Greenwashing: Measurement and Implications

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Abstract

This study leverages earnings conference call transcripts and the FinBERT machine learning model to measure greenwashing (GW) intensity across a broad sample of U.S. public firms from 2007 to 2021. We document an economy-wide increase in GW intensity following the 2015 Paris Agreement, with a significant rise in GW among fossil fuel and stranded asset industries. Higher GW intensity is linked to more future environmental incidents and EPA enforcement actions, and higher carbon emissions, but not to increased green innovation. GW is associated with lower cumulative abnormal stock returns post-earnings calls and poorer future operating performance, especially in firms with greater information asymmetry and weaker institutional monitoring. GW firms receive higher future environmental ratings, face lower forced CEO turnover, exhibit reduced CEO pay-for-performance sensitivity, and are more likely to link CEO pay to corporate environmental performance. Additionally, these firms show reduced risk-taking behaviors. Our findings suggest an agency motivation for GW, where managers engage in GW to enhance their job security and compensation at the expense of shareholders.

Keywords: Greenwashing, Machine Learning, FinBERT, Stock Returns, Operating Performance, Forced Turnover, CEO Incentives

JEL Classification: G10, G30, M10

"Nearly three-quarters of executives said most organizations in their industry would be caught greenwashing if they were investigated thoroughly, according to a survey of nearly 1,500 executives across 17 countries and seven industries conducted in January by the Harris Poll on behalf of Google Cloud."

Rochelle Toplensky, April 13, 2023, The Wall Street Journal

1. Introduction

The pursuit of sustainability has become an important focus in today's corporate world. However, there is a concern that some companies are engaging in greenwashing, which involves creating a misleading environmental image.[1] This includes making statements that misrepresent past environmental performance and/or mischaracterize future environmental intent. Greenwashing can, therefore, be defined as *a discrepancy between corporate green talk and actual green walk* (e.g., Delmas and Burbano, 2011; Walker and Wan, 2012; Pizzetti, Gatti, and Seele, 2021). Greenwashing misleads consumers, investors, and other stakeholders, erodes their trust, and undermines authentic sustainability efforts. Goldstein and Yang (2019) point out that some disclosures have negative consequences for decision-makers. Greenwashing is an example of such disclosures.

We use an advanced finance-specialized machine learning technique to develop a reliable firm-level measure of corporate greenwashing (hereafter "greenwashing" or "GW") for a broad sample of U.S. firms. Our GW measure captures *the distance between a firm's green talk and its green walk*. We use earnings conference call transcripts to capture the firm's green talk, which refers to *positive* statements made by its corporate executives that are *specific* to the firm's environmental performance and initiatives. We quantify green walk using the firm's actual environmental incidents.

Earnings conference calls, which are conducted quarterly following the release of a publicly traded firm financial results for the preceding quarter, serve as a platform for the company to furnish investors and analysts with updates regarding its financial performance and prospects. These calls also allow investors and analysts to ask questions and gain deeper insights into the firm's business operations, risks, and

[1] Our focus is on company or corporate greenwashing rather than product-level greenwashing, which involves misrepresenting the environmental benefits of a product or service.

opportunities. Due to the substantial wealth of firm-specific information embedded in earnings conference call transcripts, an emerging body of literature employs these transcripts to gauge a firm's exposure to diverse facets, such as political risk (e.g., Hassan, Hollander, Van Lent, and Zhang, 2019), corporate culture (e.g., Li, Mai, Shen, and Yan, 2021), climate change (e.g., Li, Shan, Tang, and Yao, 2023; Sautner, Van Lent, Vilkov, and Zhang, 2023), and labor-shortage exposures (e.g., Harford, He, and Qiu, 2023). Hence, we expect earnings conference call transcripts to be an excellent source of textual data for capturing green talk emanating from corporate executives.[2]

To capture a firm's green talk, we segment each transcript into individual sentences. Subsequently, we harness the capabilities of a cutting-edge machine learning model, *FinBERT* (e.g., Huang, Wang, and Yang, 2022), to efficiently discern whether a sentence qualifies as a green talk sentence or not.[3] To ensure that the identified green talk reflects *positive* statements made by corporate executives that are *specific* to the firm's environmental performance and initiatives, we train *FinBERT* to exclude any general (non-firm-specific) climate talk or discussions on the firm's past environmental incidents. Our fine-tuned *FinBERT* model achieves a remarkable 90% accuracy rate in detecting green talk sentences. Based on the green talk sentences identified by our *FinBERT* model, we rank the sample firms that are identified as engaging in green talk within a given year into percentiles, based on a firm's green talk intensity in its conference call transcripts of that year.

[2] Among the myriad channels for corporate disclosures, earnings conference calls and 10-K reports emerge as pivotal components shaping stakeholders' perceptions. While 10-K reports play a crucial role, their adherence to strict formatting requirements results in a standardized and regulated template, limiting the narrative and expression of corporate nuances, primarily designed for regulatory compliance. In contrast, conference calls provide a dynamic and flexible platform for communication. The interactive and less rigid nature of conference calls allows corporate managers to convey their message in a more conversational and unstructured manner, significantly amplifying the potential for greenwashing. Essentially, conference calls stand out as a strategic venue for managers aiming to greenwash their corporate images. The nuanced presentations facilitated by the interactive nature of these discussions are important in shaping stakeholders' perceptions. Therefore, we leverage earnings conference call transcripts as a powerful tool to capture the nuances of a firm's green talk, recognizing their significance in portraying and potentially influencing the perception of environmental initiatives within the corporate landscape.

[3] *FinBERT* is a machine learning model developed on the foundation of *BERT* (Devlin, Chang, Lee, and Toutanova, 2018), a pre-trained large language model adept at comprehending the intricacies of English language syntax and semantics. However, *FinBERT* distinguishes itself as a finance-specialized variant, undergoing further training with financial text data such as 10-K filings and earnings conference call transcripts. Huang, Wang, and Yang (2022) document that *FinBERT* surpasses *BERT* in terms of performance, particularly in discerning sentence sentiment and identifying environmental, social, and governance (ESG) sentences within financial contexts.

We employ RepRisk incidents as a metric to measure the actual environmental performance of a firm. Unlike other environmental, social, and governance (ESG) rating datasets that are often based on corporate self-disclosures, RepRisk identifies event-level risk incidents for firms from over 100,000 media sources in 23 languages daily. Because these negative incidents are generally not manipulatable by the firms themselves and RepRisk intentionally excludes corporate self-disclosures from its data sources, the RepRisk environmental incident data provides us with an objective assessment of a firm's actual environmental performance. As stated on their website, "*RepRisk's unique perspective serves as a reality check for how companies conduct their business around the world – do they walk their talk?*".[4]

We count the number of environmental incidents in each firm-year and rank the sample firms into percentiles each year based on the environmental incident count. We further multiply the incident count percentile by -1, so that a lower value indicates the worse actual environmental performance of a firm. Our firm-level greenwashing measure is thus the difference between the green talk percentile and the (negative) environmental incident count percentile in each year, scaled by 100. Higher values of the greenwashing measure signify a greater discrepancy between green talk and actual green walk.[5] After removing non-missing stock returns and financial data, our final sample consists of 30,364 firm-year observations related to 107,464 earnings conference call transcripts and 4,060 unique U.S. public-listed firms.

We conduct various validation tests for our firm-level GW measure. First, we observe that the economy-wide aggregate GW measure increased markedly after the 2015 Paris Agreement, which brings all nations together to combat climate change. Second, we rank the measure by Fama-French 48 industries and find that the utility industry has the highest level of greenwashing intensity among all industries. Third, we exploit the adoption of the 2015 Paris Agreement, which significantly increased the attention of investors, regulators, and other stakeholders on climate change and sustainability issues, as a quasi-natural experiment. Using difference-in-differences regressions, we find that relative to other firms, firms in the

[4] See https://www.reprisk.com/news-research/resources/methodology.

[5] Firms without any green talk in a year are given a value of 0 for the greenwashing measure regardless of their actual environmental performance. Our analysis indicates that while both talk and walk components make an important contribution to the greenwashing measure, talk has a bigger influence.

fossil fuel industries or the broader stranded asset industries (i.e., utilities; energy equipment & services; oil, gas & consumable fuels; construction materials; metals and mining), experienced a significant increase in greenwashing intensity after the adoption of the Paris Agreement.

Fourth, we find that cross-sectionally, firms with higher greenwashing intensity incur more future environmental incidents, experience more future environmental enforcement actions from the U.S. Environmental Protection Agency (EPA), and have higher future carbon emissions. Fifth, we find that despite their higher likelihood of experiencing future environmental incidents and EPA enforcement actions and greater future carbon emissions, greenwashing firms do *not* produce more green innovations than non-greenwashing firms.

After validating the firm-level GW measure, we explore its association with firm stock price reactions following earnings conference calls and future operating performance. We observe that firms with higher greenwashing intensity experience significantly lower cumulative abnormal returns (CAR) within the five days following the earnings conference calls. A one-standard-deviation increase in the firm-level greenwashing measure corresponds to a 0.09 percentage-point decrease in the five-day CAR. Furthermore, we do not identify any return reversals after the initial negative stock price reactions. Additionally, we find that the measure of firm-level GW intensity robustly and negatively predicts one-year-ahead corporate operating performance. Specifically, a one-standard-deviation increase in firm-level greenwashing intensity, on average, predicts a 0.9-percentage-point decrease in one-year-ahead return on assets (ROA), and a 0.6-percentage-point reduction in one-year-ahead operating cash flow. These findings suggest that GW is associated with lower stock price reactions and poorer future firm operating performance. Furthermore, we find that the negative relationships between GW and stock price reactions, as well as future operating performance, are significantly more pronounced for firms with greater information asymmetry and weaker institutional monitoring.

Given that GW is negatively related to stock price movements and future operating performance, a natural question to ask is why managers engage in greenwashing. To explore this question, we first investigate the relation between firm-level greenwashing intensity and corporate environmental ratings using the rating data from MSCI KLD, Refinitiv, and Sustainalytics. We find that firms with greater greenwashing intensity receive higher environmental rating scores from the rating agencies. Since higher environmental ratings may benefit corporate executives in terms of greater job security and higher compensation, this finding of a positive relation between greenwashing and environmental ratings indicate that corporate executives may engage in greenwashing to benefit themselves at the expense of shareholders and other stakeholders.

Our additional results show that after the Paris Climate Accords adoption in 2015, GW is indeed related to outcomes that benefit the CEO. First, GW is significantly and negatively associated with both the forced turnover likelihood and the forced-turnover-to-operating-performance sensitivity, suggesting that top executives' job security increases when they conduct greenwashing. Second, GW intensity is associated with lower CEO pay-for-stock-performance sensitivity (delta) and CEO wealth-to-stock-volatility sensitivity (vega). Third, firms with greater GW intensity are also more likely to link their CEO compensation with corporate environmental performance in compensation contracts. Hence, top executives' compensation is less sensitive to corporate operating performance and more closely linked to corporate environmental performance, incentivizing executives to engage in greenwashing.

We conjecture that with their enhanced job security, increased environmental-performance-linked compensation and decreased pay-for-stock-performance sensitivity, executives of greenwashing firms may enjoy a quieter life (e.g., Bertrand and Mullainathan, 2003) and hence reduce their risk-taking activities (even though such risk-taking activities may be profitable to shareholders). Consistent with this conjecture, we find that greenwashing is related to lower future R&D and acquisition activities, lower future financial leverage, and greater future cash holdings. Overall, our evidence is consistent with the agency explanation for greenwashing activities.[6] Vargas and Kuhn (2023) examine the way the remuneration system at DWS, a Deutsche Bank subsidiary, undermines sustainability and climate goals and they note that *"The structuring of bonus-related sustainability targets has proven to be highly problematic, though, because it*

[6] Such an agency-based explanation of greenwashing is consistent with our earlier finding that greenwashing is negatively associated with stock price reactions and future operating performance.

gives top management massive incentives to pursue systematic greenwashing." Our results suggest that the link between agency issues and greenwashing is widespread.

Our study contributes to the burgeoning literature on greenwashing (e.g., Laufer, 2003; Walker and Wan, 2012; Lyon and Montgomery, 2015; Marquis, Toffel, and Zhou, 2016; Tashman, Marano, and Kostova, 2019; Yu, Luu, and Chen, 2020; Pizzetti, Gatti, and Seele, 2021; Duchin, Gao, and Xu, 2024). Measuring greenwashing intensity for a broad sample of firms can be challenging and time-consuming. For example, Walker and Wan (2012) construct a greenwashing measure for 103 Canadian firms in the single year 2008 by manually reading materials from the companies' websites to detect their green talk and actual environmental actions. Tashman, Marano, and Kostova (2019) capture green talk by manually coding CSR reports of 353 global emerging firms in 1,348 firm-year observations. To increase the sample size, several studies use third-party environmental ratings as proxies for green talk or even greenwashing activities (e.g., Marquis, Toffel, and Zhou, 2016; Yu, Luu, and Chen, 2020). However, recent research suggests that third-party environmental ratings can be sensitive to corporate self-disclosures and rating methodologies (e.g., Berg, Koelbel, and Rigobon, 2022; Christensen, Serafeim, and Sikochi, 2022). Moreover, Duchin, Gao, and Xu (2024) show that firms may employ the divestiture of polluting plants as a greenwashing strategy in response to environmental pressures, yet such actions do not lead to a reduction in pollution levels.

We contribute to this literature by using earnings conference call transcripts and a state-of-the-art machine learning model, *FinBERT*, to detect green talk, and match the green talk with the actual environmental incidents from RepRisk to construct a comprehensive measure of firm-level GW intensity for a broad sample of U.S. public firms. We validate the reliability of the GW measure. While it is not possible to establish causality, we show that GW does have implications on corporate performance and executive incentives.

Moreover, the study contributes to the literature on textual analysis in finance (e.g., Loughran and McDonald, 2011; Garcia and Norli, 2012; Hoberg and Phillips, 2016; Gentzkow, Kelly, and Taddy, 2019; Harford, He, and Qiu, 2023; Florackis, Louca, and Michaely, 2023). The extant literature uses a "bag-of-words" (keyword dictionary) approach to measure different topics of interest (e.g., Baker, Bloom, and Davis, 2016, Hassan, Hollander, Van Lent, Schwedeler, and Tahoun, 2023, Hassan, Hollander, Van Lent, and Tahoun, 2024, Caldara and Iacoviello, 2022). Some studies have started to adopt machine learning techniques to broaden the scope of the dictionary. For example, Li, Mai, Shen, and Yan (2021) apply the *Word2vec* model to measure corporate culture. Sautner, Van Lent, Vilkov, and Zhang (2023) adopt a keyword discovery algorithm to measure firm-level climate change exposure. In contrast to the dictionary approach, Baker, Larcker, McClure, Saraph, and Watts (2024) use a machine learning model based on *BERT* to identify diversity, equity, and inclusion sentence, and Harford, He, and Qiu (2023) employ the *FinBERT* model developed by Huang, Wang, and Yang (2023), to measure firm-level labor-shortage exposures. We contribute to this literature by using *FinBERT* to capture the firm-level GW intensity.

Third, our study contributes to the longstanding literature on the agency problem of corporate managers (e.g., Jensen and Meckling, 1976; Fama and Jensen, 1983). We add to this literature by showing that greenwashing is another manifestation of the corporate agency problem, and corporate managers tend to commit greenwashing to benefit themselves at the expense of shareholders and other stakeholders of the firm. In this sense, our study responds to the call for more research on managerial ESG motivations by Laura Starks in the 2023 American Finance Association Presidential Address. As she notes *"this analysis is particularly important given frequent claims of corporate greenwashing."* (Starks, 2023, p. 1847).

The rest of the paper proceeds as follows. Section 2 describes the data and our sample construction. In Section 3, we discuss how we measure firm-level greenwashing intensity using *FinBERT*. Section 4 reports the results from the validation tests. Section 5 studies the implications of firm-level greenwashing on stock price reactions following earnings conference calls and future operating performance. Section 6 explores corporate executives' incentives to commit greenwashing. Section 7 concludes. The Online Appendix provides variable definitions, the prediction performance of our fine-tuned *FinBERT* model, examples of the identified green talk and non-green talk sentences using the *FinBERT* model, and additional robustness results.

2. Data and Sample

2.1 Earnings Conference Call Transcripts

We use earnings conference call transcripts as text data to capture green talk activities. Typically, public-listed firms will host seasonal earnings conference calls starting with management presentation sessions in which the company executives discuss the firm's quarterly operating performance and business conditions, followed by Q&A sessions where financial analysts raise questions to the executives. Consistent with prior literature (e.g., Hassan, Hollander, Van Lent, and Tahoun, 2019; Sautner, Van Lent, Vilkov, and Zhang, 2023), we primarily use the entire earnings call transcript (including both the management presentation and Q&A sessions) to identify a firm's green talk, but we consider each call transcript component separately in robustness checks. We first collect transcripts from the Standard & Poor Capital IQ database (CIQ) during the 2005-2021 period. The raw dataset includes 217,006 earnings call transcripts related to 9,925 unique firms.

2.2 Corporate Environmental Activities

To measure a firm's actual environmental performance, we use the firm-level negative environmental incidents provided by RepRisk from 2007 to 2021. RepRisk detects corporate risk incidents using over 100,000 public sources in 23 languages daily. Each incident is further classified as ESG-related. The advantage of using RepRisk is that, unlike other ESG ratings that are sensitive to self-disclosure of firms and rating methodologies and thus lack consistency (e.g., Berg, Koelbel, and Rigobon, 2022; Christensen, Serafeim, and Sikochi, 2022), risk incidents are truly incurred and thus should reflect arguably more of a firm's actual environmental performance. We focus on environmental-related incidents, which include topics such as climate change, greenhouse gas emissions, pollution, and waste of resources.

In addition to corporate risk incidents, we acquire plant-level environmental enforcement cases from the EPA's Integrated Compliance Information System (ICIS). We then aggregate the number of environmental enforcement cases from plant-year to firm-year level. We also measure carbon emissions and carbon emissions intensity using data from S&P Trucost (e.g., Bolton and Kacperczyk, 2021). To measure a firm's environmental rating performance, we exploit ESG data from MSCI KLD, Refinitiv, and

Sustainalytics. Finally, we capture green innovation using patent grant data from Kogan, Papanikolaou, Seru, and Stoffman (2017) and green patent classification from Haščič and Migotto (2015).

2.3 Corporate Stock Return, Financial, and CEO-Related Information

We use stock return data from the Center for Research in Security Prices (CRSP), analyst forecast data from IBES, and financial data from Compustat. We obtain forced CEO turnover data from 1993 to 2019 from Peters and Wagner (2014), who manually identify involuntary executive departure from press reports. To capture CEO risk-taking incentives, we leverage two proxies provided by Coles, Daniel, and Naveen (2006): CEO pay-for-performance sensitivity (or *Delta*), which is calculated as the value change of the option or restricted stock grants, shareholdings, and any accumulated restricted stock and option holdings for a 1% change in the stock price; and CEO wealth to stock volatility sensitivity (or *Vega*), which is measured as the value change of the CEO's option grant and any accumulated option holdings for a 1% change in the annualized standard deviation of stock returns. To determine whether a firm's executive compensation package is linked to corporate environmental performance, we follow He et al. (2023) and use textual analysis to see whether the environmental-related keywords, generated using the machine learning model *Word2Vec*, are surrounded by executive-related and compensation-related keywords in the proxy statement of the firm in a year. Finally, the CEO-level control variables are constructed using data from Execucomp.

3. Identifying Greenwashing Activities

According to the *Oxford English Dictionary*, greenwashing[7] is defined as "*Misleading publicity or propaganda disseminated by an organization, etc., so as to present an environmentally responsible public image; a public image of environmental responsibility promulgated by or for an organization, etc.,*

[7] The concept of "greenwashing" was first introduced in 1986 by the environmentalist Jay Westerveld, who used the term to criticize hotel sector's towel reuse promotion. While this activity was claimed to protect the environment, Jay Westerveld found that the hotels did not make contribution to environmental protection but merely save laundry costs from towel reuse.

regarded as being unfounded or intentionally misleading."[8] Analogously, in academia, researchers characterize firms' greenwashing behaviors as positive corporate communications from firms to deceive investors about the actual environmental performance, with the intention of generating a misleading public perception of their brands (e.g., Laufer, 2003; Lyon and Montgomery, 2015; Marquis, Toffel, and Zhou, 2016). In other words, greenwashing can be defined as the discrepancy between green talk and actual green walk (e.g., Walker and Wan, 2012; Pizzetti, Gatti, and Seele, 2021). Motivated by this theoretical framework, in this paper, we aim to construct a firm-level greenwashing measure that captures the distance between a firm's green talk and its actual environmental performance. Poor current environmental behavior, coinciding with green talk about future positive environmental intent, is not necessarily evidence of greenwashing if the firm takes steps to change its future environmental approach. With this in mind, we take several steps to validate our greenwashing measure, which are discussed in Section 4.

Measuring greenwashing behavior for a broad sample of firms is challenging because, without frontier technology support, identifying green talk requires intensive manual work (e.g., Walker and Wan, 2012; Tashman, Marano, and Kostova, 2019). Some studies (e.g., Marquis, Toffel, and Zhou, 2016; Yu, Luu, and Chen, 2020) increase their sample size using third-party environmental ratings as proxies for green talk or even greenwashing activities. However, Berg, Koelbel, and Rigobon (2022) and Christensen, Serafeim, and Sikochi (2022) highlight that these ratings are sensitive to the methodologies used and corporate self-disclosure strategies. Therefore, relying on these ratings to measure greenwashing behaviors is far from perfect.

We address these challenges by using earnings conference call transcripts as raw text data, combined with the state-of-the-art machine learning model, *FinBERT*, to detect the green talk activities of a broad sample of U.S. public-listed firms. To measure the actual environmental incidents, we employ the truly incurred environmental incidents of firms provided by RepRisk. We then calculate the discrepancy between

[8] Similarly, *Cambridge English Dictionary* defines greenwashing as "*behaviour or activities that make people believe that a company is doing more to protect the environment than it really is*."

green talk and actual environmental performance for each firm-year, which serves as our targeted greenwashing measure.[9] In the rest of this section, we explain how we construct this measure in detail.

3.1. Green Talk

Earnings conference calls are important communication channels through which firms engage with investors on corporate financial performance and business strategies. A burgeoning literature leverages earnings conference call transcripts to capture various dimensions of firm-level information, such as political risk (e.g., Hassan, Hollander, Van Lent, and Tahoun, 2019), executive extreme languages (Bochkay, Hales, and Chava, 2020), corporate culture (e.g., Li, Mai, Shen, and Yan, 2021), and climate change exposure (e.g., Li, Shan, Tang, and Yao, 2023; Sautner, Van Lent, Vilkov, and Zhang, 2023). In this paper, we follow prior studies and analyze earnings conference call transcripts to identify green talk by corporate executives. This refers to *positive* statements *specifically* related to the firm's environmental performance and initiatives. We expect these transcripts to provide valuable insights into how management teams positively discuss their firms' environmental efforts, especially considering the growing public concern over global warming and climate change.

Several studies employ different textual analysis techniques to capture corporate climate-related discussions in earnings call transcripts (e.g., Chava, Du, and Malakar, 2021; Dzielinski, Eugster, Sjöström, and Wagner, 2022; Bratten and Cheng, 2023). For example, Sautner, Van Lent, Vilkov, and Zhang (2023) use a keyword discovery algorithm to identify climate-related keywords and then construct three firm-level climate change measures: physical risk exposure, regulatory exposure, and opportunity exposure. Similarly, Li, Shan, Tang, and Yao (2023) manually build up a climate-risk-related keyword dictionary to measure corporate environmental risk. While we acknowledge that the methodologies provided by these studies can

[9] Our proposed methodology is in spirit with two contemporaneous working papers by Andrikogiannopoulou, Krueger, Mitali, and Papakonstantinou (2022) who construct a fund-level greenwashing measure by calculating the discrepancy between a fund's ESG talk in its prospectus and its actual ESG investments, and Baker, Larcker, McClure, Saraph, and Watts (2024) who generate a firm-level diversity washing measure by taking the difference between a firm's diversity claims and their actual hiring diversity.

identify insightful climate-related exposure from firms' earnings conference calls, a large amount of these discussions may not be related to green talk.

For instance, in Southern Company's 2010Q4 earnings conference call, the executive stated that "*In August of this year, the Alabama Public Service Commission granted Alabama Power the ability to increase accruals to its natural disaster reserve*", which is related to physical climate risk. Similarly, in the 2011Q4 earnings conference call, NextEra Energy Inc's CEO explained to the investors that "*The weaker wind resource was the primary driver of the negative $0.04 contribution from existing wind assets relative to the prior year comparable quarter*", of which the content is about the negative performance of green investments.

If only relying on climate-related keywords, we will capture a lot of such false positives that are unrelated to green talk. The green talk we want to capture are those positive discussions by corporate executives who promote their firms' environmental investments, efforts, and performance. As such, identifying green talk should depend on a sentence's context. However, the keyword approach is context-independent, implying that any sentence containing the pre-specified climate-related words will be classified as green talk, irrespective of its actual context.[10] A more advanced technique is indeed necessary.

3.1.1. The Advantage of BERT

To overcome the shortcomings of the keyword approach and more accurately measure green talk from earnings transcripts, we use the Bidirectional Encoder Representations from Transformers (*BERT*), which is a state-of-the-art natural language processing (NLP) technique.

BERT, developed by Devlin, Chang, Lee, and Toutanova (2018), is a large language model (LLM) based on deep learning architecture. The advantage of *BERT* is that it can provide latent representations of words in context (i.e., words have different vectors depending on the actual language contexts) after pre-training using large text data.[11] By reading text sentences from left to right and right to left (the so-called

[10] For example, the sentences "*We have a very good business climate*" and "*Our company cares about climate change*" will be classified as green talk because of the occurrence of the keyword "*climate*". However, as human beings, we can clearly see the different meanings of the word by understanding the context.
[11] *BERT* is trained using 2.5 billion words from Wikipedia and 800 million words from Google's BooksCorpus.

"bidirectional") and combining training strategies of the Masked Language Model and Next Sentence Prediction, *BERT* can recognize the syntax and semantics of the English language well.[12] As such, using *BERT* suits our goal as the green talk that we want to capture is highly dependent on context. An emerging accounting and finance research has also started to apply *BERT* to measure different aspects. For example, Rajan, Ramella, and Zingales (2023) use *BERT* to categorize corporate goals in shareholder letters. Bingler, Kraus, Leippold, and Webersinke (2022) develop a *ClimateBERT* to identify corporate climate commitments. Li, Shan, Tang, and Yao (2023) apply *FinBERT* to detect environmental and social issues from analyst reports. Similarly, Harford, He, and Qiu (2023) leverage *FinBERT* to measure corporate labor-shortage exposure.

Specifically, we follow Li, Shan, Tang, and Yao (2023) and Harford, He, and Qiu (2023) and use *FinBERT* to identify green talk in earnings calls. *FinBERT* is a *BERT*-based model pre-trained using financial text data by Huang, Wang, and Yang (2023).[13] As it is not pre-trained using general text data (e.g., Wikipedia), Huang, Wang, and Yang (2023) show that *FinBERT* has a superior understanding of financial contexts. For example, the testing results show that compared with *BERT*, *FinBERT* obtains a higher accuracy rate in predicting ESG sentences. Therefore, we adopt *FinBERT* and expect it to yield better performance in identifying green talk sentences.

3.1.2. Fine-Tuning FinBERT

Although the raw *FinBERT* model has a generalized understanding of the financial context, it is necessary to construct a training sample that includes both green talk sentences and non-green talk sentences to further fine-tune *FinBERT* to increase model performance in the downstream task of green talk detection. The steps for training sample construction are as follows. First, we exploit Stanza (e.g., Qi, Zhang, Zhang, Bolton, and Manning, 2020), a Python NLP package, to split the earnings call transcripts into sentences.

[12] Masked Language Model (MLM) refers to hiding a word from a sentence and then asking *BERT* to fill up the masked word based on the sentence context. For example, "*The weather is very [MARK] today and let's go hiking.*" The marked word will be predicted by *BERT*. Next Sentence Prediction is to ask *BERT* to predict the next sentence based on the current sentence. These two mechanisms significantly improve BERT's language reading ability. Please see https://huggingface.co/blog/bert-101 for more information.

[13] The financial text data include 10-Ks and 10-Qs reports, analyst reports, and earnings conference call transcripts.

For brevity, we call this sentence sample ***X***. Second, from sample ***X***, we collect the climate-related sentences as we expect that the green talk sentences should be a subset of the climate-related sentences. Specifically, to identify climate-related sentences, we leverage the climate-change bigrams developed by Sautner, Van Lent, Vilkov, and Zhang (2023).[14] The authors use a keyword discovery algorithm to identify climate-change-related keywords from the *Intergovernmental Panel on Climate Change* (IPCC) research reports. A comprehensive list of around 9,000 climate-change bigrams is eventually constructed. As such, we expect these climate-change bigrams can adequately capture climate-related discussions from the earnings transcripts. Based upon these bigrams, we further search through sentence sample ***X*** and only include those sentences with at least one of the climate-change bigrams into sentence sample ***Y***. In this step, we find around 134,471 climate-related sentences in this sample ***Y***.

Third, we randomly select 4,000 sentences from ***Y*** as our *initial sample*. Each co-author manually and independently labels whether a climate-related sentence is related to green talk or not. We adopt the mode label from the co-author team as the sentence's final label. After this process, our classification results show that for the 4,000 sentences, only 691 are about green talk (labeled as positive), and the remaining 3,309 are not related to green talk (labeled as negative). The significant different proportions between positive and negative sentences will lead to the so-called sample imbalance issue in machine learning literature (e.g., He and Garcia, 2009; Lemaître, Nogueira, and Aridas, 2017), which indicates that if training a model with such imbalanced sample, the model will overclassify the majority class (in this case the negative ones) due to the higher prior probability.[15]

To address this issue, we include 1,000 more climate-related sentences from sentence sample ***Y***. In this round, to increase the likelihood of obtaining green talk sentences, we further require these 1,000 additional sentences to contain at least one highly possible green talk keyword. We rely on our past classification experience (i.e., the 4,000 initial sample classification) in constructing this green talk keyword

[14] We thank Ruishen Zhang and their team for sharing these climate-change bigrams with us.
[15] In fact, using this training sample to fine-tune the model results in poor performance as the accuracy rate of detecting a green talk sentence is only 52%, slightly better than a random guess.

list. Table A2 in the Online Appendix presents the green talk keyword dictionary. We manually classify these 1,000 additional sentences as positive or negative sentences. In this case, as expected, we find that 539 out of the 1,000 sentences are green talk related. To further balance the sample, we randomly drop 1,500 non-green talk sentences from the training sample and thus, our *final sentence sample* includes 3,500 (4,000 plus 1,000 minus 1,500) sentences, with 1,230 (691 plus 539) green talk sentences and 2,270 (3,309 plus 461 minus 1,500) non-green talk sentences.[16]

After constructing the sentence sample, we use it to fine-tune *FinBERT*. We follow the prior literature to stratify it and use 90% of observations as a training sample (3,150 sentences) to adjust the parameters in the neural network of *FinBERT*. The remaining 10% (350 sentences) is regarded as the testing sample for model performance evaluation.[17] We discuss the prediction performance of *FinBERT* in the next subsection.

3.1.3. FinBERT Prediction Performance

After the fine-tuning process, we evaluate the prediction performance of *FinBERT* using the testing sample. Table A3 in the Online Appendix reports the results. We show the overall accuracy, macro average accuracy, and weighted average accuracy of the model. Moreover, for each sentence class (positive or negative), we report the precision rate (i.e., the ability of *FinBERT* to correctly label a positive sentence), recall rate (i.e., the ability of *FinBERT* to detect all the positive sentences), and F1-score (i.e., a harmonic mean of the precision rate and recall rate).[18]

We find that the fine-tuned *FinBERT* demonstrates remarkable performance in identifying green talk sentences from the testing set. An overall accuracy rate of 90% is achieved, indicating that 315 out of the total 350 testing sentences are correctly classified. Importantly, we observe that the fine-tuned *FinBERT* can not only predict negative sentences accurately (with an F1-Score of 92%) but also capture positive

[16] Note that randomly dropping negative sentences from the training sample is analogous to adding more positive sentences to the training sample. Both strategies are used to improve the training sample quality.

[17] In terms of model parameter setting, we follow Huang, Wang, and Yang (2023) to use five epochs and learning rate of 2e-5 for model fine-tuning.

[18] Precision rate is computed as *TP*/(*TP*+*FP*), where *TP* refers to the number of true positives and *FP* denotes as the number of false positives. The recall rate is calculated as *TP*/(*TP*+*FN*), where *TP* indicates the number of true positives and *FN* refers to the number of false negatives. The F1-score is calculated as 2×(precision×recall)/(precision+recall).

sentences properly (with an F1-Score of 86%). Take recall rate as an example: our model correctly predicts 92% of the 227 negative sentences (non-green talk) and 88% of the 123 positive sentences (green talk). Table A4 in the Online Appendix further illustrates 20 randomly selected climate-change-related sentences from the conference call transcripts, where 10 sentences are predicted as green talk and 10 as non-green talk by our fine-tuned *FinBERT*. An initial screening of these sample sentences confirms that our fine-tuned machine learning model can differentiate green talk—positive statements by corporate executives specific to the firm's environmental performance and initiatives—from other climate discussions.

Taken together, the superior testing performance shows that our fine-tuned *FinBERT* model can reliably detect the green talk in the earnings conference call transcripts. We then apply the fine-tuned *FinBERT* model to capture green talk in earnings call transcripts.[19]

3.2. Firms' Actual Environmental Performance

Prior studies widely use ESG metrics from rating agencies such as MSCI KLD and Refinitiv to proxy for firms' environmental and social performance. However, these ESG rating databases typically suffer from endogeneity concerns because an increase in a firm's ESG score may not be ascribed to its improved actual ESG performance but related to the firm's strategic self-disclosure and greenwashing activities. Moreover, Berg, Koelbel, and Rigobon (2022) show that there is a lack of consistency across ESG rating agencies due to the various evaluation criteria the agencies adopt. As such, estimating the actual environmental performance of firms using the ratings could incur non-trivial measurement errors.

Instead of using ESG ratings, we use RepRisk incidents to measure corporate actual environmental performance. Researchers have started to use RepRisk to investigate whether firms' ESG incidents affect corporate policies and stakeholder decisions (e.g., Houston and Shan, 2022; Derrien, Krueger, Landier, and Yao, 2022; Houston, Lin, Shan, and Shen, 2023). RepRisk focuses on how companies conduct their

[19] The finetuned *FinBERT* model detected a total of 16,128 green talk sentences in the earnings call transcripts. Among these, 85.6% (14.4%) originated from the management presentation (Q&A) sections of the transcripts. In contrast, the management presentation (Q&A) section typically constitutes about 39.1% (60.9%) of the sentences in a transcript. This indicates that the majority of green talk are delivered by corporate management during their presentations in the conference calls.

business and whether the companies walk their talk.[20] Specifically, RepRisk identifies event-level risk incidents for firms, covering 28 ESG issues from over 100,000 media sources in 23 languages daily. Since these negative incidents are arguably less manipulatable by the firms themselves compared to other ESG ratings, RepRisk provides us with a more objective reality check on a firm's actual environmental performance. Therefore, it aligns with the goal of this study.

RepRisk classifies each risk incident of a firm as ESG-related. We focus only on environmental incidents, including topics such as climate change, greenhouse gas emissions, pollution, and waste of resources. We then count the number of environmental incidents and aggregate them to the firm-year level. The greater number of environmental incidents a firm incurs in a year indicates worse actual environmental performance for that firm in that year. The sample covers from 2007 to 2021.

3.3. Greenwashing Measure Construction

Having obtained firms' green talk and actual environmental performance, we next generate the greenwashing measure by computing the discrepancy between these two components in the same year. The intuition is that a positive deviation between green talk and the actual environmental performance captures greenwashing activities.

Specifically, we first compute the percentile ranking of green talk intensity of a firm in a year. A firm's green talk intensity is specified as follows:

$$Green\ Talk\ Intensity_{i,t} = \frac{Average\ number\ of\ green\ talk\ sentences_{i,t}}{Average\ number\ of\ total\ sentences_{i,t}} \tag{1}$$

where *Green Talk Intensity* of firm *i* in year *t* is measured as the average number of green talk sentences (predicted by our fine-tuned *FinBERT*) divided by the average number of total sentences in the earnings conference call transcripts for that firm in that year. If a firm does not talk itself green in a year (i.e., the average number of green talk sentences equals zero), we treat its *Green Talk Intensity* as missing when computing the percentile ranking of green talk intensity. In other words, we only compute the percentile ranking of green talk intensity, $Rank_{i,t}^{GreenTalk}$, for sample firms with non-zero green talk intensity in a

[20] See https://www.reprisk.com/news-research/resources/methodology.

given year. Furthermore, we count the number of environmental incidents in a firm-year, as reported by RepRisk. If a sample firm has no environmental incident in a certain year, we assign the value zero for that firm-year's incident count.[21] We then compute $Rank^{EnvIncidents}$ as the percentile ranking of a firm's number of environmental incidents in a year. Finally, we multiply $Rank^{EnvIncidents}$ by -1 (so that low rank indicates worse environmental performance) and calculate the greenwashing intensity $GW_{i,t}$ of firm *i* in year *t* using the following equation:

$$GW_{i,t} = \frac{Rank_{i,t}^{GreenTalk} - (-1) * Rank_{i,t}^{EnvIncidents}}{100} \tag{2}$$

In Equation (2), the greenwashing intensity measure of firm *i* in year *t* is calculated as the difference between firm *i*'s percentile ranking of green talk intensity and its (negative) percentile ranking of the number of environmental incidents in year *t*, further divided by 100 for ease of interpretation. Note that if a firm does not have any green talk in a year, the value of $Rank^{GreenTalk}$ will become missing in Equation (2), which will then result in *GW* being a missing value. However, by definition, if a firm does not talk itself green, it should not be considered greenwashing. As such, we replace the missing *GW* of these firms with 0, meaning that they do not incur greenwashing activities during the year. Finally, the value of *GW* ranges from 0 to 2, where 0 indicates non-greenwashing firms and 2 indicates intensive greenwashing firms (i.e., ranked 100 in green talk and -100 in environmental performance).

After merging the datasets and requiring non-missing variables, our final sample consists of 30,364 firm-year observations related to 107,464 earnings conference call transcripts and 4,060 unique U.S. public-listed firms. Table 1 reports the summary statistics of the variables used in this study. Panel A of Table 1 shows that the mean (median) of the annual *GW* measure in our firm-year sample is 0.092 (0), with the standard deviation being 0.313. Thus, while the mean value of *GW* is small, there is significant variation of the measure in the sample. The annual green talk intensity rank measure, $Rank^{Green\ Talk}$, has a mean (median) of 0.498 (0.490), with 3,519 non-missing firm-year observations. The annual environmental incident rank

[21] The intuition behind this treatment is that we expect RepRisk can well capture a firm's environmental incidents from over 100,000 public sources. If the value is missing, then it is most likely the firm does not have any reported environmental incident in that year.

measure, $Rank^{Env\ Incidents}$, has a mean (median) of 0.127 (0.010). The summary statistics of the quarterly measures in our firm-quarter sample are qualitatively similar to those of the annual measures.

Panel B of Table 1 indicates that there is a positive correlation between $Rank^{GreenTalk}$ and $Rank^{EnvIncidents}$ in the firm-year sample. However, the correlation coefficient is only 0.062, suggesting a weak association between poor environmental outcomes and companies positively discussing their green credentials. The *GW* measure shows a stronger association with $Rank^{GreenTalk}$ (correlation 0.604) than with $Rank^{EnvIncidents}$ (correlation 0.396). Additionally, *GW* exhibits high temporal persistence, with a correlation of 0.568 between current-year greenwashing and greenwashing four years ago. Table A1 in the Online Appendix provides detailed variable definitions and data sources.

[Please insert Table 1 here]

A potential concern is that the identified green talk might be a result of corporate executives discussing and explaining past environmental incidents within the firm. If this is true, then our greenwashing measure may not accurately reflect what it intends to capture. We take care to train our *FinBERT* model *not* to classify discussions that explain the firm's past environmental incidents as green talk. To ensure the accuracy of the greenwashing measure, we take further steps. First, from the sample of identified green talk sentences, we select those containing the word "incident." This filtering yields only 31 sentences. Upon manual review of these sentences, we find that they are all unrelated to firms' explanations of past environmental incidents. Instead, these sentences predominantly consist of corporate executives' self-touted environmental performance, highlighting their firms' environmental protection efforts.[22]

Second, we further examine the relationship between a firm's green talk intensity and the number of environmental incidents in the four quarters before the current conference call quarter. The firm-quarter regression results are presented in Table A5, showing no significant relationship between corporate green

[22] For example, in the 2017Q2 conference call, the CEO of PDC Energy Inc. stated, *"We anticipate this will result in an extremely strong second quarter, and I am proud we executed this without a single significant environmental or safety incident."* Similarly, the manager of International Petroleum mentioned in the 2021Q4 conference call that *"ESG side, no material safety or environmental incidents, second sustainability report published alongside our second quarter results, fully GRI-compliant and on track to deliver our net emissions intensity reduction by 50% through the end in 2025."*

talk intensity and the number of environmental incidents. The results from both qualitative and quantitative analyses confirm that the green talk sentences identified by our fine-tuned *FinBERT* model are unlikely to be influenced by the firms' past environmental incidents.

Table A6 in the Online Appendix further compares firm characteristics between greenwashing firms (with *GW* greater than 0 in a firm-year) and non-greenwashing firms (with *GW* equals 0 in a firm-year). Panel A reports the differences in firm fundamentals, revealing significant distinctions between the two types of firms. Greenwashers, on average, are larger firms with higher profitability, sales growth, stock returns, leverage ratio, and capital expenditures, but lower market-to-book ratio and R&D expenses. Panel B compares their environmental performance, showing that greenwashers generally have higher environmental ratings (proxied by Refinitiv, KLD, and Sustainalytics) than non-greenwashers. This finding aligns with the literature suggesting that ESG ratings are subject to self-disclosure bias.

4. Greenwashing Measurement Validation

In this section, we seek to validate the greenwashing measure using several approaches. First, in our univariate validations, we plot the measure serially and cross-sectionally to show that the GW phenomenon has indeed evolved dramatically in recent years and concentrates on naturally polluting industries. Second, we conduct multivariate analyses to associate the ex-ante greenwashing promises with ex-post environmental outcomes as well as market reactions. We confirm our priors that GW firms do not engage in any meaningful green patenting activities, but rather predict future environmental issues (i.e., incidents, enforcements, violations, and penalties), and hence receive negative responses from their shareholders.

4.1. Time-series Variation of Greenwashing

In Figure 1, we present the cross-sectional means for the GW measure and plot them over time from 2007 through 2021. In general, the GW behavior is stable in the years before the 2015 Paris Agreement with around 200 firms engaging in this exercise, accounting for about 10% of sample firms. In this pre-Paris Agreement period, there is an exception of a brief uptick around the Global Financial Crisis with the share of GW firms of 11%, 13.5%, and 13.4% for 2008, 2009, and 2010, respectively. This is likely due to the firms attempting to talk more about social values in general, and environmental responsibility in particular to distract investors from negative financial reports and revitalize their trust in stock performance (Lins, Servaes, and Tamayo, 2017).

[Insert Figure 1 about here]

The phenomenon of greenwashing hit its lowest point in 2014 and 2015 but started to rise significantly after 2017. Notably, in 2021, 479 firms (representing 25.1%) engaged in greenwashing, compared to just 162 firms (8.6%) in 2014 and 15 firms (7%) in 2007. This underscores the role of the 2015 Paris Agreement as a catalyst that heightens market participants' awareness of the importance of environmental protection. While making fundamental changes in environmental performance, such as investing in greener and cleaner technologies, can be time-consuming and require substantial funds, many firms are motivated to opt for a quicker and more cost-efficient solution, which is to improve their environmental image through greenwashing. Furthermore, Figure A1 in the Online Appendix illustrates that the significant increase in greenwashing intensity in recent years is primarily due to a marked increase in green talk, rather than a surge in environmental incidents.

4.2. Cross-industry Variation of Greenwashing

In Figure 2, we identify the top-ten industries (using the Fama-French 48 Industry Classification) based on the average GW intensity. In the top-ten list of GW intensity, Utilities takes the highest position of 0.907. The next largest GW industries include Electrical Equipment at 0.339, Precious Metals at 0.291, Coal at 0.259, Chemicals at 0.218, Construction at 0.199, Steel Works, etc. at 0.187, Business Supplies at 0.180, and Candy & Soda at 0.177. It is worth noting that the top-ten industries are environmentally harmful and fossil fuel intensive with GW behavior being the most prevalent among Utilities companies, more than triple those in the next highest. Given these types of firms are most likely to receive increasing attention from market participants, greenwashing their image potentially brings in the best reputational effects.

[Insert Figure 2 about here]

On the opposite end, we find that the least GW firms belong to industries such as Insurance and Banking, Entertainment and Recreation, Restaurants, Hotels, Motels, Personal Services, Healthcare and

Pharmaceutical Products, Printing and Publishing with GW intensity close to zero. These industries are the least polluting and service-oriented by nature and hence receive relatively fewer benefits from window dressing their environmental reality and from providing empty green promises.

4.3. Greenwashing around the 2015 Paris Agreement

As noted in the time-series univariate plot of the GW measure above, we observe a sharp increase in the overall GW behavior from 2016/2017 which coincides with post Paris Agreement period. In this section, we perform formal tests to see if firms that are most likely affected by the policy shock are the most active greenwashers. To this end, we specify a difference-in-differences (DiD) model where treated firms are those in either fossil fuel industries or stranded assets industries (control firms are those in other industries), and post period is from 2016 onwards (the pre-period is from 2015 backward). Consistent with Shimbar (2021), we generate an indicator variable, *Fossil Fuel Industry*, that equals one if a firm is operating in the fossil fuel industry (SIC 1220, 1221, 1311, 1381, 1382, 1389, 3533, 2911, 4610, 4922, 4923, and 4924), and otherwise equals zero. We also follow Krueger, Sautner, and Starks (2020) and Nguyen and Phan (2020) and generate another indicator variable, *Stranded Asset Industries*, that equals one if a firm is operating in following Global Industry Classification Standard (GICS) industries: 1) Energy Equipment & Services; 2) Oil, Gas & Consumable Fuels; 3) Construction Materials; 4) Metals and Mining, and 5) Utilities.

To investigate differences in GW intensity between the polluting industries and others after the Paris Agreement shock, we estimate the DiD regressions and report the results in Table 2. We find that the estimated coefficients on the interaction terms of interest, *Fossil Fuel Industries* × *Post_2015* and *Stranded Asset Industries* × *Post_2015*, are positive and highly statistically significant across all models. This means that firms in relatively more environmentally harmful industries (i.e., either fossil fuel or stranded assets industries) intensify their greenwashing activities after the 2015 Paris Agreement policy shock.

[Insert Table 2 about here]

To verify the parallel-trend assumption underlying our DiD analyses, we further specify a dynamic DiD model where we create a time dummy to indicate each year in the 2011-2020 period, with a base year of 2010. We augment the standard DiD above by replacing the *Post_2015* dummy and interacting each of the newly created time dummies with either *Fossil Fuel Industries* or *Stranded Asset Industries* treatment variables. We present the dynamic DiD estimation results in Figure 3. The interaction coefficients are relatively small and statistically insignificant for the years before 2015. More importantly, the interaction coefficients become larger in magnitude from 2016 and statistically significant from 2017. These trends can be seen in the plots with the interaction coefficients being close to zero for the years 2011-2015, and significantly deviating above the zero line afterward. In sum, the dynamic DiD test results confirm the parallel-trends assumption is satisfied, and hence highlight the role of the 2015 Paris Agreement shock as a trigger in the GW behavior of firms in fossil fuel-intensive or stranded assets industries.

[Insert Figure 3 about here]

4.4. Greenwashing and Future Environmental Performance

Firms may experience poor environmental performance in a given year but could express commitment to better performance in future periods, discussing their plans in that year's conference calls. If better environmental performance occurs subsequently, negative actions (green walk) and positive statements (green talk) in the same year would not constitute greenwashing. Therefore, if our greenwashing measure really identifies greenwashing, we should not expect companies classified as GW firms to deliver better future environmental performance. To validate this premise, we thus regress the actual environmental outcomes, measured in the following year *t*+1, on the *GW* measure from the current year *t*. We control for various firm characteristics and industry and year (or industry-by-year) fixed effects. We do not control for firm fixed effects in our empirical analyses because we want to exploit across-firm variation to investigate how *GW* is related to future corporate environmental performance and other firm-level outcomes.[23] Table 3 reports the results.

[23] As shown earlier, the *GW* measure exhibits high time persistence. Consequently, many of our results become insignificant when we replace industry fixed effects with firm fixed effects. Our decision to focus on inter-firm variation is consistent with the existing literature (e.g., Sautner, Van Lent, Vilkov, and Zhang, 2023; Baker, Larcker, McClure, Saraph, and Watt, 2024). By examining inter-firm differences, we capture broader variations across firms rather than within-firm temporal changes (which are minimal due to the time persistence), providing more meaningful insights into the effects of greenwashing.

We first examine the relationship between *GW* and a firm's future environmental incident count in columns 1 and 2 of Panel A. For count-dependent variables, we employ fixed-effects Poisson regression models following the literature (Cohn, Liu, and Wardlaw, 2022; Chen and Roth, 2023). Consistent with our expectation, both regression specifications show positive and statistically significant coefficient estimates on the *GW* measure at the 1% significance level. The effect size is economically substantial as well. For instance, the GW coefficient estimate of 0.298 in column 2 suggests that a one-standard-deviation increase in *GW* on average correlates with a 9.8% rise (i.e., $e^{0.298*0.313}$ - 1) in the number of environmental incidents in year *t*+1. In columns 3 and 4, we introduce the indicator variable *Env Incident* (which equals one if a firm experiences at least one environmental incident in year *t*+1 and zero otherwise) to gauge the likelihood of such incidents. Similarly, we find that *GW* significantly predicts greater likelihood of future environmental incidents at the 1% level in OLS regressions. Column 4 indicates that a one-standard-deviation increase in *GW* on average corresponds to a 4.1% higher likelihood of experiencing environmental incidents in year *t*+1 (i.e., 0.131*0.313).

In Panel B of Table 3, we further investigate the relationship between *GW* and future EPA environmental enforcement actions against firms. We gather data on plant-level environmental enforcement from the EPA's Integrated Compliance Information System (ICIS), aggregating them to the firm-year level. Consistently, we find that greenwashing intensity is statistically and positively associated with future EPA environmental enforcement actions against firms. In terms of economic impact, consider the Poisson regression results in columns 2 and 4 as examples: a one-standard-deviation increase in *GW* is on average linked to an 8.7% increase (i.e., $e^{0.267*0.313}$ - 1) in formal enforcements and a 5.0% increase (i.e., $e^{0.157*0.313}$ - 1) in informal enforcements, respectively.

We also investigate the relationship between *GW* and future firm carbon emissions. We obtain scope-1 carbon emissions data from the S&P Trucost database. There is an ongoing debate on whether it is more appropriate to focus on total emissions or emissions intensity (total emissions scaled by firm sales) (e.g., Aswani, Raghunandan, and Rajgopal, 2023; Bolton and Kacperczyk, 2023). Thus, we include both measures. As these emissions measures are highly skewed, we use fixed-effects Poisson regressions for our estimation (Cohn, Liu, and Wardlaw, 2022). The results in Panel C indicate that *GW* is statistically and positively associated with both future total carbon emissions and carbon emissions intensity in year *t*+1. In terms of economic magnitudes, columns 2 and 4 indicate that a one-standard-deviation increase in *GW* is, on average, related to an 11.3% (i.e., $e^{0.342*0.313} - 1$) increase in total carbon emissions and an 18.0% (i.e., $e^{0.529*0.313} - 1$) increase in carbon emissions intensity, respectively.

Taken together, the results in this section consistently suggest that the greenwashing measure significantly predicts worse actual environmental performance in the following year.

[Insert Table 3 about here]

4.5. Greenwashing and Future Green Patenting

In this section, we examine the future green patenting of GW firms. If these greenwashers do not live up to their promises, we will not observe any significant changes in their green patenting performance (e.g., Sautner, Van Lent, Vilkov, and Zhang, 2023). We obtain patent grant data from Kogan, Papanikolaou, Seru, and Stoffman (2017) and green patent classification from Haščič and Migotto (2015). We construct two measures, green patent count and green patent citations count, to capture the quantity and quality of this type of activity, respectively. We then run fixed-effects Poisson regressions of green patenting measured in the next three years from *t*+1 to *t*+3 on *GW* measured in the current year *t*. Table 4 reports the results.

[Insert Table 4 about here]

The results reveal no meaningful differences in green patenting outcomes between GW and non-GW firms. The estimated coefficients on *GW* are all statistically insignificant across different regressions. This evidence indicates that GW firms, while talking positively about their current and future environmental responsibility, do not walk the talk and contribute to the green innovation process. Cohen, Gurun, and Nguyen (2023) show that firms in fossil fuel industries spend more on green innovation than firms in many other industries. Our results suggest that while GW firms are more likely to operate in fossil fuel industries, such firms do not actually produce more green innovation than non-GW firms in the future.

As shown in Table 1, the *GW* measure has a stronger correlation with the $Rank^{GreenTalk}$ component (correlation 0.604) than with the $Rank^{EnvIncidents}$ component (correlation 0.396). To further examine the relationships of these two components with future environmental performance and green patenting activities, we replace *GW* with the two components and re-estimate the regressions in Tables 3 and 4. The results presented in Table A7 indicate that while both components are positively related to the number and likelihood of future environmental incidents, $Rank^{EnvIncidents}$ is significantly related to both the number and likelihood of future environmental incidents at the 1% level (columns 1 and 2 of Table A7). Moreover, while both $Rank^{GreenTalk}$ and $Rank^{EnvIncidents}$ are positively associated with the numbers of formal and informal EPA enforcements, the coefficient estimates of both components are marginally insignificant (columns 3 and 4). Further, both components are significantly and positively related to future total carbon emissions and carbon emissions intensity at least at the 5% level (columns 5 and 6). Finally, both components show insignificant relationships with future green patenting activities (columns 7 and 8). Overall, the results indicate that both the talk and walk components of the *GW* measure contribute to its relationships with future actual environmental performance and green patenting activities.

In summary, the various validation tests in Section 4 indicate that there is a significant increase in economy-wide greenwashing following the 2015 Paris Agreement, with fossil fuel firms experiencing the largest increase. In addition, firms with higher greenwashing intensity have worse future actual environmental performance but no increase in green innovation activities. These findings support the validity of the machine-learning-based GW measure.

5. Implications

In this section, we first examine whether and how shareholders react to greenwashing by firm managers. Extant literature suggests that investors appear to reward (punish) firms for their good (bad) environmental performance. For example, Griffin, Lont, and Sun (2017), and Matsumura, Prakash, and Vera-Munoz (2014) show that investors discount approximately \$79 per ton of CO2 emissions of a firm's market value, which is, in the aggregate, equivalent to 0.5% of the firm's market capitalization. Dowell, Hart, and Yeung (2000), and Ferrell, Liang, and Renneboog (2016) report that firms with more stringent global environmental standards or environmental ratings enjoy significantly higher market values. However, the literature also shows that investors may not be able to differentiate greenwashing from actual environmental performance (e.g., Du, 2015; Andrikogiannopoulou, Krueger, Mitali, and Papakonstantinou, 2022), and consequently incorrectly evaluate firms' environmental activities (e.g., Glossner, 2021; Hawn and Ioannou, 2016), and make investment decisions based on an overestimation of green performance (e.g., Hartzmark and Sussman, 2019; Raghunandan and Rajgopal, 2022).

We regress cumulative abnormal stock returns over a five-day window from the earnings call date (CAR (0, 4)) on the greenwashing intensity in the same year-quarter controlling for various firm characteristics and fixed effects. The results are reported in Table 5. We find that greenwashing intensity is significantly and negatively associated with the five-day CAR following the conference call. In terms of economic magnitude, a one-standard-deviation increase in the firm-level greenwashing measure is related to a 0.09-percentage-point decrease in the five-day CAR (i.e., -0.004*0.221). This result cannot be attributed to the effect of earnings surprise since we have included that as a control variable. As expected, earnings surprise exhibits a positive impact on CAR.[24]

[Insert Table 5 about here]

Since greenwashing is a deceptive tactic that firm managers may use to mask weak performance or inflate marginal achievement on the firm's environmental practices, we expect that it can occur more often or easily when the firm has a poor information environment or weak corporate governance. To measure a firm's information environment, we follow prior literature and use four proxies: i) bid-ask spreads estimated using daily high and low stock prices of a firm following Corwin and Schultz (2012); ii) idiosyncratic

[24] Table A8 in the Online Appendix further reports the regression results that investigate the relation between corporate greenwashing intensity and longer-term abnormal stock returns. The dependent variable CAR (5, 60) is cumulative abnormal stock returns from the fifth day to the 60^{th} day following the earnings conference calls. We find that GW has an insignificant relation with the longer-term abnormal returns, indicating no return reversals after the initial negative stock price reactions.

volatility measured as the standard deviation of the residuals from regressing daily individual stock returns on the Fama-French three-factors (e.g., Rajgopal and Venkatachalam, 2011); iii) the number of analysts following from I/B/E/S (e.g., Frankel and Li, 2004), and iv) firm size (e.g., Diamond and Verrecchia, 1991). Finally, we use a firm's institutional ownership to capture the firm's monitoring level and governance quality (e.g., Hartzell and Starks, 2003).

We next examine the conjecture by interacting the GW with several proxies for firm information and governance quality, effective spread, idiosyncratic volatility, analyst following, firm size, and institutional ownership.[25] We depict the effects of the interactions between GW and these proxies in Figure 4A. The results are consistent with our expectation that the negative association between GW and CAR is more pronounced for firms with high information asymmetry, as indicated by high effective spread, high idiosyncratic volatility, low analyst following, and small market capitalization, and those with weak institutional monitoring, as denoted by low institutional ownership.

Furthermore, we test whether greenwashing is also associated with the firm's future operating performance. Specifically, we regress firm ROA and operating cash flows in year *t*+1 on greenwashing intensity in year *t*. The results are reported in Table 6. Consistent with the negative shareholder reaction to greenwashing, we find that greenwashing is a significant predictor of poor future firm performance. A one-standard-deviation increase in firm-level greenwashing intensity, on average, predicts a 0.9-percentage-point lower one-year-ahead ROA (i.e., -0.029*0.313), and a 0.6-percentage-point reduction in one-year-ahead operating cash flow (i.e., -0.019*0.313).

[Insert Table 6 about here]

We also test whether the predictability of GW on a firm's operating performance is conditional on the quality of its information environment and institutional monitoring. Figure 4B shows that the interaction terms between GW and various proxies for information quality and institutional monitoring are all statistically significant when ROA is the dependent variable. These results indicate that a poor information

[25] See Table A1 in the Online Appendix for the detailed descriptions of these variables.

environment and weak corporate monitoring by institutional investors tend to increase the predictability of GW on a firm future ROA. Furthermore, Figure 4C conveys a similar message that GW predicts negative future operating cash flows better for firms with high information asymmetry and weak institutional monitoring.

In addition, in Table A9 in the Online Appendix, we compare the impact of greenwashing on CAR, distinguishing between the intensive margin (Panel A) and the extensive margin (Panel B). Our findings indicate that greenwashing affects stock price reactions primarily at the extensive margin, not the intensive margin. In other words, investors tend to react negatively to the occurrence of greenwashing talk rather than the intensity of such communication. We also compare the intensive margin (Panel C) and extensive margin (Panel D) of the greenwashing effect on future operating performance. Our findings reveal that greenwashing has an impact on future operating performance at both the extensive and intensive margins. In other words, both the occurrence and the intensity of greenwashing are associated with worse future corporate operating performance.

Table A10 in the Online Appendix further shows that the negative effects of firm-level greenwashing intensity on stock price reactions around earnings conference calls and future operating performance do not significantly differ between first-time and repeated greenwashers. Specifically, the coefficient estimates on the interaction term between GW and first-time GW are positive and statistically insignificant across all regressions. These results suggest that both first-time greenwashing and repeated greenwashing are similarly associated with lower stock price reactions and poorer future operating performance.

We further control for firm-level climate change exposure, as developed by Sautner, Van Lent, Vilkov, and Zhang (2023), to account for the possibility that firms with higher exposure to climate change may also engage in more greenwashing activities. The results from Table A11 in the Online Appendix show that *GW* remains significantly and negatively associated with five-day CARs and one-year ahead operating performance.[26] The findings are qualitatively similar when we control for the overall climate change

[26] The pairwise correlations of *GW* with *CCExposure*, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are 0.621, 0.531, 0.468, and 0.104, respectively.

exposure or the three categories (i.e., opportunity, regulatory, and physical) of climate change exposure of firms. This suggests that the *GW* measure indeed captures different information from the general climate change exposure of firms.

6. Why Do Managers Engage in Greenwashing?

A positive share price reaction to greenwashing could indicate that firms engage in greenwashing as a rational strategy. Making genuine environmental performance improvements can be time-consuming and costly. Therefore, if the market reacts favourably to misleading signals of positive environmental performance, firm management might believe that greenwashing benefits shareholders. However, our results do not support this explanation. Instead, the results reveal that the share price reaction to greenwashing is negative, and that greenwashing is associated with worse future operating performance.

This points to the possibility of an agency explanation for greenwashing—that is, managers engage in greenwashing to benefit themselves at the expense of external shareholders. In this section, we investigate this motivation. To benefit from greenwashing, CEOs need to create a perception among stakeholders that the firm's environmental performance has improved. Therefore, we first examine whether the environmental ratings assigned to firms by rating agencies show improvement following greenwashing. These ratings are closely followed by stakeholders (e.g., Hartzmark and Sussman, 2019).

Measuring environmental performance is challenging and involves consideration of numerous dimensions. There is significant variation in these ratings across different rating companies (e.g., Avramov, Cheng, Lioui, and Tarelli, 2021; Berg, Koelbel, and Rigobon, 2022). To address this, we consider three different ESG ratings: Refinitiv (previously known as Asset4), KLD, and Sustainalytics. We regress the environmental scores of each firm in the next year on the *GW* measure and various control variables. The results, presented in Table 7, indicate a clear pattern of higher environmental ratings in the next year following greenwashing. This result holds across all three environmental ratings and is robust to different regression specifications. Thus, we conclude that greenwashing indeed results in higher future environmental ratings for firms.

[Insert Table 7 about here]

We now turn our attention to investigating whether CEOs personally benefit from greenwashing. Chen, Liao, Tsang, and Yu (2023) document a significant link between firm ESG reporting and CEOs' career concerns. They find that CEOs early in their tenure, who have more pronounced career concerns, are more likely to voluntarily disclose ESG information. These CEOs benefit through higher compensation, better reputations, and reduced turnover compared to those later in their tenure. The relevance of ESG information for CEO tenure is further emphasized by Burke (2021), who finds that negative ESG commentary in the media is a likely catalyst for CEO dismissal. Additionally, Dai, Gao, Lisic, and Zhang (2023) find that CEOs are less likely to leave the company when there is a recent significant improvement in ESG performance and more likely to leave when there is a decline. Moreover, this ESG performance affects the ability of CEOs to secure new positions and the compensation they receive at their new firms.

We present results that test the relation between forced CEO turnover and greenwashing in Panel A of Table 8. The forced CEO turnover data is obtained from Peters and Wagner (2014), where they define CEO turnover as involuntary if firms' press reports clearly state that the managers are fired, forced out, or retired/resigned because of corporate pressures or policy changes. Thus, our dependent variable, *Forced Turnover*, equals 1 if the CEO's departure is forced out, and zero otherwise.[27]

The results in column 2 of Panel A indicate that there is a negative relation between forced turnover and greenwashing in the previous year following the 2015 Paris Agreement (which is the period during which environmental concerns have been the most prominent). This suggests that greenwashing is associated with a reduction in the likelihood of CEOs losing their job. Furthermore, in the post-2015 period, there is evidence that greenwashing by firms with weaker ROA is related to less CEO forced turnover in the following year (column 3 of Panel A).[28] Given this and the evidence that forced turnover is more likely in firms where industry-adjusted ROA was lower in the previous year, the evidence points to greenwashing

[27] Please see Peters and Wagner (2014) for more information on the construction of forced CEO turnover. The data can be obtained here https://www.florianpeters.org/data/. We thank Florian Peters and their team for sharing the data with us.

[28] The results are qualitatively similar to one-year or three-year average industry-adjusted ROA.

being used to mitigate the likelihood of poor operating performance leading to forced CEO turnover. The other control variable results indicate that forced turnover is more likely in firms where in the previous year leverage was higher, and stock returns were lower. It is more likely in value firms and in firms with younger CEOs who are earlier in their tenure, and in firms where CEOs own less company stock. Our results are consistent with Qin and Yang (2022) who find that CEO turnover to performance sensitivity is lower in firms where CEO compensation is linked to ESG criteria. They suggest that including ESG criteria helps signal a firm's commitment to long-term strategies and builds trust with investors. Our results show that tying CEO compensation to ESG is also associated with greenwashing.

Another consideration of CEOs when conducting greenwashing might be their pay incentives. We follow Coles, Daniel, and Naveen (2006) and calculate *Delta* as the natural logarithm of one plus the dollar change in CEO's wealth associated with a 1% change in the firm's stock price and *Vega* as the natural logarithm of one plus the dollar change in CEO's wealth (in $000s) associated with a 1% change in the standard deviation of the firm's stock returns. In the regressions, we use *Delta* and *Vega* in the next year t+1. We also measure how much executive compensation is tied to environmental performance. As Flammer, Hong, and Minor (2019) note, "CSR contracting" or "pay for environmental performance" has become increasingly prevalent. We source the data from He, Nguyen, Qiu, and Zhang (2023), who capture the environmental contracting adoption of firms using machine learning analyses in DEF14A Proxy Statements.[29] The dependent variable *E Pay* is an indicator that equals one if a firm adopts environmental contracting in executive compensation in a year, and otherwise equals zero. *E Pay Intensity* is the number of occurrences of environmental contracting words divided by the total number of words in a proxy statement of a firm in a year.

[Insert Table 8 about here]

The results in columns 1-4 in Panel B of Table 8 indicate that more greenwashing is associated with less stock price-linked performance pay the following year. The relationships between *Delta* and *GW*, as

[29] We thank the authors for sharing the data with us. Please refer to their paper for detailed information on variable constructions.

well as *Vega* and *GW*, are negative for the entire period (columns 1 and 3), with the *Vega*-*GW* relation being particularly strong following 2015 (column 4). These findings align with our earlier results, which suggest that greenwashing is associated with unfavorable stock price reactions and poorer future operational performance.

Interestingly, CEOs are not necessarily penalized for greenwashing through lower performance-related remuneration. On the contrary, there is strong evidence indicating that higher greenwashing is associated with increased environmental-linked performance pay. The results in columns 5 and 6 (columns 7 and 8) in Panel B show that the coefficient estimates on *GW* are significantly positive at the 1% level (at least at the 5% level) when *E Pay* (*E Pay Intensity*) is the dependent variable. Combined with our earlier findings that greenwashing is positively related to higher future environmental ratings from different rating firms, the results indicate that CEOs may benefit from greenwashing through their remuneration. The results of Flammer, Hong, and Minor (2019) and Cohen, Kadach, Ormazabal, and Reichelstein (2023) indicate that including ESG criteria in executive compensation can positively impact ESG outcomes. However, our findings suggest a potential downside: it may also incentivize greenwashing.

In Panel C of Table 8, we consider whether there is a link between greenwashing and CEO risk-taking behaviors in the following year. The results indicate that more greenwashing is related to lower future R&D expenditure, acquisition expenses, total investment, and leverage, and higher future cash holdings. This suggests that CEO risk-taking is lower in the year following greenwashing. This is consistent with an agency motivation for greenwashing. CEOs in greenwashing firms, benefiting from increased job security, increased environmental-performance-linked compensation, and decreased sensitivities of their pay to stock performance and risk-taking, tend to enjoy quieter lives (Bertrand and Mullainathan, 2003) and engage in fewer risk-taking activities (even if those activities might be profitable for shareholders). These findings align with Coles, Daniel, and Naveen (2006), who show that a greater sensitivity of CEO wealth to stock volatility (*Vega*) is associated with more risk-taking, including increased investment in R&D and higher leverage. More recent studies, such as Armstrong and Vashishtha (2012) and Shue and

Townsend (2017), also find that executive compensation linked to stock price incentivizes CEOs to take more risks.

Finally, we examine the robustness of the results using a firm-level greenwashing measure constructed from the management presentation section or the Q&A section of the earnings conference call transcripts. GW^{MGMT} ($GW^{Q\&A}$) is a firm's greenwashing intensity measured using the management presentation section (the Q&A section) of the earnings conference call transcripts in a year (or year-quarter for the results on CAR). The results, reported in Table A12 in the Online Appendix, consistently indicate that the documented relationships of greenwashing with future actual environmental performance, stock price reactions, operating performance, environmental ratings, forced CEO turnover, pay for performance, environmental-linked pay, and risk-taking are stronger when we use the greenwashing intensity measure constructed from the management presentation section (i.e., GW^{MGMT}) than from the Q&A section (i.e., GW^{MGMT}).

This disparity is not surprising and is likely because firm management has more control over the content and delivery of the management presentation section, allowing them to craft and emphasize points that align with their greenwashing narrative. In contrast, the Q&A section is more spontaneous and interactive, making it harder to manipulate. During the Q&A, management must respond to questions posed by analysts and investors in real-time, reducing their ability to premeditate responses that might contribute to greenwashing. Thus, if firm management intends to greenwash during conference calls, they are more likely to do so in the management presentation section rather than the Q&A section.

7. Conclusion

This study employs earnings conference call transcripts and a state-of-the-art machine learning model, *FinBERT*, to measure greenwashing intensity for a broad sample of U.S. public-listed firms spanning the 2007-2021 sample period. We validate the firm-level GW measure in multiple ways.

First, we observe that the economy-wide aggregate GW measure markedly increased after the 2015 Paris Agreement. Second, we find that the utility industry has the highest level of GW intensity among all industries. Third, we exploit the adoption of the 2015 Paris Agreement as a quasi-natural experiment and find that relative to other firms, firms in the fossil fuel industry or the broader stranded asset industries, experienced a significant increase in greenwashing intensity after the Paris Agreement. Fourth, we find that firms with higher greenwashing intensity incur a greater amount of future environmental incidents, experience a higher amount of future EPA enforcement actions, and have higher future carbon emissions. Fifth, despite their higher likelihood of experiencing future environmental incidents and EPA enforcement, we find no evidence that GW firms produce more green innovation than other firms.

We further explore the implications of greenwashing on firm stock price reactions following earnings conference calls and on future operating performance. Our findings indicate that GW is associated with lower cumulative abnormal stock returns after earnings conference calls and predicts poorer future corporate operating performance. These results suggest that GW is not a rational strategy for management to benefit shareholders. The observed negative relationships between GW and stock price reactions to conference calls, as well as future operating performance, are more pronounced for firms with greater information asymmetry and weaker institutional monitoring. This highlights the detrimental effect of greenwashing, particularly in environments where transparency is limited and oversight is weak.

To investigate the question of why corporate managers commit greenwashing, we study the relations between GW and corporate environmental ratings and document that firms with greater GW intensity tend to receive higher future environmental ratings from different rating companies. Moreover, we find that greenwashing is negatively related to both the forced CEO turnover likelihood and the forced-turnover-to-operating-performance sensitivity after the Paris Agreement adoption in 2015. This finding suggests that after the Paris Accord, there is a positive relation between GW and top executives' future job security.

We further explore the relationships between GW and executive compensation structure. The results show that GW is associated with lower CEO pay-for-performance sensitivity and lower CEO wealth-to-stock-volatility sensitivity, particularly after the adoption of the Paris Agreement. Additionally, greenwashing firms are more likely to link their CEO pay with corporate environmental performance in their compensation contracts. These findings suggest an agency explanation for greenwashing: managers engage in greenwashing to increase their job security and compensation, at the expense of shareholders and other stakeholders.

Consistent with this explanation, we find that GW firms have lower future R&D and acquisition activities, lower future leverage, and greater future cash holdings. This indicates that managers reduce their risk-taking efforts and enjoy a quieter life, as GW helps enhance their job security. Given the increasing concern about greenwashing eroding stakeholder trust and undermining authentic sustainability efforts, the novel GW measure developed in this study can be a valuable tool for investors, regulators, and academics in addressing greenwashing-related issues.

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Figure 1. Annual Variation of Greenwashing Intensity

This figure illustrates the number of greenwashing firms (pink bars), the equal-weighted aggregate greenwashing intensity (blue line), and the percentage of greenwashing firms (green line, measured as the number of greenwashing firms divided by the number of total firms) by year from 2007 to 2021.

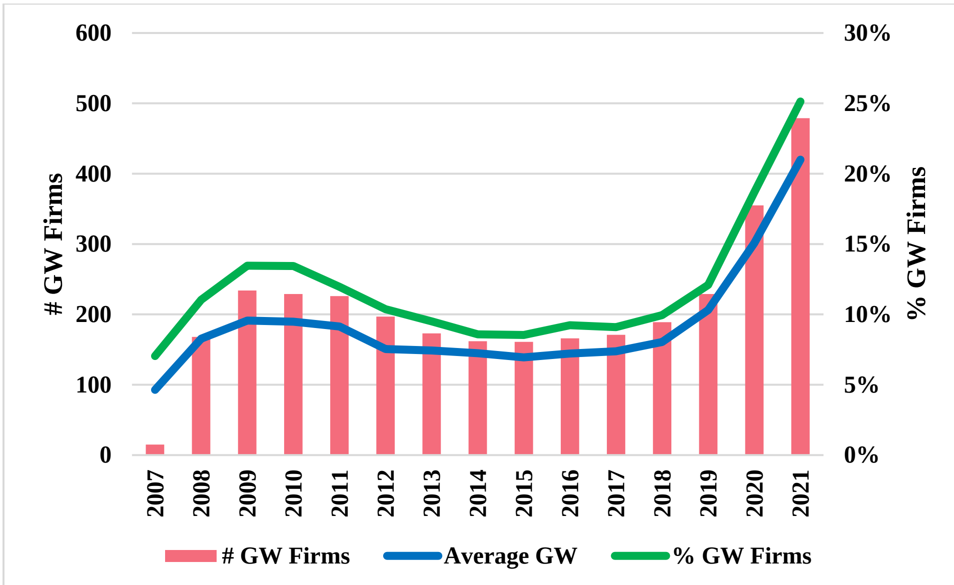

Figure 2. Top-ten Industries by Average Greenwashing Intensity

This figure illustrates the greenwashing intensity for the top-ten industries (based on the Fama-French 48 industry classification).

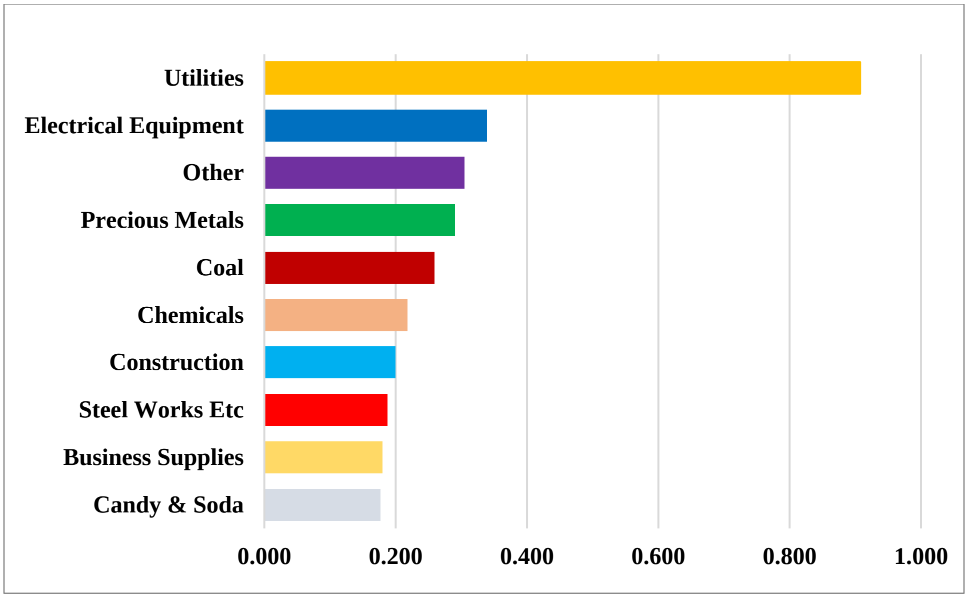

Figure 3. The Dynamic Effect of the Paris Agreement on Greenwashing Intensity

This figure shows the dynamic treatment effect of the 2015 Paris Agreement Adoption on greenwashing intensity between treatment and control groups over [-5, 5] window. In Figure 3A, we define the treatment group as the firms operating in the fossil fuel industry (SIC 1220, 1221, 1311, 1381, 1382, 1389, 3533, 2911, 4610, 4922, 4923, and 4924), and the control group as the firms operate in other industries. In Figure 3B, we define the treatment group as the firms operate in the following stranded asset industries: 1) Energy Equipment & Services; 2) Oil, Gas & Consumable Fuels; 3) Construction Materials; 4) Metals and Mining, and 5) Utilities. The control group is the firms operating in other industries. We then use the following dynamic difference-in-differences (DiD) regression framework to estimate the dynamic treatment effect:

$$GW_{i,t} = \sum_{j=2011}^{10} \beta_j Treated_{i,t} \times Year_j + \sum_{k=1}^{K} \gamma_k Controls_{k,i,t-1} + \omega_i + \mu_t + \epsilon_{i,t}$$

where *GW* is the greenwashing intensity of firm *i* in year *t*, and *Treated* is an indicator that equals one if firms are in the fossil fuel industry or stranded asset industries and zero otherwise. *Year* is an indicator that equals one if the year is after 2015 and zero otherwise. We further control for various lagged firm characteristics as well as firm fixed effects ω_i and year fixed effects μ_t. We use the year 2010 as a reference year. The coefficients of interest, β, are plotted on the y-axis in the following figures. The bars represent 90 percent confidence intervals. Standard errors are clustered at the firm level. Table A1 in the Online Appendix provides detailed variable definitions.

Figure 3A. Firms in Fossil Fuel Industry vs. Firms in Other Industries

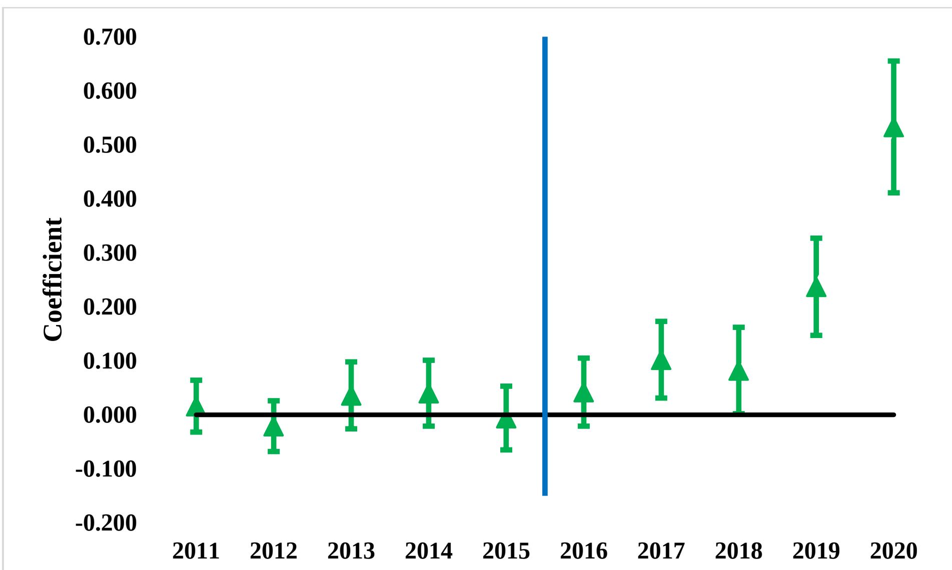

Figure 3B. Firms in Stranded Asset Industries vs. Firms in Other Industries

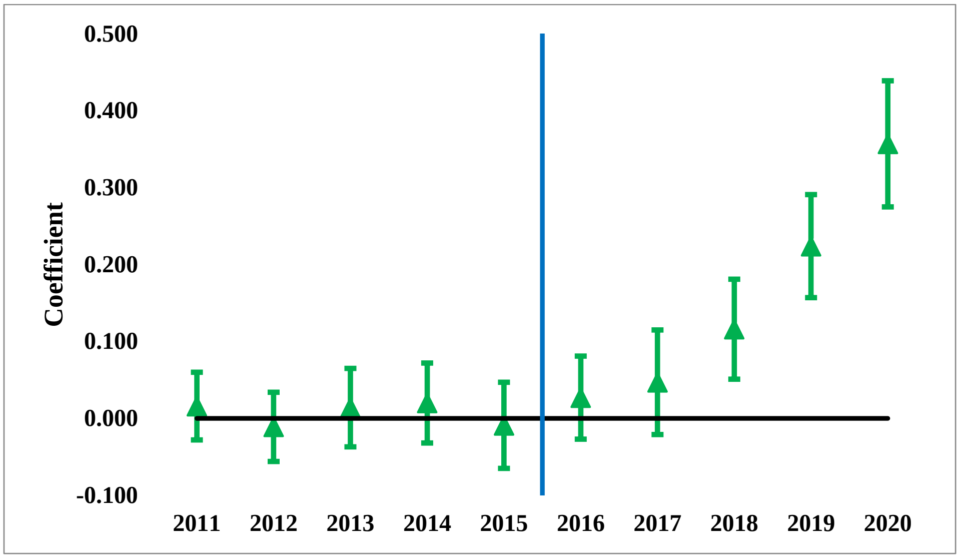

Figure 4. Heterogeneous Effects of Greenwashing Intensity: The Role of Information Asymmetry and Institutional Monitoring

This figure explores the heterogenous effects of greenwashing intensity on stock return reaction (Figure 3A) and one-year ahead operating performance (Figures 3B and 3C). It presents estimates from the following equation in which GW interacts with a set of indicators related to the firm's information asymmetry condition and institutional monitoring level:

$$CAR_{i,j,q} = \beta GW_{i,q}^{Q} \times I_{i,q-1} + \sum_{k=1}^{K} \gamma_k Controls_{k,i,j,q-1} + \sigma_{jq} + \epsilon_{i,j,q}$$

where *CAR* represents the CAR of firm *i* in industry *j* within the five days following the earnings conference call (i.e., *CAR (0, 4)*) in year-quarter *q*, GW^{Q} represents the quarterly greenwashing intensity of firm *i* in industry *j* in year-quarter *q*, and *I* represent a set of indicators that partition firms into high-low groups based on the information asymmetry and institutional monitoring level in the past quarter *q-1*. We further control for various firm characteristics as well as industry-by-year-quarter fixed effect σ_{iq}. Similarly, we use the following firm-year equation to estimate the heterogeneous effects of greenwashing intensity on corporate operating performance:

$$Y_{i,j,t+1} = \beta GW_{i,t} \times I_{i,t} + \sum_{k=1}^{K} \gamma_k Controls_{k,i,j,t} + \sigma_{jt} + \epsilon_{i,j,t+1}$$

Where *Y* represents the *ROA* or *Operating Cash Flow* of firm *i* in industry *j* in year *t+1*, GW represents the annual greenwashing intensity of firm *i* in industry *j* in year *t*, and *I* represents a set of indicators that partition firms into high-low groups based on the information asymmetry and institutional monitoring level in the same year *t*. We further control for various firm characteristics as well as industry-by-year fixed effect σ_{it}. The information asymmetry is proxied by the following firm-year level measures: 1) stock effective spread; 2) idiosyncratic volatility, 3) the number of analysts following, and 4) firm size. The institutional monitoring is proxied by a firm's institutional ownership in a year. The bars represent 90 percent confidence intervals. Standard errors are clustered at the firm level. Table A1 in the Online Appendix provides detailed variable definitions.

Figure 4A. Stock Market Reaction to Greenwashing

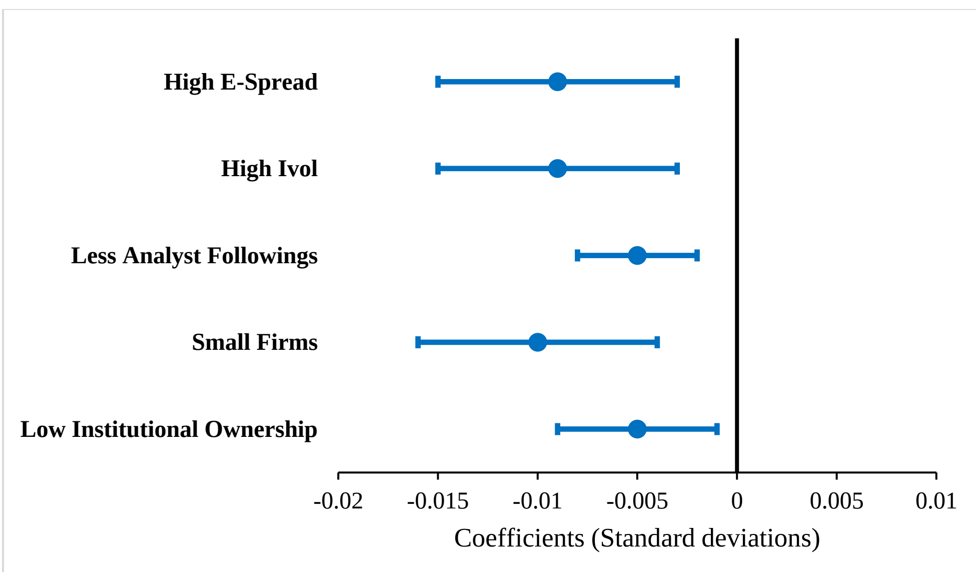

Figure 4B. Return on Assets (ROA)

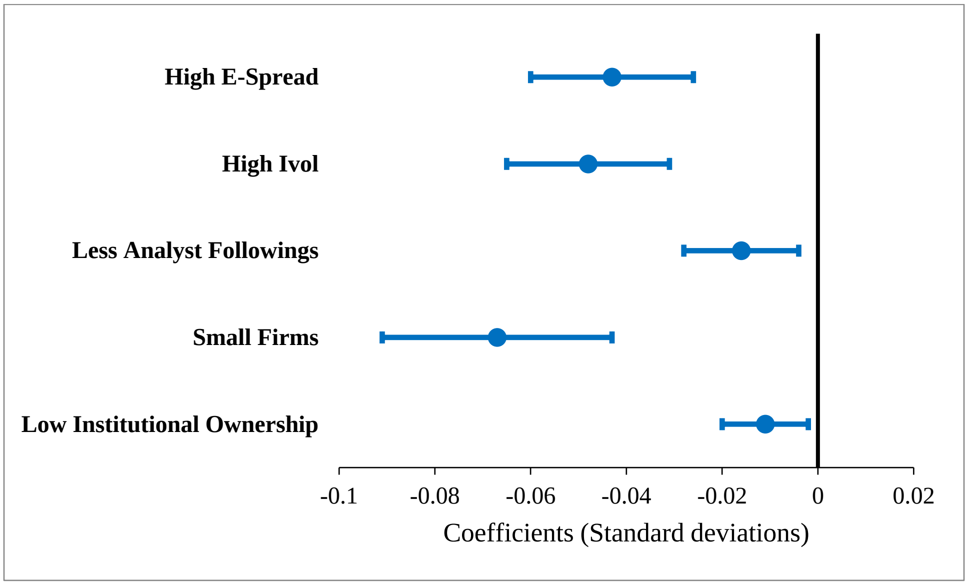

Figure 4C. Operating Cash Flow

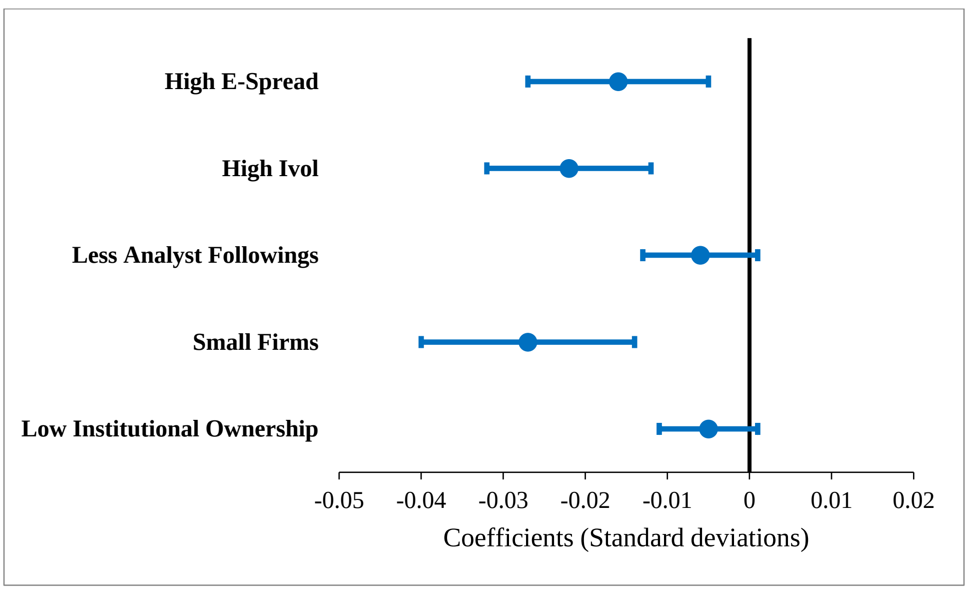

Table 1. Summary Statistics

This table reports the summary statistics (Panel A) for the variables used in this study and the correlation matrix (Panel B and C) for the greenwashing-related variables. The sample period spans from 2007 to 2021. We report the number of observations, mean, 10th percentile, median, 90th percentile, and standard deviation for each variable used in the study. All financial variables are winsorized at the 1st and 99th percentiles. Table A1 in the Online Appendix provides detailed variable definitions.

Panel A. Summary Statistics

	Obs.	**Mean**	**P10**	**Median**	**P90**	**STD.**
Greenwashing Variables – Full sample						
GW	30,364	0.092	0.000	0.000	0.200	0.313
$Rank^{Green\ Talk}$	3,519	0.498	0.100	0.490	0.910	0.297
$Rank^{Env\ Incidents}$	30,364	0.127	0.010	0.010	0.880	0.306
GW^{Q}	107,464	0.045	0.000	0.000	0.000	0.221
$Rank^{Green\ Talk – Q}$	6,138	0.525	0.130	0.530	0.920	0.288
$Rank^{Env\ Incidents – Q}$	107,464	0.118	0.010	0.010	0.890	0.299
Greenwashing Variables – Non-zero sample						
GW	3,519	0.796	0.160	0.730	1.680	0.536
GW^{Q}	6,138	0.790	0.180	0.710	1.660	0.514
Dependent Variables						
# Green Patent	30364	0.005	0.000	0.000	0.001	0.063
#Green Patent Citations	30364	0.008	0.000	0.000	0.000	0.103
# Env Incident	30097	0.449	0.000	0.000	1	1.899
Env Incident	30,364	0.120	0.000	0.000	1.000	0.325
# Formal Enforcements	30097	0.056	0.000	0.000	0.000	0.300
# Informal Enforcements	30097	0.157	0.000	0.000	0.000	0.613
Raw CO2 Emissions (in thousand tonnes)	13,735	1,373.215	0.955	29.771	1,697.431	5,927.645
CO2 Emissions Intensity	13,735	0.195	0.001	0.014	0.307	0.704
CAR (0, 4)	107,464	-0.0004	-0.1183	0.0003	0.1161	0.102
ROA	30,364	-0.004	-0.145	0.028	0.117	0.170
Operating Cash Flow	27,145	0.058	-0.060	0.081	0.183	0.155
Refinitiv Env Scores	16,620	28.317	0.000	21.040	72.130	27.476
KLD Env Scores	19,456	0.257	0.000	0.000	1.000	0.861
Sustainalytics Env Scores	7,518	51.107	36.083	48.873	69.667	12.661
Forced Turnover	17,943	0.027	0.000	0.000	0.000	0.161
Delta	14,481	5.220	3.364	5.209	7.152	1.522
Vega	14,478	3.302	0.000	3.697	5.846	2.106
E Pay	19,471	0.401	0.000	0.000	1.000	0.490
E Pay Intensity	19,471	0.0001	0.0000	0.0000	0.0002	0.0001
Acquisition Expense	29,172	0.025	0.000	0.000	0.082	0.061
Total Investment	29,172	0.109	0.004	0.075	0.257	0.113
Cash Holdings	30,000	0.135	0.009	0.084	0.330	0.152
Independent Variables						
Firm Size	30,364	7.327	4.690	7.316	9.998	2.027
Leverage	30,364	0.220	0.000	0.190	0.494	0.193
Sales Growth	30,364	0.106	-0.161	0.058	0.351	0.382
Stock Return	30,364	0.156	-0.310	0.104	0.628	0.466
CAPEX	30,364	0.040	0.002	0.025	0.093	0.049
MTB	30,364	0.840	-0.163	0.743	2.008	0.910
R&D	30,364	0.044	0.000	0.000	0.139	0.092
Earnings Surprise	107,464	0.009	-0.500	0.045	0.643	1.607

Panel B. Correlation Matrix

	GW	$Rank^{Green\ Talk}$	$Rank^{Env\ Incidents}$	GW^{Q}	$Rank^{Green\ Talk\text{-}\ Q}$	$Rank^{Env\ Incidents\text{-}Q}$
GW	1.000					
$Rank^{Green\ Talk}$	0.604	1.000				
$Rank^{Env\ Incidents}$	0.396	0.062	1.000			
GW^{Q}				1.000		
$Rank^{Green\ Talk\text{-}\ Q}$				0.579	1.000	
$Rank^{Env\ Incidents\text{-}Q}$				0.255	0.022	1.000

Panel C. Correlation Matrix of GW over Time

	GW_{t}	GW_{t-1}	GW_{t-2}	GW_{t-3}	GW_{t-4}
GW_{t}	1.000				
GW_{t-1}	0.696	1.000			
GW_{t-2}	0.638	0.696	1.000		
GW_{t-3}	0.598	0.644	0.689	1.000	
GW_{t-4}	0.568	0.610	0.644	0.684	1.000
	GW^{Q}_{t}	GW^{Q}_{t-1}	GW^{Q}_{t-2}	GW^{Q}_{t-3}	GW^{Q}_{t-4}
GW^{Q}_{t}	1.000				
GW^{Q}_{t-1}	0.605	1.000			
GW^{Q}_{t-2}	0.564	0.602	1.000		
GW^{Q}_{t-3}	0.551	0.564	0.601	1.000	
GW^{Q}_{t-4}	0.541	0.552	0.562	0.605	1.000

Table 2. Validation: The Effect of the 2015 Paris Agreement on Greenwashing Intensity

This table presents a validation test of our greenwashing intensity. Columns 1-2 report the difference-in-differences (DiD) regression results using the adoption of the 2015 Paris Agreement as an exogenous shock on greenwashing intensity between firms in the fossil fuel industry (treatment group) and those in other industries (control group). Columns 3-4 compare the greenwashing intensity between firms in the stranded asset industry (treatment group) and those in other industries (control group) before and after the Paris Agreement adoption. The dependent variable *GW* is a firm's greenwashing intensity in a year. The independent variable *Fossil Fuel Industry* is an indicator variable that equals one if a firm is operating in the fossil fuel industry (SIC 1220, 1221, 1311, 1381, 1382, 1389, 3533, 2911, 4610, 4922, 4923, and 4924), and otherwise equals zero. *Stranded Asset Industries* is an indicator variable that equals one if a firm is operating in the following Global Industry Classification Standard (GICS) industries: 1) Energy Equipment & Services; 2) Oil, Gas & Consumable Fuels; 3) Construction Materials; 4) Metals and Mining, and 5) Utilities. $Post_{2015}$ is an indicator that equals one if the year is after 2015 otherwise equals zero. All columns include firm and year fixed effects. We also include lag firm control variables in columns 2 and 4. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
	GW			
Fossil Fuel Industry × $Post_{2015}$	**0.160*** **	**0.167*** **		
	(0.030)	**(0.030)**		
Stranded Asset Industries × $Post_{2015}$			**0.131*** **	**0.137*** **
			(0.023)	**(0.023)**
Firm Size $_{t-1}$		0.002		0.004
		(0.006)		(0.006)
ROA $_{t-1}$		0.041***		0.040***
		(0.013)		(0.013)
Leverage $_{t-1}$		-0.016		-0.011
		(0.019)		(0.019)
Sales Growth $_{t-1}$		-0.003		-0.003
		(0.004)		(0.004)
Stock Return $_{t-1}$		-0.007**		-0.008**
		(0.003)		(0.003)
CAPEX $_{t-1}$		0.096		0.091
		(0.080)		(0.079)
MTB $_{t-1}$		0.003		0.004
		(0.004)		(0.004)
R&D $_{t-1}$		0.056*		0.060*
		(0.034)		(0.034)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Obs.	21,428	21,428	21,403	21,403
Adj. R2	0.603	0.603	0.604	0.604

Table 3. Validation: Greenwashing Intensity, Environmental Incidents, EPA Enforcement Actions, and CO2 Emissions

The table presents the regression results investigating the relationship between a firm's greenwashing intensity, environmental incidents, and EPA enforcement actions in year *t+1*. Panel A reports the association between greenwashing intensity and future environmental incidents. Panel B reports the association between a firm's greenwashing intensity and future EPA enforcement actions. Panel C reports the association between a firm's greenwashing intensity and future scope-1 CO2 emissions. The dependent variable *# Env Incident* is measured as the raw number of environmental incidents a firm incurred in a year. *Env Incident* is an indicator that equals one if a firm has incurred one or more environmental incidents in a year. *# Formal Enforcements* is measured as the raw number of EPA formal enforcements a firm incurred in a year. *# Informal Enforcements* is measured as the raw number of EPA informal enforcements a firm incurred in a year. *RAW CO2 Emissions* is measured as the quantity (in thousand tonnes) of scope 1 CO2 emissions a firm releases in a year. *CO2 Emissions Intensity* is measured as the quantity (in thousand tonnes) of scope 1 CO2 emissions a firm releases, divided by the sales of the firm in a year. The independent variable *GW* is a firm's greenwashing intensity in a year. All specifications include firm controls. Columns 1 and 3 control for year fixed effects and industry fixed effects. Columns 2 and 4 control for industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables and the CO2 emissions variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Greenwashing Intensity and Future Environmental Incidents

	(1)	(2)	(3)	(4)
	# Env Incident $_{t+1}$		Env Incident $_{t+1}$	
GW	**0.250***** **(0.073)**	**0.298***** **(0.087)**	**0.105***** **(0.013)**	**0.131***** **(0.013)**
Firm Size	1.057*** (0.038)	1.067*** (0.039)	0.067*** (0.003)	0.066*** (0.003)
ROA	0.609 (0.469)	0.818 (0.533)	-0.114*** (0.013)	-0.115*** (0.014)
Leverage	-0.473 (0.344)	-0.374 (0.382)	-0.123*** (0.016)	-0.119*** (0.016)
Sales Growth	-0.467*** (0.117)	-0.504*** (0.138)	-0.026*** (0.004)	-0.025*** (0.004)
Stock Return	-0.108 (0.099)	-0.058 (0.125)	-0.005 (0.003)	-0.004 (0.003)
CAPEX	0.882 (1.022)	1.326 (1.077)	0.122* (0.073)	0.091 (0.078)
MTB	0.233*** (0.059)	0.210*** (0.068)	0.020*** (0.003)	0.019*** (0.003)
R&D	-0.191 (1.715)	-0.265 (1.739)	0.040 (0.030)	0.053* (0.031)
Model	Poisson	Poisson	OLS	OLS
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	27,024	25,533	30,364	30,364
Pseudo R2/Adj. R2	0.694	0.708	0.299	0.328

Panel B. Greenwashing Intensity and Future EPA Enforcement Actions

	(1)	(2)	(3)	(4)
	# Formal Enforcements $_{t+1}$		# Informal Enforcements $_{t+1}$	
GW	**0.245***	**0.267***	**0.162**	**0.157***
	(0.093)	**(0.099)**	**(0.075)**	**(0.080)**
Firm Size	0.441***	0.436***	0.402***	0.402***
	(0.036)	(0.036)	(0.026)	(0.027)
ROA	-0.716	-0.661	0.089	-0.047
	(0.449)	(0.435)	(0.386)	(0.379)
Leverage	-0.536*	-0.504	-0.305	-0.292
	(0.318)	(0.321)	(0.269)	(0.270)
Sales Growth	-0.076	-0.076	-0.113	-0.151
	(0.146)	(0.149)	(0.087)	(0.095)
Stock Return	0.065	0.126	-0.026	-0.034
	(0.088)	(0.096)	(0.061)	(0.066)
CAPEX	-1.356	-1.740	-1.340	-1.439
	(1.027)	(1.100)	(0.982)	(1.044)
MTB	0.135**	0.128*	0.094	0.097
	(0.066)	(0.069)	(0.059)	(0.061)
R&D	-7.340***	-7.472***	-4.452***	-4.683***
	(2.227)	(2.260)	(1.154)	(1.145)
Model	Poisson	Poisson	Poisson	Poisson
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	26,826	18,419	26,485	23,029
Pseudo R2	0.283	0.256	0.269	0.264

Panel C. Greenwashing Intensity and Future Scope-1 CO2 Emissions

	(1)	(2)	(3)	(4)
VARIABLES	Raw CO2 Emissions $_{t+1}$		CO2 Emissions Intensity $_{t+1}$	
GW	**0.326***	**0.342***	**0.522***	**0.529***
	(0.087)	**(0.091)**	**(0.079)**	**(0.080)**
Firm Size	0.824***	0.852***	0.073*	0.094**
	(0.055)	(0.055)	(0.040)	(0.042)
ROA	0.057	-0.462	-0.475**	-0.482**
	(0.508)	(0.514)	(0.231)	(0.237)
Leverage	1.072*	1.068*	1.318***	1.428***
	(0.564)	(0.571)	(0.369)	(0.379)
Sales Growth	-0.167	-0.138	-0.171*	-0.144
	(0.133)	(0.156)	(0.098)	(0.104)
Stock Return	0.172**	0.176*	0.211***	0.154*
	(0.085)	(0.106)	(0.068)	(0.082)
CAPEX	-2.146	-2.303	0.858	0.951
	(1.332)	(1.510)	(1.166)	(1.319)
MTB	-0.110*	-0.114*	-0.321***	-0.321***
	(0.064)	(0.066)	(0.057)	(0.058)
R&D	-17.744***	-16.687**	-3.639**	-3.177**
	(6.827)	(6.642)	(1.704)	(1.551)
Model	Poisson	Poisson	Poisson	Poisson
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	13,735	13,726	13,735	13,726
Pseudo R2	0.848	0.860	0.534	0.543

Table 4. Validation: Greenwashing Intensity and Green Patents Developments

The table presents the regression results investigating the relationship between a firm's greenwashing intensity and its green patent developments from year *t+1* to *t+3*. The dependent variable *# Green Patent* is measured as the raw number of green patents a firm has applied for (and later granted) in a year. *# Green Patent Citations* is measured as the raw number of citations received from green patents that a firm applied (and later granted) in a year. The independent variable *GW* is a firm's greenwashing intensity in a year. All specifications are estimated using Poisson regressions, and all include firm controls. Columns 1 and 3 control for year fixed effects and industry fixed effects. Columns 2 and 4 control for industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
	# Green Patent $_{t+1, t+3}$		# Green Patent Citations $_{t+1, t+3}$	
GW	**0.084**	**0.155**	**0.107**	**0.172**
	(0.176)	**(0.234)**	**(0.195)**	**(0.223)**
Firm Size	1.128***	1.134***	1.109***	1.135***
	(0.061)	(0.063)	(0.082)	(0.093)
ROA	1.715**	1.595**	2.107**	1.719*
	(0.731)	(0.778)	(0.823)	(0.939)
Leverage	0.324	0.314	-0.272	-0.599
	(0.570)	(0.579)	(0.851)	(0.853)
Sales Growth	-0.174	-0.186	0.042	0.030
	(0.202)	(0.243)	(0.212)	(0.224)
Stock Return	-2.042	-2.163	1.359	1.446
	(1.517)	(1.763)	(2.390)	(2.986)
CAPEX	-0.120	-0.178	0.060	0.110
	(0.100)	(0.124)	(0.138)	(0.180)
MTB	0.181	0.238	0.169	0.160
	(0.138)	(0.152)	(0.151)	(0.182)
R&D	11.233***	10.889***	11.918***	11.820***
	(1.242)	(1.268)	(1.442)	(1.412)
Model	Poisson	Poisson	Poisson	Poisson
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	26,206	22,370	23,505	19,659
Pseudo R2	0.519	0.518	0.486	0.505

Table 5. Stock Price Reaction to Greenwashing Intensity

This table reports the regression results investigating the stock price reaction to greenwashing intensity. The dependent variable *CAR (0, 4)* is cumulative abnormal stock returns during a five-day event window of (0, 4) following the earnings conference calls. We calculate cumulative abnormal returns using the market-adjusted model. The independent variable GW^Q is a firm's greenwashing intensity in that year-quarter (measured using the earnings conference call transcript). All regression specifications except Column 1 include firm control variables. Columns 1-2 do not include any fixed effect. Column 3 includes year-quarter fixed effects. Column 4 includes both year-quarter fixed effects and industry fixed effects. Column 5 includes industry-by-year-quarter fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
			CAR (0, 4)		
GW^Q	**-0.003***** **(0.001)**	**-0.004***** **(0.001)**	**-0.003***** **(0.001)**	**-0.003**** **(0.001)**	**-0.004***** **(0.001)**
Firm Size $_{q-1}$		0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.000** (0.000)
ROA $_{q-1}$		0.135*** (0.011)	0.126*** (0.011)	0.133*** (0.011)	0.134*** (0.011)
Leverage $_{q-1}$		-0.002 (0.002)	-0.003* (0.002)	-0.003 (0.002)	-0.002 (0.002)
Sales Growth $_{q-1}$		0.016*** (0.001)	0.016*** (0.001)	0.015*** (0.001)	0.015*** (0.001)
Stock Return $_{q-1}$		0.157*** (0.002)	0.192*** (0.003)	0.192*** (0.003)	0.203*** (0.003)
CAPEX $_{q-1}$		0.044*** (0.012)	-0.003 (0.013)	-0.000 (0.014)	-0.001 (0.015)
MTB $_{q-1}$		-0.004*** (0.000)	-0.004*** (0.000)	-0.004*** (0.000)	-0.003*** (0.000)
R&D $_{q-1}$		0.008 (0.005)	0.007 (0.005)	0.008 (0.006)	0.007 (0.007)
Earnings Surprise $_{q-1}$		0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)
Industry FE				✓	
Year-Quarter FE			✓	✓	
Industry-Year-Quarter FE					✓
Obs.	107,464	107,464	107,464	107,464	107,464
Adj. R2	0.000	0.171	0.200	0.200	0.217

Table 6. Greenwashing Intensity and Future Operating Performance

This table reports the regression results investigating the association between greenwashing intensity and one-year-ahead operating performance. The dependent variable *ROA* is measured as a firm's one-year-ahead income before extraordinary items divided by its total value of assets. *Operating Cash Flow* is measured as a firm's one-year-ahead operating cash flow divided by its total value of assets. The independent variable *GW* is a firm's greenwashing intensity in a year. All specifications include firm characteristics controls. Columns 1 and 3 include year fixed effects and industry fixed effects. Columns 2 and 4 include industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
	ROA $_{t+1}$		Operating Cash Flow $_{t+1}$	
GW	**-0.024*** **	**-0.029*** **	**-0.014*** **	**-0.019*** **
	(0.004)	**(0.004)**	**(0.002)**	**(0.003)**
Firm Size	0.019***	0.019***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
ROA			0.446***	0.451***
			(0.015)	(0.015)
Leverage	-0.136***	-0.135***	-0.023***	-0.023***
	(0.008)	(0.008)	(0.006)	(0.006)
Sales Growth	-0.007*	-0.008*	-0.018***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)
Stock Return	0.039***	0.040***	-0.003	-0.003
	(0.003)	(0.003)	(0.002)	(0.002)
CAPEX	-0.007	0.018	0.308***	0.348***
	(0.033)	(0.034)	(0.022)	(0.023)
MTB	0.041***	0.041***	0.016***	0.017***
	(0.002)	(0.002)	(0.001)	(0.001)
R&D	-0.987***	-0.986***	-0.305***	-0.302***
	(0.039)	(0.039)	(0.030)	(0.030)
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	30,364	30,364	27,145	27,145
Adj. R2	0.389	0.403	0.569	0.577

Table 7. The Motivation of Greenwashing Behaviors: External Environmental Rating

This table reports the regression results investigating the association between greenwashing intensity and one-year-ahead external environmental ratings. The dependent variable *Refinitiv Env Score* is a firm's environmental score in a year measured by the agency Refinitiv. *KLD Env Score* is a firm's environmental score in a year measured by the agency MSCI KLD. *Sustainalytics Env Score* is a firm's environmental score in a year measured by the agency Sustainalytics. The independent variable *GW* is a firm's greenwashing intensity in a year. All specifications include firm characteristics controls. Columns 1, 3, and 5 include year fixed effects and industry fixed effects. Columns 2, 4, and 6 include industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Refinitiv Env Score $_{t+1}$		KLD Env Score $_{t+1}$		Sustainalytics Env Score $_{t+1}$	
GW	**8.202*****	**8.033*****	**0.102****	**0.088***	**2.611*****	**2.682*****
	(1.057)	**(1.124)**	**(0.051)**	**(0.051)**	**(0.689)**	**(0.727)**
Firm Size	11.272***	11.273***	0.222***	0.224***	4.632***	4.663***
	(0.278)	(0.283)	(0.012)	(0.012)	(0.269)	(0.277)
ROA	3.521	4.628*	0.158**	0.194***	6.406***	6.876***
	(2.533)	(2.632)	(0.072)	(0.073)	(2.475)	(2.639)
Leverage	-8.524***	-9.043***	-0.177***	-0.187***	1.668	1.973
	(2.036)	(2.105)	(0.058)	(0.059)	(1.879)	(1.993)
Sales Growth	-4.161***	-4.103***	-0.081***	-0.077***	-4.321***	-4.602***
	(0.472)	(0.475)	(0.015)	(0.015)	(0.655)	(0.754)
Stock Return	-2.285***	-2.736***	-0.097***	-0.082***	-1.037**	-1.212**
	(0.466)	(0.494)	(0.016)	(0.017)	(0.432)	(0.483)
CAPEX	-8.346	-3.007	0.307	0.453*	8.482	11.108
	(8.537)	(9.268)	(0.235)	(0.252)	(6.697)	(7.145)
MTB	3.142***	3.115***	0.108***	0.115***	1.260***	1.261***
	(0.454)	(0.472)	(0.015)	(0.015)	(0.405)	(0.435)
R&D	28.859***	30.236***	0.684***	0.729***	34.497***	36.253***
	(6.426)	(6.684)	(0.184)	(0.183)	(9.696)	(10.168)
Industry FE	✓		✓		✓	
Year FE	✓		✓		✓	
Industry-Year FE		✓		✓		✓
Obs.	16,544	16,519	17,585	17,580	7,384	7,367
Adj./Pseudo R2	0.515	0.522	0.259	0.295	0.393	0.380

Table 8. The Motivation of Greenwashing Behaviors: CEO Incentives

This table reports the regression results investigating the association between greenwashing intensity and CEO incentives. Panel A reports the relationship between a firm's greenwashing intensity and the CEO's future forced turnover likelihood. Panel B presents the relationship between a firm's greenwashing intensity and CEO pay incentives. Panel C examines the relationship between a firm's greenwashing intensity and CEO risk-taking behaviors. The dependent variable *Forced Turnover* is an indicator that equals one if the CEO of a firm is forced to leave in a year. *Delta* is measured as the natural logarithm of one plus delta (i.e., the dollar change in the CEO's wealth associated with a 1% change in the firm's stock price). *Vega* is measured as the natural logarithm of one plus vega (i.e., the dollar change in the CEO's wealth (in $000s) associated with a 1% change in the standard deviation of the firm's stock returns). *E Pay* is an indicator that equals one if a firm adopts environmental contracting in executive compensation in a year, and otherwise equals zero. *E Pay Intensity* is measured as the number of occurrences of environmental contracting words divided by the total number of words in a proxy statement of a firm in a year. *CAPEX* is measured as a firm's capital expenditures divided by its total value of assets. *R&D* is measured as a firm's research and development expenses divided by its total value of assets. *Acquisition Expense* is measured as a firm's acquisition expenses divided by its total value of assets. *Total Investment* is measured as the sum of a firm's capital expenditures, R&D expenses, and acquisition expenses divided by its total value of assets. *Leverage* is measured as a firm's total debt divided by its total value of assets. *Cash Holdings* is measured as a firm's cash divided by its total value of assets. The independent variable *GW* is a firm's greenwashing intensity in a year. $Post_{2015}$ is an indicator that equals one if the year is after 2015 otherwise equals zero. *Ind-adj. ROA* is measured as a firm's one-year-ahead income before extraordinary items divided by its total value of assets minus the industry average *ROA* in the same year. All specifications include firm characteristics controls and industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Greenwashing and Forced CEO Turnover

	(1)	(2)	(3)
		Forced Turnover $_{t+1}$	
GW	0.000	0.007	0.009
	(0.004)	(0.006)	(0.006)
GW × Post$_{2015}$		**-0.018****	**-0.020****
		(0.007)	**(0.008)**
GW × Ind-adj. ROA			-0.110
			(0.080)
ROA × Post$_{2015}$			0.011
			(0.025)
GW × Ind-adj. ROA × Post$_{2015}$			**0.162***
			(0.092)
Firm Size	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Ind-adj. ROA	-0.025*	-0.025*	-0.026
	(0.014)	(0.014)	(0.016)
Leverage	0.031***	0.031***	0.030***
	(0.009)	(0.009)	(0.009)
Sales Growth	-0.008	-0.008	-0.008
	(0.005)	(0.005)	(0.005)
Stock Return	-0.010**	-0.010**	-0.010**
	(0.005)	(0.005)	(0.005)
CAPEX	0.014	0.015	0.015
	(0.038)	(0.038)	(0.038)
MTB	-0.011***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)
R&D	0.029	0.029	0.028
	(0.029)	(0.029)	(0.029)
CEO Age	-0.029***	-0.029***	-0.029***

	(0.011)	(0.011)	(0.011)
CEO Tenure	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)
CEO Ownership	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Industry-Year FE	✓	✓	✓
Obs.	17,943	17,943	17,943
Adj. R2	0.011	0.011	0.011

Panel B. Greenwashing and CEO Pay Incentives

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Delta $_{t+1}$		Vega $_{t+1}$		E Pay $_{t+1}$		E Pay Intensity $_{t+1}$	
GW	**-0.123****	**-0.093**	**-0.250***	**-0.126**	**0.069*****	**0.066*****	**0.005*****	**0.002****
	(0.060)	**(0.063)**	**(0.151)**	**(0.158)**	**(0.017)**	**(0.024)**	**(0.001)**	**(0.001)**
GW × Post_2015		**-0.170**		**-0.704*****		**0.007**		**0.005*****
		(0.129)		**(0.231)**		**(0.030)**		**(0.002)**
Firm Size	0.549***	0.549***	0.564***	0.564***	0.056***	0.056***	0.001***	0.001***
	(0.015)	(0.015)	(0.031)	(0.031)	(0.005)	(0.005)	(0.000)	(0.000)
ROA	1.107***	1.111***	0.384	0.402	-0.095*	-0.095*	-0.002	-0.002
	(0.147)	(0.147)	(0.249)	(0.249)	(0.056)	(0.056)	(0.001)	(0.001)
Leverage	-0.863***	-0.863***	-0.491*	-0.490*	0.064	0.064	0.001	0.001
	(0.128)	(0.128)	(0.258)	(0.257)	(0.045)	(0.045)	(0.001)	(0.001)
Sales Growth	0.152***	0.151***	-0.145*	-0.146*	-0.014	-0.014	-0.000	-0.000
	(0.057)	(0.057)	(0.086)	(0.087)	(0.017)	(0.017)	(0.000)	(0.000)
Stock Return	0.300***	0.301***	-0.148***	-0.145***	0.004	0.004	0.000	0.000
	(0.041)	(0.041)	(0.054)	(0.054)	(0.011)	(0.011)	(0.000)	(0.000)
CAPEX	0.651	0.657	-0.283	-0.259	0.277	0.276	0.011**	0.010**
	(0.445)	(0.446)	(0.959)	(0.959)	(0.184)	(0.184)	(0.005)	(0.005)
MTB	0.478***	0.478***	0.305***	0.302***	0.003	0.003	0.000	0.000
	(0.028)	(0.028)	(0.052)	(0.052)	(0.010)	(0.010)	(0.000)	(0.000)
R&D	0.869**	0.876**	2.273***	2.301***	0.007	0.007	-0.002	-0.002
	(0.392)	(0.391)	(0.659)	(0.659)	(0.143)	(0.143)	(0.003)	(0.003)
CEO Age	-0.876***	-0.875***	-0.967***	-0.966***	-0.091	-0.091	0.000	0.000
	(0.160)	(0.160)	(0.322)	(0.322)	(0.061)	(0.061)	(0.001)	(0.001)
CEO Tenure	0.420***	0.420***	0.168***	0.169***	-0.000	-0.000	0.000	0.000
	(0.021)	(0.021)	(0.041)	(0.041)	(0.008)	(0.008)	(0.000)	(0.000)
CEO Ownership	0.120***	0.120***	0.008	0.008	-0.000	-0.000	0.000	0.000
	(0.007)	(0.007)	(0.009)	(0.009)	(0.002)	(0.002)	(0.000)	(0.000)
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	11,149	11,149	11,146	11,146	18,292	18,292	18,292	18,292
Adj. R2	0.526	0.526	0.249	0.250	0.131	0.131	0.217	0.220

Panel C. Greenwashing and Firm Risk-taking

	(1) CAPEX $_{t+1}$	(2) R&D $_{t+1}$	(3) Acquisition Expense $_{t+1}$	(4) Total Investment $_{t+1}$	(5) Leverage $_{t+1}$	(6) Cash Holdings $_{t+1}$
GW	**0.001**	**-0.004****	**-0.004*****	**-0.004*****	**-0.025*****	**0.009*****
	(0.002)	**(0.002)**	**(0.001)**	**(0.001)**	**(0.006)**	**(0.003)**
Firm Size	-0.001***	-0.003***	-0.001***	-0.002***	0.027***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
ROA	0.006**	-0.207***	0.032***	0.038***	-0.289***	-0.071***
	(0.002)	(0.009)	(0.003)	(0.005)	(0.016)	(0.014)
Leverage	0.002	-0.069***	0.003	-0.005		-0.145***
	(0.003)	(0.004)	(0.003)	(0.003)		(0.008)
Sales Growth	0.004***	0.009***	0.002*	0.003*	0.016***	-0.003
	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)
Stock Return	0.002**	-0.003**	0.005***	0.010***	-0.019***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)
CAPEX		-0.075***	-0.089***	0.584***	0.247***	-0.192***
		(0.014)	(0.010)	(0.014)	(0.068)	(0.027)
MTB	0.004***	0.018***	0.004***	0.005***	0.040***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
R&D	-0.030***		-0.040***	0.831***	-0.549***	0.366***
	(0.006)		(0.007)	(0.012)	(0.035)	(0.035)
Industry-Year FE	✓	✓	✓	✓	✓	✓
Obs.	30,136	30,364	28,880	28,856	30,364	29,943
Adj. R2	0.422	0.576	0.072	0.620	0.283	0.423

ONLINE APPENDIX

Figure A1. Annual Variation of Green Talk and Environmental Incidents

This figure illustrates the green talk score (green line) and the number of environmental incidents measured from RepRisk (blue line) by year from 2007 to 2021.

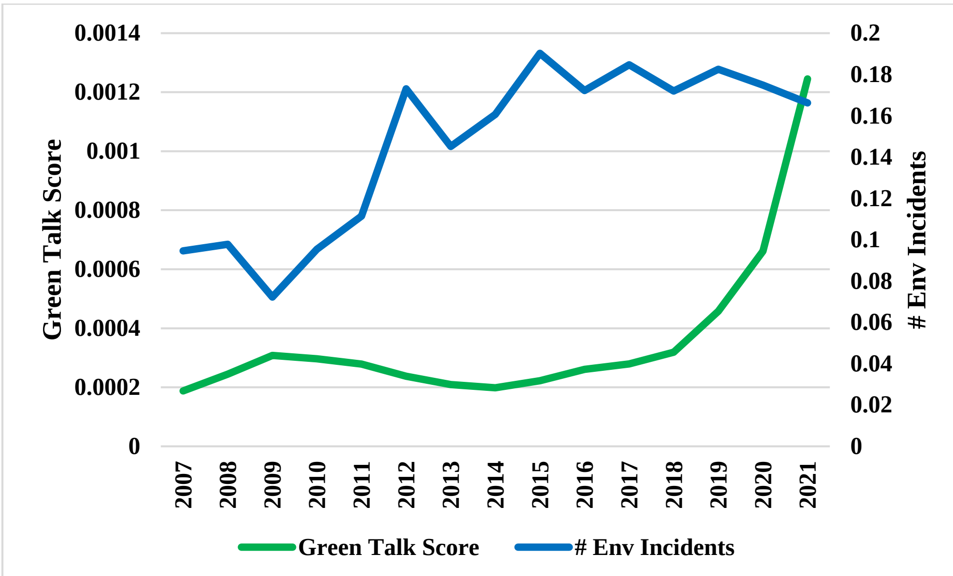

Table A1. Variable Definition

Variables	Definition
Dependent Variables	
GW	The ranking of a firm's green talk intensity minus the negative ranking of a firm's number of environmental incidents in a year, further divided by 100. ***Source:*** Conference earnings call transcripts from S&P Capital IQ, fine-tuned machine learning model, and Reprisk.
$\text{Rank}^{\text{Green Talk}}$	The ranking of a firm's green talk ratio in a year. The raw ranking is divided by 100 thus the variable ranges from 0 to 1. ***Source:*** Conference earnings call transcripts from S&P Capital IQ, fine-tuned machine learning model
$Rank^{Env\ Incidents}$	The ranking of a firm's environmental incidents in a year. The raw ranking is divided by 100 thus the variable ranges from 0 to 1. ***Source:*** Reprisk
# Green Patent	The raw number of green patents a firm has applied (and later granted) in a year. ***Source:*** Kogan, Papanikolaou, Seru, and Stoffman (2017) patent dataset; Haščič and Migotto (2015) green patent definitions.
# Green Patent Citations	The raw number of citations received from green patents that a firm applied (and later granted) in a year. ***Source:*** Kogan, Papanikolaou, Seru, and Stoffman (2017) patent dataset; Haščič and Migotto (2015) green patent definitions.
# Env Incident	The raw number of environmental incidents a firm incurred in a year. ***Source:*** Reprisk.
Env Incident	An indicator that equals one if a firm has incurred one or more environmental incidents in a year. ***Source:*** Reprisk.
# Formal Enforcements	The raw number of EPA formal enforcements a firm incurred in a year. ***Source***: EPA's Enforcement and Compliance History Online (ECHO).
# Informal Enforcements	The raw number of EPA informal enforcements a firm incurred in a year. ***Source***: EPA's Enforcement and Compliance History Online (ECHO).
Raw CO2 Emissions	The quantity (in thousand tonnes) of scope 1 CO2 emissions a firm releases in a year. ***Source:*** S&P Trucost
CO2 Emissions Intensity	The quantity (in thousand tonnes) of scope 1 CO2 emissions a firm releases, divided by the sales of the firm in a year. ***Source:*** S&P Trucost
CAR(0, 4)	Cumulative abnormal stock returns within a five-day event window of (0, 4) following the earnings conference calls. ***Source***: CRSP
ROA	A firm's earnings before extraordinary items divided by the book value of assets. ***Source***: Compustat.
Operating Cash Flow	A firm's operating cash flow divided by the book value of assets. ***Source***: Compustat.
Refinitiv Env Scores	A firm's environmental score in a year measured by the agency Refinitiv. ***Source***: Refinitiv.
KLD Env Scores	A firm's environmental score in a year measured by the agency MSCI KLD. ***Source***: MSCI KLD.
Sustainalytics Env Scores	A firm's environmental score in a year measured by the agency Sustainalytics. ***Source***: Sustainalytics.
Forced Turnover	An indicator that equals one if the CEO of a firm is forced to leave in a year. ***Source:*** Peters and Wagner (2014).
Delta	The natural logarithm of one plus delta (i.e., the dollar change in CEO's wealth associated with a 1% change in the firm's stock price). ***Source:*** Coles, Daniel, and Naveen (2006).
Vega	The natural logarithm of one plus vega (i.e., the dollar change in CEO's wealth (in $000s) associated with a 1% change in the standard deviation of the firm's stock returns). ***Source:*** Coles, Daniel, and Naveen (2006).
E Pay	An indicator that equals one if a firm adopts environmental contracting in executive compensation in a year, and otherwise equals zero. ***Source:*** DEF14A Proxy Statements.
E Pay Intensity	The number of occurrences of environmental contracting words divided by the total number of words in a proxy statement of a firm in a year. ***Source:*** DEF14A Proxy Statements.
Acquisition Expense	A firm's acquisition expenses divided by its total value of assets. ***Source***: Compustat.
Total Investment	Total Investment is measured as the sum of a firm's capital expenditures, R&D expenses, and acquisition expenses divided by its total value of assets. ***Source***: Compustat.

Cash Holdings	A firm’s number of employees (in thousands) divided by the book value of assets. ***Source***: Compustat.
Independent Variables	
Firm Size	Natural logarithm of the sales of a firm in a year. ***Source***: Compustat.
Leverage	The sum of a firm’s current liabilities and long-term debt divided by the book value of assets. ***Source***: Compustat.
Sales Growth	A firm's value of sales in year t minus the firm's value of sales in year *t-1*, further divided by the value of sales in year *t-1*. ***Source***: Compustat.
Stock Return	Buy-and-hold stock return of a firm. ***Source***: CRSP
CAPEX	A firm’s capital expenditures divided by the book value of assets. ***Source***: Compustat.
MTB	The natural logarithm of a firm's market value of assets divided by quarterly book value of total assets. ***Source***: Compustat.
R&D	A firm’s research and development expenses divided by the book value of total assets. ***Source***: Compustat.
Earnings Surprise	Actual quarterly earnings per share (EPS) announced in a quarter minus median analyst forecasted EPS made before the EPS announcement quarter, scaled by absolute stock price at the end of the quarter before the EPS announcement quarter. ***Source:*** I/B/E/S and CRSP

Table A2. Green Talk Keyword List

Green talk keywords	decarbonize, carbon intensity, carbon emission, net zero, net-zero, zero-carbon, carbon neutral, greenhouse gas, energy footprint, carbon footprint, climate change, emission target, green energy, low-carbon, carbon capture, Paris Climate Agreement, renewable energy, energy transition, clean energy, ESG, environmental footprint, zero-emission, sustainability, greenhouse initiative, climate goals, climate strategy, lower carbon, carbon dioxide, global warming, green building, emission goal, less carbon, environmental quality, environmental responsibility, environmental performance, reduce emission, carbon disclosure

Table A3. Prediction Performance in Classifying Green talk Sentences

This table presents the prediction performance in classifying green talk sentences in the testing sample using the fine-tuned *FinBert*. The testing sample contains 350 sentences, of which 227 are non-green talk (negative) and 123 are green talk (positive). The 350 testing sentences are randomly selected from the full sample of 3,500 sentences and are manually and independently labeled by the co-authors. For each sentence category, we compare three dimensions of prediction performance, which are precision, recall, and f1-score, respectively. For the total testing sentence sample, we also report the overall accuracy, macro average, and weighted average. The overall accuracy is measured as the number of correctly classified sentences divided by the total number of sentences in the testing sample. The macro average represents the unweighted mean value for each category and does not take label imbalance into account. The weighted average represents the weighted mean value for each category and takes into account the label imbalance. The precision is calculated as *true positives/(true positives + false positives)*. The recall is calculated as *true positives/(true positives + false negatives)*. The f1-score represents a harmonic mean of the precision and recall, which is measured as *2 × (precision × recall) / (precision + recall)*.

	Precision	**Recall**	**F1-score**	**# Sentence**
Negative	0.93	0.92	0.92	227
Positive	0.85	0.88	0.86	123
Accuracy			**0.90**	350
Macro avg	0.89	0.90	0.89	350
Weighted avg	0.90	0.90	0.90	350

Table A4. Climate-Change-related Sample Sentences from Conference Call Transcripts

This table reports 20 randomly selected climate-change-related sentences that are predicted by the fine-tuned *FinBert* model.

Examples of Climate-change-related Sentence	Company	Year-Quarter	Green Talk
1. And our air quality improvement technologies ensure the safe, clean production of lead-acid and lithium-ion batteries that are playing an important role in this energy transformation.	CECO ENVIRONMENTAL CORP	2017Q3	Yes
2. The next-generation B&W is focused on meeting customer and market needs by providing technology solutions to help achieve a clean, sustainable energy and industrial infrastructure.	BABCOCK & WILCOX ENTERPRISES	2020Q3	Yes
3. We're excited about the progress that we're making to combat climate change and enable a cleaner, more sustainable world.	DELTA AIR LINES INC	2021Q2	Yes
4. Our coal fleet will be one of the most environmentally compliant coal fleets in the country by the end of 2012.	DYNEGY INC	2012Q1	Yes
5. This renewable energy group was created in response to customers' growing interest in sustainability and our concern for the environment.	INTEGRYS ENERGY GROUP INC	2008Q2	Yes
6. Environmentally, we are fully compliant and leading the industry with our new mercury scrubbing emissions technology and other updates that we've made to the property under the terms of the Consent Decree with the Nevada Department (sic) [Division] of Environmental Protection.	VERIS GOLD CORP	2011Q4	Yes
7. As a company, we committed to reducing our greenhouse gas emissions from our fleet and facilities by 20% by the year 2025.	SOUTHWEST GAS HOLDINGS INC	2020Q1	Yes
8. And it reduced the environmental footprint and made the social environment simpler.	TOREX GOLD RESOURCES INC	2018Q3	Yes
9. As a result, we've just announced that we are committed to reducing our absolute carbon emissions by 20% by 2030 to help address climate change.	HEXION INC	2021Q2	Yes
10. As just a few examples, we participated in the New York Stock Exchange Earth Day opportunity to highlight ESG and sustainability, including our commitment to reduce emissions and provide solutions for more efficient energy use and conducting business with environmental responsibility.	MACERICH CO	2019Q2	Yes
11. Climate change is the defining issue of this generation.	PAO NOVATEK	2020Q3	No
12. In fact from a flooding standpoint, it was certainly in the areas where -- which are non-coastal areas where we operate it was much less of an event than the events last year between Hurricane Irene and Tropical Storm Lee, were much more problematic in terms of flooding.	UGI CORP	2012Q4	No
13. The Rangoon Wind Farm development is in the process of gaining development approval also, and any investment decision will likely not be 'till about 2022.	MERIDIAN ENERGY LTD	2021Q1	No
14. The weaker wind resource was the primary driver of the negative $0.04 contribution from existing wind assets relative to the prior year comparable quarter.	NEXTERA ENERGY INC	2011Q4	No
15. Our earnings did include impairments totaling $42.7 million, to reduce the carrying value of certain Wind River properties to their fair market value.	HIGHPOINT RESOURCES CORP	2006Q1	No
16. And secondly, this will mean better flexibility, because as you know blast furnaces are built for running 24/7 without any stoppages for 15 years.	SSAB AB	2018Q2	No
17. Oil & Gas, we have a natural relative decline here of the importance of this end market to stop a business where we have introduced fuel cells as a sustainable energy source here for this industry and where we see our customers getting even tax credits for the fact that they are replacing natural gas generators burning the gas here with disastrous CO_2 footprint by our EFOY fuel cells.	SFC ENERGY AG	2021Q1	No
18. Now, extreme weather led to reduced production volumes in June.	ROAN RESOURCES INC	2011Q3	No

19. In the classical autonomous vehicle paradigm, the assumption is that vehicles are going to talk to one another.	EVERSPIN TECHNOLOGIES INC	2017Q2	No
20. In August of this year, the Alabama Public Service Commission granted Alabama Power the ability to increase accruals to its natural disaster reserve.	SOUTHERN CO	2010Q4	No

Table A5. Green Talk Intensity and Environmental Incidents

The table presents the firm-quarter regression results investigating the relationship between a firm's green talk intensity and environmental incidents. The dependent variable *Green Talk Intensity* is measured as the number of green talk sentences predicted by the fine-tuned *FinBERT* model divided by the number of total sentences in the conference earnings call transcript for a firm in a quarter. The independent variable *# Past 4 Quarters' Env Incidents* is measured as the number of environmental incidents a firm incurred in the four quarters before the current earnings conference call. Columns 1 and 2 do not include firm controls, while columns 3 and 4 further add firm control variables. Columns 1 and 3 include industry fixed effects and year-quarter fixed effects. Columns 2 and 4 further include industry-by-year-quarter fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
	Green Talk Intensity			
# Past 4 Quarters' Env Incidents	**0.0000**	**0.0000**	**0.0000**	**0.0000**
	(0.0000)	**(0.0000)**	**(0.0000)**	**(0.0000)**
Firm Size $_{q-1}$			0.0000	0.0000
			(0.0000)	(0.0000)
ROA $_{q-1}$			-0.0012***	-0.0012***
			(0.0003)	(0.0003)
Leverage $_{q-1}$			-0.0002**	-0.0002**
			(0.0001)	(0.0001)
Sales Growth $_{q-1}$			-0.0000	-0.0000
			(0.0000)	(0.0000)
Stock Return $_{q-1}$			0.0000	0.0000
			(0.0000)	(0.0000)
CAPEX $_{q-1}$			0.0003	0.0003
			(0.0006)	(0.0006)
MTB $_{q-1}$			-0.0000	-0.0000
			(0.0000)	(0.0000)
R&D $_{q-1}$			-0.0004**	-0.0004**
			(0.0002)	(0.0002)
Industry FE	Yes	No	Yes	No
Year-Quarter FE	Yes	No	Yes	No
Industry-Year-Quarter FE	No	Yes	No	Yes
Observations	107,464	107,464	107,464	107,464
Adj.R2	0.1858	0.1858	0.1865	0.1865

Table A6. Greenwashing vs. Non-Greenwashing Firm Characteristics

This table compares firm characteristics between greenwashing firms and non-greenwashing firms. Panel A presents the results of basic firm characteristics comparison between greenwashing (GW) firms and non-greenwashing (Non-GW) firms. Panel B reports the results of environmental-related comparisons between GW and non-GW firms. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Basic Firm Characteristics

	GW			Non-GW				
	Obs.	**Mean**	**Median**	**Obs.**	**Mean**	**Median**	**Mean Difference**	**Median Difference**
Firm Size	3,512	8.160	8.160	26,582	7.211	7.186	0.949***	0.974***
ROA	3,512	0.031	0.031	26,582	-0.005	0.028	0.036***	0.003***
Leverage	3,512	0.276	0.276	26,582	0.215	0.178	0.061***	0.098***
Sales Growth	3,512	0.042	0.042	26,582	0.109	0.059	-0.067***	-0.017***
Stock Return	3,512	0.110	0.110	26,582	0.156	0.103	-0.046***	0.007***
CAPEX	3,512	0.039	0.039	26,582	0.039	0.023	0.000	0.016***
MTB	3,512	0.691	0.691	26,582	0.855	0.759	-0.164***	-0.068***
R&D	3,512	0.000	0.000	26,582	0.047	0.000	-0.047***	0.000

Panel B. Environmental-Related Performance

	GW			Non-GW				
	Obs.	**Mean**	**Median**	**Obs.**	**Mean**	**Median**	**Mean Difference**	**Median Difference**
Refinitiv Env Scores	2,308	45.628	46.810	14,131	25.448	17.87	20.180***	28.940***
KLD Env Scores	2,063	0.376	0.000	17,214	0.241	0.000	0.134***	0.000***
Sustainalytics Env Scores	1,099	53.992	52.917	6,419	50.614	48.000	3.378***	4.917***
Log(1+Env Incident Count)	3,519	0.421	0.000	26,845	0.129	0.000	0.292***	0.000***
Log(1+# Formal Enforcements)	3,519	0.086	0.000	26,845	0.034	0.000	0.052***	0.000***
Log(1+# Informal Enforcements)	3,519	0.177	0.000	26,845	0.083	0.000	0.094***	0.000***
Log(1+# Violations)	3,519	0.384	0.000	26,845	0.174	0.000	0.210***	0.000***
Log(1+Green Patent Count)	3,519	0.013	0.000	26,845	0.004	0.000	0.009***	0.000***
Log(1+Green Patent Citations)	3,519	0.016	0.000	26,845	0.006	0.000	0.010***	0.000***

Table A7. Greenwashing Intensity Decomposition

The table decomposes the greenwashing intensity into two components, the ranking of green talk and the ranking of environmental incidents, and presents the regression results investigating the relationships between the two components and firms' future environmental incidents, EPA enforcement actions, CO2 emissions, and green patenting outputs. The dependent variable *# Env Incident* is measured as the raw number of environmental incidents a firm incurred in a year. *Env Incident* is an indicator that equals one if a firm has incurred one or more environmental incidents in a year. *# Formal Enforcements* is measured as the raw number of EPA formal enforcements a firm incurred in a year. *# Informal Enforcements* is measured as the raw number of EPA informal enforcements a firm incurred in a year. *# Green Patent* is measured as the raw number of green patents a firm has applied for (and later granted) in a year. *# Green Patent Citations* is measured as the raw number of citations received from green patents that a firm applied (and later granted) in a year. *RAW CO2 Emissions* is measured as the quantity (in thousand tonnes) of scope 1 CO2 emissions a firm releases in a year. *CO2 Emissions Intensity* is measured as the quantity (in thousand tonnes) of scope 1 CO2 emissions a firm releases, divided by the sales of the firm in a year. $Rank^{Green\ Talk}$ is the ranking of a firm's green talk ratio in a year. $Rank^{Env\ Incidents}$ is the ranking of a firm's environmental incidents in a year. All specifications include firm controls and industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables and the CO2 emissions variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

VARIABLES	(1) Env Incident Count $_{t+1}$	(2) 1 (Env Incident) $_{t+1}$	(3) # Formal Enforcements $_{t+1}$	(4) # Informal Enforcements $_{t+1}$	(5) Raw CO2 Emissions $_{t+1}$	(6) CO2 Emissions Intensity $_{t+1}$	(7) # Green Patent Count $_{t+1, t+3}$	(8) # Green Patent Citations $_{t+1, t+3}$
Rank$^{Green\ Talk}$	**0.125**	**0.018**	**0.345**	**0.223**	**0.540*** **	**0.758*** **	**0.733**	**0.570**
	(0.158)	**(0.012)**	**(0.224)**	**(0.184)**	**(0.187)**	**(0.159)**	**(0.471)**	**(0.493)**
Rank$^{Env\ Incidents}$	**2.003*** **	**0.440*** **	**0.185**	**0.100**	**0.417** **	**0.625*** **	**-0.164**	**0.459**
	(0.120)	**(0.014)**	**(0.115)**	**(0.092)**	**(0.168)**	**(0.116)**	**(0.198)**	**(0.306)**
Firm Size	0.803***	0.038***	0.421***	0.394***	0.813***	0.039	1.172***	1.066***
	(0.041)	(0.002)	(0.039)	(0.028)	(0.064)	(0.047)	(0.072)	(0.097)
ROA	0.645	-0.073***	-0.622	-0.018	-0.448	-0.423*	1.662**	1.947**
	(0.468)	(0.009)	(0.445)	(0.384)	(0.518)	(0.243)	(0.769)	(0.912)
Leverage	-0.485	-0.070***	-0.461	-0.270	1.085*	1.518***	0.247	-0.350
	(0.347)	(0.010)	(0.321)	(0.269)	(0.568)	(0.373)	(0.567)	(0.819)
Sales Growth	-0.363***	-0.015***	-0.071	-0.148	-0.113	-0.104	-0.191	0.056
	(0.131)	(0.003)	(0.149)	(0.094)	(0.157)	(0.103)	(0.235)	(0.209)
Stock Return	-0.083	-0.002	0.131	-0.032	0.168	0.149*	-0.198*	0.149
	(0.125)	(0.003)	(0.095)	(0.066)	(0.116)	(0.086)	(0.120)	(0.179)
CAPEX	0.376	0.068	-1.780	-1.468	-2.205	0.814	-2.442	1.028
	(1.014)	(0.052)	(1.115)	(1.052)	(1.494)	(1.300)	(1.802)	(2.955)
MTB	0.156**	0.011***	0.118*	0.091	-0.123*	-0.340***	0.255*	0.100
	(0.063)	(0.002)	(0.069)	(0.062)	(0.069)	(0.058)	(0.154)	(0.196)
R&D	-0.948	0.017	-7.396***	-4.648***	-16.575**	-2.904**	11.120***	11.940***
	(1.553)	(0.019)	(2.254)	(1.143)	(6.689)	(1.472)	(1.264)	(1.399)
Model	Poisson	OLS	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Obs.	25,533	30,364	18,419	23,029	13,726	13,726	22,370	19,659
Pseudo R2/Adj. R2	0.750	0.437	0.255	0.264	0.863	0.546	0.519	0.508

Table A8. Medium-term Stock Price Reaction to Greenwashing Intensity

This table reports the regression results that investigate the medium-term stock price reaction to greenwashing intensity. The dependent variable *CAR (5, 60)* is cumulative abnormal stock returns from the fifth day to the 60th day following the earnings conference calls. We calculate cumulative abnormal returns using the market-adjusted model. The independent variable GW^Q is a firm's greenwashing intensity in that year-quarter (measured using the earnings conference call transcript). All regression specifications except Column 1 include firm control variables. Columns 1-2 do not include any fixed effect. Column 3 includes year-quarter fixed effects. Column 4 includes both year-quarter fixed effects and industry fixed effects. Column 5 includes industry-by-year-quarter fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)
			CAR (5, 60)		
GW^Q	**0.000**	**0.001**	**-0.002**	**-0.002**	**-0.002**
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**
Firm Size $_{q-1}$		-0.001***	-0.001***	-0.001**	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
ROA $_{q-1}$		-0.083***	-0.068***	-0.084***	-0.063***
		(0.023)	(0.021)	(0.022)	(0.022)
Leverage $_{q-1}$		-0.001	0.002	0.003	0.002
		(0.003)	(0.003)	(0.003)	(0.003)
Sales Growth $_{q-1}$		0.006**	0.001	0.002	0.003
		(0.003)	(0.003)	(0.003)	(0.003)
Stock Return $_{q-1}$		0.103***	0.128***	0.127***	0.125***
		(0.004)	(0.004)	(0.004)	(0.004)
CAPEX $_{q-1}$		0.065***	-0.001	0.058***	0.012
		(0.018)	(0.018)	(0.022)	(0.022)
MTB $_{q-1}$		-0.005***	-0.002***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
R&D $_{q-1}$		0.038***	0.034***	0.039***	0.039***
		(0.010)	(0.010)	(0.012)	(0.012)
Earnings Surprise $_{q-1}$		-0.004***	-0.003***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Industry FE				✓	
Year-Quarter FE			✓	✓	
Industry-Year-Quarter FE					✓
Obs.	107,464	107,464	107,464	107,464	107,464
Adj. R2	0.000	0.021	0.080	0.081	0.168

Table A9. Intensive vs. Extensive Margin

This table compares the intensive and extensive margin of stock price reaction to greenwashing intensity, and the association between greenwashing intensity and future operating performance. We implement the intensive margin analyses by restricting to the sample of greenwashing firms (i.e., *GW* is larger than zero in a firm-year). We implement the extensive margin analyses by replacing the continuous greenwashing intensity with an indicator *I (GW)* that equals one if *GW* is larger than zero, and equals zero otherwise. Panel A (B) examines the intensive (extensive) margin of stock price reactions to greenwashing activities, while Panel C (D) examines the intensive (extensive) margin of the association between greenwashing activities and future operating performance. The dependent variable *CAR (0, 4)* is cumulative abnormal stock returns during a five-day event window of (0, 4) following the earnings conference calls. We calculate cumulative abnormal returns using the market-adjusted model. *ROA* is measured as a firm's one-year-ahead income before extraordinary items divided by its total value of assets. *Operating Cash Flow* is measured as a firm's one-year-ahead operating cash flow divided by its total value of assets. In Panels A and B, all regression specifications (except Column 1) include firm control variables. Columns 1-2 do not include any fixed effect. Column 3 includes year-quarter fixed effects. Column 4 includes both year-quarter fixed effects and industry fixed effects. Column 5 includes industry-by-year-quarter fixed effects. In Panels C and D, all regression specifications include firm control variables. Columns 1 and 3 include industry fixed effects and year fixed effects. Columns 2 and 4 include industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Intensive Margin Analysis: Stock Price Reactions to Greenwashing Activities

	(1)	(2)	(3)	(4)	(5)
			CAR (0, 4)		
GW	**0.000**	**0.000**	**-0.001**	**-0.001**	**-0.001**
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**
Firm Controls		✓	✓	✓	✓
Industry FE				✓	
Year-Quarter FE			✓	✓	
Industry-Year-Quarter FE					✓
Obs.	6,138	6,138	6,138	5,546	5,546
Adj. R2	0.000	0.144	0.170	0.198	0.198

Panel B. Extensive Margin Analysis: Stock Price Reactions to Greenwashing Activities

	(1)	(2)	(3)	(4)	(5)
			CAR (0, 4)		
I (GW)	**-0.004*** **	**-0.006*** **	**-0.004*** **	**-0.004*** **	**-0.004*** **
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Firm Controls		✓	✓	✓	✓
Industry FE				✓	
Year-Quarter FE			✓	✓	
Industry-Year-Quarter FE					✓
Obs.	107,464	107,464	107,464	107,464	107,464
Adj. R2	0.000	0.171	0.200	0.217	0.217

Panel C. Intensive Margin Analysis: Greenwashing Activities and Future Operating Performance

	(1)	(2)	(3)	(4)
	ROA $_{t+1}$		Free Cashflow $_{t+1}$	
GW	**-0.029******	**-0.031******	**-0.014******	**-0.016******
	(0.006)	**(0.007)**	**(0.004)**	**(0.004)**
Firm Controls	✓	✓	✓	✓
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	3,518	3,382	3,431	3,297
Adj. R2	0.406	0.424	0.575	0.590

Panel D. Extensive Margin Analysis: Greenwashing Activities and Future Operating Performance

	(1)	(2)	(3)	(4)
	ROA $_{t+1}$		Free Cashflow $_{t+1}$	
I (GW)	**-0.023******	**-0.025******	**-0.015******	**-0.018******
	(0.004)	**(0.004)**	**(0.002)**	**(0.002)**
Firm Controls	✓	✓	✓	✓
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	30,364	30,364	27,145	27,145
Adj. R2	0.389	0.403	0.565	0.571

Table A10. First-time Greenwashing vs. Repeated Greenwashing

This table reports the regression results that investigate the implications of first-time versus repeated greenwashing activities on stock price reactions (Panel A) and future operating performance (Panel B). The dependent variable *CAR (0, 4)* is cumulative abnormal stock returns during a five-day event window of (0, 4) following the earnings conference calls. We calculate cumulative abnormal returns using the market-adjusted model. *ROA* is measured as a firm's one-year-ahead income before extraordinary items divided by its total value of assets. *Operating Cash Flow* is measured as a firm's one-year-ahead operating cash flow divided by its total value of assets. The independent variable *GW* is a firm's greenwashing intensity in a year. *First-time GW* is an indicator variable that equals one if the firm conducts greenwashing for the first time in the earnings conference calls of the year (and did not greenwash in any of the years before the current year), and equals zero otherwise. In Panel A, all regression specifications (except Column 1) include firm control variables. Columns 1-2 do not include any fixed effect. Column 3 includes year-quarter fixed effects. Column 4 includes both year-quarter fixed effects and industry fixed effects. Column 5 includes industry-by-year-quarter fixed effects. In Panel B, all regression specifications include firm control variables. Columns 1 and 3 include industry fixed effects and year fixed effects. Columns 2 and 4 include industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Stock Price Reactions to Greenwashing

	(1)	(2)	(3)	(4)	(5)
			CAR (0, 4)		
GW	-0.003**	-0.004***	-0.002**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First-time GW	0.000	-0.003	-0.003	0.001	0.001
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
GW × First-time GW	-0.010	-0.005	-0.008	-0.012	-0.012
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Firm Control		✓	✓	✓	✓
Industry FE				✓	
Year-Quarter FE			✓	✓	
Industry-Year-Quarter FE					✓
Obs.	107,464	107,464	107,464	107,464	107,464
Adj. R2	0.000	0.171	0.200	0.217	0.217

Panel B. Greenwashing and Future Operating Performance

	(1)	(2)	(3)	(4)
	ROA $_{t+1}$		**Free Cashflow $_{t+1}$**	
GW	-0.023***	-0.029***	-0.013***	-0.019***
	(0.004)	(0.005)	(0.003)	(0.003)
First-time GW	-0.009*	-0.008	-0.006	-0.008*
	(0.005)	(0.005)	(0.004)	(0.004)
GW × First-time GW	0.003	0.009	-0.003	0.006
	(0.007)	(0.008)	(0.005)	(0.005)
Firm Control	✓	✓	✓	✓
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	30,364	30,364	27,145	27,145
Adj. R2	0.389	0.403	0.569	0.577

Table A11. Control for Firm-Level Climate Change Exposure

This table investigates the stock price reaction to greenwashing intensity and the association between greenwashing intensity and future operating performance, further controlling for a firm's exposure to climate change. The dependent variable *CAR (0, 4)* is cumulative abnormal stock returns during a five-day event window of (0, 4) following the earnings conference calls. We calculate cumulative abnormal returns using the market-adjusted model. *ROA* is measured as a firm's one-year-ahead income before extraordinary items divided by its total value of assets. *Operating Cash Flow* is measured as a firm's one-year-ahead operating cash flow divided by its total value of assets. The independent variable *GW* is a firm's greenwashing intensity in a quarter (columns 1-2) or in a year (columns 3-6). *CCExposure* is the overall climate change exposure of a firm in a year. $CCExposure^{Opp}$ is the opportunities-related climate change exposure of a firm in a year. $CCExposure^{Reg}$ is the regulatory-shock-related climate change exposure of a firm in a year. $CCExposure^{Phy}$ is the physical-risk-related climate change exposure of a firm in a year. All regression specifications include firm control variables. Columns 1 and 2 include industry-year-quarter fixed effects. Columns 3-6 include industry-by-year fixed effects. Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**CAR (0, 4)**		**ROA $_{t+1}$**		**Operating Cash Flow $_{t+1}$**	
GW	**-0.003***	**-0.003****	**-0.017*****	**-0.018*****	**-0.020*****	**-0.025*****
	(0.001)	**(0.001)**	**(0.004)**	**(0.004)**	**(0.004)**	**(0.004)**
CCExposure	-0.179		-2.743***		-3.064***	
	(0.124)		(0.812)		(0.649)	
$CCExposure^{Opp}$		-0.197		-4.837***		-5.312***
		(0.226)		(1.671)		(1.394)
$CCExposure^{Reg}$		-0.454		-6.059		0.426
		(1.012)		(4.347)		(3.371)
$CCExposure^{Phy}$		-0.244		2.008		4.114
		(1.499)		(7.177)		(7.570)
Firm Controls	✓	✓	✓	✓	✓	✓
Industry-Year-Quarter FE	✓	✓				
Industry-Year FE			✓	✓	✓	✓
Obs.	107,464	102,607	28,868	28,868	25,947	25,947
Adj. R2	0.217	0.215	0.394	0.394	0.423	0.423

Table A12. Greenwashing Intensity: Management Presentation vs. Q&A sections

The table examines the robustness of the results using firm-level greenwashing intensity constructed from the management presentation section or the Q&A section of the earnings conference call transcripts. GW^{MGMT} is a firm's greenwashing intensity measured using the management presentation section of the earnings conference call transcripts in a year (or year-quarter for the results on CAR). $GW^{Q\&A}$ is a firm's greenwashing intensity measured using the Q&A section of the earnings conference call transcripts in a year (or year-quarter for the results on CAR). Table A1 in the Online Appendix provides detailed variable definitions. Robust standard errors clustered at the firm level are provided in parentheses. All financial variables and the CO2 emissions variables are winsorized at the 1st and 99th percentiles. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Validation: Future Environmental Incidents and EPA Enforcement Actions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	# Env Incident Count $_{t+1}$			1 (Env Incident) $_{t+1}$			# Formal Enforcements $_{t+1}$			# Informal Enforcements $_{t+1}$		
GW^{MGMT}	0.278***		0.251***	0.112***		0.103***	0.235**		0.220**	0.175**		0.153*
	(0.080)		(0.075)	(0.013)		(0.013)	(0.106)		(0.103)	(0.085)		(0.082)
GW^{QA}		0.222***	0.142**		0.086***	0.038***		0.157	0.090		0.183	0.137
		(0.070)	(0.056)		(0.015)	(0.014)		(0.120)	(0.113)		(0.114)	(0.110)
Model	Poisson	Poisson	Poisson	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	25,533	25,533	25,533	30,364	30,364	30,364	18,419	18,419	18,419	23,029	23,029	23,029
Pseudo R2/Adj. R2	0.707	0.706	0.708	0.324	0.319	0.324	0.255	0.254	0.255	0.264	0.264	0.264

Panel B. Validation: Future Green Innovation and Carbon Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	# Green Patent $_{t+1, t+3}$			# Green Patent Citations $_{t+1, t+3}$			Raw CO2 Emissions $_{t+1}$			CO2 Emissions Intensity $_{t+1}$		
GW^{MGMT}	0.248		0.252	0.423*		0.444*	0.277***		0.273***	0.430***		0.401***
	(0.245)		(0.239)	(0.242)		(0.237)	(0.081)		(0.078)	(0.081)		(0.079)
GW^{QA}		-0.012	-0.045		-0.510	-0.536*		0.114*	0.016		0.269***	0.095*
		(0.171)	(0.147)		(0.329)	(0.278)		(0.059)	(0.040)		(0.068)	(0.051)
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	22,370	22,370	22,370	19,659	19,659	19,659	13,726	13,726	13,726	13,726	13,726	13,726
Pseudo R2/Adj. R2	0.518	0.517	0.518	0.506	0.506	0.507	0.859	0.854	0.859	0.538	0.531	0.538

Panel C. CAR and Future Operating Performance

VARIABLES	(1)	(2) CAR (0,4)	(3)	(4)	(5) ROA $_{t+1}$	(6)	(7)	(8) Operating Cash Flow $_{t+1}$	(9)
GW^{MGMT}	-0.004***		-0.004***	-0.025***		-0.023***	-0.017***		-0.016***
	(0.001)		(0.001)	(0.004)		(0.004)	(0.002)		(0.002)
GW^{QA}		-0.002	-0.001		-0.019***	-0.009**		-0.015***	-0.008***
		(0.002)	(0.002)		(0.004)	(0.004)		(0.003)	(0.003)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year-Quarter FE	✓	✓	✓						
Industry-Year FE				✓	✓	✓	✓	✓	✓
Obs.	107,464	107,464	107,464	30,364	30,364	30,364	26,561	26,561	26,561
Adj. R2	0.217	0.217	0.217	0.403	0.402	0.403	0.571	0.570	0.571

Panel D. Future Environmental Ratings

VARIABLES	(1)	(2) Refinitive Env Scores $_{t+1}$	(3)	(4)	(5) KLD Env Scores $_{t+1}$	(6)	(7)	(8) Sustainalytics Env Scores $_{t+1}$	(9)
GW^{MGMT}	7.408***		6.954***	0.092		0.079	2.867***		2.659***
	(1.160)		(1.111)	(0.057)		(0.056)	(0.725)		(0.677)
GW^{QA}		5.104***	1.999		0.097	0.065		2.062**	1.033
		(1.399)	(1.255)		(0.067)	(0.065)		(1.037)	(0.958)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	16,519	16,519	16,519	17,580	17,580	17,580	7,367	7,367	7,367
Adj. R2	0.521	0.517	0.521	0.295	0.295	0.295	0.380	0.377	0.380

Panel E. CEO Forced Turnover

VARIABLES	(1)	(2)	(3)	(4) 1 (Forced Turnover) $_{t+1}$	(5)	(6)
GW^{MGMT}	-0.002		-0.001	0.006		0.006
	(0.004)		(0.005)	(0.006)		(0.006)
GW^{QA}		-0.005	-0.004		0.001	-0.001
		(0.005)	(0.005)		(0.007)	(0.008)
GW^{MGMT} × Post_2015				-0.019**		-0.017**
				(0.007)		(0.008)
GW^{QA} × Post_2015					-0.015*	-0.007

					(0.008)	(0.009)
Model	OLS	OLS	OLS	OLS	OLS	OLS
Firm Controls	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓
Obs.	17,943	17,943	17,943	17,943	17,943	17,943
Adj. R2	0.011	0.011	0.011	0.011	0.011	0.011

Panel F. CEO Pay Incentives

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES		Log (Delta) $_{t+1}$			Log (Vega) $_{t+1}$			1 (E Pay) $_{t+1}$			E Pay Intensity $_{t+1}$	
GW^{MGMT}	-0.173***		-0.174***	-0.414**		-0.426***	0.058***		0.055***	0.005***		0.005***
	(0.061)		(0.060)	(0.165)		(0.158)	(0.018)		(0.018)	(0.001)		(0.001)
GW^{QA}		-0.065	0.005		-0.115	0.058		0.036*	0.013		0.004**	0.002
		(0.070)	(0.068)		(0.166)	(0.144)		(0.019)	(0.019)		(0.002)	(0.002)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	11,149	11,149	11,149	11,146	11,146	11,146	18,292	18,292	18,292	18,292	18,292	18,292
Adj. R2	0.526	0.526	0.526	0.250	0.248	0.250	0.131	0.130	0.131	0.217	0.210	0.218

Panel G. Firm Risk-taking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES		CAPEX $_{t+1}$			R&D $_{t+1}$			Acquisition Expense $_{t+1}$			Total Investment $_{t+1}$			Leverage $_{t+1}$			Cash Holdings $_{t+1}$	
GW^{MGMT}	0.002		0.003	-0.003**		-0.003*	-0.003**		-0.002	-0.002		-0.001	-0.018***		-0.016***	0.008***		0.007**
	(0.002)		(0.002)	(0.002)		(0.002)	(0.001)		(0.001)	(0.001)		(0.002)	(0.006)		(0.006)	(0.003)		(0.003)
GW^{QA}		-0.000	-0.002		-0.002	-0.001		-0.004***	-0.003**		-0.004**	-0.003*		-0.017**	-0.010		0.009***	0.006*
		(0.002)	(0.002)		(0.002)	(0.002)		(0.001)	(0.002)		(0.002)	(0.002)		(0.007)	(0.006)		(0.003)	(0.003)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	30,136	30,136	30,136	30,364	30,364	30,364	28,880	28,880	28,880	28,856	28,856	28,856	30,364	30,364	30,364	29,943	29,943	29,943
Adj. R2	0.422	0.422	0.422	0.576	0.576	0.576	0.072	0.072	0.072	0.620	0.620	0.620	0.282	0.282	0.282	0.423	0.423	0.423