhancing causal interpretation relative to OLS. The consistency of the results in terms of sign, magnitude, and significance with our baseline OLS highlights the robustness of our findings.

Table 7.6: Propensity score matching results: Impact of public ownership on ESG scores

	Treated	Matched	ATET	Std.	z	$P > \mid z \mid$	95% CI
ESG score	547	547	–0.0534***	0.0172	–3.11	0.002	–0.0871 — –0.0200
Balance diagnostics							
Propensity score							
Standardized difference	1.7273	0.0001					
Variance ratio	1.4475	0.9996					
Controls	Yes						
Year	Yes						
Industry	Yes						

Notes: The table presents propensity score matching (PSM) estimates of the impact of public ownership on ESG scores. First, we estimate a logit model for the likelihood of being publicly listed, including seven company-level covariates alongside year and 4-digit GICS-industry fixed effects. Predicted propensity scores are then used for 1 : 1 nearest-neighbour matching without replacement (caliper = 0.05), matching all 547 treated (public) companies to 547 of 939 private companies. “Balance diagnostics” report standardized differences and variance ratios of the propensity score, pre- and post-matching. ATET denotes the average treatment effect on the treated (public companies), i.e., the mean difference in ESG scores between matched public and private companies. *** denotes statistical significance at the 1% level.

(ii) Alternative ESG score construction. As an additional robustness check, we replicate all analyses using an alternative ESG measure constructed by first aggregating the equal-weighted pillar scores and then calibrating the composite ESG score against LSEG benchmarks. The empirical results remain qualitatively unchanged, indicating that our findings are not sensitive to the specific construction of the ESG score.

7.5 Concluding remarks and discussion

This study investigates the relationship between ESG performance, financial outcomes, and ownership structure in Brazil, an emerging market with evolving regulatory institutions. Drawing on a unique panel of public and private companies from 2017 to 2023, we offer several insights that extend the ESG–corporate finance literature.

First, we document systematically lower ESG scores among publicly listed companies compared to private companies, primarily due to weaker governance. This finding contrasts with evidence from developed markets, where listing is often associated with stronger ESG disclosure incentives (Gillan et al., 2021; Grewal et al., 2019), and instead supports the “amoral drift” perspective of Hart and Zingales (2017). In Brazil’s institutional environment, short-term market pressures appear to discourage genuine ESG investment, particularly under the voluntary disclosure regime that characterized most of our sample period prior to CVM Resolution No. 59. Second, we find that profitability is positively associated with ESG performance, but only under conditions of lower external financial pressure (low leverage, low liquidity, or low capital intensity) or in environmentally sensitive industries. This pattern aligns with the financial slack theory (Cyert and March, 1963; Bourgeois, 1981; Waddock and Graves, 1997; Seifert et al., 2004), which suggests that slack resources lead to ESG engagement only when competing financial demands are less significant. Third, family ownership has a mixed impact. It strengthens ESG strategies in private companies, which aligns with their long-term strategic outlooks (Berrone et al., 2010; Campopiano and De Massis, 2015). However, it can impede ESG investments in public companies when ownership is entrenched (Block and Wagner, 2015). Fourth, we observe that companies transitioning from public to private ownership experience a significant increase in their ESG scores. This finding highlights the importance of ownership form beyond the scope of regulation. Finally, the implementation of CVM Resolution No. 59 in 2021 led to measurable and sustained improvements in ESG scores among listed companies. This suggests that regulatory interventions can mitigate the ESG underperformance of public companies, aligning with international evidence on the effects of mandatory ESG disclosure regimes (Ioannou and Serafeim, 2011; Christensen et al., 2021; Krueger et al., 2024).

These findings have important implications for investors and regulators. For investors, the ownership structure is a critical lens through which to interpret ESG and financial data. In emerging markets, private companies, especially family-owned ones, may deliver stronger sustainability outcomes than their public counterparts. For regulators, our evidence indicates that mandatory disclosure enhances ESG scores without reducing profitability, supporting a “no downside” view of ESG reporting mandates. This is particularly relevant as Brazil’s securities commission (CVM) announced in 2024 that ESG reporting will become compulsory for all public companies by 2026.[5] Based on our results, we expect such reforms to improve the quality and comparability of disclosures among listed companies. However, it remains an open question whether similar gains will extend to private companies.

[5]See: https://www.thomsonreuters.com/en-us/posts/legal/brazil-lawyers-esg/

Appendix

Table A.1: Definitions and measurements for ESG variables

Pillar	Category	Variable	Measurement
E pillar	Emissions	Emissions and climate factors in investments	D: 1 if the company includes the factors emissions and climate in investments, 0 otherwise.
		Carbon neutrality target year	How soon does the company have a public commitment to become carbon neutral? (0: no commitment, 1: >15 years, 2: $11-15$ years, 3: $6-10$ years, 3(median): sector is not considered as main CO2 emitter, 4: $0-5$ years).
		Carbon absorbation target year	Does the company have a public commitment to absorb more carbon than it emits in how long? (0: no, 1: >15 years, 2: $11-15$ years, 3: $6-10$ years, 3(median): sector is not considered as main CO2 emitter, 4: $0-5$ years).
		Climate certificates	D: 1 if the company has climate-related certificates, 0 otherwise.
	Innovation	Cost reduction through ESG actions	Has the company implemented sustainability and ESG actions that have contributed to a reduction in costs? If so, how much does this reduction represent in relation to net revenue? (0: no actions, 1: $<5\%$, 2: $5.1\%-10\%$, 3: $10.1\%-15\%$, 4: $15.1\%-20\%$, 5: $>20\%$).
		ESG investments	The percentage of net revenue invested in sustainability and ESG last year. (0: 0%, 1: $0.01\%-0.5\%$, 2: $0.51\%-1\%$, 3: $1.01\%-2\%$, 4: $2.01\%-3\%$, 5: $3.01\%-4\%$, 6: $>4\%$).
		Green R&D investments	The percentage of the R&D (Research and Development) budget invested in research and development of green technologies. (0: no measurement, 1: $<=20\%$, 2: $21\%-40\%$, 3: $41\%-60\%$, 4: $61\%-80\%$).
	Resource use	Environmental and social supplier monitoring	D: 1 if the company monitors its suppliers for environmental and social aspects (including labor), 0 otherwise.
		Environmental and social supplier programs	D: 1 if the company has programs to develop the social and environmental practices of its suppliers, 0 otherwise.
S pillar	Community	Products for low-income communities	D: 1 if the company offers products and services for the benefit of the inclusion of low-income people and disadvantaged communities in the sector in which it operates, 0 otherwise.
		Income-generating opportunities for poor communities	D: 1 if the company creates income-generating opportunities for poor communities, 0 otherwise.
		Hiring employees from vulnerable groups	D: 1 if the company has targets for hiring employees from the most vulnerable groups in the region where it operates (e.g. illiterate people, people over 60, black people, women, others), 0 otherwise.
		Local development strategy	D: 1 if the company follows a local development strategy with shared goals with NGOs, local governments and other companies, 0 otherwise.
		Structured dialog processes with stakeholders	D: 1 if the company has structured dialog processes (identification of stakeholders, engagement planning, treatment of stakeholder opinions, others) in its relations with its stakeholders, 0 otherwise.
	Human rights	Number of labor lawsuits filed by employees	$1-$ total number of labor lawsuits filed by employees, regardless of outcome.
		Number of labor lawsuits filed by third parties	$1-$ total number of labor lawsuits filed by third parties, regardless of outcome
	Product responsibility	Percentage of revenue from sustainable products	The percentage of net revenue obtained from new, more sustainable products and services. (0: 0%, 1: $<5\%$, 2: $10.1\%-15\%$, 3: $15.1\%-20\%$, 4: $20.1\%-25\%$, 5: $>50\%$).
	Workforce	Frequency of performance appraisal process	The frequency of the companies formal performance appraisal process carried out.
		Employee education	Count variable determining how the company encourages continuing education for employees. (Internal training, agreements with schools and universities, online training, corporate university, no offer).
		Identification of employee training needs	Count variable determining how the company identifies training needs. (Strategic planning, evaluation of performance, company performance indicators, request from supervisors and managers, negotiated between employees and supervisors, needs in employee's Individual Development Plans (IDPs), others, no formal evaluation).

Notes: This table provides definitions and measurements of the variables used to construct the ESG scores. All variables are sourced from survey data. Variable encoding is in parentheses. "D" determines dummy variable.

Table A1: continued

Pillar	Category	Variable	Description
		Employee training results	Count variable determining how the evaluation of training results is verified. (Optimization of work process, achievement of strategic planning goals, individual performance indicators, organizational performance indicators, others, no formal evaluation).
		Dealing with learning and retraining needs	Count variable determining how the company deals with the need for continuous learning, retraining and updating on the part of its professionals. (Facilitate access to short courses, facilitate access to postgraduate courses, enrollment in courses to think openly and innovatively, training system/platform or content, partnership with entity that provides training or courses, sending to innovation events in Brazil, sending to innovation events abroad, no actions on trainings).
		Employee dialogue channel	Which open channel for dialogue does the company use the most? (0: none, 1: ombudsman, 2: telephone line, 3: e-mail/mailbox/confidential intranet, 4: confidential intranet/mobile app).
		Deadline for answering questions	How is the deadline set for answering questions registered through the ‘open channel’? (0: no answer, 1: answered according to the availability of the team responsible, 2: answered within a pre-established timeframe by the responsible team).
		Employee satisfaction	How satisfied are most employees with the company? (1: $< 60\%$, 2: $60\% - 79.9\%$, 3: $80\% - 89.9\%$, 4: $90\% - 100\%$).
		Employee health plan	Offering of health plan by the company. (0: no offer, 1: fully paid by employee, 2: mostly paid by employee, 3: paid 50/50 by company and employee, 4: mostly paid by company, 5: fully paid by company).
G pillar	CSR strategy	Performance reporting	Do the performance reports present economic-financial results and results relating to environmental and social responsibility issues? (0: no, 1: partially, 2: yes).
		Public performance reporting	C: Are performance reports containing economic and financial results and results relating to environmental and social responsibility issues made available to the external public? (0: no, 1: partially, 2: yes).
		Sustainability report	Count variable determining the structure of the company’s sustainability report. (Performance indicators developed with stakeholder engagement, includes negative results, is independently audited, indicators are presented with their time series, includes results on gender equality targets, GRI standard not adopted, not published).
	Management	Compliance board	D: 1 if governance is existent in the company, 0 otherwise.
		Compliance advisory board	D: 1 if the company has an advisory board, 0 otherwise.
		Number of women in board	Number of women in board.
		Number of different nationalities in board	Number of board members of different nationalities or Brazilians living abroad (people living in other cultures).
		Board age difference	Difference in years between the age of the oldest board member and the youngest board member.
		Board evaluation	D: 1 if the company has a formal individual assessment process for the reappointment of board members, 0 otherwise.
		CEO performance evaluation	D: 1 if the company’s board of directors evaluate the performance of the CEO (even if he/she is the owner or a member of the controlling family, in the case of family businesses), 0 otherwise.
		Employees taking part in setting their own targets	Do employees take part in setting their own targets? (0: no, 1: yes, everyone, 2: yes, only strategic, 3: yes, strategic and tactical, 4: yes, tactical and operational).

Notes: This table provides definitions and measurements of the variables used to construct the ESG scores. All variables are sourced from survey data. Variable encoding is in parentheses. “D” determines dummy variable.

Table A.2: Descriptive statistics for ESG variables

Pillar	Category	Variable	Obs.	Mean	Std.	Min	Median	Max
E pillar	Emissions	Emissions and climate factors in investments	1,058	0.76	0.43	0.00	1.00	1.00
		Carbon neutrality target year	850	2.89	1.75	0.00	3.00	5.00
		Carbon absorbation target year	845	2.98	1.95	0.00	3.00	5.00
		Climate certificates	1,248	0.38	0.49	0.00	0.00	1.00
	Innovation	Cost reduction through ESG actions	473	1.05	0.81	0.00	1.00	5.00
		ESG investments	504	2.55	1.96	0.00	2.00	6.00
		Green R&D investments	527	1.25	1.50	0.00	1.00	5.00
	Resource use	Environmental and social supplier monitoring	2,366	0.82	0.38	0.00	1.00	1.00
		Environmental and social supplier programs	2,312	0.51	0.50	0.00	1.00	1.00
S pillar	Community	Products for low-income communities	1,936	0.65	0.48	0.00	1.00	1.00
		Income-generating opportunities for poor communities	2,242	0.77	0.42	0.00	1.00	1.00
		Hiring employees from vulnerable groups	2,118	0.54	0.50	0.00	1.00	1.00
		Local development strategy	2,267	0.60	0.49	0.00	1.00	1.00
		Structured dialog processes with stakeholders	2,314	0.89	0.32	0.00	1.00	1.00
	Human rights	Number of labor lawsuits filed by employees	1,516	−256.91	911.41	−14,104	−38.00	0.00
		Number of labor lawsuits filed by third parties	1,260	−153.06	443.91	−5,859	−25.00	0.00
	Product responsibility	Percentage of revenue from sustainable products	196	1.83	2.04	0.00	1.00	5.00
	Workforce	Frequency of performance appraisal process	2,453	3.11	0.91	1.00	3.00	6.00
		Employee education	2,208	2.92	1.01	0.00	3.00	4.00
		Identification of employee training needs	2,487	3.22	1.52	0.00	3.00	7.00
		Employee training results	2,453	1.87	1.31	0.00	2.00	5.00
		Dealing with learning and retraining needs	1,516	3.79	2.00	0.00	4.00	7.00
		Employee dialogue channel	1,859	2.01	1.19	0.00	2.00	4.00
		Deadline for answering questions	1,751	1.86	0.36	0.00	2.00	2.00
		Employee satisfaction	2,287	2.57	0.94	1.00	3.00	4.00
		Employee health plan	2,043	3.88	0.95	0.00	4.00	5.00
G pillar	CSR strategy	Performance reporting issues	1,336	1.48	0.72	0.00	2.00	2.00
		Public performance reporting	469	1.54	0.69	0.00	2.00	2.00
		Sustainability report	1,151	2.44	1.90	0.00	3.00	5.00
	Management	Compliance board	557	0.76	0.43	0.00	1.00	1.00
		Compliance advisory board	127	0.48	0.50	0.00	0.00	1.00
		Number of women in board	445	1.74	1.02	1.00	1.00	8.00
		Number of different nationalities in board	115	2.63	1.74	1.00	2.00	7.00
		Board age difference	247	26.91	10.66	1.00	27.00	60.00
		Board evaluation	1,451	0.42	0.49	0.00	0.00	1.00
		CEO performance evaluation	899	0.74	0.44	0.00	1.00	1.00
		Employees taking part in setting their own targets	1,809	1.86	1.17	0.00	1.00	4.00

Notes: This table reports summary statistics on the ESG variables pre standardization and aggregation into ESG pillar scores.

Table A.3: Definitions of variables

Variable	Measurement	Source
ESG score	Environmental, social, governance (ESG) score.	Own calculation / survey
E score	Environmental pillar score.	Own calculation / survey
S score	Social pillar score.	Own calculation / survey
G score	Governance pillar score.	Own calculation / survey
LSEG ESG score	LSEG's environmental, social, governance (ESG) score divided by 100.	LSEG
LSEG E score	LSEG's environmental pillar score divided by 100.	LSEG
LSEG S score	LSEG's social pillar score divided by 100.	LSEG
LSEG G score	LSEG's governance pillar score divided by 100.	LSEG
Public	D: 1 if the company is listed on the Brazilian stock exchange B3, 0 otherwise.	Survey
Family	D: 1 if the company is family-owned?, 0 otherwise.	Survey
ROA	Return on assets in percent.	Survey
Size	(Logarithm of) total assets.	Survey
Leverage	Total short-term loans and financing plus total long-term loans and financing, divided by total assets.	Survey
Liquidity	(Logarithm of) liquidity.	Survey
Capital intensity	Depreciation divided by total assets.	Survey
B2B	D: 1 if the company is primarily engaged in business-to-business activities, 0 otherwise.	Survey
R&D operations	D: 1 if the company has Research and Development (R&D) / innovation operations in Brazil, 0 otherwise.	Survey
Foreign operations	D: 1 if the company operates abroad, 0 otherwise.	Survey
Go private	D: 1 if the company changed its ownership status from public to private, 0 otherwise.	Survey
Go public	D: 1 if the company changed its ownership status from private to public, 0 otherwise.	Survey

Notes: This table provides the definitions of the variables, which are used in econometric analyses. "D" determines dummy variable.

Table A.4: Correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	ESG score	1.00																			
2	E score	0.24	1.00																		
3	S score	0.18	0.31	1.00																	
4	G score	0.24	0.13	0.23	1.00																
5	LSEG ESG score	0.69	0.33	0.22	0.23	1.00															
6	LSEG E score	0.57	0.38	0.26	0.26	0.88	1.00														
7	LSEG S score	0.65	0.31	0.19	0.18	0.92	0.75	1.00													
8	LSEG G score	0.61	0.19	0.11	0.21	0.81	0.56	0.63	1.00												
9	Public	−0.03	0.10	0.08	−0.21	−0.25	−0.21	−0.22	−0.24	1.00											
10	Family	−0.05	−0.05	−0.08	−0.16	−0.39	−0.25	−0.48	−0.21	−0.08	1.00										
11	ROA	0.04	−0.07	0.02	−0.02	−0.04	−0.05	0.02	−0.08	−0.15	0.22	1.00									
12	Size	0.13	0.23	0.24	0.07	0.37	0.39	0.34	0.25	0.52	−0.19	−0.19	1.00								
13	Leverage	0.05	0.07	0.03	0.04	0.13	0.22	0.12	0.02	0.20	0.08	−0.34	0.19	1.00							
14	Liquidity	−0.05	−0.09	−0.04	−0.09	−0.21	−0.30	−0.14	−0.08	0.09	0.22	0.28	−0.10	−0.21	1.00						
15	Capital intensity	0.08	0.09	0.08	0.10	0.26	0.21	0.18	0.32	0.01	−0.00	−0.07	0.01	0.13	−0.22	1.00					
16	B2B	0.13	0.02	0.01	−0.02	0.08	0.06	0.08	0.09	−0.14	0.13	0.14	−0.22	−0.03	0.15	0.10	1.00				
17	R&D operations	0.10	0.14	0.20	0.12	0.21	0.24	0.20	0.14	0.12	0.02	0.03	0.23	0.01	0.06	−0.00	−0.00	1.00			
18	Foreign operations	0.06	−0.01	0.17	0.05	0.18	0.20	0.11	0.19	0.01	0.04	0.12	0.16	0.01	0.05	0.01	0.21	0.18	1.00		
19	Go private	0.04	0.02	0.04	0.06					−0.06	−0.03	−0.05	0.03	0.07	−0.05	0.03	−0.03	−0.01	−0.03	1.00	
20	Go public	0.03	−0.01	0.03	−0.04	−0.07	−0.11	0.01	−0.14	0.15	0.02	−0.01	0.04	−0.00	−0.04	−0.03	−0.00	0.01	−0.02	−0.01	1.00

Notes: This table reports the pairwise Pearson correlation coefficients.

Chapter 8

Conclusion

8.1 Limitations and future research

While this dissertation advances our understanding of sustainable finance and corporate behavior across distinct domains, several natural limitations might be acknowledged. At the same time, it should be noted that the chosen data and empirical settings provide important strengths.

Although the analysis of green bond liquidity (Chapter 2) relies on one of the most extensive datasets examined so far, the green bond market remains relatively young and continuously evolving. Nonetheless, the findings appear robust within the current market context and provide a valuable benchmark for future research as the market further develops. The LOT liquidity estimate is based on fewer observations, which slightly limits its comparability with the other considered liquidity measures. Moreover, intra-day liquidity was not assessed due to the absence of high-frequency data.

The studies of corporate greenwashing (Chapters 3–6) draw on hand-collected cases for STOXX Europe 600 companies between 2011 and 2023. The information gathering and processing followed several structural steps, including systematic screening of media and NGO sources, standardized inclusion criteria, and independent severity assessment by multiple trained researchers to ensure the validity of the dataset. The credibility of this dataset is also reflected in the choice of empirical setting. Conceptually, greenwashing is a subjective and context-dependent phenomenon that requires ex-post validation by multiple stakeholders to establish credible cases (Seele and Gatti, 2017). A European setting, with its active media landscape, engaged NGOs, and increasing regulatory scrutiny, offers favorable conditions for the public exposure and documentation of greenwashing cases. This enables the detection of a sufficient number of incidents across years, countries, industries, and severities. Practically, the use of a broad and consistent reference index (STOXX Europe 600) combined with comprehensive company-level data allowed us to construct a longitudinal panel that captures greenwashing behavior over time. This facilitates a thorough empirical investigation of greenwashing patterns and their determinants. Moreover, a worldwide search on Google Trends[1] for the term *Greenwashing* from 2011 to 2023 revealed that eight out of the top ten countries with the highest search volume are European, showing Europe's central role in the debate on greenwashing. Finally, Europe's leadership in global sustainable finance[2] and regulatory initiatives such as the EU Taxonomy, the Corporate Sustainability Reporting Directive (CSRD), the Sustainable Finance Disclosure Regulation (SFDR), and the Green Claims Directive (GCD) provide an ideal setting for studying corporate greenwashing due to the the high data availability and strong public scrutiny (European Parliament and the Council of the European Union, 2020, 2022, 2019; European Commission, 2023).

Nevertheless, some natural limitations remain. Allegations that are unobserved or less visible may not be fully reflected, which implies that hidden-variable bias could play a role to some degree. As a result, the set of greenwashing incidents may understate true company behavior, and our severity scores based on independent human judgments may be subject to some measurement error introduced by individual biases. However, the human-based approach likely yielded more reliable results in both allegation identification and severity assessment, drawing on the evaluators' experience and contextual knowledge, than would have been possible by relying solely on automated text-processing techniques, individual controversy variables from rating providers such as RepRisk, or alternative approaches in the literature that measure greenwashing by comparing ESG disclosure with ESG performance scores (e.g., Peng and Xie, 2024; Yu et al., 2020; Zhang, 2023b). Importantly, our analyses yield statistically significant and economically meaningful empirical relationships that align with the theoretical concepts of corporate greenwashing and misconduct behavior. Therefore, it is unlikely that missed incidents or minor biases in severity scores would materially alter our results.

Brazil offers a particularly compelling setting to study ESG behavior for three reasons. First, it is one of the world's largest economies, the largest in Latin America, and among the top greenhouse gas emitters, making corporate sustainability practices highly salient for climate and development goals (International Monetary Fund, 2025; International Energy Agency, 2023). Second, Brazilian capital markets contrast stringent disclosure and governance obligations for publicly traded companies with limited transparency for large private companies, allowing for significant ownership-based comparisons (La Porta et al., 1999; Leal and Carvalhal-da-Silva, 2005). Third, the introduction of CVM Resolution No. 59 in 2021 mandated ESG disclosure for listed companies and created a quasi-natural experiment to observe the effect of this regulation on the sustainability behavior of companies in an emerging market. Chapter 7 uses a new company-level dataset compiled from a large, nationwide business journal survey to study these relationships. The survey covers the country's top revenue-generating companies, representing a broad spectrum of industries and ownership structures. Due to its economic relevance, institutional heterogeneity, and regulatory

[1] Data retrieved from Google Trends: https://trends.google.de/trends/explore?date=2011-01-01%202023-12-31&q=greenwashing&hl=de.

[2] https://www.alfi.lu/en-gb/news/europe-remains-a-global-leader-in-sustainable-fina (accessed on September 16, 2025)

change, Brazil is a uniquely suitable case for analyzing ownership, disclosure, and ESG performance in emerging markets.

At the same time, some limitations might be acknowledged. The comparison of ESG performance and financial returns between public and private Brazilian companies is based on self-reported survey responses from 2017 to 2023. The dataset is inherently limited in both size and frequency: companies that opted into the survey may differ systematically from their peers, and because disclosure was voluntary until CVM 59 took effect, our sample may overrepresent companies that are more sustainability-minded. These concerns are mitigated by benchmarking survey-based ESG scores against LSEG ESG scores, applying regression-based weighting to ensure comparability, controlling for industry-specific heterogeneity via fixed effects, and normalizing by year. Additionally, the difference-in-differences design around CVM 59 helps account for potential selection effects, alleviating concerns that the results are driven solely by voluntary participation.

Beyond data constraints, some external validity challenges remain across the empirical settings examined in the dissertation. Greenwashing behaviors in Europe may differ from those in the United States, Asia, or Latin America due to varying levels of media scrutiny, regulatory pressure, and NGO activism. Furthermore, the study of ESG and financial performance in public and private companies relies on Brazil as one case of an emerging market. Different ownership structures, regulatory regimes, and stakeholder pressures in other economies could result in varying ESG performance dynamics. Furthermore, the seven-year span does not capture long-term ESG trends. The possibility cannot be ruled out that the observed ESG outperformance of private relative to public companies will flatten or reverse over the course of a decade. Furthermore, it remains uncertain whether public companies will eventually catch up once disclosure quality improves.

Given these limitations, readers are encouraged to view the results as contextually robust insights that provide a basis for further exploration beyond the settings that were studied. Future work could use higher-frequency trading data to better understand green-bond liquidity. It could also expand hand-collected greenwashing databases to include non-European contexts and more granular time frames. Additionally, it could employ machine-learning tools for case detection and severity scoring. For example, natural language processing (NLP) models could be trained on textual disclosures and media coverage to identify potential greenwashing incidents, while supervised learning could calibrate severity assessments against human-coded benchmarks to improve scalability and consistency. Similarly, assembling larger panels of private companies from multiple emerging and developed markets would enable more robust testing of ESG performance dynamics. Nevertheless, by documenting how green bond liquidity is associated with third-party verification through greenness ratings, how company characteristics determine and forecast greenwashing behavior, and how ownership structures, ESG performance, and financial performance interact in an emerging market context, the dissertation lays a foundation for further research that can test robustness across periods, regions, and company types.

8.2 Implications and outlook

As sustainability considerations move from niche concerns to core business imperatives, the term ESG itself may evolve or be replaced by broader concepts. For example, Edmans (2023) advocates a shift toward "rational sustainability," emphasizing evidence-based, long-term value creation rather than rigid adherence to a fixed ESG acronym.

Regardless of the terminology used, the fundamental insight remains the same: stakeholders demand reliable information on a company's sustainability performance, and companies must understand their social and environmental impacts if they wish to manage risk and seize emerging opportunities. In this sense, the various chapters of this dissertation presage a future in which sustainability becomes an essential part of corporate decision-making, alongside finance and strategy.

In the domain of sustainable finance, practitioners will need to embed sustainability not only as a screen for exclusionary investing but as a driver of risk-mitigating portfolio construction and product design that advances both ecological and economic returns. Green bonds, green loans, and other labeled instruments may coexist alongside a growing class of "transition" debt and equity products that aim to decarbonize real-economy assets. As capital allocators integrate ESG-related risk factors, ranging from carbon-price exposure to biodiversity-loss risk, into credit models and portfolio optimization (e.g., Dumrose and Höck, 2023; Duong et al., 2025; Garel et al., 2024), sustainable finance will resemble a specialized branch of risk management. Chapter 2 illustrates this evolution by showing that green bonds verified by third-party greenness ratings are associated with higher secondary-market liquidity. This demonstrates how credible sustainability information may enhance the efficiency of financial markets. In this context, it is crucial to consistently reduce information asymmetries. Asset managers, rating agencies, and regulators should all demand more transparent, standardized, and verifiable sustainability disclosures.

Regulatory frameworks have made important strides. European initiatives such as the EU Taxonomy, the CSRD, the GCD, and the SFDR indicate that policymakers intend to enforce higher transparency standards for companies and financial intermediaries (European Parliament and the Council of the European Union, 2020, 2022; European Commission, 2023; European Parliament and the Council of the European Union, 2019). Yet these rules should become more impact-oriented rather than process-oriented: to be fully effective, they should (1) broaden their coverage to include mid-sized private companies and financial products beyond flagship European markets, (2) mandate third-party verification (or at least assurance) of key sustainability claims, and (3) explicitly measure whether reported activities translate into real-world outcomes such as reduced emissions, better labor practices, or improved corporate biodiversity performance. In the years ahead, researchers and regulators should evaluate the impact of these frameworks on capital allocation patterns, corporate behavior, and ultimate social and environmental outcomes.

Yet even the strongest rules cannot entirely eliminate information asymmetries. Greenwashing is unlikely to disappear just because marketing-centric claims are becoming less credible. Stricter enforcement and elevated scrutiny by the media, NGOs, and civil society watchdogs can curtail overstated slogans and symbolic disclosures. However, more subtle forms of greenwashing may persist or even become more prevalent. For example, companies may set ambitious climate targets but then veer off course. Alternatively, they may engage in cosmetic "executional greenwashing," using green imagery (de Freitas Netto et al., 2020; Parguel et al., 2015). These emerging practices are harder to detect and measure. At the company level, Chapters 3 and 4 provide analytical frameworks to better understand these dynamics. Chapter 3 develops a systematic framework and human-assessed severity score to identify and classify greenwashing behavior, while Chapter 4 links ESG performance and disclosure quality to greenwashing risk. Together, they highlight the double-edged nature of ESG metrics: while strong sustainability performance and transparent disclosure can signal genuine commitment, ESG scores may emphasize disclosure quality over substantive impact, meaning that high ratings do not necessarily reflect real environmental or social progress. In order to stay ahead of the evolving landscape of sustainability communication, new methodologies will be necessary, such as the natural language analysis of corporate reports. As the dissertation's Chapter 6 argues, a combined approach of case-based severity scoring and machine-learning forecasting can help stakeholders estimate and price in greenwashing risk. Looking ahead, it will be crucial to refine these measurement and prediction tools so that investors, regulators, and civil society actors can integrate qualitative watchdog assessments with quantitative risk models.

From a company-level perspective, corporate managers should view their ESG scores and greenwashing indices not as peripheral KPIs but as central inputs to governance and strategic planning. Chapter 6 demonstrated that company size, cash-to-assets ratios, capital intensity, and ESG (disclosure) scores are all related to greenwashing behavior. Additionally, the event study in Chapter 5 showed that greenwashing allegations can trigger significant negative stock market reactions, especially for smaller companies and cases related to compliance or perceived as financially material. However, high ESG scores can mitigate negative market reactions in specific contexts. These findings suggest that managers who downplay the risk of greenwashing may expose their companies to reputational damage and valuation losses. This emphasizes the importance of proactive governance mechanisms, such as independent audits, whistleblower hotlines, and board-level ESG committees. In parallel, Chapter 7 showed that private companies can outperform comparable public companies in terms of ESG performance. Meanwhile, public companies under regulatory pressure can quickly improve their ESG performance once disclosure becomes mandatory. However, without careful internal alignment, these ESG performance gains can mask superficial improvements rather than substantive progress. In all cases, third-party validation, whether via accredited auditors, specialized data providers, or academic partnerships, will be essential to signal credibility.

Finally, information asymmetry remains the overarching challenge. Whether investors are comparing green bonds, screening for greenwashing risk, or evaluating public versus private companies, they need data that are not only timely and consistent but also comparable across industries and regions. Therefore, improving the regulation of sustainability disclosure through tighter definitions, harmonized taxonomies, and direct linkages to impact metrics is not merely a compliance cost. It provides essential infrastructure for capital markets and society at large. Well-designed disclosure rules can reduce transaction costs, improve market efficiency, and encourage capital to flow toward genuinely sustainable activities. However, regulation alone is not enough. Civil society, professional associations, and industry-led coalitions should also continue developing best practices, conducting empirical research, and pushing for continuous improvement.

In summary, although the specific terminology around ESG may shift, the long-term imperative is unlikely to change: sustainability information is expected to become an increasingly fundamental component of corporate strategy and financial analysis, comparable in importance to earnings statements and balance sheets. Sustainable finance should evolve from voluntary aspiration to integrated practice, embedding sustainability considerations into risk models and portfolio construction. Regulators should press beyond mere disclosure to meaningful, outcome-oriented reporting with robust third-party validation. Scholars and practitioners alike will need increasingly sophisticated tools to ensure that capital flows reward real environmental and social progress. These tools could include machine-learning models to forecast greenwashing or comparative frameworks to assess ownership effects.

Reducing information asymmetries is essential to this task. The event study in Chapter 5 indicates that greenwashing behavior can lead to negative market reactions, emphasizing that the costs of misrepresenting sustainability performance should not be overlooked. In this sense, António Guterres' call at COP27 for "zero tolerance for net-zero greenwashing" is not merely rhetoric but a market imperative: only credible and verifiable sustainability information allows capital to flow toward companies that deliver genuine sustainability performance. Ultimately, the future of sustainable finance depends on whether markets can rise to the challenge of transforming transparency into trust and trust into tangible progress for economies and the planet.

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