Corporate Greenwashing, Firm Performance, and CEO Incentives

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Abstract

We construct a novel measure of firm-level greenwashing based on a FinBERT machine learning model and earnings conference call transcripts. We show that firms with higher greenwashing have more future environmental incidents, increased EPA enforcement, and no increase in green innovation. The stock price and future operating performance both decline. However, third-party environmental ratings improve. CEOs benefit from increased job security, and lower future pay-for-performance sensitivity and wealth-to-stock-volatility sensitivity. Following greenwashing, managers take less risk with reduced future R&D and acquisition activities, lower leverage, and increased cash holdings. Our results support an agency motivation for corporate greenwashing.

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.

We use an advanced finance-specialized machine learning technique to develop a reliable firm-level measure of corporate greenwashing (hereafter "greenwashing") for a broad sample of U.S. firms. Our 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 is a firm-specific, positive talk by its corporate executives about their firm's past and/or future environmental investments, efforts, and performance.[2] 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 offer an avenue for investors and analysts to ask questions and gain deeper insights into the firm's business operations, risks, and opportunities. Due to the substantial wealth of firm-specific information embedded in earnings

[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.

[2] Firm statements about future environmental aspirations that are made at a time of poor environmental performance are not necessarily indicative of greenwashing if they are matched by a change in future firm behavior. We show that this does not drive our results.

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.[3] To evaluate 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.[4] Our fine-tuned *FinBERT* model achieves a remarkable 90% accuracy rate in detecting green-talk-related sentences. Based on the green-talk-related sentences identified by our machine learning 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.

We employ RepRisk incidents as a metric to measure the actual environmental performance of a firm. Unlike other environmental, social, or governance (ESG) rating datasets that are potentially subject to corporate self-disclosures and manipulations, RepRisk identifies event-level risk incidents for firms from over 100,000 media sources in 23 languages daily. Because these negative incidents are not manipulatable

[3] 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 structure, 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.

[4] 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.

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?".[5] 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 thus signify a greater discrepancy between green talk and actual green walk.[6] 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 greenwashing measure. First, we observe that the economy-wide aggregate greenwashing 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 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.

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

[6] Firms without any green talk in a year are given a value of 0 for the greenwashing measure regardless of their actual environmental performance.

Fourth, we find that cross-sectionally, firms with higher greenwashing intensity incur more future environmental incidents and experience more future environmental enforcement actions from the U.S. Environmental Protection Agency (EPA), confirming the significant discrepancy between their green talk and actual green walk. Fifth, after controlling for various firm characteristics and industry and year (or industry-by-year) fixed effects, we find that despite their higher likelihood of experiencing future environmental incidents and EPA enforcement actions, greenwashing firms do *not* produce more green innovations than non-greenwashing firms.

After validating the firm-level greenwashing measure, we next explore its implications on firm stock price reactions following earnings conference calls and operating performance. We first perform a variance decomposition of the greenwashing measure. The results reveal that around 30% of the variation in greenwashing intensity is at the industry level, while around 60% of the variation resides at the firm level. This finding indicates that it is firm-level heterogeneities that explain most of the variation in greenwashing intensity. We also 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, our measure of firm-level greenwashing 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 greenwashing has significant effects on a firm's future operating performance and abnormal stock returns following earnings conference calls. We further find that the negative effects of greenwashing on stock price reactions to conference calls and future operating performance are more pronounced for firms with greater information asymmetry and weaker institutional monitoring.

Given the negative effects of greenwashing on stock price reactions to conference calls and future operating performance, a natural question to ask is why managers still greenwash. 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 suggests that corporate executives may engage in greenwashing to benefit themselves at the expense of shareholders and other stakeholders. An agency explanation of greenwashing is also consistent with our earlier finding that greenwashing negatively impacts stock price reactions and future operating performance. The effects are more pronounced for firms with greater information asymmetry and weaker institutional monitoring, as such firms are generally more susceptible to managerial agency problems due to their weak corporate governance.

Our findings indeed point to the agency motive behind greenwashing after the Paris Climate Accords adoption in 2015. First, greenwashing significantly decreases both the forced turnover likelihood and the forced-turnover-to-operating-performance sensitivity. Second, top executives' job security increases when they conduct greenwashing. Third, greenwashing intensity is associated with lower CEO pay-for-stock-performance sensitivity (delta) and CEO wealth-to-stock-volatility sensitivity (vega). Fourth, firms with greater greenwashing 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 firms have 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. 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 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). 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).

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 greenwashing intensity for a broad sample of U.S. public-listed firms. We further validate the reliability of the measure and investigate the implications of greenwashing 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, 2023, 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, 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 greenwashing 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 Calls Transcripts

We use earnings conference call transcripts as text data to capture green talk activities. Generally, 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 use the entire earnings call transcript (including both the management presentation and Q&A sessions) to identify a firm's green talk. 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 U.S. Environmental Protection Agency's Integrated Compliance Information System (ICIS). We then aggregate the number of environmental enforcement cases from plant-year to firm-year level. 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., regarded as being unfounded or intentionally misleading.*"[8] Analogously, in academia, researchers characterize firms' greenwashing behaviors as positive corporate communications from firms to deceive

[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.

[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*."

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 expresses 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. We discuss these 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 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.

[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,

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). Hence, in this paper, we follow prior studies and use earnings conference call transcripts to identify green talk activities.[10] We expect these earnings transcripts to contain meaningful information on how corporate management teams tout their environmental performance, given the increasing public attention to global warming and climate-change-related issues.

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 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

and Watts (2022) who generate a firm-level diversity washing measure by taking the difference between a firm's diversity claims and their actual hiring diversity.

[10] We define corporate green talk as firms' executives positively discussing their past and/or future environmental investments, efforts, and performance.

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 talks we want to capture are those climate discussions from the corporate executives who tout 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.[11] 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.[12] By reading text sentences from left to right and right to left (the so-called "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.[13] As such, using

[11] 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.

[12] *BERT* is trained using 2.5 billion words from Wikipedia and 800 million words from Google's BooksCorpus.

[13] 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.

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).[14] 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. 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).[15] The authors use a keyword discovery algorithm to identify climate-

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

[15] We thank Ruishen Zhang and their team for sharing these climate-change bigrams with us.

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 (in the team of six) manually and independently labels whether a climate-related sentence is related to green talk or not. We adopt the mode label from the team as the sentence's final label. If three of the authors consider a sentence as green talk, while the remaining three consider it as non-green talk, we will treat this sentence as non-green talk for conservativeness. 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.[16]

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 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

[16] 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.

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.[17]

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.[18] 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).[19]

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 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

[17] 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.
[18] 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.
[19] 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).

from the conference call transcripts, where 10 sentences are predicted as green talk and 10 as non-green talk by our fine-tuned *FinBERT*. By initial screening of these sample sentences, we gain confidence that the model indeed can distinguish green talk from general 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.[20]

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 business and whether the companies walk their talk.[21] 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

[20] 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.

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

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 which include 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 incurred in a year indicates worse actual environmental performance for that firm in that year. The sample covers from 2007 to 2021.

3.3. Constructing Greenwashing Measure

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:

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

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 will replace its *Green Talk Intensity* as missing. In other words, we only compute the percentile ranking of green talk intensity in a year if the green talk intensity is non-zero. Furthermore, we count the number of environmental incidents in a firm-year, as reported by RepRisk. If a sample firm does not have any environmental incident in a certain year, we assign the value zero for that firm-year's incident count.[22] We then compute $Rank^{EnvIncidents}$ as the percentile

[22] 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.

ranking of a firm's number of environmental incidents in a year, further multiplied by -1 (lower rank indicates worse environmental performance). Finally, we generate the greenwashing intensity of a firm in a year using the following equation:

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

In Equation (2), the greenwashing intensity measure, *GW*, of firm *i* in year *t* is calculated as the difference between the percentile rankings of green talk intensity and the number of environmental incidents of that firm in that year, 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, which leads *GW* to be 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. Table A1 in the Online Appendix provides detailed variable definitions and data sources.

[Please insert Table 1 here]

Table A5 in the Online Appendix further compares firm characteristics between the 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. We find that these two types of firms are significantly different. The greenwashers, on average, are larger firms, with higher profitability, sales growth, stock returns, leverage ratio, and capital expenditures, but with lower market-to-book ratio and R&D expenses. Panel B compares their environmental performance. Intuitively, the greenwashers generally have higher environmental ratings (proxied by Refinitiv, KLD, and Sustainalytics) than non-greenwashers, consistent with the literature showing that the ESG ratings are subject to self-disclosure bias.

4. Greenwashing Measurement Validation

In this section, we seek to validate our newly constructed greenwashing index using several approaches. First, in our univariate validations, we plot the measure serially and cross-sectionally to show that the GW phenomenon indeed evolves dramatically in recent years and concentrates in 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 index 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 rank our GW index in the top 10 and bottom 10 using the Fama-French 48 Industry Classification. In the top 10 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 10 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, 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 index 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 Environmental Incidents/Enforcements

If our measure is indeed identifying greenwashing, we would not expect companies that we classify as GW to improve their environmental practices. To validate this prior, we first count the number of environmental incidents a firm commits and the number of formal/informal environmental enforcements, violations, and total penalties a firm receives each year. We then regress this type of environmental outcome measured in the next year *t*+1 on our GW index measured in the current year *t* and expect a positive relation. Similarly, to other tests that also use count measures as the dependent variables, we estimate both OLS and Poisson models with and without taking log transformations.

We collect data on plant-level environmental enforcements and violations from the U.S. Environmental Protection Agency's Integrated Compliance Information System (ICIS) and further aggregate to a firm-year level. The results are reported in Table 3. In Panel A, we investigate the relationship between GW and future firms' environmental incidents. Consistent with our prediction, we observe positive and statistically significant (all at 1% level) coefficients on our GW index. The magnitudes of the effects are also economically meaningful. For example, the GW coefficient estimates of 0.286 in column 2 and 0.131 in column 4 suggest that a one-standard-deviation increase in the GW index is associated with a 55% (i.e., 0.286*0.313/0.162) increase in the natural logarithm of one plus the number of environmental incidents (*Log(1+# Env Incident)*) and 34% (i.e., 0.131*0.313/0.120) increase in the likelihood of environmental incidents (*Env Incident*), relative to the respective sample mean.

In Panel B, we further shed light on the association between GW and future firms' environmental enforcement actions. Similarly, we continue to find that the greenwashing intensity is statistically and positively related to future environmental enforcement actions. In terms of economic magnitudes, take column 2, 4, and 6 as examples, a one-standard-deviation increase in the GW index is associated with 24% (=0.034*0.286/0.040) increase in the formal enforcements, 13% (=0.044*0.286/0.094) increase in the informal enforcements, and 10% (=0.071*0.286/0.198) increase in the violations, relative to their sample mean. Taken together, the results suggest that the behavior of engaging in greenwashing in the current year can significantly predict a worsening in the firm actual environmental performance in the following year.

[Insert Table 3 about here]

4.5. Greenwashing and Green Patenting

In this section, we examine the 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 which are logs of one plus green patent count and green patent citations to capture the quantity and quality of this type of activity, respectively. We then run regressions of green patenting measured in the next three years from t+1 to t+3 on our GW index measured in the current year t and report the OLS results in Table 2. Given that our main dependent variables in this case are count ones, as recommended by Cohn, Liu, and Wardlaw (2022), we also estimate Poisson regression models with and without taking logs and present the results in Online Appendix Table A7

[Insert Table 4 about here]

Both the OLS and Poisson regression results reveal no meaningful differences in green patenting outcomes between GW and non-GW firms. In particular, the estimated coefficients on the GW index in our OLS regressions in Table 4 are very small, close to zero, and statistically insignificant. This is the case regardless of whether we include year and industry fixed effects separately, or industry-by-year interaction fixed effects to control for unobservable time-varying industry shocks. In other words, this evidence lends support to our prediction that these 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 show that while GW firms are more likely to operate in fossil fuel industries, such firms do not produce more green innovation than non-GW firms.

4.6. Decomposition of Greenwashing Intensity

After validating the firm-level greenwashing measure, we compute a variance decomposition of the greenwashing measure based on the incremental adjusted-R-squared from a projection of the firm-level greenwashing measure on different sets of fixed effects including year, industry, industry and year, and firm-level fixed-effects. The results are presented in Table 5.

[Insert Table 5 about here]

We find that approximately 30% of the variation in greenwashing intensity is at the industry level, while the majority 60% of the variation resides at the firm level. The results remain consistent across different definitions of industries including Fama-French 48 industries, 2-digit, 3-digit, and 4-digit SICs. This finding indicates that it is firm-level heterogeneities that explain most of the variation in GW intensity.

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 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 6. We find that greenwashing intensity is significantly and negatively associated with the five-day CAR following the conference call, suggesting that investors can detect greenwashing by firm managers and react unfavorably to it. 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.[23]

[Insert Table 6 about here]

In Panel A of Table A9 in the Online Appendix, we use the components of GW to examine which component drives the negative relationship between CAR and GW. We find that the component of green talk is the main driver of such a relationship. 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 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.[24] We depict the effects of the interactions between GW and these proxies in Figure 4A. The

[23] 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 60th 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.

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

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 an important signal for 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 7. 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 7 about here]

As shown in Panel B of Table A9 in the Online Appendix, both rankings of the green talk and *RepRisk* environmental incidents are statistically significant predictors of future poor operating performance. However, the coefficient magnitude of the green talk component is approximately twice as large as that of the environmental incident component. 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 environment and weak corporate monitoring by institutional investors tend to increase the predictability of GW on a firm future ROA. While the interaction results are relatively weaker for low analyst following and institutional ownership in Figure 4C, they convey 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 A10 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 green washing talk rather than the intensity of such communication. We also conduct a comparison between 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, not only the occurrence of greenwashing but also the intensity of greenwashing hurts future corporate operating performance.

Table A11 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.

Finally, we further control the firm-level climate change exposure developed by Sautner, Van Lent, Vilkov, and Zhang (2023) to account for the possibility that firms with higher exposure to climate change may also conduct more greenwashing activities. The results from Table A12 in the Online Appendix show that GW remains significantly and negatively associated with the five-day CARs and one-year ahead operating performance.[25] The findings are qualitatively similar if we control for the overall climate change exposure, or the three categories (i.e., opportunity, regulatory, and physical) of climate change exposure of firms. It suggests that the greenwashing measure that we construct indeed captures different information from the general climate change exposure of firms.

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

6. Why Do Managers Engage in Greenwashing?

The results presented so far indicate that greenwashing does not improve firm performance. Rather, future ROA and operating cash flow decline following greenwashing. Furthermore, the share price reaction to greenwashing is negative. This points to the possibility of an agency explanation for greenwashing—that is, managers commit 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 investigate 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 important variation in these ratings across rating companies (e.g., Avramov, Cheng, Lioui, and Tarelli, 2021; Berg, Koelbel, and Rigobon, 2022) so we consider three different ESG ratings. These include the Refinitiv (previously known as Asset4), KLD, and Sustainalytics ratings. We regress the environmental score of each company in the year following greenwashing on our greenwashing measure and various control variables. The results in Table 8 indicate a clear pattern of higher environmental ratings in the years following greenwashing. This result holds for the three environmental ratings and is robust to different regression specifications. We conclude that greenwashing does indeed result in higher environmental ratings.

[Insert Table 8 about here]

We now turn our attention to investigating whether CEOs personally benefit from greenwashing. Chen, Liao, Tsang, and Yu (2023) document an important link between firm ESG reporting and the career concerns of CEOs. They find that CEOs who are early in their tenure and, therefore, have more pronounced career concerns are more likely to voluntarily disclose ESG information. They benefit from this through higher compensation, better reputation, and less turnover than CEOs 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. Furthermore, Dai, Gao, Lisic, and Zhang (2023) find that CEOs are less (more) likely to leave the company when there is a large recent improvement (decline) in ESG. Moreover, this ESG performance impacts the ability of CEOs to find a new position and the compensation they receive at their new firm.

We present results that test the relation between forced CEO turnover and greenwashing in Panel A of Table 9. 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.[26]

The results 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 benefits CEOs personally by reducing their likelihood of losing their job. Furthermore, in the post-2015 period, there is evidence that greenwashing by firms with weaker ROA results in less CEO forced turnover in the following year.[27] 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 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

[26] 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.
[27] The results are qualitatively similar to one-year or three-year average industry-adjusted ROA.

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. 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 9 about here]

The results in Panel B of Table 9 indicate that more greenwashing is associated with less stock price-linked performance pay the following year. The link between *Delta* and greenwashing and *Vega* and greenwashing is negative for the entire period, with the *Vega* greenwashing relation being particularly strong following 2015. This is consistent with earlier results, which show negative stock returns and weaker operational performance following greenwashing. CEOs are not penalized for the greenwashing, via lower performance-related remuneration. On the contrary, CEOs benefit from greenwashing via remuneration as there is strong evidence that higher greenwashing is associated with higher environmental-linked performance pay. The results of Flammer, Hong, and Minor (2019) and Cohen, Kadach, Ormazabal, and Reichelstein (2023) indicate that including ESG criteria in executive compensation can benefit ESG outcomes. Our findings indicate that it can also have the downside of incentivizing greenwashing.

In Panel C of Table 9, 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). This is consistent with Coles, Daniel, and Naveen (2006) who show that a greater sensitivity of CEO wealth to stock volatility (*Vega*) is associated with more risk, including more investment in R&D and higher leverage. More recent studies, such as Armstrong and Vashishtha (2012) and Shue and Townsend (2017) also find executive compensation linked to stock price provides CEOs with an incentive to take more risk.

7. Conclusion

This study employs earnings conference call transcripts and a state-of-the-art machine learning model, *FinBERT*, to measure greenwashing intensity. We show that our fine-tuned *FinBERT* model achieves an impressive 90% accuracy rate in detecting green talk. We match the green talk identified by the *FinBERT* model with the actual corporate environmental incidents from RepRisk to construct a comprehensive measure of firm-level greenwashing intensity for a broad sample of U.S. public-listed firms spanning the 2005-2021 sample period.

We validate the firm-level greenwashing measure in multiple ways. First, we observe that the economy-wide aggregate greenwashing measure markedly increased after the 2015 Paris Agreement. Second, we find that the utilities industry has the highest level of greenwashing 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 and experience a higher amount of future EPA enforcement actions. Fifth, despite their higher likelihood of experiencing future environmental incidents and EPA enforcement, we find no evidence that greenwashing 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 future operating performance. We find that firm-level heterogeneities explain most of the variation in greenwashing intensity, and greenwashing is associated with lower cumulative abnormal stock returns following earnings conference calls and predicts lower future corporate operating performance. The uncovered negative effects of greenwashing on stock price reactions to conference calls and future operating performance are found to be more pronounced for firms with greater information asymmetry and weaker institutional monitoring.

To investigate the question of why corporate managers commit greenwashing, we study the relations between greenwashing and corporate environmental ratings and document that firms with greater greenwashing intensity tend to receive higher future environmental ratings. Moreover, we find that greenwashing significantly decreases 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 Accords, top executives' job security increases when they engage in greenwashing.

We further explore the relations between greenwashing and executive compensation structure. The results show that greenwashing is associated with lower CEO pay-for-performance sensitivity and CEO wealth-to-stock-volatility sensitivity, particularly after the Paris Agreement adoption. Greenwashing firms are also more likely to link their CEO pay with corporate environmental performance in corporate compensation contracts. These findings suggest an agency explanation for greenwashing, that is, managers commit greenwashing to increase their job security and compensation, at the expense of shareholders and other stakeholders. Consistent with this explanation, we find that greenwashing firms have lower future R&D and acquisition activities, lower future leverage, and greater future cash holdings, indicating that managers reduce their risk-taking efforts and enjoy a quieter life, given that greenwashing helps increase their job security. Given the increasing concern about greenwashing eroding stakeholder trust and undermining authentic sustainability efforts, the novel and comprehensive greenwashing 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.

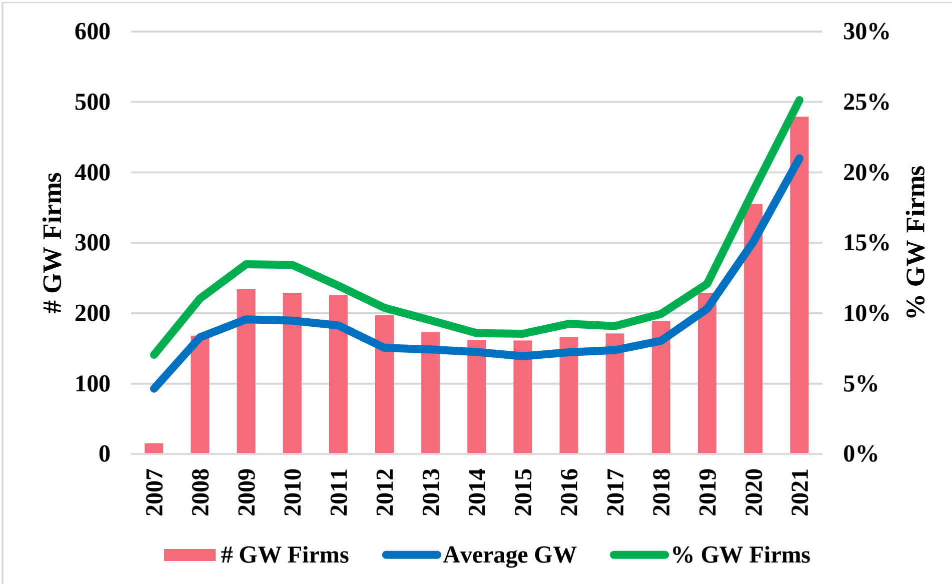

Figure 2. Top-10 Industries by Average Greenwashing Intensity

This figure illustrates the greenwashing intensity for the top-10 industries (based on the Fama-French 48 industry classification).

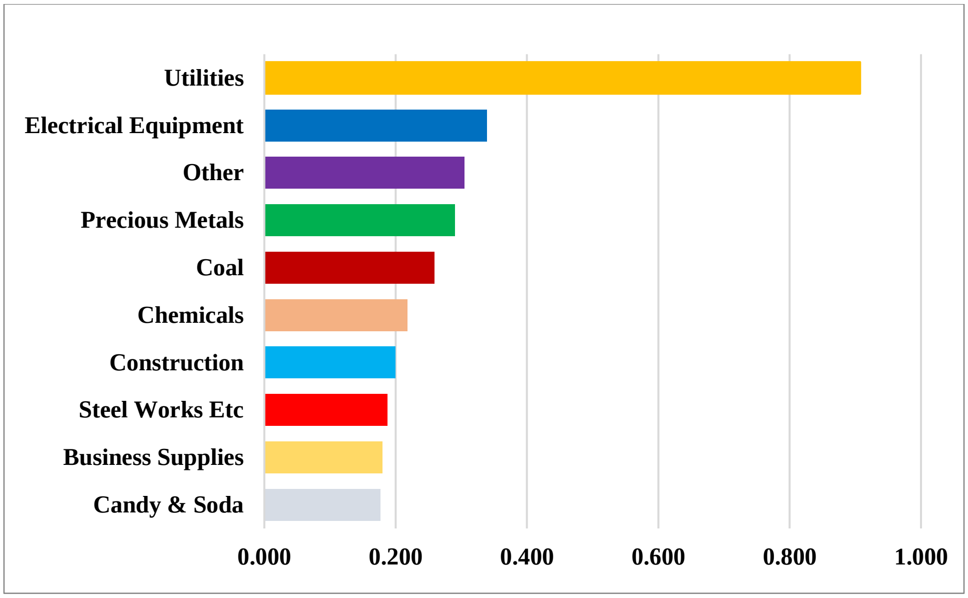

Figure 3. The Dynamic Effect of the Paris Agreement on Greenwashing Intensity

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

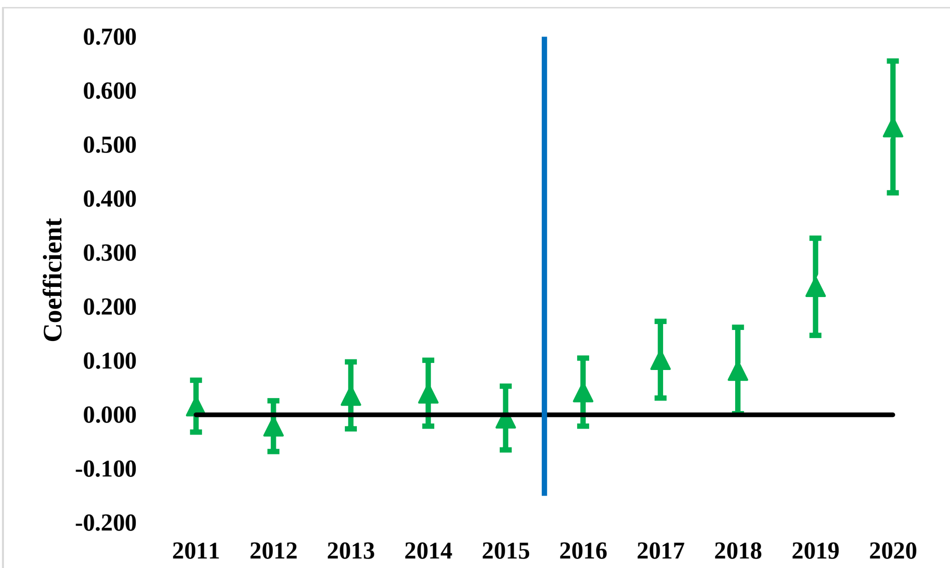

Figure 3B. Firms in Stranded Asset Industries vs. Firms in Other Industries

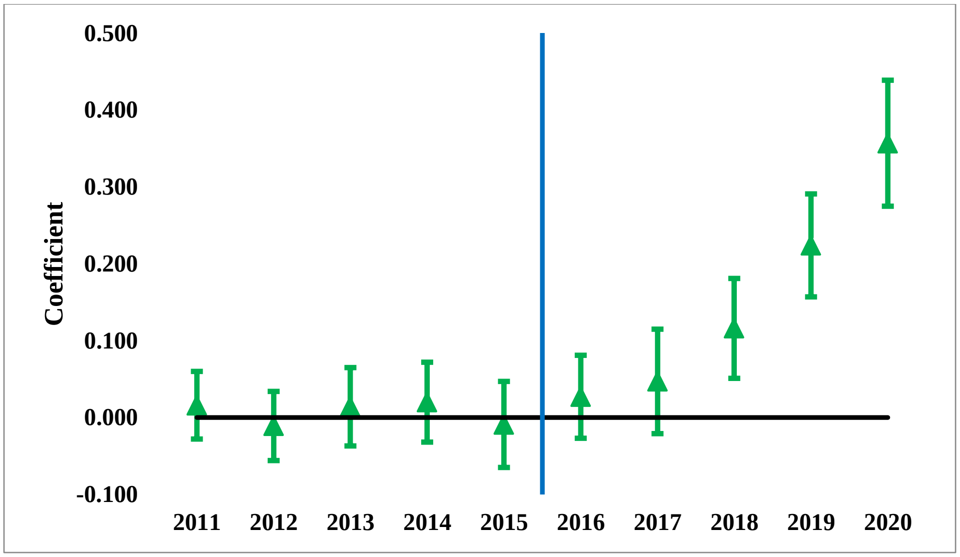

Figure 4. Heterogeneous Effects of Greenwashing Intensity: The Role of Information Asymmetry and Institutional Monitoring

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

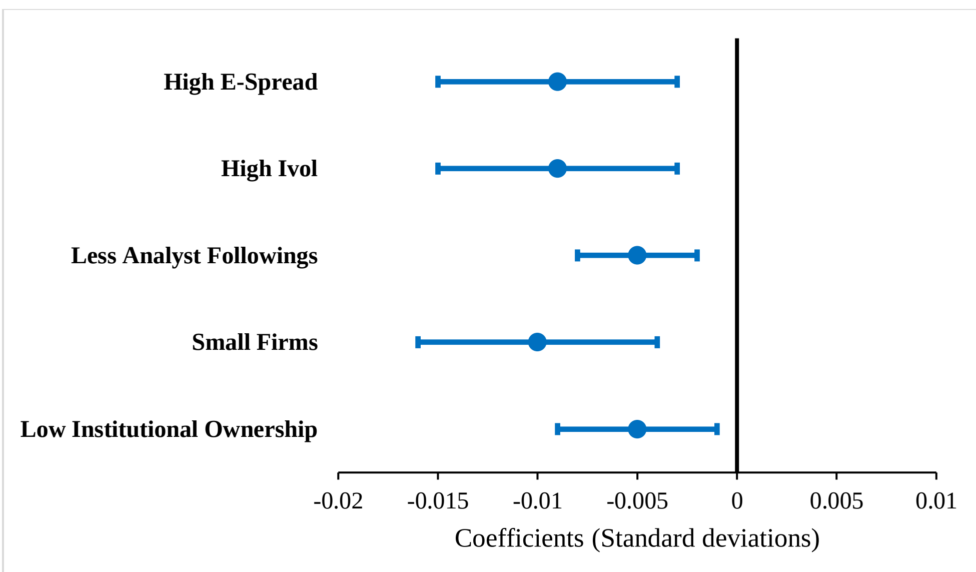

Figure 4B. Return on Assets (ROA)

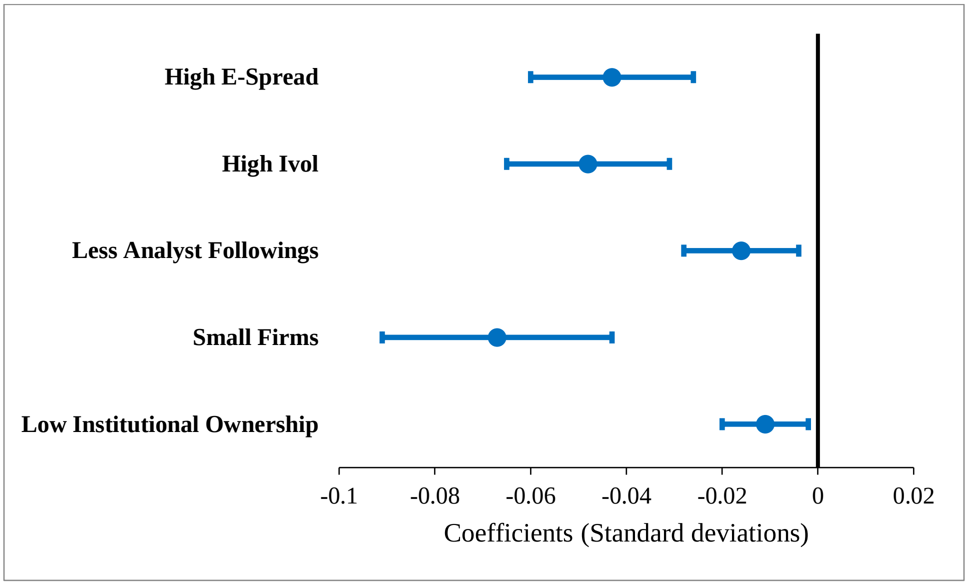

Figure 4C. Operating Cash Flow

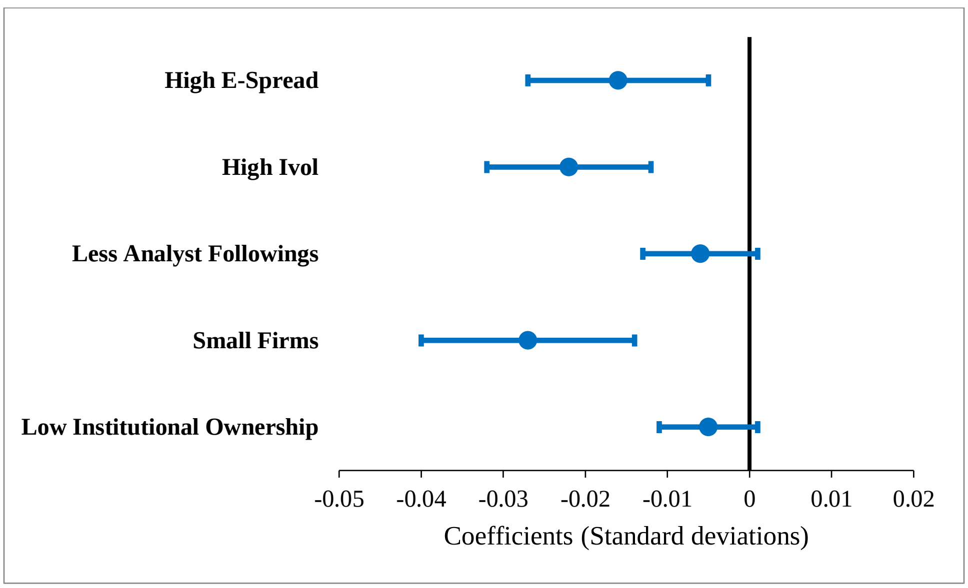

Table 1. Summary Statistics

This table reports the summary statistics for our final sample. 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.

	Obs.	Mean	P10	Median	P90	STD.
Greenwashing Variables						
GW	30,364	0.092	0.000	0.000	0.200	0.313
GW^{Q}	107,464	0.045	0.000	0.000	0.000	0.221
Dependent Variables						
Log(1+Green Patent Count)	30,364	0.004	0.000	0.000	0.001	0.040
Log(1+Green Patent Citations)	30,364	0.006	0.000	0.000	0.000	0.056
Log(1+# Env Incident)	30,364	0.162	0.000	0.000	0.693	0.518
Env Incident	30,364	0.120	0.000	0.000	1.000	0.325
Log(1+# Formal Enforcements)	30,364	0.040	0.000	0.000	0.000	0.211
Log(1+# Informal Enforcements)	30,364	0.094	0.000	0.000	0.000	0.327
Log(1+# Violations)	30,364	0.198	0.000	0.000	0.693	0.615
CAR (0, 4)	107,464	-0.0004	-0.1183	0.0003	0.1161	0.1016
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
RepRisk Env Incidents	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

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, and EPA Enforcement Actions

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. The dependent variable *Log(1+# Env Incident)* is measured as the natural logarithm of one plus the 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. *Log(1+# Formal Enforcements)* is measured as the natural logarithm of one plus the number of EPA formal enforcements a firm incurred in a year. *Log(1+# Informal Enforcements)* is measured as the natural logarithm of one plus the number of EPA informal enforcements a firm incurred in a year. *Log(1+# Violations)* is measured as the natural logarithm of one plus the number of EPA violations a firm incurred 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 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)
	Log(1+# Env Incident) $_{t+1}$		Env Incident $_{t+1}$	
GW	**0.237*** **	**0.286*** **	**0.105*** **	**0.131*** **
	(0.032)	**(0.035)**	**(0.013)**	**(0.013)**
Firm Size	0.110***	0.108***	0.067***	0.066***
	(0.007)	(0.007)	(0.003)	(0.003)
ROA	-0.166***	-0.173***	-0.114***	-0.115***
	(0.024)	(0.024)	(0.013)	(0.014)
Leverage	-0.216***	-0.216***	-0.123***	-0.119***
	(0.034)	(0.035)	(0.016)	(0.016)
Sales Growth	-0.041***	-0.041***	-0.026***	-0.025***
	(0.006)	(0.006)	(0.004)	(0.004)
Stock Return	-0.007	-0.005	-0.005	-0.004
	(0.006)	(0.005)	(0.003)	(0.003)
CAPEX	-0.269*	-0.345**	0.122*	0.091
	(0.142)	(0.159)	(0.073)	(0.078)
MTB	0.031***	0.029***	0.020***	0.019***
	(0.006)	(0.007)	(0.003)	(0.003)
R&D	0.198***	0.209***	0.040	0.053*
	(0.059)	(0.060)	(0.030)	(0.031)
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	30,364	30,364	30,364	30,364
Adj. R2	0.319	0.351	0.299	0.328

Panel B. Greenwashing Intensity and Future EPA Enforcement Actions

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(1+# Formal Enforcements) $_{t+1}$		Log(1+# Informal Enforcements) $_{t+1}$		Log(1+# Violations) $_{t+1}$	
GW	**0.022****	**0.034*****	**0.029****	**0.044*****	**0.038**	**0.071****
	(0.011)	**(0.012)**	**(0.014)**	**(0.015)**	**(0.031)**	**(0.032)**
Firm Size	0.016***	0.015***	0.034***	0.034***	0.067***	0.066***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
ROA	-0.027***	-0.026***	-0.045***	-0.047***	-0.062**	-0.071**
	(0.008)	(0.008)	(0.014)	(0.014)	(0.028)	(0.029)
Leverage	-0.024**	-0.022*	-0.029*	-0.025	-0.033	-0.028
	(0.011)	(0.011)	(0.018)	(0.018)	(0.033)	(0.034)
Sales Growth	-0.005**	-0.005**	-0.010***	-0.011***	-0.027***	-0.029***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.007)
Stock Return	0.003	0.003	-0.001	-0.002	0.001	-0.002
	(0.002)	(0.002)	(0.004)	(0.004)	(0.007)	(0.007)
CAPEX	-0.100*	-0.140**	-0.158**	-0.197**	-0.281**	-0.362**
	(0.051)	(0.061)	(0.079)	(0.088)	(0.141)	(0.154)
MTB	0.006**	0.005**	0.013***	0.013***	0.020**	0.020**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.008)	(0.009)
R&D	-0.022	-0.021	-0.070**	-0.077**	-0.112*	-0.119*
	(0.017)	(0.018)	(0.031)	(0.032)	(0.068)	(0.070)
Industry FE	✓		✓		✓	
Year FE	✓		✓		✓	
Industry-Year FE		✓		✓		✓
Obs.	30,364	30,364	30,364	30,364	30,364	30,364
Adj. R2	0.104	0.118	0.145	0.158	0.192	0.210

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 *Log(1+Green Patent Count)* is measured as the natural logarithm of one plus the number of green patents a firm has applied for (and later granted) in a year. *Log(1+Green Patent Citations)* is measured as the natural logarithm of one plus the 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 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)
	Log(1+Green Patent Count) $_{t+1,\ t+3}$		Log(1+Green Patent Citations) $_{t+1,\ t+3}$	
GW	**0.003**	**0.004**	**0.002**	**0.003**
	(0.003)	**(0.004)**	**(0.004)**	**(0.004)**
Firm Size	0.008***	0.008***	0.010***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
ROA	-0.008**	-0.008**	-0.008*	-0.008
	(0.004)	(0.004)	(0.005)	(0.005)
Leverage	-0.009	-0.009	-0.020*	-0.020*
	(0.009)	(0.009)	(0.012)	(0.012)
Sales Growth	-0.001	-0.001*	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Stock Return	-0.002*	-0.002*	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
CAPEX	-0.001	-0.004	0.036	0.031
	(0.025)	(0.028)	(0.032)	(0.036)
MTB	0.002	0.002	0.003*	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
R&D	0.039***	0.040***	0.056***	0.058***
	(0.011)	(0.011)	(0.015)	(0.016)
Industry FE	✓		✓	
Year FE	✓		✓	
Industry-Year FE		✓		✓
Obs.	17,052	17,034	17,052	17,034
Adj. R2	0.115	0.101	0.088	0.076

Table 5. Variance Decomposition of Greenwashing Intensity

The table reports the results on the incremental adjusted-R-squared from a projection of *GW* on different sets of fixed effects. Column 1 classifies industry based on the Fama-French-48-industry code. Column 2 classifies the industry based on a two-digit SIC code. Column 3 classifies the industry based on a three-digit SIC code. Column 4 classifies the industry based on a four-digit SIC code.

	FF48 (1)	**2-Digit SIC** (2)	**3-Digit SIC** (3)	**4-Digit SIC** (4)
Year FE	1.86%	1.86%	1.86%	1.86%
Industry FE	27.55%	26.12%	35.59%	36.88%
Industry × Year FE	3.09%	2.67%	3.54%	3.67%
"Firm Level"	**67.50%**	**69.35%**	**59.01%**	**57.59%**
Permanent differences across firms within industries (Firm FE)	27.91%	29.66%	20.76%	20.30%
Variation over time in identity of firms within industries (residual)	39.59%	39.69%	38.25%	37.29%

Table 6. 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*** **	**-0.004*** **	**-0.003*** **	**-0.003** **	**-0.004*** **
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Firm Size $_{q-1}$		0.001***	0.001***	0.001***	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)
ROA $_{q-1}$		0.135***	0.126***	0.133***	0.134***
		(0.011)	(0.011)	(0.011)	(0.011)
Leverage $_{q-1}$		-0.002	-0.003*	-0.003	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Sales Growth $_{q-1}$		0.016***	0.016***	0.015***	0.015***
		(0.001)	(0.001)	(0.001)	(0.001)
Stock Return $_{q-1}$		0.157***	0.192***	0.192***	0.203***
		(0.002)	(0.003)	(0.003)	(0.003)
CAPEX $_{q-1}$		0.044***	-0.003	-0.000	-0.001
		(0.012)	(0.013)	(0.014)	(0.015)
MTB $_{q-1}$		-0.004***	-0.004***	-0.004***	-0.003***
		(0.000)	(0.000)	(0.000)	(0.000)
R&D $_{q-1}$		0.008	0.007	0.008	0.007
		(0.005)	(0.005)	(0.006)	(0.007)
Earnings Surprise $_{q-1}$		0.006***	0.006***	0.006***	0.006***
		(0.000)	(0.000)	(0.000)	(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 7. 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***** **(0.004)**	**-0.029***** **(0.004)**	**-0.014***** **(0.002)**	**-0.019***** **(0.003)**
Firm Size	0.019*** (0.001)	0.019*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
ROA			0.446*** (0.015)	0.451*** (0.015)
Leverage	-0.136*** (0.008)	-0.135*** (0.008)	-0.023*** (0.006)	-0.023*** (0.006)
Sales Growth	-0.007* (0.004)	-0.008* (0.004)	-0.018*** (0.004)	-0.017*** (0.004)
Stock Return	0.039*** (0.003)	0.040*** (0.003)	-0.003 (0.002)	-0.003 (0.002)
CAPEX	-0.007 (0.033)	0.018 (0.034)	0.308*** (0.022)	0.348*** (0.023)
MTB	0.041*** (0.002)	0.041*** (0.002)	0.016*** (0.001)	0.017*** (0.001)
R&D	-0.987*** (0.039)	-0.986*** (0.039)	-0.305*** (0.030)	-0.302*** (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 8. 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 *Refinitive 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)
	Refinitive 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 9. 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 Intensity and Future Forced Turnover Likelihood

	(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 Intensity 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 Intensity and CEO Risk-taking Behaviors

	(1)	(2)	(3)	(4)	(5)	(6)
	CAPEX $_{t+1}$	R&D $_{t+1}$	Acquisition Expense $_{t+1}$	Total Investment $_{t+1}$	Leverage $_{t+1}$	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.

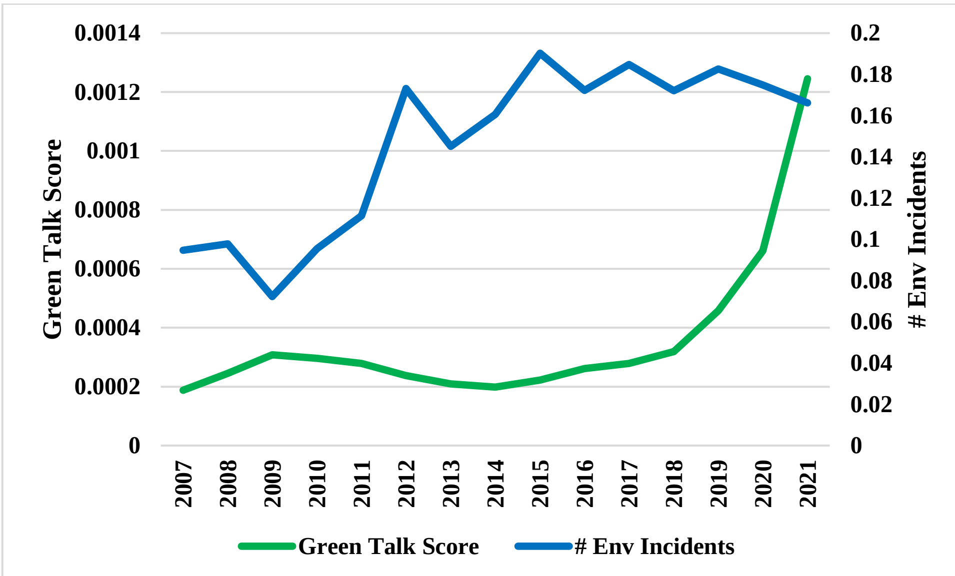

Table A1. Variable Definition

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.
Log(1+Green Patent Count)	The natural logarithm of one plus the 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.
Log(1+Green Patent Citations)	The natural logarithm of one plus the 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.
Log(1+# Env Incident)	The natural logarithm of one plus the 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.
Log(1+# Formal Enforcements)	The natural logarithm of one plus the number of EPA formal enforcements a firm incurred in a year. ***Source***: EPA's Enforcement and Compliance History Online (ECHO).
Log(1+# Informal Enforcements)	The natural logarithm of one plus the number of EPA informal enforcements a firm incurred in a year. ***Source***: EPA's Enforcement and Compliance History Online (ECHO).
Log(1+# Violations)	The natural logarithm of one plus the number of EPA violations a firm incurred in a year. ***Source***: EPA's Enforcement and Compliance History Online (ECHO).
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-related (negative) and 123 are green-talk-related (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 CO2 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. 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 A6. Validation: Greenwashing Intensity, Environmental Incidents, and EPA Enforcement Actions (Poisson Regression)

The table presents the Poisson 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 results where the dependent variables are a raw count of environmental incidents, enforcements, and violations, while Panel B reports the results using the logarithm transformation of the count variables. The dependent variable *# Env Incident* is measured as the number of environmental incidents a firm incurred in a year. *# Formal Enforcements* is measured as the number of EPA formal enforcements a firm incurred in a year. *# Informal Enforcements* is measured as number of EPA informal enforcements a firm incurred in a year. *# Violations* are measured as the number of EPA violations a firm incurred in a year. The independent variable *GW* is a firm's greenwashing intensity in a year. All specifications include firm controls. Columns 1, 3, 5, and 7 control for year fixed effects and industry fixed effects. Columns 2, 4, 6, and 8 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.

Panel A. Poisson Regressions with Raw Count

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# Env Incident $_{t+1}$		# Formal Enforcements $_{t+1}$		# Informal Enforcements $_{t+1}$		# Violations $_{t+1}$	
GW	**0.250***	**0.298***	**0.240***	**0.283****	**0.225****	**0.230****	**0.160**	**0.172**
	(0.073)	**(0.087)**	**(0.133)**	**(0.139)**	**(0.098)**	**(0.102)**	**(0.134)**	**(0.139)**
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓		✓		✓		✓	
Year FE	✓		✓		✓		✓	
Industry-Year FE		✓		✓		✓		✓
Obs.	27,024	25,533	27,076	18,556	26,733	23,306	27,076	24,273
Pseudo R2	0.694	0.708	0.323	0.308	0.286	0.293	0.351	0.370

Panel B. Poisson Regressions with Log Transformation of Count Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(1+# Env Incident) $_{t+1}$		Log(1+# Formal Enforcements) $_{t+1}$		Log(1+# Informal Enforcements) $_{t+1}$		Log(1+# Violations) $_{t+1}$	
GW	**0.210***	**0.235***	**0.222****	**0.243****	**0.150****	**0.146***	**0.063**	**0.076**
	(0.053)	**(0.059)**	**(0.098)**	**(0.104)**	**(0.071)**	**(0.076)**	**(0.078)**	**(0.082)**
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓		✓		✓		✓	
Year FE	✓		✓		✓		✓	
Industry-Year FE		✓		✓		✓		✓
Obs.	27,024	25,533	27,076	18,556	26,733	23,306	27,076	24,273
Pseudo R2	0.455	0.461	0.269	0.241	0.240	0.232	0.285	0.277

Table A7. Validation: Greenwashing Intensity and Green Patents Developments (Poisson Regression)

The table presents the Poisson regression results that investigate the relationship between a firm's greenwashing intensity and its green patent developments from years *t+1* to *t+3*. The dependent variable *Green Patent Count* is measured as the number of green patents a firm has applied for (and later granted) in a year. *Green Patent Citations* are measured as the number of citations received from green patents that a firm applied (and later granted) in a year. *Log(1+Green Patent Count)* is measured as the natural logarithm of one plus the number of green patents a firm has applied for (and later granted) in a year. *Log(1+Green Patent Citations)* is measured as the natural logarithm of one plus the 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 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)	(5)	(6)	(7)	(8)
	Green Patent Count $_{t+1, t+3}$		Green Patent Citations $_{t+1, t+3}$		Log(1+Green Patent Count) $_{t+1, t+3}$		Log(1+Green Patent Citations) $_{t+1, t+3}$	
GW	**0.084**	**0.155**	**0.107**	**0.172**	**0.146**	**0.234**	**0.213**	**0.286**
	(0.176)	**(0.234)**	**(0.195)**	**(0.223)**	**(0.170)**	**(0.225)**	**(0.179)**	**(0.209)**
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓		✓		✓		✓	
Year FE	✓		✓		✓		✓	
Industry-Year FE		✓		✓		✓		✓
Obs.	26,206	22,370	23,505	19,659	15,184	13,697	13,960	12,234
Pseudo R2	0.519	0.518	0.486	0.505	0.408	0.409	0.375	0.388

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. Components of Greenwashing Intensity, Stock Price Reaction, and Operating Performance

This table decomposes the greenwashing intensity into two components, the ranking of green talk intensity and the ranking of corporate environmental incidents. The regression results in panel A show the stock price reaction to the ranking of green talk intensity and environmental incidents, respectively. In Panel B, we further report the regression analyses that investigate the relationship between the ranking of green talk intensity and environmental incidents and future corporate 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. The independent variable $Ranking^{Green\ Talk}$ is the percentile ranking of a firm's green talk intensity in a year-quarter (measured using the earnings conference call transcript in that year-quarter) or a year (measured using the average green talk in the earnings conference call transcripts in that year). $Ranking^{Env\ Incidents}$ is the percentile ranking of a firm's number of environmental incidents that occurred in a year-quarter or a year. 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 Reaction

	(1)	(2)	(3)	(4)	(5)
			CAR (0, 4)		
$Ranking^{Green\ Talk}$	**-0.006*** **	**-0.008*** **	**-0.005** **	**-0.004***	**-0.005** **
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**
$Ranking^{Env\ Incidents}$	**0.001**	**-0.000**	**-0.001**	**-0.001**	**-0.001**
	(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	0.200	0.217

Panel B. Operating Performance

	(1)	(2)	(3)	(4)
VARIABLES	ROA_{t+1}		Free Cashflow $_{t+1}$	
$Ranking^{Green\ Talk}$	**-0.042*** **	**-0.049*** **	**-0.026*** **	**-0.033*** **
	(0.008)	**(0.009)**	**(0.005)**	**(0.005)**
$Ranking^{Env\ Incidents}$	**-0.024*** **	**-0.024*** **	**-0.011*** **	**-0.014*** **
	(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	0.391	0.405	0.570	0.577

Table A10. 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***** **(0.006)**	**-0.031***** **(0.007)**	**-0.014***** **(0.004)**	**-0.016***** **(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***** **(0.004)**	**-0.025***** **(0.004)**	**-0.015***** **(0.002)**	**-0.018***** **(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 A11. 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 Activities

	(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 Activities 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 A12. 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	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	No	No	No	No
Industry-Year FE	No	No	Yes	Yes	Yes	Yes
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