Yongheng Sun

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Dear Professors,

I am writing to apply for the PhD Student Workshop on Climate Finance to be held on October 9, 2025, in Cambridge, MA. I am a third-year PhD student in Finance at Singapore Management University. My research examines how financial systems can facilitate the global sustainability transition. I expect to complete my PhD by mid-2028. My primary adviser, Professor Hao Liang, Associate Professor of Finance and Ho Bee Professorship in Sustainability Management at Singapore Management University, can serve as a reference for my application and may be reached at hliang@smu.edu.sg.

My current work centers on transition finance, which refers to the provision of capital to high-emission ("brown") firms to support their shift toward greener business models. While much of the sustainable finance literature focuses on financing already-green activities, my research asks whether lowering financing costs can accelerate the green transformation of brown firms. Using a novel dataset that measures the revenue greenness of all Chinese-listed firms, I find that lower debt costs are associated with a greater reliance on green activities for revenues, especially among brown firms. I identify a causal effect by leveraging a policy shock to debt costs and confirm similar patterns in an international sample. These findings underscore the importance of transition finance as a policy and investment strategy for facilitating the green transition.

In addition, I am working on a project that investigates the role of key financial market participants in addressing sustainability issues. Using internal engagement records from a large European asset management company, I identify environmental, social, and governance (ESG) controversies as a primary trigger for institutional investors' engagement decisions. I further document both financial and non-financial motivations behind these actions and examine how such engagement influences firms' ESG performance and financial outcomes. This project thus provides new evidence on the triggers and motivations for ESG engagement and uncovers the specific channels through which it can enhance firm value.

Together, my projects aim to contribute to the literature on how finance can address climate change and promote sustainable development. Looking ahead, I plan to extend my research to explore how sustainability concerns could in turn shape financial markets, such as the corporate bond market, and influence major corporate decisions, including mergers and acquisitions.

Thank you for considering my application. I believe this workshop will provide a valuable opportunity to receive feedback from leading scholars in climate finance and to refine my work. I have enclosed my CV and working papers for your review, and I look forward to the opportunity to present my research and engage with fellow participants and faculty.

Sincerely,

Yongheng Sun
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Singapore Management University

Yongheng Sun (孙永恒)

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Education

Singapore Management University *2023–2028 (Expected)*
PhD Candidate in Finance

Xiamen University *2020–2023*
Master's Degree in Finance

Southwestern University of Finance and Economics *2016–2020*
Bachelor's Degree in Accounting

Research Interests

ESG and sustainability topics in corporate finance

Working Papers

Greening "Brown" Firms with Transition Financing
with Hao Liang and Tianhao Yao

Abstract: We examine whether reduced financing costs facilitate firms' green transition, proxied by the share of revenue from sustainable activities (green revenue). Using a unique dataset on the green revenue of publicly listed firms in China, we document a negative association between firms' cost of debt and their green revenue share, particularly among firms in brown sectors. The effect is more pronounced for smaller firms and those with green technologies. Exploiting policy-induced reductions in borrowing costs, we provide evidence of a plausibly causal effect. Reduced debt costs are further associated with increased green investment. We also confirm this relationship in an international sample. Our findings underscore the importance of transition finance in facilitating the green transition.

From Incidents to Actions: The Dynamics of ESG Engagement in Asset Management
with Hao Liang and Mandy Tham

Abstract: This paper examines why institutional investors decide to engage with portfolio firms on ESG issues. Using a proprietary dataset of detailed ESG engagement records from a European asset management company, we find that engagement is triggered by both firms' own ESG incidents and those of their suppliers. We further show that engagement decisions are driven not only by financial considerations but also by non-financial ones, with reputational concerns representing a key non-financial motivation. Finally, we demonstrate that engagement enhances firm value, potentially through an improvement in ESG performance, and identify increased cash flows as the main source of value creation. Together, these findings shed light on the triggers and motivations for ESG engagement and reveal the specific channels through which it enhances firm value.

- **Conferences:** 2025 FMA Asia/Pacific Conference (*Scheduled*)

Research Before PhD

Unwatched Corporate Social Responsibility: The Impact of Releasing Political Pressure
with Shusen Qi and Jieyu Zhou

Abstract: China's *Rule 18* in 2013 mandated political officials to resign as independent directors from listed companies. We exploit this quasi-natural experiment to examine the long-term effects of political pressures on CSR. Based on hand-collected data and difference-in-differences models, we find that firms' CSR performance decreases after they are released from political pressures. The results suggest that while political pressures can increase CSR engagement, politically induced CSR is generally not persistent. We further reveal that politically induced CSR could turn into firms' spontaneous behavior only when firms have stronger incentives to conduct CSR, when the strength of political pressures is moderate, and when firms have greater bargaining power against political pressure. Finally, we show that firms are more likely to discontinue CSR that is less lined up with their best self-interest and that CSR activities induced by political pressures are generally economically inefficient. Our research is among the first to provide evidence regarding the persistency of politically induced CSR activities.

- **Conferences:** Academy of Management Annual Meeting 2024

Industry Articles

Greening Brown Sectors through Transition Finance (Link) ***Asian Management Insights***
with Hao Liang and Tianhao Yao

Chapter 1 in "Navigating Climate Risks and Opportunities: How Institutional Investors Respond to the Transition of High-Carbon Sectors" [in Chinese] (Link) ***Caixin Insights***
with Hao Liang

Research Grants

ASEAN Business Research Initiative Grant *2024–2025*
Co-Principal Investigator

Honors and Awards

SMU PhD Full Scholarship *2023–Present*
China National Scholarship *2019*

Language and Skills

Language: Chinese (native), English (fluent)
Programming: Stata, Python, LaTeX

Greening "Brown" Firms with Transition Financing

Hao Liang * Yongheng Sun† Tianhao Yao‡

July 24, 2025

Abstract

We examine whether reduced financing costs facilitate firms' green transition, proxied by the share of revenue from sustainable activities (green revenue). Using a unique dataset on the green revenue of publicly listed firms in China, we document a negative association between firms' cost of debt and their green revenue share, particularly among firms in brown sectors. The effect is more pronounced for smaller firms and those with green technologies. Exploiting policy-induced reductions in borrowing costs, we provide evidence of a plausibly causal effect. Reduced debt costs are further associated with increased green investment. We also confirm this relationship in an international sample. Our findings underscore the importance of transition finance in facilitating the green transition.

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1 Introduction

Climate change is one of the most urgent challenges facing humanity today. According to the Intergovernmental Panel on Climate Change (IPCC), global temperatures over the past 50 years have risen at the fastest rate in the past two millennia. To address this alarming trend, substantial capital has flowed into sustainable investment vehicles over the past decade, aiming to address the climate crisis through capital market solutions.

However, traditional sustainable investment strategies—such as divestment from carbon-intensive industries—may be counterproductive in achieving a low-carbon economy (e.g., Hartzmark and Shue, 2023; Xu and Kim, 2022). When faced with high financing costs, these "brown" firms may increase carbon emissions or pollution to prioritize short-term cash flows over long-term green initiatives. A recent concept in sustainable investment, known as transition finance, has emerged to address this issue. In essence, transition finance refers to financial investments that support high-emitting companies or sectors in reducing their greenhouse gas (GHG) emissions over time, in alignment with pathways to net-zero emissions.[1]

In this paper, we provide early evidence on whether the logic of transition finance is effective. We employ a direct measure of green transition—the share of firms' green and brown revenue—for a sample of publicly listed Chinese firms to assess their transition efforts. This measure, based on China's green taxonomy issued by the National Development and Reform Commission, reflects the extent to which firms are fundamentally shifting their business models toward greater sustainability. Compared to alternative indicators such as carbon emissions, this revenue-based measure more accurately captures firms' long-term commitment to green transition.

We focus on China for two main reasons. First, we leverage a proprietary dataset that includes detailed information on green revenue, brown revenue, and green projects for a comprehensive list of publicly listed Chinese firms. This enables us to examine multiple dimensions of firms' green transition processes. Second, China is a global leader in implementing transition finance. For example, in 2021, the People's Bank of China initiated research on transition finance and established foundational principles for its implementation. By the end of 2024, China

[1]Formally, the OECD defines transition finance as "finance deployed or raised by corporates to implement their net-zero transition, in line with the temperature goal of the Paris Agreement and based on credible corporate climate transition plans" (OECD, 2022), and states, "Transition finance focuses on raising and providing funds to decarbonise high-emitting economic activities and industries that currently do not have a fully feasible zero- or near-zero emission alternative" (OECD, 2023).

had issued ¥64.86 billion (US $8.9 billion) in transition-labelled bonds, making it the world's second-largest market for transition finance, following Japan.

We begin by describing and validating our measure of firms' green and brown revenue. In the time series, we observe a gradual increase in the ratio of green revenue and a decline in the ratio of brown revenue, consistent with China's ongoing green transition. In the cross-section, a firm's net green ratio is negatively correlated with its GHG carbon emissions—both in total and in intensity—and positively correlated with commonly used environmental scores from ESG rating providers. These correlations also hold within industries, suggesting that green revenue effectively captures firms' efforts toward a green transition.

Next, we examine how financial constraints affect firms' green transition. We start by testing the cross-sectional correlation between firms' cost of debt and their green revenue. Firms are ex ante classified as "green," "brown," or "neutral" based on the industry-level shares of green, brown, and neutral taxonomies in their revenue. We then interact these indicators with the firm's cost of debt. Our analysis employs a panel regression with firm and time fixed effects, controlling for firm characteristics such as size, liquidity, leverage, investment, and growth.

We find that lower debt costs are associated with a lower brown revenue ratio. The economic magnitude is substantial: a one-standard-deviation decline in borrowing costs reduces the brown revenue share by 0.77 percentage points, equivalent to 11% of its unconditional mean. Importantly, this effect is concentrated in firms operating in brown industries—those with the greatest abatement potential.

Next, we explore the heterogeneity of this effect. We find that the relationship between lower debt costs and greener revenue is driven primarily by smaller firms, consistent with their greater organizational flexibility facilitating green transitions. Moreover, the effect is stronger among firms with richer ex-ante green technology portfolios. This evidence suggests that lower debt costs enhance green transition efforts mainly in firms that are already technologically equipped.

We complement the green revenue data with novel information on green investment. Specifically, we begin by identifying keywords related to green activities based on green taxonomies issued by the Chinese government. We then search for these keywords in firms' project descriptions and classify a project as "green" if its title contains any of the identified keywords. We construct our measure of green investment as scaled aggregate annual value of investment in identified green projects.

We find a positive correlation between green investment and green revenue. Using a similar regression framework as before, we also find that lower debt costs are associated with higher

green investment, corroborating the conclusion that relaxed financial constraints facilitate the green transition.

The above evidence may be subject to endogeneity concerns. We then conduct an analysis to establish a plausibly causal link between financing costs and the green transition. In particular, we leverage a series of tax policy changes in China to achieve this. Between 2014 and 2019, China's Ministry of Finance introduced policies allowing firms in selected industries to adopt accelerated depreciation methods. These policy changes provide exogenous variation in firms' tax liabilities, thereby increasing cash holdings. As a result, it improves firms' perceived creditworthiness and, in turn, lowers borrowing costs. We empirically verify that the policy leads to a decline in firms' cost of debt. After the policy change, firms' cost of debt decreased by 0.5 percentage points, which corresponds to 8.3% of the unconditional sample mean.

We then examine how these changes in the cost of debt affect firms' green transition. Using a stacked difference-in-differences analysis, we test whether treated firms—those that benefit from lower borrowing costs under the policy changes—expand their green transition efforts. We find that treated firms, particularly those operating in brown (hard-to-abate) industries, increase their green revenue. The economic magnitude of this effect is substantial: treated firms raise their green revenue ratio by 3.2 percentage points, equivalent to 64% of the sample mean. This evidence further supports the notion that financing costs have a plausibly causal impact on firms' green transition.

Finally, we extend our analysis beyond Chinese firms and examine the relationship between financing costs and green revenue in an international context. Specifically, we use the S&P Global EU Taxonomy dataset, which identifies firm revenues linked to sustainable economic activities deemed eligible under the EU Taxonomy. In the global sample, we find a negative relationship between firms' cost of capital—proxied by market-based measures—and their share of revenue derived from sustainable activities. This evidence suggests that the effect of financing costs on green transition is a global phenomenon rather than one unique to China.

Our results have important implications for understanding the green transition of the economy. We provide novel evidence that financing brown firms can indeed facilitate green investment and support a shift in business models toward greater reliance on green revenues. Using China as a laboratory, we demonstrate the effectiveness of this mechanism. Furthermore, using an international sample, we provide suggestive evidence that this logic may generalize to a broader set of markets.

Related Literature We contribute to several strands of literature. First, we add to the litera-

ture examining how financing constraints affect environmental outcomes. Hartzmark and Shue (2023) show that reallocating capital from brown to green firms can be counterproductive, as it makes brown firms more brown but does not make green firms greener. Along similar lines, Xu and Kim (2022) find that financial constraints lead to higher pollution levels. Additionally, Cohen et al. (2024) show that brown sectors generate the most highly cited green innovations. Collectively, this evidence suggests that divesting from brown firms may hinder progress toward a greener economy. We contribute to this strand by showing that higher financing costs impede firms' transition toward green business models, measured by the share of green revenue. Using a novel policy shock that provides exogenous variation in financing costs, we provide evidence of a plausibly causal effect. Our study is also related to a growing theoretical literature on socially responsible investing and its implications for firm behavior and market outcomes (Heinkel et al., 2001; Edmans et al., 2022; Lanteri and Rampini, 2023; Landier and Lovo, 2025; Oehmke and Opp, 2025).

Our measure of green revenue of firms is related to Klausmann et al. (2024), who examine firms' green revenue in a global sample of firms using measures defined by the EU taxonomy. They document an accelerated expansion of firms' green revenue after the Paris Agreement, particularly those with ex-ante green patents and with support from ESG institutional investors. We complement their study and examine how financing cost affects the green revenue of firms, as a proxy for the green transition of firms. Moreover, different from the EU taxonomy which only defines green and non-green revenue, the data in our paper allows us to separately examine brown revenue and green revenue (relative to neutral revenue). We document that some transition happens by moving away from brown revenue. Relatedly, Bassen et al. (2025) and Sautner et al. (2025) also examine EU taxonomy green revenue from different perspectives.

Our paper is also related to the broad literature on sustainable investment, cost of capital and environmental externalities of firms. Chava (2014), Gormsen et al. (2024), Van der Beck (2021), Pástor et al. (2021), Pástor et al. (2022), Bolton and Kacperczyk (2021) and Berk and Van Binsbergen (2025) examine firms' cost of capital in the equity market under sustainable investment. Green and Vallee (2022) show how banks' divestment from fossil-fuel assets reduces carbon emissions.

The rest of the paper is organized as follows. Section 2 describes the data and sample. Section 3 presents descriptive evidence on firms' green revenue and its correlation with other firm-level sustainability measures. Section 4 presents results on baseline analysis of firms' cost of debt and green revenue. Section 5 examines the heterogeneity of such effects. Section 6 shows

results regarding green investments. Section 7 presents results from analysis identifying a causal effect. Section 8 presents results using an international sample. Finally, Section 9 concludes.

2 Data and Sample

Our research sample consists of all Chinese-listed companies from 2010 to 2022. We exclude firms in the financial industry, those under special treatment, and those with missing key variables. [2] The final sample comprises 29,265 observations.

2.1 Green Revenue

We have access to a unique dataset developed by the Central University of Finance and Economics (CUFE) that tracks the green revenue of Chinese listed companies. This dataset is based on the revenue breakdown by main business segments, which every listed company is required to disclose in its annual reports. Firms typically report the name of each business segment along with its corresponding revenue. The contribution of each segment to the total revenue can also be calculated accordingly.

Based on the name of each business segment, The CUFE team classifies them as either green, brown, or neutral. The classification follows the *Green Industry Guidance Catalog (2019)*, a Chinese green taxonomy issued by the National Development and Reform Commission (NDRC), an executive department of China's State Council responsible for macroeconomic management, together with other Chinese authorities. This taxonomy outlines a comprehensive list of green economic activities, comprising six main categories, thirty sub-categories, and 211 specific business types, each accompanied by a detailed description. The CUFE team assigns each business segment to the appropriate green category within this taxonomy through a combination of keyword search and human verification.

For the identification of brown businesses, the CUFE team outlines a list of typically polluting

[2] Firms under extreme financial distress or abnormal operations are designated as specially treated by the Shanghai and Shenzhen Stock Exchanges to signal high investment risk. There are two types of special treatment labels. The first, **ST*, indicates a high risk of forced delisting. Firms receive this label after reporting negative net profits for two consecutive years or receiving a disclaimer or adverse opinion from auditors. The second, *ST*, highlights significant risks in other areas. This label is assigned when firms are unable to operate normally for at least three months or when controlling shareholders or related parties seriously misappropriate funds. As firms under special treatment are often financially distressed or face major governance issues, making them potential outliers, we exclude them from the sample.

businesses within eight widely recognized high-emission sectors in China: power generation, steel, building materials, non-ferrous metals, petrochemicals, chemicals, papermaking, and aviation. [3] They establish a system of brown businesses comprising eight categories and thirty-eight specific business types. Then, using both keyword search and human verification, they assess whether each business segment falls within this system to identify brown businesses. The CUFE Green Revenue dataset covers 5,242 Chinese listed companies and spans the period from 2010 to 2022.

To illustrate this classification, Table IA.1 in the Appendix presents an example from Guangdong Shaoneng Group Co., Ltd. (Ticker: 000601.SZ) in 2010. The firm reported that its total revenue came from six main businesses that year: hydropower generation, cement, paper & paper products, thermal power generation, trade & services, and transmission & gear products. In the CUFE dataset, hydropower generation is classified as green, belonging to category 3.1.4 (Hydropower & Pumped Storage Equipment Manufacturing) in the taxonomy. Cement, paper & paper products, and thermal power generation are classified as brown, corresponding to label 3011 (Cement Manufacturing), label 2221 (Machine-made Paper & Paperboard Manufacturing), and label 4411 (Thermal Power Generation) in CUFE's brown business system. Trade & services and transmission & gear products are classified as neutral.

In our later analysis, we utilize S&P Global EU Taxonomy data to extend our research from Chinese firms to global firms. Similar to the CUFE data, the S&P Global EU Taxonomy data breaks down each company's total revenue into different economic activities and maps them to those outlined in the EU Taxonomy, a classification system established by the EU to define sustainable economic activities. Economic activities listed in the EU Taxonomy are considered able to contribute substantially to at least one of the environmental objectives set by the EU and are referred to as eligible activities. Based on this mapping, the dataset provides the EU Taxonomy-eligible revenue ratio for each firm.[4] It covers 24,611 firms worldwide and spans the period from 2005 to 2020.

[3] According to a report on the website of China's State Council, these eight sectors account for approximately 75% of China's total emissions. The Chinese government also plans to incorporate these sectors into the national emissions trading system to regulate their emissions. Source: https://www.gov.cn/zhengce/202402/content_6934526.htm

[4] It is important to note, however, that being eligible under the EU Taxonomy is not the same as being aligned with it. For an activity to be considered aligned, it must meet three criteria: (1) make a substantial contribution to at least one of the six environmental objectives, (2) do no significant harm to any other objective, and (3) meet the minimum safeguards. Therefore, the eligible revenue ratio should be interpreted as a suggestive indicator of a firm's greenness, representing the proportion of its revenue derived from activities that could potentially be sustainable.

2.2 Financial Data

The firm financial data for Chinese listed companies is from CSMAR. Data on green patents are sourced from the Chinese Research Data Services (CNRDS). For the global sample, our analysis involves financial data, stock prices, and analyst earnings forecasts. We obtain financial and stock price data from Compustat North America and Compustat Global. Analyst earnings forecast data comes from I/B/E/S. When necessary, we convert all currencies to USD using exchange rates from Compustat Global.

2.3 Variable Definitions

To characterize firm greenness, we aggregate the revenue shares of green and brown businesses to derive three key metrics: the green ratio (proportion of revenue from green businesses), the brown ratio (proportion from brown businesses), and the net ratio (the difference between green and brown ratios). Following the example in Table IA.1, the firm generated 42.94% of its revenue from brown businesses and 35.79% from green businesses. Thus, its brown ratio is 42.94%, its green ratio is 35.79%, and its net green ratio is -7.15%.

The variable of interest, *Debt Cost*, is proxied by the total cost of raising debt, which includes interest expenditure, other financial expenses, and capitalized interest expenditure. This is scaled by the total amount of debt, including short-term loans, non-current liabilities due within one year, long-term loans, bond payables, and long-term accounts payable. While we acknowledge that this is a noisy proxy for debt cost, given that no bank loan data is publicly available in China, it is the best proxy we may obtain based on public data. An alternative, potentially more precise measure could be the credit spread of corporate bonds. However, only a small proportion of Chinese listed companies finance through corporate bonds, making this approach less feasible. For example, according to the statistics provided by Geng and Pan (2024) in their Table IA.I, only 1,444 non-financial firms issued corporate bonds in the Chinese credit market between 2010 and 2020, whereas over 4,000 firms were listed in the Chinese stock market by the end of 2020. Therefore, the debt cost measure proposed here may be the best choice considering both data availability and data coverage.

2.4 Summary Statistics

Panel A of Table 1 presents the summary statistics for the key variables in the regression analysis of the Chinese sample. On average, green businesses account for 5% of firm revenue, while brown

businesses contribute 7%. The majority of sample firms are classified as neutral (76%), while brown firms and green firms represent 19% and 5% of the sample, respectively. Additionally, the average cost of debt is 6%. Panel B of Table 1 presents the summary statistics for the key variables in the regression analysis of the global sample. On average, firms generate 36% of revenue from economic activities listed in the EU Taxonomy. The average implied cost of capital is around 9% using either analyst earnings forecasts or model-based earnings forecasts.

3 Green and Brown Revenue in Chinese Firms

3.1 Time Trends and Industry Decomposition

Figure 1 shows the overall times series of green, brown, and net revenue ratios for all firms covered by the CUFE dataset. It suggests that firms have become increasingly greener during the sample period, with the net ratio rising from -7.25% in 2010 to 0.63% in 2022. During this period, we observe both a significant increase in the green ratio (by 100%) and a substantial decrease in the brown ratio (by 45%). The figure also suggests that, on average, firms still derive most of their revenue from neither-green-nor-brown businesses, as green or brown businesses each account for below 10% of total revenue. Klausmann et al. (2024) obtained a similar dataset on the ratio of green revenue for publicly listed firms worldwide from FTSE Russell for the period 2008–2023. The magnitude of the green revenue ratio in our dataset is comparable to that reported for the Chinese subsample in their study, supporting the validity of our data.

Figure 2 lists the industries with the highest average green, brown, and net green revenue ratios. Subfigure (a) shows that the *Ecological Protection & Environmental Governance* has the highest green revenue ratio (61%), followed by *Forestry* (42%) and the *Water Production & Supply* (39%). Subfigure (b) shows that the industries with the highest brown revenue ratios are generally those related to papermaking, ferrous metals, power generation, nonferrous metals, petroleum, chemicals, non-metallic mineral products, and aviation, which broadly correspond to the eight conventionally recognized high-emitting industries in China. Subfigure (c) shows that industries with high green revenue ratios usually also rank high in net green ratios. One notable exception is the *Production & Supply of Electric Power & Heat*. Since this industry includes both hydropower and thermal power generation, it ranks high in both green and brown revenue ratios, leading to a relatively low net green ratio. Thus, it is important to consider both green and brown activities when evaluating the overall greenness of an industry. Overall, these figures suggest that the green revenue dataset successfully identifies industries that are conventionally

considered green or brown.

3.2 Correlations with Common Greenness Measures

Table 2 presents the correlations between the green, brown, and net revenue ratios and several commonly used measures of firm greenness. The first set of measures comes from Trucost and captures greenhouse gas (GHG) emissions. We examine both emission intensities and total emission levels, considering Scope 1, Scope 2, and their combination. Rows (4) to (9) show that GHG emission measures are positively correlated with the brown ratio (36% to 57%), modestly correlated with the green ratio (2% to 8%), and negatively correlated with the net ratio (33% to 43%).

The second set of measures relates to climate change exposure, as developed by Sautner et al. (2023). Rows (10) to (13) indicate that both green and brown ratios are positively correlated with overall climate change exposure. When decomposing this exposure into opportunities, regulatory risk, and physical risk, the brown ratio is particularly associated with regulatory and physical risks, whereas the green and net ratios are more strongly correlated with climate-related opportunities.

The third set of measures includes environmental and climate-related performance scores from major ESG data providers, namely Refinitiv and MSCI. From Refinitiv, we use the environmental pillar score and the emissions score; from MSCI, we use the environmental pillar score, the climate change theme score, and the environmental opportunities theme score. Rows (14) and (15) show that the revenue-based ratios are only weakly correlated with Refinitiv scores and, in some cases, suggest patterns of greenness that differ from those implied by Refinitiv. In contrast, Rows (16) to (18) indicate a much stronger correlation between the revenue ratios and MSCI scores, with both sets of measures pointing to similar assessments of firm-level greenness.

The final set of measures is event-based. First, we use the number of ESG incidents related to the environment and GHG emissions from RepRisk.[5] Second, we use the ESG performance score from the FactSet Truvalue SASB Scores on the dimension of GHG emissions, which captures firm performance as reflected in external reports related to GHG-related events and practices. [6] Rows (19) to (21) show that environmental incidents are positively correlated with the brown

[5]RepRisk identifies ESG incidents on a daily basis from a broad range of public sources in 23 languages and classifies each of them as related to environmental, social, or governance issues.

[6]FactSet Truvalue SASB Scores apply machine learning and natural language processing to assess the semantic content of millions of external ESG-related documents. It provides ESG performance metrics by issue and overall, based on SASB definitions

ratio and negatively correlated with the net ratio. However, the revenue ratios do not exhibit significant correlations with GHG-specific incidents or related performance scores.

In addition to simple correlations, we employ a regression-based approach to examine the relationships between the green, brown, and net revenue ratios and other measures of firm greenness. Table 3 shows that, after controlling for firm characteristics, industry-specific factors, and year-specific factors, the net ratio is negatively associated with carbon emissions, positively associated with Refinitiv and MSCI environmental ratings, and negatively associated with environmental incidents, broadly consistent with the correlations reported in Table 2. Further analysis in Table IA.3 reveals that firms with higher green revenue ratios tend to exhibit lower carbon emissions, stronger environmental ratings, and fewer environmental incidents, in contrast to firms with higher brown revenue ratios.

We identify two main insights from the preceding analysis. First, the green, brown, and net revenue ratios capture firm-level greenness in a way that is generally consistent with carbon emissions, climate change exposure, ESG performance scores, and incident-based measures, supporting the validity of the revenue-based measures. More importantly, the revenue-based greenness measures exhibit only moderate correlations with most of the existing metrics, suggesting that they capture distinct and complementary information.

3.3 Variance Decomposition

We follow Sautner et al. (2023) in decomposing the variance of the green, brown, and net revenue ratios across different levels. Panel A of Table 4 shows that the majority of the variance is concentrated at the firm level, ranging from 62% to 74%. In contrast, 24% to 37% of the variance is attributable to industry-level differences, while only 0.2% to 0.4% is associated with time-level variation. Panel B further breaks down the variance into components explained by firm and industry-by-year fixed effects, and a residual component interpreted as time-varying firm-level variation. The results indicate that 85% to 89% of the total variance is accounted for by time-invariant firm-level effects and time-varying industry-level effects, whereas time-varying firm-level variance explains only 11% to 15%.

The variance decomposition reveals that revenue-based greenness measures are relatively stable over time, distinguishing them from more volatile climate change exposure measures. Using climate-related keywords in earnings calls, Sautner et al. (2023) find that 44% to 55% of the total variance in firm-level climate exposure arises from within-firm variation over time. In contrast, our analysis shows that only 11% to 15% of the variance in green, brown, and

net revenue ratios is attributable to time-varying firm-level effects. This contrast suggests that while firms' exposure to climate risks may fluctuate considerably across years, changes in their underlying business models occur more gradually, reflecting the inherently long-term nature of the green transition.

4 Baseline: Cost of Debt and Corporate Green Transition

Our baseline analysis investigates how the cost of capital affects firms' green transition and how this effect varies across different types of firms. We use the Taxonomy-based green revenue share to capture firm green transition. Unlike reducing carbon emissions in production and operations, which primarily incurs costs with limited financial returns, shifting to greener businesses allows firms to generate revenue from environmentally beneficial products and services. Thus, it represents a more sustainable transition approach as it integrates economic incentives into carbon abatement.

Our approach to measuring the green transition using the Taxonomy-based revenue ratio aligns with the recent work of Klausmann et al. (2024). They identified the passage of the Paris Agreement as a regime shift for green transition and found that both green technology and institutional ownership drove this transition after the Agreement. Moreover, both theoretical and empirical research suggest that a lower cost of capital helps facilitate firm investment in green technology. For example, Lanteri and Rampini (2023) analyzed how firms with varying financial constraints choose between green and brown technologies. They found that, in equilibrium, financially unconstrained firms optimally invest in green projects, while constrained firms invest in brown projects due to the higher down payment required for green projects. Empirical evidence further supports this view, showing that limited access to credits hinders firms' adoption of green technology (De Haas et al., 2024) and that financially constrained firms tend to have higher toxic emissions (Xu and Kim, 2022). Building on these findings, we argue that a lower cost of capital can support firms' green transition by promoting green investment and thus increasing the share of green products and services in their business portfolios.

When examining how the cost of capital affects firms' green transition, we argue that the cost of debt is particularly relevant in the Chinese context. First, debt financing, especially bank loans, is the dominant external financing channel in China. According to the People's Bank of China, loans accounted for around 60% of the aggregate financing to the real economy at the end of 2020, while stock financing accounted for only 2.9%, consistent with the statistics in Cong

et al. (2019). [7] Second, debt plays a crucial role in financing green transition activities in China, through instruments such as transition bonds, sustainability-linked bonds, and sustainability-linked loans. Given these industry practices, examining the effect of debt cost on green transition is especially relevant.

Also, we believe it is essential to distinguish between different types of firms based on their initial level of greenness. Hartzmark and Shue (2023) presents a simple model to explain why brown and green firms may respond differently to changes in the cost of capital. The intuition is that higher capital costs make investment projects less attractive, particularly those with back-loaded cash flows. While such projects are typically green for brown firms, they are not necessarily so for green firms, whose investments generally have negligible environmental impact. Consequently, the environmental impact of brown firms is more sensitive to changes in the cost of capital. Similarly, in our context, while brown firms must choose between green and brown technologies, green firms' investment projects are predominantly green. Therefore, a lower cost of capital may have different implications for the green revenue ratios of green and brown firms.

4.1 Method

Based on the above analysis, we estimate a model that regress green, brown, and net ratios on debt cost interacted with dummies for green firms (*Green*), brown firms (*Brown*), and neutral firms (*Neutral*). We first compute the average green, brown, and neither-green-nor-brown revenue ratios within each industry in the first year it appears in the green revenue data. Industries where the neither-green-nor-brown ratio exceeds 90% are classified as neutral. Among the remaining industries, those with a higher green ratio than brown ratio are classified as green, while the rest are classified as brown. Table IA.1 in the Appendix presents each industry's greenness profile. Firms are classified as green, brown, or neutral based on their industry classification.

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 \cdot Green_{i,t-1} \cdot Debt\ Cost_{i,t} + \beta_2 \cdot Brown_{i,t-1} \cdot Debt\ Cost_{i,t} \\ + \beta_3 \cdot Neutral_{i,t-1} \cdot Debt\ Cost_{i,t} + \boldsymbol{\beta}_4 \cdot \boldsymbol{X}_{i,t-1} + \lambda_i + \eta_t + \varepsilon_{it} \end{aligned} \tag{1}$$

We estimate the above regression model, where i indexes firms and t denotes years. The dependent variable is firm greenness, measured collectively by the green ratio, the brown ratio, and the net ratio. $\boldsymbol{X}_{i,t-1}$ is a set of control variables, including *Firm Size*, *Cash Ratio*, *Tangible*

[7] Source: http://www.pbc.gov.cn/en/3688247/3688978/3709140/4162135/index.html

Ratio, *Leverage*, *CapEx*, and *Sales Growth*. λ_i and η_t denote firm and year fixed effects, respectively. We also include more restrictive sector $\times$ year fixed effects and greenness $\times$ year fixed effects in different model specifications. There could be sector-level, time-varying factors that confound the effects of interest. For example, as green technologies in certain industries become more profitable over time, they could simultaneously enhance firm greenness by fostering green products and lower debt costs by improving firm fundamentals. With sector $\times$ year fixed effects, such confounding factors are controlled. Additionally, there may be more general confounding factors that are specific to green, brown, or neutral firms and vary over time. For example, brown firms may choose to develop and expand green businesses due to increased pressure from regulators, investors, or customers. This could coincide with broader macroeconomic conditions that reduce debt costs for firms. Such factors are controlled for by including greenness $\times$ year fixed effects. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are consistently clustered at the firm level.

4.2 Results

Table 5 presents the baseline results. The first three columns indicate a significant positive correlation between debt cost and the brown ratio, as well as a significant negative correlation between debt cost and the net green ratio. Moreover, these effects are particularly pronounced among brown firms. The results are not only statistically significant but also economically important. The second column suggests that a one-standard increase in the cost of debt (five percentage points) corresponds to a 0.77 percentage point increase in the brown ratio, equivalent to 11% of its mean value (7%).

In the following columns, we replace year fixed effects with more restrictive sector $\times$ year fixed effects or greenness $\times$ year fixed effects to better account for sector- or greenness-specific time-varying variations in firm greenness. The results remain robust under these alternative specifications. Taken together, we find that a lower cost of debt is associated with greener business operations, and this effect is particularly pronounced among brown firms. The inclusion of firm and year fixed effects makes the analysis rely on within-firm time-series variation. Thus, it further supports a transition-based interpretation, suggesting that when a firm experiences a lower cost of debt, it tends to become greener over time.

5 Heterogeneity

In this section, we conduct heterogeneity tests to examine the conditions under which green transition is more likely to occur. We begin by assessing how the main effects vary between large and small firms. Since the variance decomposition suggests that firms' green revenue remains largely static over time, we expect the green transition to be more pronounced among smaller firms, which tend to be more flexible. We divide the sample based on the median firm size and perform subsample analyses. Panel A of Table 6 shows that the main effects are concentrated among small firms, consistent with our expectation. This finding suggests that smaller firms, potentially due to greater operational flexibility, tend to adopt green transitions more rapidly than their larger counterparts.

Next, we analyze the role of green technology in facilitating green transition. We partition the sample based on the median value of the cumulative number of green patents applied for in previous years. Panel B of Table 6 shows that the main effects are concentrated among firms with more existing green technology. The results suggest that for brown firms with a stronger green technology base, a lower cost of debt is associated not only with a lower brown revenue ratio, as shown in the main results, but also with a higher green revenue ratio. Together, these effects lead to a higher net green revenue ratio. The findings indicate that existing green technology plays a critical role in enabling firms to shift toward more sustainable business models.

6 Cost of Debt and Firm Green Investement

In this section, we investigate whether a lower cost of debt incentivizes firms to increase their investment in green projects, which we refer to as green investment. Chinese-listed firms are required to disclose a list of projects under construction at the end of each fiscal year in their annual reports, enabling us to track their green investment on an annual basis. The basic idea is to identify green projects within the project list and aggregate the investment allocated to these projects.

We identify green projects based on their names. To do so, we first compile a list of green keywords from two versions of green taxonomies published by the Chinese government in 2019 and 2024. [8] Each document provides a comprehensive list of green industries along with a

[8]Green Industry Guidance Catalog (2019 Edition) by the National Development and Reform Commission (NDRC) et al. and Guidance Catalog for Green and Low Carbon Transition Industries (2024 Edition) by NDRC et al.

detailed description of each industry. We tokenize the text from both documents to compile a list of contained words. Next, we use ChatGPT to determine whether each keyword is related to green or sustainable economic activities. We then manually review the tagged words and retain those that we agree are green. After this process, we identified 448 green keywords.

With this curated list, we identify green projects by searching for the presence of these green keywords in project names. Projects that contain any green keyword are classified as green projects, and a firm's green investment is calculated as the total investment in green projects within a given year. Table IA.2 in the Appendix lists the 279 green keywords that are associated with at least one project and the number of unique project names they are associated with. The keywords that identify most green project names include "Photovoltaic" (1,666), "Environmental Protection" (1,445), "Wind Power" (1,314), "Wastewater Treatment" (1,173), and "Energy Conservation" (1,080). On average, firms in the regression sample invest 28.90 million RMB in green projects. Green investment accounts for, on average, 0.22% of total assets, 0.59% of total revenue, and 10.1% of total investment in new projects.

In Table 7, we examine the effects of debt cost on green investment. Panel A presents the correlation between green investment and the net green revenue ratio. The results indicate a significant positive relationship, suggesting that green investment is closely tied to a firm's overall greenness. Panel B investigates the impact of debt cost on green investment. The results show that a lower cost of debt is significantly associated with increased green investment. A one-standard-deviation decrease in the cost of debt is associated with a 4.8% increase in the logarithm of green investment amount, a 13.6% increase in green investment as a share of total assets, and a 14.4% increase in ln green investment as a share of total revenue, relative to the sample mean of each respective outcome variable. The results suggest that increased investment in green projects may be one channel through which firms become greener.

7 Identification: Accelerated Depreciation Policy

7.1 Institutional Background

We try to strengthen the causal interpretation of the baseline findings with exogenous shock to the debt cost. The identification strategy leverages a series of policies introduced by China's Ministry of Finance that allow firms in specific industries to accelerate the depreciation of their assets. By adopting an accelerated depreciation accounting method, firms can recognize a larger portion of an asset's depreciation costs in its earlier years. Consequently, these policies reduce

the tax base, enabling firms to pay less tax and preserve more cash. Since higher cash reserves typically signal a firm's ability to repay debt, we expect this policy to ultimately reduce firms' cost of debt.

Three such policies were issued in 2014, 2015, and 2019, each outlining several industries eligible to adopt an accelerated depreciation accounting method. [9] Table IA.2 in the Appendix lists the treatment year of each treated industry. [10] For example, the first document, issued on 20 October 2014, allowed firms in six specified industries to accelerate the recognition of depreciation costs for fixed assets purchased after 1 January 2014. This could be achieved by shortening the depreciation period, adopting the double-declining balance method, or using the sum-of-the-years' digits method. The second document, issued on 17 September 2015, extended this policy to four additional sectors for assets purchased after 1 January 2015. The final policy, issued on 23 April 2019, expanded eligibility to all manufacturing industries.

To verify the validity of this identification setting, we conducted a back-of-the-envelope calculation to assess its impact on firm cash flow, the mechanism through which we expect it to lower firms' cost of debt. The average treated firm in our final sample invested 355 million in fixed assets the year before the treatment. Assuming these assets are fully depreciated over the next ten years, under the normal straight-line depreciation method, the firm would recognize 35.5 million in expenses in the first year, reducing its tax payment by 8.9 million, given a 25% tax rate. By adopting the double-declining balance method, the firm could recognize 71 million in expenses, lowering its tax payment by 17.8 million. Therefore, by switching to an accelerated depreciation method, the average firm could save 8.9 million in cash flow, equaling up to 20.3% of its net cash flow in the year before the treatment. We continue to examine the policy's effect on firm debt cost and firm greenness in the next section by estimating a stacked DID model.

[9] Please see the following pages for the original files: a. 2014: https://www.gov.cn/zhengce/2014-10/20/content_5023495.htm; b. 2015: https://www.gov.cn/zhuanti/2015-12/14/content_5023664.htm; c. 2019: https://www.gov.cn/zhengce/zhengceku/2019-10/16/content_5440614.htm.

[10] The original documents define industries according to the "Industrial Classification for National Economic Activities". We map these industries to the classification system used by the China Securities Regulatory Commission (CSRC). The latter is based on the former, so we can easily establish the mapping. The original documents sometimes define industries at a broader or narrower level than the CSRC classification. Thus, there may be discrepancies in the number of treated industries between the original documents and Table IA.2.

7.2 Identification Strategy

Given the staggered nature of the treatment, we estimate the stacked DID model below. The model specification below allows us to identify the policy's dynamic effects on green, brown, and neutral firms, respectively.

$$Y_{ict} = \sum_{h \in \{\text{green,brown,neutral}\}} \sum_{\substack{k=-2 \\ k \neq 0}}^{3} (\beta_{hk} \cdot D_{ic} \cdot 1[t = k] \cdot 1[g = h]) + \lambda_{ci} + \eta_{cjt} + \delta_{cgt} + \varepsilon_{ict} \quad (2)$$

The analysis is conducted at the firm-cohort-time level. In the model, i indicates the firm, c represents the cohort, t denotes the time, j refers to the sector to which firm i belongs, and g represents firm i's greenness category. Here, a cohort means all treated firms in a treatment event plus all clean control firms for that event, which consist of firms that are treated at least three periods after the focal event or never treated. Thus, this model has three cohorts in the current setting, corresponding to the three treatment years of 2014, 2015, and 2019. Time is defined relative to the policy issuance year, with value 0 representing the policy issuance year. To avoid compositional changes that could bias the dynamic effect estimates, as noted by Wing et al. (2024), the sample is restricted to observations within two periods before and three periods after each event. Consequently, time ranges from -2 to 3, with time 0 omitted as the benchmark.

D_{ic} equals 1 if firm i is in the treatment group of cohort c and equals 0 otherwise. $1[t = \cdot]$ and $1[g = \cdot]$ are dummies for each time and greenness category. I include firm fixed effects (λ_{ci}), sector $\times$ time fixed effects (η_{cjt}), and greenness $\times$ time fixed effects (δ_{cgt}). Following Baker et al. (2022) and Cengiz et al. (2019), all fixed effects are in a cohort-specific form. Sector $\times$ time fixed effects control for time-varying factors specific to each sector that may confound the effects of the policy shock. For example, differences in firm greenness between the treatment and control groups after the policy may stem from other systematically correlated shocks that improve firm greenness in sectors with a high concentration of treated firms. Greenness $\times$ time fixed effects additionally account for similar yet broader confounding shocks that specifically affect green, brown, or neutral firms. Interacting the fixed effects with cohorts further allows them to vary across cohorts. Standard errors are clustered at the cohort $\times$ firm level.

Table 8 presents the static DID estimates. Essentially, we combine the post-treatment periods together (t = 1, 2, 3) and the pre-treatment periods together (t = -2, -1, 0) in Model 2. Then we compare the difference in firm greenness between the treatment and control groups after the policy with their difference before the policy. The first column shows that the policy significantly

reduced the cost of debt, validating it as an exogenous shock to debt cost. After the policy, the debt cost for the treated firms decreased by 0.5 percentage points compared to control firms, which corresponds to 8.3% of the sample mean (6%) and 10% of the sample standard deviation (5%). The next three columns reveal that the treated brown firms became significantly greener after the policy. Their green ratio increased by 3.2 percentage points, equivalent to 64% of the sample mean (5%) and 17% of the sample standard deviation (18%). Additionally, their net green ratio increased by 5.2 percentage points, equivalent to 17.9% of the sample standard deviation (29%).

We proceed to examine the dynamic effects of the policy. Figure 3 illustrates the policy's impact on the cost of debt. The results show that the debt cost for treated firms remained stable before the policy but declined significantly afterward relative to control firms, further confirming the policy as an exogenous shock to firm debt cost. Figure 4 displays the dynamic effects on firm greenness. Prior to the policy intervention, the treatment and control groups exhibited comparable green, brown, and net revenue ratios. However, following the policy, brown firms experienced a significant increase in their green ratio and a decline in their brown ratio, leading to an overall rise in their net ratio, as shown in subfigures (b), (e), and (h). In contrast, neutral firms showed a modest increase in greenness, as illustrated in subfigures (c), (f), and (i), while green firms exhibited no significant changes, as depicted in subfigures (a), (d), and (g).

Taken together, our findings suggest that firms become greener following an exogenous shock that reduces the cost of debt. This observation further reinforces the causal interpretation of our main result: a lower cost of debt leads to an increase in firm greenness.

8 International Sample: Implied Cost of Capital and EU Taxonomy Eligibility Ratio

While we have demonstrated that a lower cost of debt is associated with improved firm greenness among Chinese firms, it remains unclear whether this finding is unique to China or reflects a more general phenomenon that we could also observe in other countries. While we believe the role of debt cost is particularly relevant in the Chinese context, we shift our focus to equity cost when extending the analysis to a global setting. This is because, in global discussions on addressing climate risk, the role of institutional investors is especially emphasized. For example, the survey conducted by Stroebel and Wurgler (2021) reveals that finance academics, practitioners, and regulators consider pressure from institutional investors to be the most influential financial

mechanism driving firms to reduce their climate risk exposure. Moreover, evidence indicates that institutional investors worldwide actively manage and engage with firms on climate risk (Krueger et al., 2020), thereby transforming firm behavior, such as enhancing climate disclosure (Ilhan et al., 2023). More importantly, Hartzmark and Shue (2023) suggests that in economies other than China, such as the United States, firm greenness is largely influenced by equity costs. Given that equity cost is closely tied to capital from institutional investors, it becomes especially relevant in the global context. To verify our main findings in the global sample, we estimate the following model.

$$Eligible\ Ratio_{i,t} = \beta_0 + \beta_1 \cdot ICC_{i,t} + \boldsymbol{\beta}_2 \cdot \boldsymbol{X}_{i,t-1} + \lambda_i + \eta_t + \varepsilon_{it} \tag{3}$$

In this model, i denotes firms and t represents years. The dependent variable is the eligible ratio, defined as the proportion of a firm's revenue derived from activities specified in the EU Taxonomy. We obtain this data from the S&P Global EU Taxonomy dataset. The key explanatory variable is the firm's implied cost of capital (ICC), calculated following the model proposed by Gebhardt et al. (2001) and the approach of Eskildsen et al. (2024). This calculation requires forecasts of future earnings. We use analysts' forecasts from I/B/E/S and complement them with earnings predictions from models proposed by previous literature: the HVZ Model (Hou et al., 2012), the Earnings Persistence Model (EP) by Li and Mohanram (2014), and the Residual Income Model (RI), also by Li and Mohanram (2014). [11] $\boldsymbol{X}_{i,t-1}$ represents a set of control variables, including firm size (*Size*), cash holdings (*Cash*), tangible assets (*Tangible*), leverage ratio (*Leverage*), sales growth (*Sales Growth*), and capital expenditure (*CAPX*). λ_i and η_t denote firm and year fixed effects, respectively. Firm fixed effects control for unobserved firm-specific factors that could lead to spurious relationships between ICC and the eligible ratio. For instance, some firms may systematically possess more profitable green technologies that are valued by the stock market and simultaneously contribute to a higher eligible ratio. Moreover, firm fixed effects allow for a transition interpretation of the results, as the estimation relies on within-firm time-series variation. We exclude firms in the financial sector (SIC code between 6000 to 6999), winsorize all continuous variables at the 1% and 99% levels, and cluster the standard error at the firm level.

[11] Although the original motivation for model-based forecasts is to increase the coverage of ICC data, we find that solving for ICC using these forecasts is more challenging in the global setting, ultimately leading to a smaller sample size compared to ICC estimates based on analyst forecasts.

Table 9 presents the regression results. Consistent with our findings in the Chinese sample, we observe that a lower cost of capital is associated with a higher proportion of revenue from green activities, indicating improved firm greenness. Given that firms may have put greater emphasis on green transition in recent years, we separately analyze the subsample after the Paris Agreement in the right panel. As expected, the relationship between ICC and firm greenness is even stronger during this period. Taking the first as an example, in the whole sample period, a one-standard decrease in ICC (3 percentage points) corresponds to a 0.711 percentage point increase in the eligible ratio, equivalent to 1.9% of the sample mean (37%). In contrast, the fifth column suggests that after the Paris Agreement, the same decrease in ICC is associated with a 1.257 percentage point increase in the eligible ratio, equivalent to 3.4% of the sample mean. These results suggest that our previous findings are not unique to China but instead reflect a broader pattern that could be observed in the global setting.

9 Conclusion

In this study, we examine the impact of the cost of debt on firms' green transitions. Leveraging a proprietary dataset that identifies the proportion of revenue derived from green, brown, and neutral activities for Chinese-listed companies, we find that firms with a lower cost of debt tend to become greener, particularly those classified as brown firms. The effect is especially pronounced among smaller firms, which tend to be more operationally flexible, and those with a greater stock of green technologies. We further show that a reduction in debt cost is associated with increased investment in green projects, suggesting that improved firm greenness may be partly driven by greater green capital expenditure. To address endogeneity concerns, we exploit a Chinese policy that introduces an exogenous shock to debt cost and find consistent results, supporting a causal interpretation. Finally, we find similar results in the global sample, suggesting that the relationship between lower financing costs and increased firm greenness is not unique to China.

Our findings have important implications for investors and policymakers who aim to promote a greener economy with finance. Despite the sharp growth of sustainable investing, some research suggests that it may not be as effective as anticipated. Hartzmark and Shue (2023) shows that high-emitting firms not only produce 1,700 times more emissions than low-emitting firms, but their emissions are also far more sensitive to changes in capital costs. As such, by directing funds from brown firms to green firms, the current sustainable investing may fail to exploit the substantial emissions reduction potential of high-emitting. Recognizing this issue, policymakers

have introduced transition finance as a solution, which essentially involves providing funds to high-emitting firms to help them move toward greener operations. Although this new concept has triggered considerable discussion, leading to the development of various frameworks, guidelines, and policies worldwide, there is still no systematic evidence on its feasibility. [12] Our research findings shed light on this issue and suggest that at least the fundamental logic of transition finance works — lower financing costs can facilitate firms' green transitions. In this sense, our findings highlight the significant potential of transition finance as a crucial tool for accelerating corporate sustainability efforts.

[12] Examples include "Financing Credible Transitions" by Climate Bond Initiative in 2020; "Basic Guidelines on Climate Transition Finance" by Japan in 2021; "G20 Transition Finance Framework" by G20 Sustainable Finance Working Group in 2022; "Financial Institution Net-Zero Transition Plans" by Glasgow Financial Alliance for Net Zero in 2022; "Climate Transition Finance Handbook" by International Capital Market Association in 2023; and "Japan Climate Transition Bond Framework" also by Japan in 2023.

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10 Figures

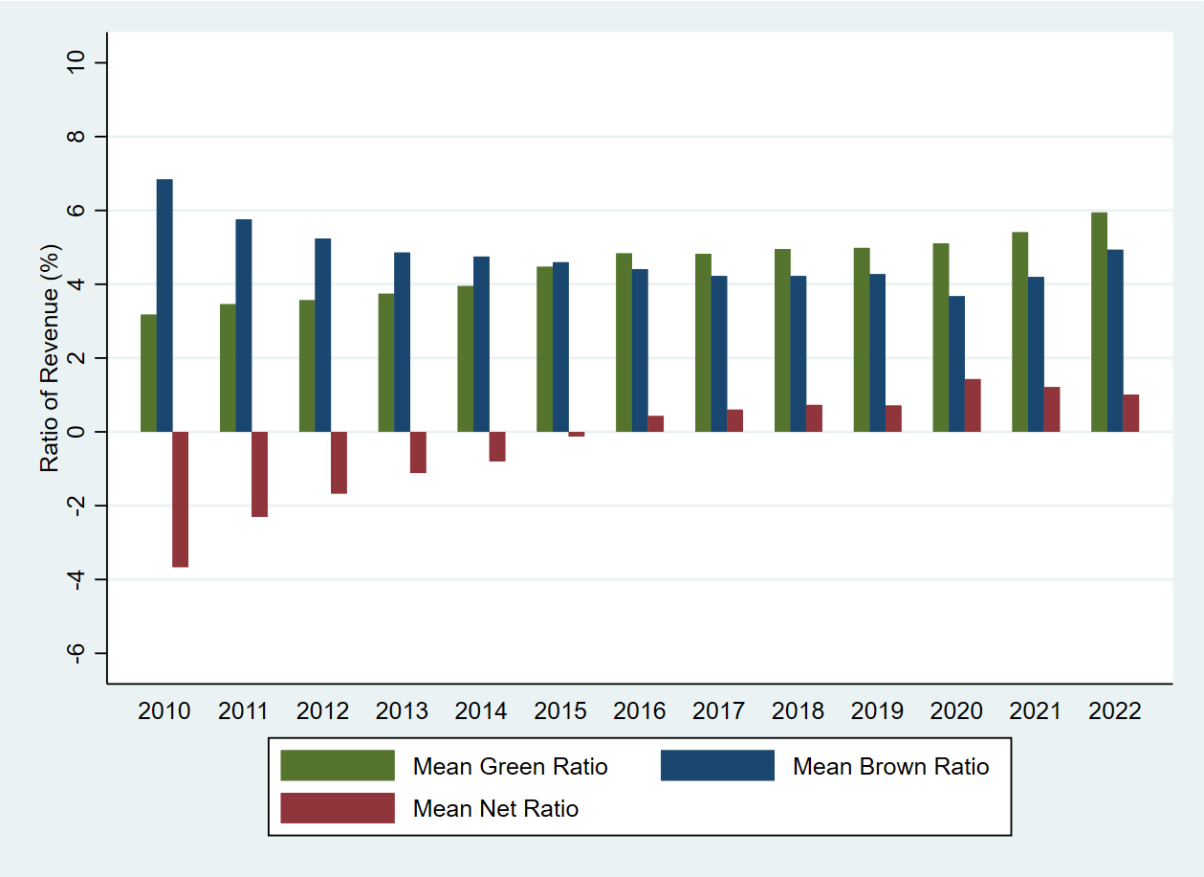
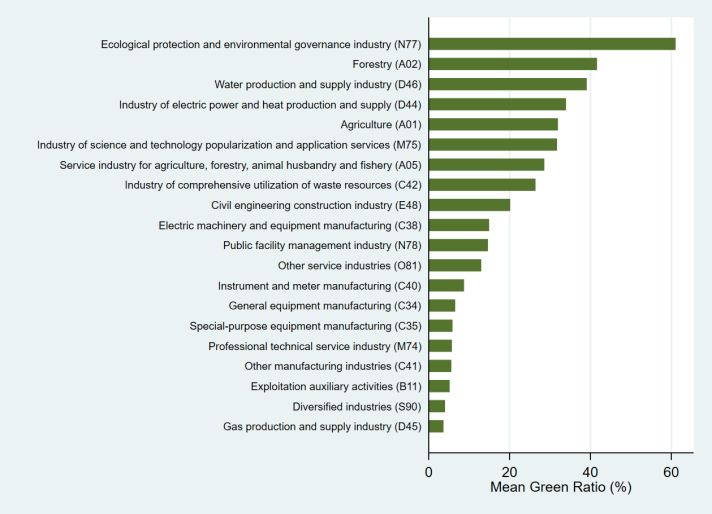
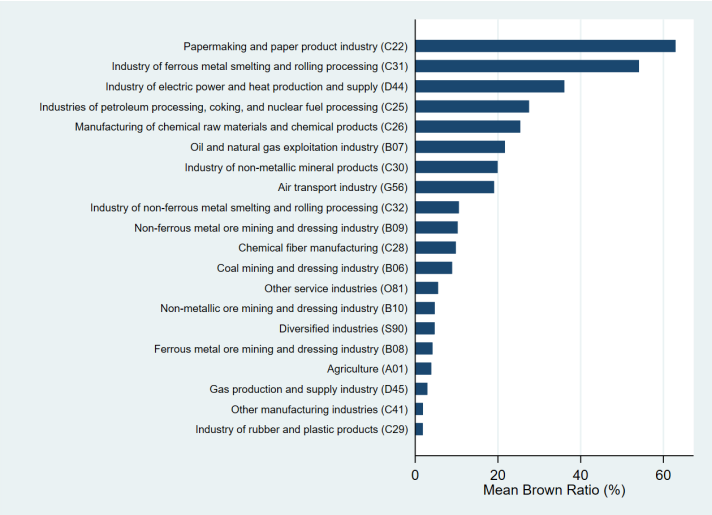


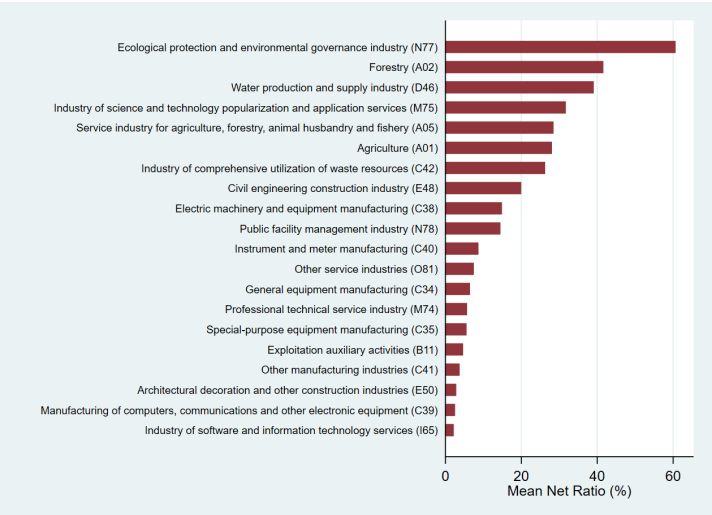
Figure 1: **Average Green, Brown, and Net Ratios of Revenue Over 2010-2022:** This figure plots the average green, brown, and net ratios from 2010 to 2022. *Green Ratio* is the proportion of firm revenue from green activities. *Brown Ratio* is the proportion of firm revenue from brown activities. *Net Ratio* is the difference between *Green Ratio* and *Brown Ratio*.



(a) Top 20 Industries by Green Ratio



(b) Top 20 Industries by Brown Ratio



(c) Top 20 Industries by Net Ratio

Figure 2: **Top Industries by Green, Brown, or Net Ratios**

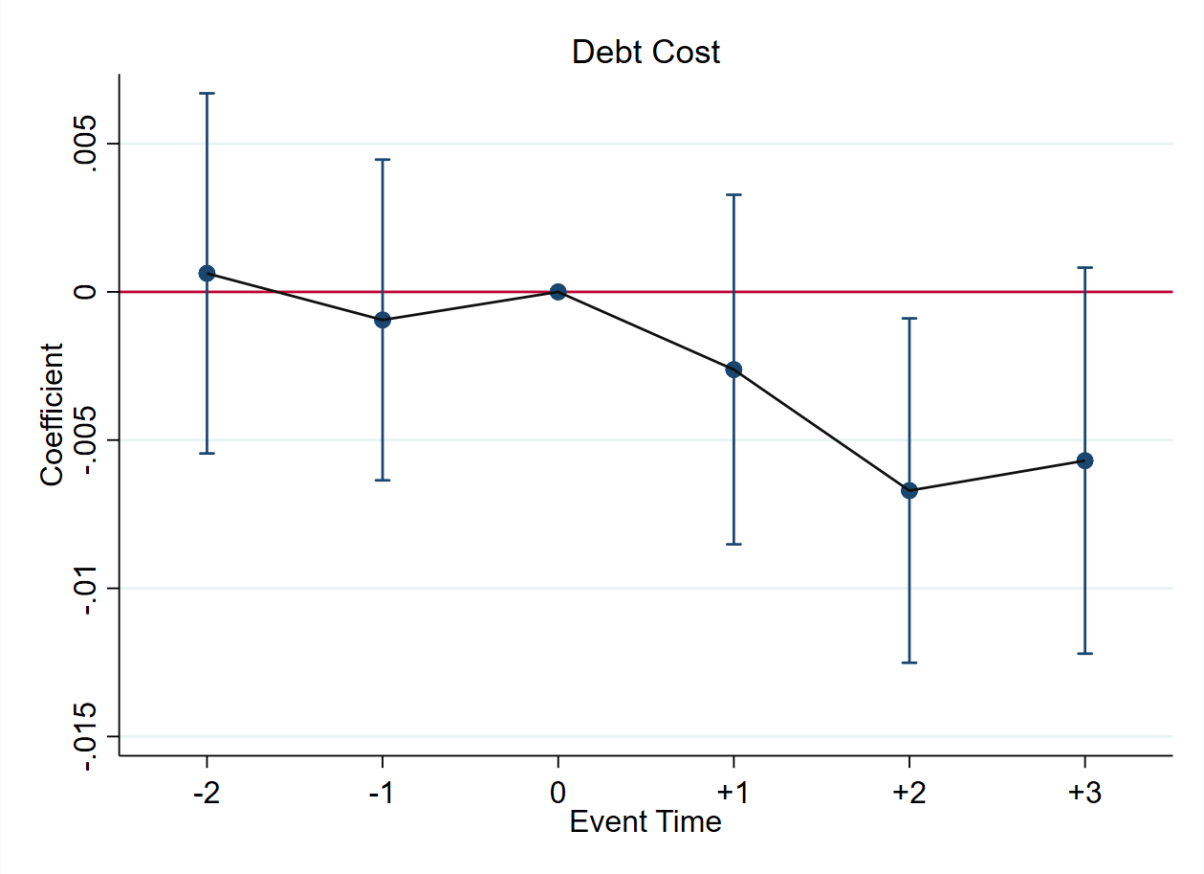
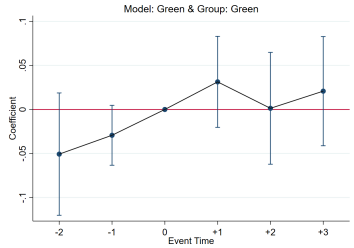
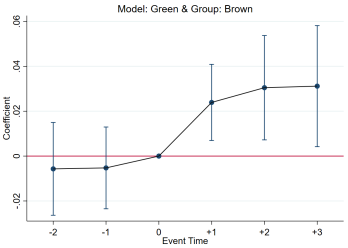


Figure 3: **Identification: Dynamic Effects of Accelerated Depreciation Policy on Debt Cost:** This figure plots the dynamic effects of the accelerated depreciation policy on debt cost. Specifically, it plots the estimates of β_k for k = -2, -1, 1, 2, 3 in the stacked DID model below: $Debt\ Cost_{iet} = \sum_{\substack{k=-2 \\ k\neq 0}}^{3} (\beta_k \cdot D_{ie} \cdot 1[t = k]) + \lambda_{ci} + \eta_{cjt} + \delta_{cgt} + \varepsilon_{ict}$.

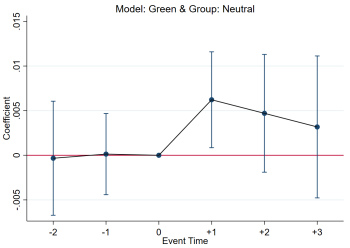
Panel A: Green Ratio



(a) Green Firms

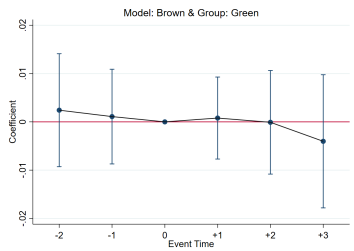


(b) Brown Firms

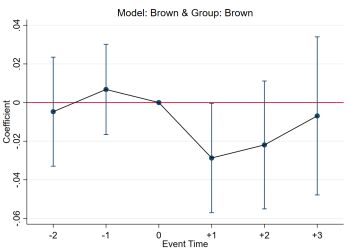


(c) Neutral Firms

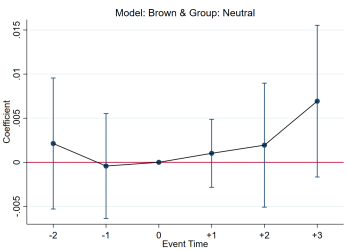
Panel B: Brown Ratio



(d) Green Firms

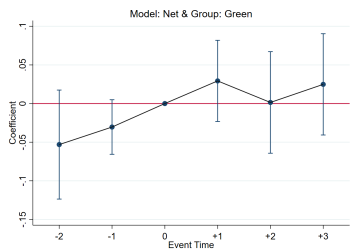


(e) Brown Firms

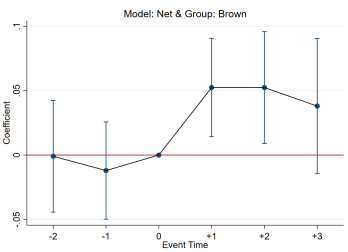


(f) Neutral Firms

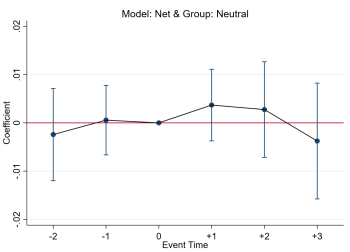
Panel C: Net Ratio



(g) Green Firms



(h) Brown Firms



(i) Neutral Firms

Figure 4: **Identification: Dynamic Effects of Accelerated Depreciation Policy on Corporate Green Transition:** This figure plots the dynamic effects of the accelerated depreciation policy on the green, brown, and net ratios of different types of firms. Specifically, subfigures (a), (b), (c) plot the estimates of $\beta_{\text{green},h}$, $\beta_{\text{brown},h}$, $\beta_{\text{neutral},h}$ for h = -2, -1, 1, 2, 3 when the dependent variable is *Green Ratio* in the model: $Y_{ict} = \sum_{h\in\{\text{green,brown,neutral}\}} \sum_{\substack{k=-2 \\ k\neq 0}}^{3} (\beta_{hk} \cdot D_{ie} \cdot 1[t=k] \cdot 1[g=h]) + \lambda_{ci} + \eta_{cjt} + \delta_{cgt} + \varepsilon_{ict}$. Subfigures (d), (e), (f) plot the estimates of $\beta_{\text{green},k}$, $\beta_{\text{brown},k}$, $\beta_{\text{neutral},k}$ for k = -2, -1, 1, 2, 3 when the dependent variable is *Brown Ratio* in the same stacked DID model. Subfigures (g), (h), (i) plot the estimates of $\beta_{\text{green},k}$, $\beta_{\text{brown},k}$, $\beta_{\text{neutral},k}$ for k = -2, -1, 1, 2, 3 when the dependent variable is *Net Ratio* in the same stacked DID model.

11 Tables

Panel A: Chinese Sample

	count	mean	sd	p25	p50	p75	min	max
Green Ratio	29,265	0.05	0.18	0.00	0.00	0.00	0.00	0.98
Brown Ratio	29,265	0.07	0.21	0.00	0.00	0.00	0.00	0.97
Net Ratio	29,265	-0.01	0.29	0.00	0.00	0.00	-0.97	0.98
Debt Cost	29,265	0.06	0.05	0.04	0.05	0.07	0.00	0.37
Green	29,265	0.05	0.22	0.00	0.00	0.00	0.00	1.00
Brown	29,265	0.19	0.39	0.00	0.00	0.00	0.00	1.00
Neutral	29,265	0.76	0.43	1.00	1.00	1.00	0.00	1.00
Size	29,265	22.43	1.29	21.53	22.26	23.17	19.94	26.31
Cash Ratio	29,265	0.14	0.10	0.06	0.11	0.18	0.01	0.58
Tangible Ratio	29,265	0.92	0.09	0.90	0.95	0.98	0.53	1.00
Leverage	29,265	0.47	0.19	0.33	0.47	0.61	0.08	0.92
CapEx	29,251	0.05	0.05	0.01	0.03	0.07	0.00	0.23
Sales Growth	29,265	0.17	0.43	-0.03	0.10	0.27	-0.58	2.61

Panel B: Global Sample

	count	mean	sd	p25	p50	p75	min	max
Eligible Ratio	48,969	0.37	0.44	0.00	0.02	0.96	0.00	1.00
ICC_Analyst	43,664	0.09	0.03	0.06	0.08	0.11	0.02	0.20
ICC_HVZ	31,544	0.09	0.06	0.05	0.07	0.10	0.02	0.41
ICC_EP	35,457	0.09	0.07	0.05	0.07	0.10	0.01	0.42
ICC_RI	35,463	0.08	0.07	0.04	0.07	0.10	0.01	0.41
Size	48,969	7.62	1.63	6.46	7.58	8.71	4.00	11.67
Cash	48,969	0.17	0.15	0.06	0.12	0.23	0.00	0.78
Tangible	48,969	0.30	0.22	0.12	0.25	0.43	0.01	0.87
Leverage	48,969	0.22	0.17	0.07	0.21	0.34	0.00	0.67
Sales Growth	48,969	0.10	0.25	-0.01	0.06	0.16	-0.45	1.55
CAPX	48,969	0.05	0.04	0.02	0.04	0.06	0.00	0.23

Table 1: **Summary Statistics:** This table reports the summary statistics for the key variables in our main regression. *Green Ratio* is the proportion of firm revenue from green activities. *Brown Ratio* is the proportion of firm revenue from brown activities. *Net Ratio* is the difference between *Green Ratio* and *Brown Ratio*. *Debt Cost* is a measure for a firm's overall debt cost, defined as *Interest Expenditure + Other (Including Commissions) + Capitalized Interest Expenditure) / (Short-Term Loan + Non-Current Liabilities Due Within One Year + Long-Term Loan + Bond Payable + Long-Term Accounts Payable*. *Green*, *Brown*, and *Neutral* are dummies for green, brown, and neutral firms, respectively, depending on our classification of each industry. Specifically, we calculated the mean value of *Green Ratio*, *Brown Ratio*, and *Neither-green-nor-brown Ratio* of all firms in each industry in the first year that any firms exist in the industry during our sample period. Industries with a mean *Neither-green-nor-brown Ratio* equal to or larger than 90% are classified as neutral industries. For the other industries, those with a mean *Green Ratio* larger than a mean *Brown Ratio* are classified as green industries, while those otherwise are classified as brown industries. See Appendix Table IA.1 for the classification of each industry. *Size* is the logarithm of 1 + total assets. *Cash Ratio* is cash and cash equivalents to total assets. *Tangible Ratio* is tangible assets to total assets. *Leverage* is total debt to total assets. *CapEx* is cash paid to acquire fixed assets, intangible assets, and other long-term assets scaled by total assets. *Sales Growth* is the growth rate of firm revenue.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) Brown Ratio	1.0000																				
	[53,850]																				
(2) Green Ratio	-0.0477***	1.0000																			
	[53,850]	[53,850]																			
(3) Net Ratio	-0.7294***	0.7179***	1.0000																		
	[53,850]	[53,850]	[53,850]																		
(4) GHG Int. S1	0.5622***	0.0718***	-0.4220***	1.0000																	
	[5,805]	[5,805]	[5,805]	[5,805]																	
(5) GHG Int. S2	0.3917***	-0.0802***	-0.3661***	0.0907***	1.0000																
	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]																
(6) GHG Int. S1+S2	0.5700***	0.0686***	-0.4302***	0.9972***	0.1304***	1.0000															
	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]															
(7) GHG Abs. S1	0.4977***	0.0271*	-0.3939***	0.7630***	0.1308***	0.7662***	1.0000														
	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]														
(8) GHG Abs. S2	0.3599***	-0.0645***	-0.3314***	0.0761***	0.4793***	0.1024***	0.3945***	1.0000													
	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]													
(9) GHG Abs. S1+S2	0.4924***	0.0228	-0.3918***	0.7430***	0.1522***	0.7485***	0.9963***	0.4378***	1.0000												
	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]	[5,805]												
(10) CCExposure	0.2125**	0.8044***	0.3292***	0.7278***	0.1607*	0.7294***	0.7371***	0.2422**	0.7389***	1.0000											
	[201]	[201]	[201]	[155]	[155]	[155]	[155]	[155]	[155]	[201]											
(11) CCExposure_Opp	0.0860	0.8940***	0.4824***	0.7259***	0.0817	0.7268***	0.6315***	0.0636	0.6248***	0.9610***	1.0000										
	[201]	[201]	[201]	[155]	[155]	[155]	[155]	[155]	[155]	[201]	[201]										
(12) CCExposure_Reg	0.3323***	0.2414***	-0.1096	0.2479**	0.1190	0.2491**	0.4138***	0.4184***	0.4347***	0.5200***	0.4243***	1.0000									
	[201]	[201]	[201]	[155]	[155]	[155]	[155]	[155]	[155]	[201]	[201]	[201]									
(13) CCExposure_Phy	0.1762*	0.2284**	0.0036	0.6308***	-0.0342	0.6307***	0.4585***	-0.0094	0.4552***	0.4283***	0.3398***	0.1901**	1.0000								
	[201]	[201]	[201]	[155]	[155]	[155]	[155]	[155]	[155]	[201]	[201]	[201]	[201]								
(14) Refinitive Env.	0.0353*	0.0534***	0.0087	-0.0358	0.0090	-0.0336	0.0691**	0.1946***	0.0783**	-0.0036	0.0502	-0.0299	-0.1563*	1.0000							
	[4,354]	[4,354]	[4,354]	[1,586]	[1,586]	[1,586]	[1,586]	[1,586]	[1,586]	[191]	[191]	[191]	[191]	[4,354]							
(15) Refinitive Emi.	0.1003***	0.0099	-0.0676***	-0.0082	0.1577***	-0.0003	0.1283***	0.3038***	0.1388***	0.1763*	0.1450*	0.1718*	-0.0516	0.7847***	1.0000						
	[4,354]	[4,354]	[4,354]	[1,586]	[1,586]	[1,586]	[1,586]	[1,586]	[1,586]	[191]	[191]	[191]	[191]	[4,354]	[4,354]						
(16) MSCI Env.	-0.2042***	0.1204***	0.2310***	-0.2065***	-0.2360***	-0.2141***	-0.2146***	-0.1787***	-0.2160***	-0.0176	0.0741	-0.1392	-0.2455***	0.1256***	0.0896***	1.0000					
	[3,071]	[3,071]	[3,071]	[1,315]	[1,315]	[1,315]	[1,315]	[1,315]	[1,315]	[182]	[182]	[182]	[182]	[2,659]	[2,659]	[3,071]					
(17) MSCI Climate Chg.	-0.2937***	0.0331	0.2415***	-0.3046***	-0.2223***	-0.3118***	-0.3043***	-0.1669***	-0.3009***	0.0984	0.1695*	-0.0226	-0.1660*	-0.0246	0.0025	0.4457***	1.0000				
	[2,933]	[2,933]	[2,933]	[1,199]	[1,199]	[1,199]	[1,199]	[1,199]	[1,199]	[143]	[143]	[143]	[143]	[2,532]	[2,532]	[2,933]	[2,933]				
(18) MSCI Env. Opp.	-0.0893***	0.3511***	0.3206***	-0.0468	-0.0898*	-0.0541	-0.0446	-0.0582	-0.0504	0.7623***	0.8304***	0.2510	0.0681	0.3014***	0.1850***	0.6110***	0.0441	1.0000			
	[1,355]	[1,355]	[1,355]	[505]	[505]	[505]	[505]	[505]	[505]	[20]	[20]	[20]	[20]	[1,133]	[1,133]	[1,355]	[1,323]	[1,355]			
(19) Env. Incident Num.	0.0879***	0.0107	-0.0578***	0.0163	0.0500**	0.0195	0.1318***	0.3006***	0.1456***	0.0547	-0.0009	0.1660	-0.0081	0.2887***	0.2069***	0.0067	-0.0580**	0.0566	1.0000		
	[21,703]	[21,703]	[21,703]	[3,608]	[3,608]	[3,608]	[3,608]	[3,608]	[3,608]	[97]	[97]	[97]	[97]	[2,807]	[2,807]	[2,074]	[1,992]	[855]	[21,703]		
(20) GHG Incident Num.	0.0117	0.0023	-0.0071	0.0436**	-0.0577***	0.0434**	0.1004***	0.1246***	0.1051***	-0.0667	-0.1029	0.0699	-0.1647	0.2738***	0.1275***	0.0324	-0.0352	0.0724*	0.5233***	1.0000	
	[21,703]	[21,703]	[21,703]	[3,608]	[3,608]	[3,608]	[3,608]	[3,608]	[3,608]	[97]	[97]	[97]	[97]	[2,807]	[2,807]	[2,074]	[1,992]	[855]	[21,703]	[21,703]	
(21) TV GHG Emission	0.0084	0.0052	-0.0024	0.0649	-0.0142	0.0678	0.0893*	-0.0260	0.0869*	0.1012	0.0773	0.1197	0.0069	0.1187***	0.1376***	0.0669*	0.0076	0.0167	0.1133***	0.0542*	1.0000
	[2,292]	[2,292]	[2,292]	[770]	[770]	[770]	[770]	[770]	[770]	[176]	[176]	[176]	[176]	[1,735]	[1,735]	[1,369]	[1,274]	[550]	[1,414]	[1,414]	[2,292]

Table 2: **Correlation with Other Environmental Measures:** This table reports the correlation between green, brown, net ratios and commonly used greenness measures. *Green Ratio* is the proportion of firm revenue from green activities. *Brown Ratio* is the proportion of firm revenue from brown activities. *Net Ratio* is the difference between *Green Ratio* and *Brown Ratio*. *GHG Int. S1*, *GHG Int. S2*, *GHG Int. S1+S2* are Scope 1, Scope 2, and both scopes combined GHG emission intensity from Trucost. *GHG Abs. S1*, *GHG Abs. S2*, *GHG Abs. S1+S2* are Scope 1, Scope 2, and both scopes combined absolute GHG emissions from Trucost. Note that our Trucost data ends in 2021 whereas the green revenue data ends in 2022. *CCExposure*, *CCExposure_ Opp*, *CCExposure_ Reg*, *CCExposure_ Phy* are climate change exposure measures from Sautner et al. (2023), corresponding to the overall, opportunity, regulation, and physical risk aspect, respectively. *Refinitive Env.* and *Refinitive Emi.* are Refinitive environmental pillar score and emission category score, respectively. *MSCI Env.*, *MSCI Climate Chg.*, and *MSCI Env.Opp.* are MSCI environmental pillar score, climate change theme score, and environmental opportunity theme score, respectively. *Env.Incident Num.* and *GHG.Incident Num.* are the number of incidents related to the environment in general and the number of incidents related to climate change, GHG emissions, and global pollution, respectively, from Reprisk. *TV GHG Emission* is the insight score in the dimension of GHG emissions from Factset Truvalue Labs. * p<.10; ** p<.05; *** p<.01. Numbers in the brackets indicate the number of observations in each pair-wise correlation.

	Net Ratio									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln GHG Int. S1+S2	-0.082***									
	(0.015)									
Ln GHG Abs. S1+S2		-0.071***								
		(0.012)								
Refinitive Env.			0.001***							
			(0.000)							
Refinitive Emi.				0.000						
				(0.000)						
MSCI Env.					0.019***					
					(0.004)					
MSCI Climate Chg.						0.010***				
						(0.004)				
MSCI Env. Opp.							0.027***			
							(0.006)			
Env. Incident Num.								-0.029***		
								(0.011)		
GHG Incident Num.									-0.018	
									(0.025)	
TV GHG Emission										0.001
										(0.001)
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,021	5,021	3,370	3,370	2,421	2,342	1,212	18,118	18,118	1,744
R^2	0.51	0.51	0.39	0.39	0.41	0.39	0.36	0.37	0.37	0.43

Table 3: **Regression on Other Environmental Measures:** This table presents the regression-based correlations between the green, brown, and net revenue ratios and commonly used measures of firm greenness. *Net Ratio* is the difference between the proportion of firm revenue from green and brown activities. *Ln GHG Int. S1+S2* is the natural logarithm of one plus the firm's GHG emission intensity, combining Scope 1 and Scope 2 emissions from Trucost. *Ln GHG Abs. S1+S2* is the natural logarithm of one plus the firm's absolute GHG emissions, also combining Scope 1 and Scope 2 from Trucost. Note that our Trucost data ends in 2021 whereas the green revenue data ends in 2022. *Refinitive Env.* and *Refinitive Emi.* are Refinitive environmental pillar score and emission category score, respectively. *MSCI Env.*, *MSCI Climate Chg.*, and *MSCI Env.Opp.* are MSCI environmental pillar score, climate change theme score, and environmental opportunity theme score, respectively. *Env.Incident Num.* and *GHG.Incident Num.* are the number of incidents related to the environment in general and the number of incidents related to climate change, GHG emissions, and global pollution, respectively, from Reprisk. *TV GHG Emission* is the insight score in the dimension of GHG emissions from Factset Truvalue Labs. Control variables include *Size*, *Cash Ratio*, *Tangible Ratio*, *Leverage*, *CapEx*, *Sales Growth*, and *SOE*. Standard errors reported in parentheses are clustered at the firm level. * p<.10; ** p<.05; *** p<.01.

	Green Ratio	Brown Ratio	Net Ratio
Panel A: Incremental R^2			
Year Fixed Effect	0.2%	0.2%	0.4%
Industry Fixed Effect	24.4%	36.5%	27.5%
Industry × Year Fixed Effect	1.4%	1.0%	1.3%
Unexaplained	74.1%	62.2%	70.9%
Sum	100.0%	100.0%	100.0%
Panel B: Fraction of Variation			
Firm + Industry × Year Fixed Effect	84.8%	88.8%	86.7%
Unexaplained	15.2%	11.2%	13.3%
Sum	100.0%	100.0%	100.0%

Table 4: **Variance Decomposition:** This table provides a variance decomposition of the green, brown, and net ratios, following the approach of Sautner et al. (2023). Panel A reports the incremental R^2 from adding a specific fixed effect. Panel B decomposes the variation into one part that can be explained by firm and industry × year fixed effects and a residual part.

	(1) Green Ratio	(2) Brown Ratio	(3) Net Ratio	(4) Green Ratio	(5) Brown Ratio	(6) Net Ratio	(7) Green Ratio	(8) Brown Ratio	(9) Net Ratio
Debt Cost × Green	-0.044	-0.010	-0.030	0.012	-0.029	0.045	-0.077	-0.007	-0.067
	(0.058)	(0.052)	(0.088)	(0.056)	(0.050)	(0.087)	(0.061)	(0.055)	(0.093)
Debt Cost × Brown	-0.033	0.154**	-0.186**	-0.024	0.142**	-0.165**	-0.028	0.136**	-0.164**
	(0.026)	(0.068)	(0.077)	(0.024)	(0.068)	(0.075)	(0.025)	(0.067)	(0.075)
Debt Cost × Neutral	-0.022	-0.006	-0.016	-0.023*	-0.008	-0.015	-0.022	-0.008	-0.014
	(0.014)	(0.010)	(0.018)	(0.014)	(0.010)	(0.017)	(0.014)	(0.010)	(0.017)
Green	0.049**	-0.002	0.051**	0.010	-0.003	0.013			
	(0.020)	(0.009)	(0.025)	(0.031)	(0.020)	(0.047)			
Brown	0.006	0.084***	-0.078***	-0.006	0.085***	-0.091***			
	(0.010)	(0.017)	(0.023)	(0.010)	(0.018)	(0.023)			
Size	0.009***	0.003	0.006	0.008***	0.004	0.005	0.009***	0.002	0.007*
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Cash Ratio	-0.007	-0.013	0.007	-0.011	-0.013	0.002	-0.006	-0.013	0.007
	(0.012)	(0.009)	(0.016)	(0.012)	(0.009)	(0.016)	(0.012)	(0.009)	(0.016)
Tangible Ratio	0.008	0.019	-0.012	0.009	0.016	-0.008	0.009	0.020	-0.012
	(0.020)	(0.016)	(0.026)	(0.019)	(0.017)	(0.026)	(0.020)	(0.016)	(0.026)
Leverage	0.010	-0.003	0.013	0.012	-0.006	0.017	0.010	-0.009	0.019
	(0.010)	(0.010)	(0.016)	(0.010)	(0.010)	(0.015)	(0.010)	(0.010)	(0.015)
CapEx	0.078***	0.008	0.070*	0.065**	0.011	0.054	0.079***	-0.004	0.084**
	(0.027)	(0.026)	(0.040)	(0.025)	(0.026)	(0.038)	(0.027)	(0.026)	(0.040)
Sales Growth	0.003*	-0.001	0.004*	0.003	-0.002	0.004**	0.003*	-0.001	0.004*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓						
Sector × Year FE				✓	✓	✓			
Greenness × Year FE							✓	✓	✓
Observations	29,265	29,265	29,265	29,253	29,253	29,253	29,265	29,265	29,265
R^2	0.86	0.91	0.88	0.86	0.91	0.88	0.86	0.91	0.88

Table 5: **Main Results: Cost of Debt and Corporate Green Transition:** This table reports the results of our baseline regression. *Green Ratio* is the proportion of firm revenue from green activities. *Brown Ratio* is the proportion of firm revenue from brown activities. *Net Ratio* is the difference between *Green Ratio* and *Brown Ratio*. *Debt Cost* is a measure for a firm's overall debt cost, defined as *Interest Expenditure + Other (Including Commissions) + Capitalized Interest Expenditure) / (Short-Term Loan + Non-Current Liabilities Due Within One Year + Long-Term Loan + Bond Payable + Long-Term Accounts Payable*. *Green*, *Brown*, and *Neutral* are dummies for green, brown, and neutral firms, respectively, depending on our classification of each industry. Specifically, we calculated the mean value of *Green Ratio*, *Brown Ratio*, and *Neither-green-nor-brown Ratio* of all firms in each industry in the first year that any firms exist in the industry during our sample period. Industries with a mean *Neither-green-nor-brown Ratio* equal to or larger than 90% are classified as a neutral industries. For the other industries, those with a mean *Green Ratio* larger than a mean *Brown Ratio* are classified as green industries, while those otherwise are classified as brown industries. See Appendix Table IA.1 for the classification of each industry. *Size* is the logarithm of 1 + total assets. *Cash Ratio* is cash and cash equivalents to total assets. *Tangible Ratio* is tangible assets to total assets. *Leverage* is total debt to total assets. *CapEx* is cash paid to acquire fixed assets, intangible assets, and other long-term assets scaled by total assets. *Sales Growth* is the growth rate of firm revenue. Standard errors reported in parentheses are clustered at the firm level. * p<.10; ** p<.05; *** p<.01.

Panel A: Firm Size

	1[Size > Med.] == 1			1[Size > Med.] == 0		
	(1) Green Ratio	(2) Brown Ratio	(3) Net Ratio	(4) Green Ratio	(5) Brown Ratio	(6) Net Ratio
Debt Cost × Green	-0.057	0.008	-0.065	0.011	-0.027	0.042
	(0.079)	(0.036)	(0.087)	(0.057)	(0.072)	(0.103)
Debt Cost × Brown	-0.022	0.047	-0.069	-0.034	0.158**	-0.193**
	(0.042)	(0.122)	(0.135)	(0.035)	(0.076)	(0.088)
Debt Cost × Neutral	-0.013	0.010	-0.023	-0.034**	-0.014	-0.020
	(0.011)	(0.016)	(0.019)	(0.017)	(0.011)	(0.021)
Green	0.007	-0.009	0.017	0.018	0.001	0.018
	(0.017)	(0.010)	(0.022)	(0.019)	(0.009)	(0.024)
Brown	-0.016	0.076***	-0.092***	-0.006	0.048**	-0.053**
	(0.011)	(0.026)	(0.032)	(0.009)	(0.020)	(0.024)
Size	0.005	0.002	0.003	0.003	-0.002	0.005
	(0.003)	(0.006)	(0.006)	(0.005)	(0.003)	(0.006)
Cash Ratio	-0.027*	-0.034*	0.006	-0.005	-0.015	0.010
	(0.014)	(0.019)	(0.025)	(0.015)	(0.010)	(0.018)
Tangible Ratio	-0.022	0.034	-0.057	0.016	0.012	0.004
	(0.028)	(0.034)	(0.047)	(0.022)	(0.016)	(0.029)
Leverage	0.006	-0.021	0.026	0.011	0.004	0.007
	(0.010)	(0.020)	(0.024)	(0.014)	(0.011)	(0.020)
CapEx	0.034	-0.008	0.042	0.013	-0.005	0.018
	(0.030)	(0.055)	(0.068)	(0.024)	(0.026)	(0.037)
Sales Growth	-0.001	-0.004**	0.003	0.004*	0.000	0.004
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	14,432	14,432	14,432	14,387	14,387	14,387
R^2	0.92	0.93	0.92	0.86	0.90	0.87

Panel B: Cummulative Number of Green Patents in Previous Years

	1[Cum. Green Patent Num. > Med.] == 1			1[Cum. Green Patent Num. > Med.] == 0		
	(1) Green Ratio	(2) Brown Ratio	(3) Net Ratio	(4) Green Ratio	(5) Brown Ratio	(6) Net Ratio
Debt Cost × Green	0.030	-0.097	0.139	-0.068	-0.007	-0.061
	(0.092)	(0.084)	(0.120)	(0.058)	(0.014)	(0.060)
Debt Cost × Brown	-0.058**	0.303***	-0.361***	-0.048	0.067	-0.115
	(0.028)	(0.098)	(0.106)	(0.040)	(0.108)	(0.125)
Debt Cost × Neutral	-0.054**	-0.024	-0.030	-0.013	0.010	-0.022
	(0.023)	(0.016)	(0.028)	(0.009)	(0.010)	(0.014)
Green	0.051	-0.006	0.056	0.010	0.005	0.005
	(0.035)	(0.010)	(0.038)	(0.010)	(0.004)	(0.011)
Brown	0.018	0.052**	-0.035	-0.005	0.076***	-0.081***
	(0.019)	(0.025)	(0.032)	(0.005)	(0.021)	(0.023)
Size	0.009	-0.005	0.014*	0.002	0.007*	-0.005
	(0.006)	(0.005)	(0.008)	(0.003)	(0.004)	(0.005)
Cash Ratio	-0.033	-0.004	-0.029	0.011	-0.017	0.027*
	(0.023)	(0.014)	(0.028)	(0.009)	(0.010)	(0.014)
Tangible Ratio	-0.001	0.029	-0.033	0.021	0.027	-0.007
	(0.041)	(0.024)	(0.048)	(0.014)	(0.023)	(0.028)
Leverage	0.034*	0.014	0.019	-0.002	-0.008	0.006
	(0.019)	(0.014)	(0.024)	(0.008)	(0.015)	(0.018)
CapEx	0.060	-0.004	0.066	0.047**	0.006	0.042
	(0.048)	(0.042)	(0.065)	(0.020)	(0.033)	(0.041)
Sales Growth	-0.002	-0.002	0.000	0.004***	-0.000	0.004*
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	14,149	14,149	14,149	14,404	14,404	14,404
R^2	0.89	0.92	0.91	0.85	0.92	0.89

Table 6: **Heterogeneity Test:** This table reports the results of heterogeneity tests. *Green Ratio* is the proportion of firm revenue from green activities. *Brown Ratio* is the proportion of firm revenue from brown activities. *Net Ratio* is the difference between *Green Ratio* and *Brown Ratio*. *Debt Cost* is a measure for a firm's overall debt cost, defined as *Interest Expenditure + Other (Including Commissions) + Capitalized Interest Expenditure) / (Short-Term Loan + Non-Current Liabilities Due Within One Year + Long-Term Loan + Bond Payable + Long-Term Accounts Payable*. *Green*, *Brown*, and *Neutral* are dummies for green, brown, and neutral firms, respectively, depending on our classification of each industry. Specifically, we calculated the mean value of *Green Ratio*, *Brown Ratio*, and *Neither-green-nor-brown Ratio* of all firms in each industry in the first year that any firms exist in the industry during our sample period. Industries with a mean *Neither-green-nor-brown Ratio* equal to or larger than 90% are classified as a neutral industries. For the other industries, those with a mean *Green Ratio* larger than a mean *Brown Ratio* are classified as green industries, while those otherwise are classified as brown industries. See Appendix Table IA.1 for the classification of each industry. *Size* is the logarithm of 1 + total assets. *Cash Ratio* is cash and cash equivalents to total assets. *Tangible Ratio* is tangible assets to total assets. *Leverage* is total debt to total assets. *CapEx* is cash paid to acquire fixed assets, intangible assets, and other long-term assets scaled by total assets. *Sales Growth* is the growth rate of firm revenue. Standard errors reported in parentheses are clustered at the firm level. * p<.10; ** p<.05; *** p<.01.

	Panel A: Green Inv. and Firm Greenness			Panel B: Debt Cost and Green Inv.		
	(1) Net Ratio	(2) Net Ratio	(3) Net Ratio	(4) Ln Green Inv Amt	(5) Green Inv / Assets	(6) Green Inv / Rev
Ln Green Inv Amt	0.004***					
	(0.001)					
Green Inv / Assets		0.602***				
		(0.232)				
Green Inv / Rev			0.302***			
			(0.098)			
Debt Cost				-0.872***	-0.006***	-0.017***
				(0.148)	(0.001)	(0.003)
Size	0.007	0.008*	0.008*	0.282***	0.000*	0.001**
	(0.005)	(0.005)	(0.005)	(0.036)	(0.000)	(0.001)
Cash Ratio	0.003	0.003	0.003	0.422***	0.002***	0.007***
	(0.018)	(0.018)	(0.018)	(0.129)	(0.001)	(0.003)
Tangible Ratio	-0.008	-0.006	-0.007	0.584***	0.001	0.004
	(0.030)	(0.030)	(0.030)	(0.179)	(0.001)	(0.003)
Leverage	0.013	0.012	0.012	-0.386***	-0.002***	-0.006**
	(0.017)	(0.017)	(0.017)	(0.125)	(0.001)	(0.002)
CapEx	0.055	0.048	0.037	1.479***	0.012***	0.046***
	(0.040)	(0.040)	(0.038)	(0.322)	(0.002)	(0.007)
Sales Growth	0.004*	0.004*	0.004*	0.016	0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.018)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	25,803	25,803	25,803	27,252	27,252	27,252
R^2	0.89	0.89	0.89	0.54	0.39	0.42

Table 7: **Cost of Debt and Green Investment:** This table reports the effects of debt cost on firm green investment. Panel A shows the correlation between green investment and firm greenness. Panel B reports the effects of debt cost on green investment. *Net Ratio* is the proportion of firm revenue from green activities minus that from brown activities. *Ln GEXP Amt* is the logarithm of 1 + the amount of green investment. *GEXP / Assets* is the green investment amount scaled by total assets. *GEXP / Rev* is the green investment amount scaled by total revenue. *Debt Cost* is a measure for a firm's overall debt cost, defined as *Interest Expenditure + Other (Including Commissions) + Capitalized Interest Expenditure) / (Short-Term Loan + Non-Current Liabilities Due Within One Year + Long-Term Loan + Bond Payable + Long-Term Accounts Payable*. *Green*, *Brown*, and *Neutral* are dummies for green, brown, and neutral firms, respectively, depending on our classification of each industry. Specifically, we calculated the mean value of *Green Ratio*, *Brown Ratio*, and *Neither-green-nor-brown Ratio* of all firms in each industry in the first year that any firms exist in the industry during our sample period. Industries with a mean *Neither-green-nor-brown Ratio* equal to or larger than 90% are classified as neutral industries. For the other industries, those with a mean *Green Ratio* larger than a mean *Brown Ratio* are classified as green industries, while those otherwise are classified as brown industries. See Appendix Table IA.1 for the classification of each industry. *Size* is the logarithm of 1 + total assets. *Cash Ratio* is cash and cash equivalents to total assets. *Tangible Ratio* is tangible assets to total assets. *Leverage* is total debt to total assets. *CapEx* is cash paid to acquire fixed assets, intangible assets, and other long-term assets scaled by total assets. *Sales Growth* is the growth rate of firm revenue. Standard errors reported in parentheses are clustered at firm level. * p<.10; ** p<.05; *** p<.01.

	(1) Debt Cost	(2) Green Ratio	(3) Brown Ratio	(4) Net Ratio
Treat × Post	-0.005**			
	(0.002)			
Treat × Post × Green		0.042	-0.002	0.044
		(0.035)	(0.006)	(0.036)
Treat × Post × Brown		0.032**	-0.020	0.052*
		(0.015)	(0.018)	(0.029)
Treat × Post × Neutral		0.005	0.003	0.001
		(0.003)	(0.003)	(0.005)
Event × Firm FE	✓	✓	✓	✓
Event × Greenness × Event-time FE	✓	✓	✓	✓
Event × Sector × Event-time FE	✓	✓	✓	✓
Observations	29,539	29,539	29,539	29,539
R^2	0.49	0.91	0.95	0.93

Table 8: **Identification: Static Effects of Accelerated Depreciation Policy:** This table reports the stacked DID estimates for the static effects of the accelerated depreciation policy. *Treat* equals 1 for treated firms (i.e., firms in industries that were allowed to adopt an accelerated depreciation accounting method) and equals 0 for control firms. *Post* equals 1 for post-treatment periods (i.e., Event-time = 1, 2, or 3) and equals 0 periods otherwise. *Green Ratio* is the proportion of firm revenue from green activities. *Brown Ratio* is the proportion of firm revenue from brown activities. *Net Ratio* is the difference between *Green Ratio* and *Brown Ratio*. *Debt Cost* is a measure for a firm's overall debt cost, defined as *Interest Expenditure + Other (Including Commissions) + Capitalized Interest Expenditure) / (Short-Term Loan + Non-Current Liabilities Due Within One Year + Long-Term Loan + Bond Payable + Long-Term Accounts Payable*. *Green*, *Brown*, and *Neutral* are dummies for green, brown, and neutral firms, respectively, depending on our classification of each industry. Specifically, we calculated the mean value of *Green Ratio*, *Brown Ratio*, and *Neither-green-nor-brown Ratio* of all firms in each industry in the first year that any firms exist in the industry during our sample period. Industries with a mean *Neither-green-nor-brown Ratio* equal to or larger than 90% are classified as a neutral industries. For the other industries, those with a mean *Green Ratio* larger than a mean *Brown Ratio* are classified as green industries, while those otherwise are classified as brown industries. See Appendix Table IA.1 for the classification of each industry. Standard errors reported in parentheses are clustered at the event × firm level. * p<.10; ** p<.05; *** p<.01.

	Whole Period: [2010, 2020]				After 2015: [2015, 2020]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICC_Analyst	-0.237***				-0.419***			
	(0.055)				(0.072)			
ICC_HVZ		-0.026				-0.083*		
		(0.035)				(0.045)		
ICC_EP			-0.071**				-0.153***	
			(0.030)				(0.048)	
ICC_RI				-0.065**				-0.170***
				(0.032)				(0.054)
Size	0.003	0.003	0.006	0.005	0.009	0.006	0.009	0.011
	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)
Cash	-0.011	0.008	0.003	-0.004	0.013	0.031	0.023	0.016
	(0.019)	(0.022)	(0.021)	(0.021)	(0.024)	(0.027)	(0.026)	(0.026)
Tangible	0.009	0.004	0.015	0.013	0.014	-0.008	0.008	0.010
	(0.022)	(0.024)	(0.023)	(0.024)	(0.027)	(0.032)	(0.031)	(0.031)
Leverage	-0.054***	-0.047**	-0.038**	-0.047***	-0.079***	-0.069***	-0.050**	-0.067***
	(0.016)	(0.019)	(0.017)	(0.017)	(0.022)	(0.026)	(0.024)	(0.024)
Sales Growth	-0.009**	-0.009*	-0.012**	-0.012***	-0.015***	-0.010*	-0.014**	-0.015***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
CAPX	0.109***	0.073*	0.066*	0.066*	0.129***	0.072	0.076	0.067
	(0.032)	(0.038)	(0.038)	(0.038)	(0.040)	(0.048)	(0.048)	(0.048)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	43,383	30,811	34,942	34,923	31,667	23,213	26,127	26,095
R^2	0.91	0.91	0.91	0.91	0.90	0.90	0.89	0.89

Table 9: **International Sample: Implied Cost of Capital and EU Taxonomy Eligibility Ratio:** This table reports the results for the effects of ICC on the EU Taxonomy eligibility ratio in the international sample. The dependent variable is the proportion of firm revenue from eligible activities defined by the EU Taxonomy. *ICC_Analyst* is the ICC solved from Gebhardt et al. (2001) model using analyst earnings forecasts. *ICC_Analyst* is the ICC solved from Gebhardt et al. (2001) model using analyst earnings forecasts. *ICC_HVZ* is the ICC solved from Gebhardt et al. (2001) model using earnings forecasts generated by HVZ model proposed by Hou et al. (2012). *ICC_EP* is the ICC solved from Gebhardt et al. (2001) model using earnings forecasts generated by EP model proposed by Li and Mohanram (2014). *ICC_RI* is the ICC solved from Gebhardt et al. (2001) model using earnings forecasts generated by RI model proposed by Li and Mohanram (2014). *Size* is the logarithm of 1 + total assets. *Cash* is cash and short-term investments scaled by total assets. *Tangible* is property, plant, and equipment scaled by total assets. *Leverage* is long-term debt and debt in current liabilities scaled by total assets. *CAPX* capital expenditure scaled by total assets. *Sales Growth* is the growth rate of firm sales. Standard errors reported in parentheses are clustered at the firm level. * p<.10; ** p<.05; *** p<.01.

A Green Revenue Data Example

Business (Chinese)	Business (English)	Amount (CNY)	Ratio	Brown Tag	Green Tag	Category
水力发电	Hydropower Generation	759,202,283.18	0.3579		3.1.4	G
水泥	Cement	286,517,137.34	0.1351	3011		B
纸及纸制品	Paper and Paper Products	216,715,745.25	0.1022	2221		B
火力发电	Thermal Power Generation	407,558,707.47	0.1921	4411		B
贸易及服务	Trade and Services	242,700,648.32	0.1144			GB N/A
变速箱、齿轮系列产品	Transmission and Gear Products	182,409,479.31	0.0860			GB N/A
其他业务	Other Businesses	26,269,672.06	0.0124			GB N/A

Figure IA.1: **Green Revenue Data Example:** This table shows the revenue breakdown of Guangdong Shaoneng Group Co.,Ltd. (Ticker: 000601.SZ) in 2010 by business and the greenness classification of each business in the green revenue dataset.

B Greenness Definition

Code	Name	Brown	Green	Other	Net	Category
B07	Oil and natural gas exploitation industry	0.3189	0.0000	0.6811	-0.3189	brown
B08	Ferrous metal ore mining and dressing industry	0.1036	0.0000	0.8964	-0.1036	brown
B09	Non-ferrous metal ore mining and dressing industry	0.1477	0.0000	0.8523	-0.1477	brown
C22	Papermaking and paper product industry	0.7320	0.0001	0.2680	-0.7319	brown
C25	Industries of petroleum processing, coking, and nuclear fuel processing	0.3153	0.0000	0.6754	-0.3153	brown
C26	Manufacturing of chemical raw materials and chemical products	0.3164	0.0050	0.6770	-0.3114	brown
C30	Industry of non-metallic mineral products	0.3168	0.0281	0.6453	-0.2887	brown
C31	Industry of ferrous metal smelting and rolling processing	0.5486	0.0000	0.4494	-0.5486	brown
C32	Industry of non-ferrous metal smelting and rolling processing	0.1428	0.0000	0.8524	-0.1428	brown
D44	Industry of electric power and heat production and supply	0.4406	0.1954	0.3503	-0.2452	brown
G56	Air transport industry	0.2748	0.0000	0.7252	-0.2748	brown
A01	Agriculture	0.0712	0.3213	0.6074	0.2501	green
A02	Forestry	0.0000	0.1915	0.8085	0.1915	green
A05	Service industry for agriculture, forestry, animal husbandry and fishery	0.0013	0.2448	0.7504	0.2435	green
C40	Instrument and meter manufacturing	0.0000	0.1000	0.8743	0.1000	green
C42	Industry of comprehensive utilization of waste resources	0.0000	0.1333	0.8667	0.1333	green
D46	Water production and supply industry	0.0000	0.1936	0.8064	0.1936	green
E50	Architectural decoration and other construction industries	0.0399	0.1445	0.7774	0.1046	green
M74	Professional technical service industry	0.0000	0.1017	0.8984	0.1017	green
N77	Ecological protection and environmental governance industry	0.0000	0.9979	0.0021	0.9979	green
N78	Public facility management industry	0.0089	0.5596	0.4315	0.5508	green
O81	Other service industries	0.0454	0.1118	0.8427	0.0664	green
A03	Animal husbandry	0.0021	0.0000	0.9979	-0.0021	neutral
A04	Fishery	0.0000	0.0000	1.0000	0.0000	neutral
B06	Coal mining and dressing industry	0.0469	0.0000	0.9532	-0.0469	neutral
B10	Non-metallic ore mining and dressing industry	0.0000	0.0000	1.0001	0.0000	neutral
B11	Exploitation auxiliary activities	0.0000	0.0352	0.9648	0.0352	neutral
C13	Agricultural and sideline food processing industry	0.0214	0.0001	0.9667	-0.0213	neutral
C14	Food manufacturing	0.0085	0.0000	0.9915	-0.0085	neutral
C15	Alcohol, beverage and refined tea manufacturing	0.0000	0.0000	1.0000	0.0000	neutral
C17	Textile industry	0.0116	0.0002	0.9882	-0.0114	neutral
C18	Textile garment and apparel industry	0.0026	0.0185	0.9836	0.0159	neutral
C19	Leathers, furs, feathers and related products and footwear industry	0.0000	0.0000	1.0000	0.0000	neutral
C20	Wood processing and wood, bamboo, rattan, Palm fiber, and straw product industry	0.0000	0.0000	1.0000	0.0000	neutral
C21	Furniture manufacturing	0.0000	0.0000	1.0000	0.0000	neutral
C23	Printing and recording media reproduction industry	0.0000	0.0000	1.0000	0.0000	neutral
C24	Manufacturing of stationery, industrial arts, sports and entertainment supplies	0.0032	0.0000	0.9968	-0.0032	neutral
C27	Pharmaceutical industry	0.0101	0.0000	0.9843	-0.0101	neutral
C28	Chemical fiber manufacturing	0.0667	0.0000	0.9333	-0.0667	neutral
C29	Industry of rubber and plastic products	0.0294	0.0000	0.9706	-0.0294	neutral
C33	Metal product industry	0.0278	0.0185	0.9538	-0.0093	neutral
C34	General equipment manufacturing	0.0000	0.0421	0.9579	0.0421	neutral
C35	Special-purpose equipment manufacturing	0.0036	0.0667	0.9313	0.0631	neutral
C36	Automobile manufacturing	0.0024	0.0151	0.9817	0.0127	neutral
C37	Manufacturing of railways, ships, aircrafts, spacecrafts and other transportation equipment	0.0021	0.0246	0.9719	0.0225	neutral
C38	Electric machinery and equipment manufacturing	0.0004	0.0682	0.9318	0.0678	neutral
C39	Manufacturing of computers, communications and other electronic equipment	0.0003	0.0292	0.9746	0.0289	neutral
C41	Other manufacturing industries	0.0258	0.0398	0.9324	0.0140	neutral
C43	Industry of metal product, machinery and equipment repair	0.0000	0.0000	1.0001	0.0000	neutral
D45	Gas production and supply industry	0.0000	0.0000	1.0000	0.0000	neutral
E47	Building construction industry	0.0000	0.0030	0.9970	0.0030	neutral
E48	Civil engineering construction industry	0.0045	0.0593	0.9362	0.0548	neutral
E49	Construction installation industry	0.0000	0.0000	1.0000	0.0000	neutral
F51	Wholesale industry	0.0000	0.0006	0.9993	0.0006	neutral
F52	Retail industry	0.0010	0.0004	0.9847	-0.0006	neutral
G53	Railway transportation industry	0.0000	0.0000	0.9999	0.0000	neutral
G54	Road transport industry	0.0000	0.0000	1.0000	0.0000	neutral
G55	Waterway transport industry	0.0000	0.0000	0.9999	0.0000	neutral
G58	Industry of loading/unloading handling and transport agency	0.0034	0.0000	0.9966	-0.0034	neutral
G59	Storage industry	0.0000	0.0000	1.0000	0.0000	neutral
G60	Postal service industry	0.0000	0.0000	0.9999	0.0000	neutral
H61	Accommodation industry	0.0000	0.0000	1.0000	0.0000	neutral
H62	Catering industry	0.0000	0.0000	1.0000	0.0000	neutral
I63	Telecommunications, radio and television and satellite transmission services	0.0000	0.0000	1.0000	0.0000	neutral
I64	Internet and related services	0.0000	0.0656	0.9344	0.0656	neutral
I65	Industry of software and information technology services	0.0000	0.0275	0.9736	0.0275	neutral
J66	Monetary and financial services	0.0000	0.0000	0.9815	0.0000	neutral
J67	Capital market services	0.0000	0.0000	0.9903	0.0000	neutral
J68	Insurance industry	0.0000	0.0000	1.0187	0.0000	neutral
J69	Other financial industries	0.0000	0.0000	0.9551	0.0000	neutral
K70	Real estate industry	0.0044	0.0005	0.9951	-0.0038	neutral
L71	Leasing industry	0.0000	0.0000	1.0001	0.0000	neutral
L72	Commercial service industry	0.0001	0.0156	0.9840	0.0155	neutral
M73	Research and experimental development	0.0000	0.0000	1.0000	0.0000	neutral
M75	Industry of science and technology popularization and application services	0.0000	0.0000	1.0001	0.0000	neutral
O79	Resident service industry	0.0000	0.0000	1.0000	0.0000	neutral
O80	Industry of repair of motor vehicles, electronic products and household products	0.0000	0.0000	1.0000	0.0000	neutral
P82	Education	0.0000	0.0000	1.0000	0.0000	neutral
Q83	Health	0.0000	0.0000	1.0000	0.0000	neutral
R85	Press and publishing industry	0.0000	0.0000	1.0000	0.0000	neutral
R86	Radio, television, film, and film and television sound recording production industry	0.0000	0.0000	1.0000	0.0000	neutral
R87	Industry of culture and arts	0.0000	0.0000	1.0000	0.0000	neutral
R88	Sports	0.0000	0.0000	0.9999	0.0000	neutral
S90	Diversified industries	0.0493	0.0234	0.9274	-0.0259	neutral

Table IA.1: **Greenness Definition**

C Treatment Years for the Accelerated Depreciation Policy

Code	Name	Treatment Year
C27	Pharmaceutical industry	2014
C35	Special-purpose equipment manufacturing	2014
C37	Manufacturing of railways, ships, aircrafts, spacecrafts and other transportation equipment	2014
C39	Manufacturing of computers, communications and other electronic equipment	2014
C40	Instrument and meter manufacturing	2014
I63	Telecommunications, radio and television and satellite transmission services	2014
I64	Internet and related services	2014
I65	Industry of software and information technology services	2014
C13	Agricultural and sideline food processing industry	2015
C14	Food manufacturing	2015
C17	Textile industry	2015
C18	Textile garment and apparel industry	2015
C19	Leathers, furs, feathers and related products and footwear industry	2015
C20	Wood processing and wood, bamboo, rattan, Palm fiber, and straw product industry	2015
C21	Furniture manufacturing	2015
C22	Papermaking and paper product industry	2015
C23	Printing and recording media reproduction industry	2015
C24	Manufacturing of stationery, industrial arts, sports and entertainment supplies	2015
C28	Chemical fiber manufacturing	2015
C33	Metal product industry	2015
C34	General equipment manufacturing	2015
C36	Automobile manufacturing	2015
C38	Electric machinery and equipment manufacturing	2015
C15	Alcohol, beverage and refined tea manufacturing	2019
C25	Industries of petroleum processing, coking, and nuclear fuel processing	2019
C26	Manufacturing of chemical raw materials and chemical products	2019
C29	Industry of rubber and plastic products	2019
C30	Industry of non-metallic mineral products	2019
C31	Industry of ferrous metal smelting and rolling processing	2019
C32	Industry of non-ferrous metal smelting and rolling processing	2019
C41	Other manufacturing industries	2019
C42	Industry of comprehensive utilization of waste resources	2019
C43	Industry of metal product, machinery and equipment repair	2019

Table IA.2: **Treatment Years for the Accelerated Depreciation Policy**

D Keywords to Identify Green Projects

Keyword	Meaning	Number	Keyword	Meaning	Number	Keyword	Meaning	Number
光伏	Photovoltaic	1666	储能	Energy Storage	171	水性	Water-Based	54
环保	Environmental Protection	1445	减排	Emission Reduction	169	能降	Energy Reduction	50
风电	Wind Power	1314	清洁	Clean	161	制氢	Hydrogen Production	49
污水处理	Wastewater Treatment	1173	核电	Nuclear Power	149	乙醇	Ethanol	49
节能	Energy Conservation	1080	资源化	Resource Utilization	146	环境治理	Environmental Management	49
新能源	New Energy	858	绿化	Greening	139	地铁	Subway	47
回收	Recycling	632	生物质	Biomass	133	特高压	Ultra-High Voltage	46
综合利用	Comprehensive Utilization	587	回用	Reuse	131	园林	Landscape	46
风电场	Wind Farm	567	循环水	Circulating Water	111	电解槽	Electrolyzer	45
脱硫	Desulfurization	557	多晶	Polycrystalline	107	粮食	Grain	44
除尘	Dust Removal	497	变频	Variable Frequency	103	热泵	Heat Pump	44
循环	Circular	496	甲醇	Methanol	98	绿地	Greenfield	44
绿色	Green	479	能源管理	Energy Management	97	雨水	Rainwater	43
高效	Efficient	447	植物	Plant	97	净水	Water Purification	43
信息化	Informatization	437	增效	Efficiency Enhancement	97	氢能	Hydrogen Energy	43
净化	Purification	431	多晶硅	Polysilicon	93	再生资源	Recycled Resources	41
生态	Ecological	428	除尘器	Dust Collector	93	食用菌	Edible Fungi	41
锂电	Lithium Battery	417	节水	Water-Saving	87	无害	Harmless	41
太阳能	Solar Energy	401	风力	Wind Power	83	节能型	Energy-Saving	40
余热	Waste Heat	375	单晶硅	Monocrystalline Silicon	81	无害化	Harmless	39
环境	Environment	357	污染	Pollution	81	水利	Water Conservancy	38
LED	Led	320	用水	Water Use	79	氢气	Hydrogen	37
脱硝	Denitrification	319	水源	Water Source	71	调峰	Peaking Adjustment	37
排放	Emission	318	加氢	Hydrogenation	67	热能	Thermal Energy	36
水电	Hydropower	305	充电站	Charging Station	61	超临界	Supercritical	35
再生	Recycling	276	装配式	Prefabricated	60	蓄热	Thermal Energy Storage	34
废水处理	Wastewater Treatment	210	降解	Degradation	59	水质	Water Quality	33
锂离子	Lithium-Ion	207	集中供热	District Heating	58	可降解	Degradable	33
水电站	Hydropower Station	192	垃圾处理	Waste Treatment	57	有机肥	Organic Fertilizer	33
风机	Wind Turbine	190	电除尘	Electrostatic Precipitation	56	零排放	Zero Emissions	32
电动	Electric	190	水产	Aquaculture	55	燃料电池	Fuel Cell	31
光热	Solar Thermal	30	电动汽车	Electric Vehicle	15	生态环境	Ecological Environment	9
水资源	Water Resources	28	地下水	Groundwater	15	作物	Crop	9
生态农业	Eco-Agriculture	26	防洪	Flood Control	15	育苗	Nursery	9
温度	Temperature	25	水循环	Water Recycling	15	原生态	Primitive Ecology	9
地热	Geothermal	25	生态旅游	Ecotourism	14	农田水利	Farmland Water Conservancy	8
资源管理	Resource Management	25	智慧水务	Smart Water Management	14	种苗	Seedlings	8
变频器	Inverter	24	二手	Second-Hand	14	纸包	Paper Packaging	8
良种	Improved Seeds	22	农林	Agriculture And Forestry	14	热解	Pyrolysis	8
微生物	Microorganism	22	森林	Forest	14	地表水	Surface Water	8
蓄水	Water Storage	22	水轮	Water Turbine	14	冷凝水回收	Condensate Recovery	8
再生能源	Renewable Energy	21	风能	Wind Energy	14	自然	Nature	8
电能	Electrical Energy	20	降解塑料	Degradable Plastics	13	环境监测	Environmental Monitoring	8
电车	Electric Vehicle	20	水净化	Water Purification	13	聚乳酸	Polylactic Acid	7
页岩	Shale	20	清淤	Dredging	12	高效化	Efficiency Enhancement	7
回水	Return Water	19	淡水	Freshwater	12	充电机	Charger	7
电气化	Electrification	19	水产品	Aquatic Products	12	长寿命	Long Lifespan	7
可再生	Renewable	19	热交换器	Heat Exchanger	11	海绵城市	Sponge City	6
循环流化床	Circulating Fluidized Bed	18	降噪	Noise Reduction	11	堆肥	Composting	6
再造	Reconstruction	18	能效	Energy Efficiency	11	水能	Hydropower	6
脱盐	Desalination	18	植保	Plant Protection	11	林业	Forestry	6
溶剂回收	Solvent Recovery	18	核电站	Nuclear Power Plant	11	林区	Forest Area	6
现代农业	Modern Agriculture	17	绿色建材	Green Building Materials	11	水力	Hydropower	6
草种	Grass Seed	17	保育	Conservation	10	玻璃包装	Glass Packaging	6
湿地	Wetland	17	环境友好	Environmentally Friendly	10	水电工程	Hydropower Engineering	6
生物质能	Biomass Energy	17	水性涂料	Water-Based Coatings	10	城市轨道	Urban Rail	6
抽水蓄能	Pumped Storage	16	减振	Vibration Reduction	10	树林	Forest	6
土壤	Soil	16	超导	Superconducting	10	空气净化	Air Purification	6
燃气轮机	Gas Turbine	16	水源地	Water Source	10	低能	Low Energy	5
环境保护	Environmental Protection	16	水轮发电	Hydropower Generation	10	林地	Forest Land	5
苗圃	Nursery	16	防渗	Seepage Control	9	水土保持	Soil And Water Conservation	5
电除尘器	Electrostatic Precipitator	16	电动机	Electric Motor	9	复垦	Reclamation	5
水网	Water Network	5	建筑节能	Building Energy Efficiency	3	植物种	Plant Species	2
治沙	Sand Control	5	林场	Forest Farm	3	林带	Shelterbelt	2
风车	Wind Turbine	5	电动船	Electric Boat	3	节煤	Coal Saving	2
低毒	Low Toxicity	5	纸包装	Paper Packaging	3	海流	Ocean Current	2
调蓄	Regulation And Storage	5	微特电机	Micro-Specialized Motor	3	物耗	Resource Consumption	2
储氢	Hydrogen Storage	5	治污	Pollution Control	3	核能	Nuclear Energy	2
膜法	Membrane Method	5	磁悬浮	Maglev	3	精量	Precision	2
竹林	Bamboo Forest	5	污水集中	Sewage Centralization	3	碲化镉	Cadmium Telluride	2
钠离子	Sodium-Ion	5	养鱼	Fish Farming	3	动植物	Flora And Fauna	1
PEM	Proton Exchange Membrane	5	低能耗	Low Energy Consumption	3	竹子	Bamboo	1
聚光	Concentration	4	环境质量	Environmental Quality	3	苗木	Nursery Stock	1
红树林	Mangrove	4	潮汐	Tidal	2	异步电动	Asynchronous Electric	1
红树	Mangrove	4	生态农场	Eco-Farm	2	保土	Soil Conservation	1
林木	Timber	4	皂素	Saponin	2	CIGS	Cigs	1
光化	Photochemical	4	护林	Forest Protection	2	有轨电车	Tram	1
水轮机	Hydraulic Turbine	4	植被	Vegetation	2	持续性	Sustainability	1
生物肥	Biofertilizer	4	海藻	Algae	2	低噪声	Low Noise	1
气候	Climate	4	绿色食品	Green Food	2	海流能	Ocean Current Energy	1
保水	Water Retention	4	净水机	Water Purifier	2	电化学储能	Electrochemical Energy Storage	1
石漠化	Rock Desertification	4	园林绿化	Landscaping And Greening	2	电子客票	E-Ticket	1
集约化	Intensive	4	风轮	Wind Turbine	2	节水型	Water-Saving	1
净化器	Purifier	4	防护林	Protective Forest	2	江河源	River Source	1
育林	Afforestation	3	节约	Conservation	2	透水	Permeable	1
高效能	High-Efficiency	3	江源	River Source	2	农作物	Crops	1
洗船	Tank Cleaning	3	有轨	Light Rail	2	鱼礁	Fish Reef	1
速生	Fast-Growing	3	污水净化	Wastewater Purification	2	大气环境	Atmospheric Environment	1
森林公园	Forest Park	3	回收站	Recycling Station	2	稀土永磁电机	Rare Earth Permanent Magnet Motor	1
造林	Afforestation	3	基因库	Gene Bank	2	保护区	Protected Area	1
海洋能	Ocean Energy	3	液氢	Liquid Hydrogen	2	保温材料	Insulation Materials	1
土壤改良	Soil Improvement	3	生态系	Ecosystem	2	国家森林公园	National Forest Park	1
PEMS	Pems (Predictive Emissions Monitoring System)	3	生态系统	Ecosystem	2	贯流式	Through-Flow Type	1

Figure IA.2: **Keywords to Identify Green Projects**

E Validation Tests

Panel A: Green Ratio

	Green Ratio									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln GHG Int. S1+S2	-0.024**									
	(0.010)									
Ln GHG Abs. S1+S2		-0.026***								
		(0.007)								
Refinitive Env.			0.001**							
			(0.000)							
Refinitive Emi.				0.000						
				(0.000)						
MSCI Env.					0.011***					
					(0.003)					
MSCI Climate Chg.						0.003				
						(0.002)				
MSCI Env. Opp.							0.022***			
							(0.005)			
Env. Incident Num.								-0.004		
								(0.005)		
GHG Incident Num.									0.006	
									(0.014)	
TV GHG Emission										-0.000
										(0.000)
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,021	5,021	3,370	3,370	2,421	2,342	1,212	18,118	18,118	1,744
R^2	0.36	0.38	0.34	0.34	0.37	0.36	0.41	0.31	0.31	0.43

Panel B: Brown Ratio

	Brown Ratio									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln GHG Int. S1+S2	0.058***									
	(0.007)									
Ln GHG Abs. S1+S2		0.046***								
		(0.006)								
Refinitive Env.			-0.001***							
			(0.000)							
Refinitive Emi.				-0.000						
				(0.000)						
MSCI Env.					-0.008***					
					(0.003)					
MSCI Climate Chg.						-0.007**				
						(0.003)				
MSCI Env. Opp.							-0.005*			
							(0.003)			
Env. Incident Num.								0.024***		
								(0.009)		
GHG Incident Num.									0.024	
									(0.018)	
TV GHG Emission										-0.001
										(0.001)
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,021	5,021	3,370	3,370	2,421	2,342	1,212	18,118	18,118	1,744
R^2	0.64	0.63	0.53	0.53	0.52	0.51	0.48	0.47	0.47	0.52

Table IA.3: **Regression on Green and Brown Ratios on Other Environmental Variables**

From Incidents to Actions: The Dynamics of ESG Engagement in Asset Management

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Abstract

This paper examines why institutional investors decide to engage with portfolio firms on ESG issues. Using a proprietary dataset of detailed ESG engagement records from a European asset management company, we find that engagement is triggered by both firms' own ESG incidents and those of their suppliers. We further show that engagement decisions are driven not only by financial considerations but also by non-financial ones, with reputational concerns representing a key non-financial motivation. Finally, we demonstrate that engagement enhances firm value, potentially through an improvement in ESG performance, and identify increased cash flows as the main source of value creation. Together, these findings shed light on the triggers and motivations for ESG engagement and reveal the specific channels through which it enhances firm value.

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1 Introduction

Institutional investors have always played a key role in shaping firms' environmental, social, and governance (ESG) behavior. Let us take climate issues as an example. In a global survey of over 800 finance academics, practitioners, and economists, pressure from institutional investors was identified as one of the most influential forces driving firms to reduce their carbon footprints and manage climate-related risks (Stroebel and Wurgler, 2021). Numerous studies document the influence of institutional investors on firms' ESG practices (e.g., Dyck et al., 2019; Chen et al., 2020; Ilhan et al., 2023).

Recent studies highlight shareholder engagement as a powerful tool for addressing ESG issues (Broccardo et al., 2022; Kahn et al., 2023).[1] Extant research has also yielded early insights into ESG engagement practices, relying largely on proprietary data from individual institutional investors, given the inherently private nature of engagement (McCahery et al., 2016; Krueger et al., 2020; Becht et al., 2009). Pioneering work by Dimson et al. (2015), provides the first comprehensive evidence that ESG engagements are associated with positive market reactions, improved financial performance, greater institutional ownership, and enhanced corporate governance. Subsequent studies further show that engagement can strengthen ESG performance (Barko et al., 2022) and mitigate downside risk (Hoepner et al., 2024). While these contributions offer important evidence on the outcomes of engagement, much less is known about why institutional investors decide to engage in the first place. This paper seeks to fill that gap.

Following extant literature, we use a proprietary dataset of detailed ESG engagement records from a large European asset management company to examine the motivations behind its engagement decisions. The asset manager operates across Europe, the Americas, and Asia, and has been integrating ESG strategies into its fixed-income, equity, multi-asset, and private asset funds for over 35 years. From January 2010 to March 2023, the asset manager recorded 1,802 engagements involving 1,220 firms worldwide. We begin by investigating the triggers of engagement, focusing on ESG incidents, which are events that reflect poor ESG practices, since they represent adverse shocks to a firm's ESG performance. We then examine the rationale behind the asset manager's response to such incidents.

We posit that the asset manager may respond to ESG incidents based on both financial and

[1] Engagement can be understood as a set of actions institutional investors take to influence corporate behavior, particularly ESG-related behavior in our setting. It typically involves private dialogues, meetings, and other forms of communication with the focal firm. We provide further details on how the asset manager in our study engages on ESG issues in Section 2.1.

non-financial reasons. The financial motivation is to manage investment risk at their portfolio firms, as such incidents reveal a firm's exposure to material ESG risks. This motivation is supported by recent evidence on the negative financial consequences of such incidents. For example, ESG incidents have been shown to trigger negative market reactions (Krüger, 2015), lead to downward revisions in analysts' earnings forecasts (Derrien et al., 2024b), and provoke customer backlash (Duan et al., 2024; Houston et al., 2024; Bisetti et al., 2024).

To manage the financial risk of portfolio firms, an asset manager also has a choice of divesting the incident firm instead of a more costly action of engaging with the firm to improve its ESG performance. However, an asset manager that primarily chooses divestiture is unlikely to be regarded as a leader in responsible investing as it has adopted a passive strategy similar to screening out underperforming ESG companies instead of an active strategy of long-term engagement with the companies to bring about ESG improvements. Having skin in the game by engaging the incident firm on a long-term basis is less likely to be perceived by the market as cheap talk of responsible investing on the part of the asset manager.

We henceforth argue that the asset manager may also be motivated by non-financial factors, on top of financial factors, to engage with portfolio firms. For example, ESG incidents within portfolio firms may undermine the asset manager's perceived commitment to sustainability and responsible investments, prompting them to intervene through engagement to protect their own ESG reputation. This reputational pressure may originate from asset owners, who have been shown to prefer financial products with stronger sustainability profiles, as documented among mutual fund investors (Hartzmark and Sussman, 2019), hedge fund investors (Liang et al., 2022), and private equity fund investors (Duevski et al., 2024). Survey evidence further supports the importance of reputation in the ESG context. For instance, Krueger et al. (2020) find that protecting reputation was the most common reason for institutional investors to engage on climate issues.

One could argue that it is unimaginable that an asset manager would not care about its reputation which is critical to build trust between investors and asset managers. Our argument is specifically about the asset manager's *ESG reputation*. From 2021 to January 2025, 18 U.S. states introduced legislation restricting ESG considerations in investment decisions by asset managers and financial institutions. For instance, the State of Texas has anti-ESG regulations prohibiting asset managers from excluding sectors such as oil and gas, coal, and firearms. Some major financial institutions such as BlackRock, State Street, JPMorgan, and Pimco, had with-

drawn from the Climate Action 100+ coalition, a reversal of their climate-related pledges.[2] The anti-ESG rhetoric is spreading to the European Union (EU). Widespread protests by farmers throughout the EU had spurred the European Commission to withdraw its proposal for a Sustainable Use of Pesticides Regulation, which was intended to reduce pesticide use by half in the EU by 2030.[3] Against this backdrop, it cannot be assumed that asset managers care about non-financial factors such as reputation beyond financial factors.

We begin by testing the effects of firms' own ESG incidents on engagement decisions. Following prior literature (Dimson et al., 2015; Brav et al., 2008; Barko et al., 2022), we match each engaged firm with up to five non-engaged portfolio firms that are most similar in terms of market-to-book ratio and firm size, within the same industry and country. This matching approach allows us to construct a comparable control group of non-engaged firms. We find that ESG incidents significantly increase the likelihood of engagement. Benchmarking the economic significance of ESG incidents against other firm characteristics, we find that the effect is non-trivial and ranks second only to firm size.

To address concerns that our results are driven by firm-specific confounding factors, we conduct several robustness tests. First, we estimate the dynamic effects of ESG incidents by regressing the engagement indicator on the number of incidents occurring in each of the past twelve months. The results show that incidents have the strongest impact within three months of occurrence, with the effect diminishing after six months. Second, at a more granular level, we estimate a combined model in which each type of environmental, social, or governance engagement decision is regressed on all three types of incidents. We find that engagement is primarily driven by incidents in the corresponding ESG category. Together, these results suggest that our main findings are unlikely to be driven by firm-specific omitted variables.

As an extension of our discussion of the engagement trigger, we examine whether ESG incidents along the supply chain prompt engagement responses from the asset manager. We find that the asset manager is more likely to engage with portfolio firms following ESG incidents involving their suppliers, but not their customers. This asymmetric pattern is consistent with both academic research and anecdotal evidence emphasizing firms' heightened sensitivity to supplier-related ESG issues (Lin et al., 2024; Dai et al., 2021; Schiller, 2018). This novel finding also provides direct evidence in support of previous research that highlights the key role of investors in shaping corporate customers' concern over supply chain ESG issues (Bisetti et al.,

[2]Source: Climate Action 100+, 2024.

[3]Source: ARC2020, 2024.

2024).

Next, we investigate the motivations behind the engagement decision. We begin by showing that, in addition to financial considerations, non-financial factors also play a role. To examine this, we classify ESG incidents based on their implied financial impact using an event study approach, distinguishing between incidents with negative and non-negative cumulative abnormal returns (CARs). We find that the asset manager responds not only to incidents with a negative financial impact, but also to those without such an impact, at least as implied by market reactions. These results suggest that engagement is not driven solely by financial reasons, but also reflects non-financial motivations.

We delve deeper into non-financial motivations by focusing on the role of reputational concerns. To do so, we conduct heterogeneity analyses to assess whether the response is stronger when the potential reputational cost is higher. We focus on two firm characteristics: firm size and media exposure. Since larger firms and those with greater media exposure typically attract more public attention, we expect ESG incidents involving such firms to pose a greater reputational cost for the asset manager. We find that the asset manager is indeed more likely to respond to ESG incidents involving larger and more visible firms. These results support the view that reputational concerns are an important non-financial motivation behind engagement, especially given that smaller firms have been found to be more financially vulnerable to ESG incidents (Derrien et al., 2024b).

After establishing what triggers engagement and why it occurs, we examine whether engagement enhances shareholder value in our setting and, if so, through which mechanism. Using the same matched-sample design, we find that engaged firms outperform their peers by about 4 percentage points in buy-and-hold abnormal returns over the twelve months following engagement. We also document a significant improvement in firms' ESG performance after engagement, particularly on ESG issues deemed financially material to the firm's industry by the Sustainability Accounting Standards Board (SASB). This supports the view that engagement creates value by improving ESG performance. Lastly, we find that engagement is followed by stronger sales growth, but no material decline in several implied cost-of-capital measures, despite increased ownership by sustainability-focused investors. Taken together, the evidence suggests that engagement enhances firm value primarily by boosting cash flows rather than by lowering the discount rate.

Our research is most closely related to the literature on shareholder activism concerning ESG issues, particularly the ESG engagement of institutional investors. Several studies lever-

age proprietary datasets from specific asset managers to examine this topic. The seminal work by Dimson et al. (2015) shows that engagement is associated with positive market reactions and subsequent improvements in financial performance, institutional ownership, and corporate governance. Barko et al. (2022) extend this analysis to a global setting and find that engagement improves ESG performance, particularly for firms with initially weaker ESG profiles. Hoepner et al. (2024) further show that ESG engagement reduces downside risk. While much of the existing literature focuses on the outcomes of engagement, we contribute new evidence on the triggers and motivations of engagement decisions. In addition, we extend the outcome-focused literature by uncovering the specific channels through which engagement enhances firm value. A contemporaneous study by Derrien et al. (2024a) shows that climate-related incidents trigger climate-focused engagement. While their interpretation emphasizes risk management motivation, our analysis highlights that ESG incidents may also trigger engagement for non-financial reasons. Moreover, rather than limiting our scope to climate-related issues, we adopt a broader ESG perspective.

Our research is also related to recent studies on supply chain ESG issues. Prior work shows that customers are increasingly monitoring and influencing the ESG practices of their suppliers (Dai et al., 2021). They respond to supplier ESG controversies by reducing business (Bisetti et al., 2024) or even terminating relationships (Schiller, 2018). These responses are supported by both academic and anecdotal evidence showing that supplier misconduct can expose downstream firms to various risks (Lin et al., 2024). Bisetti et al. (2024) further suggest that investor pressure may shape such responses, though direct evidence on whether and how investors exert this influence remains limited. We contribute to this literature by providing such evidence, showing that institutional investors respond to supplier ESG incidents through engagement. Our findings offer novel insights into how investor pressure propagates through supply chains and extends ESG accountability beyond the focal firm.

2 Data

2.1 Engagement Data

We obtain the engagement data from one of the largest asset management companies in the Scandinavian region, which manages over 280 billion in assets as of 2024. The firm has a long-standing commitment to responsible investing, with approximately 75% of its assets managed in ESG-aligned or sustainable funds classified under Articles 8 and 9 of the EU Sustainable Fi-

nance Disclosure Regulation (SFDR).[4] It was among the earliest signatories of the UN-supported Principles for Responsible Investment and established a dedicated responsible investment team shortly thereafter. The asset manager practices active ownership to promote sustainable business conduct among portfolio firms through direct engagement, proxy voting, and exclusion strategies.

The asset manager conducts engagements on behalf of all its funds. The engagement dataset offers comprehensive and detailed records of its engagement activities from January 2010 to March 2023. Over this period, the asset manager recorded 1,802 engagements involving 1,220 firms worldwide. Each engagement record contains detailed information such as the target firm, relevant ESG issues, main objectives, initiation date, collaboration status, and engagement outcome. Each engagement typically consists of a series of activities that may span several years. For each activity, the dataset records the date and the specific engagement approach used. It also records the personnel contacted within the target firm throughout the whole process.

Figure 1 presents the number of engagements by year, disaggregated by ESG category. Most engagements occurred after 2016, although few occurred in 2017. Governance engagements represent the largest share, while environmental and social engagements have increased in recent years. Figure 2a shows that the asset manager most frequently engages with firms in the Materials, Energy, and Capital Goods sectors. According to Figure 2b, while the asset manager engages firms globally, the majority of engagements are concentrated in the United States, followed by Japan, Sweden, and Germany. Figure IA.1 illustrates the thematic focus of ESG engagements. Governance remains the most common category, followed by environmental and social issues. The asset manager places particular emphasis on four main topics: Good Governance, Climate, Human Rights, and Biodiversity. At a more granular level, the most frequently addressed sub-topics include transparency, greenhouse gas (GHG) emissions, and human rights.

Table 1 summarizes other engagement characteristics. Approximately 40% of engagements are conducted internally by the asset manager, and around 37% turned out to be successful.[5] On

[4]The SFDR is an EU regulation that requires financial institutions to disclose how they integrate ESG factors into their investment processes and how their financial products align with sustainability goals. It also requires them to classify and disclose the sustainability characteristics of their financial products in a standardized manner. Products under Article 8 of the SFDR are those that promote environmental or social characteristics, provided that the investee companies follow good governance practices, often referred to as "light green" products. In contrast, Article 9 products have sustainable investment as their explicit objective and are subject to more stringent disclosure requirements, commonly described as "dark green" products. The regulation aims to reduce greenwashing and support informed investor decision-making.

[5]In fact, 40% of the observations have missing values in the engagement result field. Among the non-missing

average, each engagement comprises 1.43 actions. The average duration between the creation of an engagement and its last recorded action is about 15 months. In terms of engagement approaches, written communication is the most frequently used, with letters involved in 47% of cases and emails in 12%. Another common approach is digital meetings, which account for 21% of engagements. Direct approaches such as meetings (2%) and phone calls (3%) are less prevalent. Although the data on personnel contacted are rather incomplete, they indicate that a range of company representatives are involved, most frequently investor relations (3%) and CEOs (2%).

The original engagement dataset contains an internally generated ID for each firm and provides a mapping table between these firm IDs and ISINs. Since most of our analysis relies on the FactSet database, we use the FactSet security identifier (*fsym_id*) as the primary identifier for the engagement data. To enable this, we rely on a one-to-one linking table between ISINs and *fsym_id*s from FactSet. Using this table, we identify all possible *fsym_id*s associated with each firm ID via its ISINs. With this approach, 152 engagement observations could not be automatically matched to any *fsym_id*. For the remaining unmatched cases, a research assistant manually identified the corresponding *fsym_id* by searching firm names in the FactSet universe. With the final matched results, we retain only those *fsym_id*s designated as the primary security ID by FactSet and manually ensure that each firm is linked to a single *fsym_id*. Through this whole process, we successfully identify *fsym_id*s for 1,137 unique firms (93.2%) involved in 1,713 engagement cases (95.1%).

2.2 ESG Incident and ESG Sentiment Data

We obtain data on ESG incidents from RepRisk, a data provider that tracks ESG-related incidents. RepRisk screens a broad range of public sources in 23 languages on a daily basis to identify such incidents. It covers over 290,000 public and private companies globally and starts from 2007. Each incident is categorized into environmental, social, governance, or cross-cutting issues, and further classified into 28 specific ESG topics. The database also includes assessments of each incident's severity, influence, and recency in relation to the affected firm. This allows us to construct firm-level measures of ESG incident frequency. A more detailed description of the dataset is provided in Derrien et al. (2024b).

We use ESG sentiment data from the FactSet Truvalue SASB Scores dataset. It leverages machine learning and natural language processing to assess the semantic content of millions of

observations, 37% are classified as successful, 3.6% as neutral, 8.8% as "None," and 10.4% as unsuccessful.

third-party media articles related to firms' ESG practices on a daily basis and covers both positive and negative events. As such, the data offers a comprehensive view of firm ESG behavior from an external perspective. Compared to measures based on self-reported information, the reliance on third-party sources enhances objectivity. Focusing on the semantic analysis of external texts, the Truvalue methodology helps mitigate the well-documented inconsistency across ESG ratings from different providers (Berg et al., 2022). The high-frequency nature of the data also allows us to track real-time changes in firms' ESG performance.

Truvalue provides two types of sentiment scores. The *Pulse* score is a short-term measure that reflects real-time reactions to new events and updates instantaneously as new information emerges. The *Insight* is a smoothed version of the *Pulse* score, designed to capture longer-term ESG sentiment. Both scores are reported for each of the 26 ESG issues defined by SASB. In addition, the dataset provides an overall score that reflects sentiment on all 26 issues, and a "material overall score" that reflects sentiment on ESG issues considered financially material to a firm's industry by SASB. Both the *Pulse* score and the *Insight* score range from 0 to 100, with 50 indicating neutral sentiment, values above 50 indicating positive sentiment, and values below 50 indicating negative sentiment. The dataset starts from 2007 and covers a broad range of public and private firms globally. For our analysis, we use the *Insight* score measured at the end of each month. The Truvalue data also provides the number of ESG-related articles for each firm over a trailing window of 12 months, which we use to measure a firm's media exposure.

2.3 Financial Data

Institutional ownership data are obtained from the FactSet Ownership database. This database also provides data on fund holdings, which allows us to identify the asset manager's portfolio firms. To obtain the portfolio firms, we first search among all funds covered by FactSet for those that are either managed by the asset manager, have the asset manager's name in the fund family name, or include the asset manager's name in the fund name. This yields 608 unique funds. We then retrieve monthly holdings for these funds from January 2009 to December 2023. Among those holdings, we retain only those classified as equities. The final holding list contains 7,737 unique securities in total and an average of 2,528 unique securities at the end of each month. The FactSet Ownership database also reports the list of institutional holders and their positions in each security at the end of each quarter. We use this data to aggregate the asset manager's holdings in individual securities on a quarterly basis.

Monthly returns of global stocks are provided by Jensen et al. (2023).[6] The authors calculate returns using CRSP stock return data and Compustat stock price data, with all prices converted to USD using exchange rates from Compustat. Following the authors' suggestion, we retain only primary securities, common stocks, and stocks listed on major exchanges, with a preference for CRSP-based returns. Market returns are computed as the value-weighted average of all securities in each country, with firm market values winsorized at the NYSE 80th percentile. Daily returns involved in the event study are obtained from CRSP and Compustat.

Estimates of global implied cost of capital (ICC) are obtained from Eskildsen et al. (2024). The dataset provides security-level ICC estimates on a monthly basis using analyst forecasts from IBES and stock price data from CRSP and Compustat.[7] It provides ICC measures based on four widely used models: Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). When both CRSP- and Compustat-based estimates are available for a security, we prioritize the CRSP-based estimate.

Firm financial data are obtained from Compustat. Information on firms' suppliers and customers is obtained from the FactSet Revere Supply Chain Relationship database.

3 ESG Incidents and Engagement Decisions

3.1 Method

Following prior literature (Dimson et al., 2015; Brav et al., 2008; Barko et al., 2022), we match the engaged firm in each engagement observation with up to five non-engaged portfolio firms that are most similar in terms of market-to-book (MB) ratio and firm size, within the same industry and headquarter country. We first standardize the MB ratio and firm size across the Compustat universe by subtracting the sample mean and dividing by the sample standard deviation, so that each variable has a mean of 0 and a standard deviation of 1. We then calculate the Euclidean distance between the engaged firm and all other firms in the same industry and country within the asset manager's portfolio at the end of the month preceding the engagement, based on financial data from the year prior to engagement. For each engagement observation, we then retain up to five firms with the smallest Euclidean distance. We require both the

[6] The dataset is available on WRDS via the "Global Stock Returns and Characteristics" query form. It is also accessible at: https://jkpfactors.com/factor-returns. We thank the authors for generously sharing their data.

[7] The data can be accessed at: https://sites.google.com/view/theis-ingerslev-jensen/data. We thank the authors for generously sharing their data.

engaged firm and potential matches to have non-missing values for all four matching criteria. Each matched firm is assigned the same engagement date and ESG category as the engagement case to which it is matched. This procedure yields a matched sample of 6,396 observations. Industries are defined at the industry group level of the Global Industry Classification Standard (GICS).

We then merge the matched sample with firm financial data from the fiscal year preceding the engagement, ownership data at the end of the previous quarter of the engagement, and the number of ESG incidents that happened within the three months prior to the engagement. We exclude observations with missing or abnormal values in key variables.[8] The final regression sample contains 5,630 observations.

$$Engagement_{i,t} = \beta_0 + \beta_1 \cdot Number\ of\ Incidents_{i,t} + \boldsymbol{\beta}_2 \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t} \quad (1)$$

To investigate the effects of ESG incidents on engagement decisions, we estimate the above cross-sectional regression model, in which i indicates firms, t indicates year-months, j indicates industries, and c indicates countries. The dependent variable, $Engagement_{i,t}$, is a dummy that equals to 1 if firm i was engaged in month t, and 0 otherwise. The key independent variable, $Number\ of\ Incidents_{i,t}$, is the logarithm of one plus the total number of ESG incidents that occurred within the three months preceding month t.

$\boldsymbol{X}_{i,t-1}$ is a set of control variables measured in the previous period of month t. Due to differences in data frequency, the timing of these variables varies. Specifically, *Size*, *Market-to-Book Ratio*, *Tobin's Q*, *Sales Growth*, *ROA*, *Leverage*, *Cash Holdings*, and *Capital Expenditures* are measured at the end of the last fiscal year of month t, while *Institutional Ownership* and *Asset Manager Ownership* are measured at the end of the last quarter of month t. Detailed definitions of all control variables are provided in Table 3. We include industry-by-month fixed effects ($\lambda_{j,t}$) and country-by-month fixed effects ($\eta_{c,t}$) throughout our analysis. These fixed effects allow for comparisons among firms within the same industry or the same country at a given point in time. They also control for time-varying industry- or country-specific shocks that may simultaneously affect ESG incidents and engagement decisions. All continuous variables except stock returns are winsorized at the 1% and 99% levels. Standard errors are clustered at the industry-by-month level.

[8] Specifically, we drop observations with a negative market-to-book ratio due to negative values of *Common/Ordinary Equity – Total (ceq)* in the Compustat database. This affects 138 observations. We also cap institutional ownership at 1, which affects 198 observations.

Panel A of Table 2 presents summary statistics for the key regression variables. Due to our matching approach, 21% observations are engaged. On average, the sample firms experience 0.64 ESG incidents over the past three months. When disaggregated by ESG category, firms experience an average of 0.22 environmental incidents, 0.34 social incidents, and 0.29 governance incidents. Institutional investors hold 59% of firm shares on average, whereas the focal asset manager has a relatively small stake in its portfolio firms, with an average ownership of 0.33%.

3.2 Results

Table 3 presents the regression results. Column (1) shows that ESG incidents significantly increase the likelihood of engagement. A one-standard-deviation increase in the number of ESG incidents over the past three months (0.77) raises the probability of engagement by approximately 10 percentage points, or about 50% of the sample mean (0.21). We note that the analysis is based on a linear probability model, which allows for the inclusion of multiple fixed effects but may yield predicted probabilities outside the [0,1] range. In addition, the estimated level of economic significance may vary with the number of matched control firms per engagement, making direct interpretation less straightforward. To better assess the relative importance of ESG incidents, we benchmark its effect against other covariates. Table IA.1 presents the results. We find that ESG incidents rank second in magnitude, following firm size (100%). Another notable variable is asset manager ownership (42%), followed by leverage (23%), Tobin's Q (16%), ROA (13%), market-to-book ratio (11%), and capital expenditure (10%). In contrast, variables such as cash holdings, sales growth, and institutional ownership have relatively modest effects (below 5%).

Columns (2) to (4) present subsample analyses by engagement type. The results show that incidents in each ESG category are positively associated with the likelihood of the corresponding type of engagement. Table IA.1 further demonstrates that each category of incidents has a non-trivial economic impact relative to other covariates. For instance, the economic significance of environmental and social incidents both rank second, following firm size. Although governance incidents have a somewhat smaller effect, ranking below firm size, leverage, and asset manager ownership, their magnitude still exceeds that of most covariates.

Since we estimate a cross-sectional regression, it is difficult to control for firm fixed effects, raising the concern that the results may be confounded by firm-specific unobserved factors. To address this concern, we conduct several robustness checks. First, we examine the dynamic effects of ESG incidents on engagement decisions. If engagements are triggered by ESG inci-

dents, their influence should be strongest shortly after the incidents and diminish over time. To test this, we regress the engagement indicator on the number of incidents occurring in each of the past twelve months. Figure 3 shows that the effect is strongest within three months of the incident and declines substantially after six months, consistent with our expectation. Second, we estimate a combined model in which each type of environmental, social, or governance engagement is regressed on all three categories of incidents. As shown in Table 4, engagements are primarily driven by incidents in the corresponding ESG category, although environmental incidents seem to have an especially strong effect on governance engagement. Together, these findings mitigate concerns that the results are driven by firm-specific omitted variables.

4 Engagement Motivation

This section examines the motivations behind engagement decisions. We begin by classifying ESG incidents based on their estimated financial impact to assess how the asset manager responds to incidents with differing financial consequences. We then conduct heterogeneity analyses to identify the cases in which the asset manager is more likely to engage.

4.1 Financial Impact of ESG Incidents

To test whether engagement is motivated solely by financial reasons or also by non-financial ones, we examine whether the asset manager responds to ESG incidents that lack observable negative financial consequences. If the engagement decision is driven solely by risk management considerations, we would expect the asset manager to respond only to incidents that pose financial risks. A response to incidents without measurable financial impact would instead suggest the presence of additional considerations beyond pure risk management.

To assess the financial impact of each incident, we compute the cumulative abnormal return (CAR) within a short window surrounding the event. Specifically, we first estimate the CAPM model using daily return data from the [-360, -60] calendar days before the incident date, requiring at least 105 return observations to ensure a reliable estimation. We then apply the estimated model to the [-1, +1] event window, calculate the daily abnormal returns, and aggregate them to obtain the CAR for each incident.[9]

[9]When the incident date does not fall on a trading day, we use the next calendar day as the event date, or the following one if necessary. The event window [1,+1] is defined as the trading days immediately before and after the event date, provided both fall within seven calendar days of the event date. We retain only those incidents for which the involved stock has a complete event window. Results based on CRSP daily returns are prioritized

With the above procedure, we are able to compute CARs for 164,651 out of 174,800 incidents (95%) involving the sample firms between 2007 and 2023. The average CAR is -0.08%, which is comparable to findings in related studies (Yun, 2024). We classify incidents into those with negative and non-negative CARs and regress the engagement decision on the numbers of these two kinds of incidents. Table 5 presents the results. The findings show that the asset manager responds not only to incidents with a negative financial impact but also to those that, at least based on market reaction, do not exhibit such an impact. This suggests that the engagement decisions are not solely driven by risk management and may also reflect non-financial reasons.

4.2 Firm Size and Media Exposure

In this section, we try to examine whether one specific non-financial motivation, the reputational concerns of the asset manager, drives engagement. If so, the asset manager should be more responsive to incidents at firms that are highly visible to the public, where potential reputational damage is greater. To test this hypothesis, we conduct heterogeneity analyses based on two proxies for firm visibility: firm size and media exposure. For media exposure, we use data on the number of ESG-related media reports referencing each firm provided in the FactSet Truvalue SASB Scores database. To mitigate concerns that article volume may be mechanically correlated with recent ESG incidents, we calculate the average number of annual articles for each firm from 2007 to 2022. We then interact the number of ESG incidents with each visibility proxy. We expect the interaction terms to be significantly positive.

Panel A of Table 6 presents the results for firm size. We find that the asset manager is indeed more likely to engage with larger firms following ESG incidents. Column (1) indicates that, conditional on the same number of ESG incidents, a one-standard-deviation increase in firm size (1.55) is associated with a 5-percentage-point higher probability of engagement. Columns (2) to (4) show that this pattern generally holds for environmental, social, and governance engagements, although the effect is not statistically significant for social ones. Notably, Derrien et al. (2024b) find that the negative impact of ESG incidents on firm value is more pronounced among smaller firms. This suggests that the observed heterogeneity is unlikely to be solely driven by differences in financial risk, but is instead more consistent with the reputational concern explanation.

Panel B reports results based on media exposure. Again, we find that the asset manager is more responsive to ESG incidents at firms with greater media exposure. Column (1) indicates

over those based on Compustat daily stock prices.

that, conditional on the same number of ESG incidents, a one-standard-deviation increase in the article number (1.73) is associated with a 5-percentage-point higher probability of engagement. Also, Columns (2) to (4) show that this pattern generally holds for environmental, social, and governance engagements, despite the insignificant effects for social engagements. Taken together, these heterogeneity results provide supporting evidence that reputational concerns are one motivation behind the asset manager's engagement decisions.

5 Supply Chain Incidents and Engagement Decisions

Recent research highlights the growing importance of supplier ESG performance for corporate customers. Customers have been shown to exert influence over their suppliers' ESG practices (Dai et al., 2021; Schiller, 2018). Moreover, ESG controversies involving suppliers can prompt customers to reduce purchases (Bisetti et al., 2024) or even terminate the relationship (Schiller, 2018). Such responses are justified by both academic and anecdotal evidence indicating that supplier ESG controversies can impose either financial or reputational costs on corporate customers (Lin et al., 2024).[10]

Current research implies that investors may play a role in shaping corporate customers' concerns over supply chain ESG performance. For example, Bisetti et al. (2024) find that customers reduce imports from suppliers involved in environmental or social (E&S) incidents, especially when their investor base is more likely to be E&S-conscious. This conclusion is based on measures such as customers' E&S ratings, customer ownership by E&S-sensitive institutional investors, and the presence of E&S-related shareholder proposals prior to the incident. However, there is still limited direct evidence on whether and through what channels investors, particularly institutional investors, actively influence such decisions. We leverage our unique dataset to examine the role of investor engagement. As a falsification test, we also investigate whether ESG incidents occurring at corporate customers trigger engagement toward suppliers and expect to find no such effects.

Panel A of Table 7 presents the results for supplier-related ESG incidents. Column (1) shows that the asset manager is indeed more likely to engage with a firm when there were more incidents at its suppliers. The effects exist after we control for firms' own incidents. Columns (2) to (4) suggest that the results are especially driven by environmental incidents. Panel B

[10]For example, Nike has faced criticism over labor rights violations within its supply chain. Reuters, 2024. Similarly, JBS, a Brazilian meatpacking company, has been publicly criticized for deforestation linked to its cattle supply chain. Reuters, 2020.

reports the results for customer-related incidents. Across all specifications, we find no evidence that ESG incidents involving customers influence the probability of engagement. Overall, these results indicate that ESG concerns arising within supply chains are taken seriously by the asset manager we study. They provide evidence that investors indeed play an important role in shaping corporate customers' concerns over supplier ESG performance and that engagement is one channel they exert influence. The absence of a response to customer-related incidents further supports the upstream ESG concerns along supply chains, as documented by Dai et al. (2021).

6 Engagement and Firm Value

In this section, we examine whether and how engagement improves firm value. While previous research documented various effects of engagement on firm financial performance, risk profiles, and ESG performance, but because the data sources are from different asset managers, it is not clear whether their conclusions hold in our data. More importantly, there remains limited knowledge of the channels through which engagement affects firm value. As such, we test the effects of engagement on firm value with our data and examine whether the effects come from an improved cash flow or a reduced discount rate.

$$\Delta Outcome_{i,t} = \beta_0 + \beta_1 \cdot Engagement_{i,t} + \boldsymbol{\beta}_2 \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t} \tag{2}$$

We estimate the above cross-sectional regression model to compare changes in firm outcomes between engaged and matched non-engaged firms following engagement. The sample includes each engagement observation along with its matched non-engaged counterparts, as described in Section 3.1. We retain only the first engagement record when a firm is engaged multiple times within the same month. The dependent variable is the change in various firm outcomes over different horizons after engagement, relative to their levels prior to engagement. The key independent variable is a dummy indicating whether the firm was engaged. Control variables and fixed effects are specified as in Equation (1) and detailed in Table 3. Standard errors are clustered at the industry-by-month level. Since prior research suggests that ESG incidents may adversely affect firm performance, we additionally include them as controls in the regression.

6.1 Buy-and-hold Abnormal Returns

To examine the effects of engagement on firm value, we analyze buy-and-hold abnormal returns (BHAR) following the engagement. We focus on long-term performance rather than conducting an event study around the engagement date for two reasons. First, many engagements could be conducted privately and may not be immediately observable to the market. Second, engagements typically involve a series of actions that take place over a long period of time. Therefore, their impact is more likely to be reflected in long-run stock performance.

$$BHAR[1M,\ TM]_{i,t} = \prod_{k=1}^{T}(1 + R_{i,t+k}) - \prod_{k=1}^{T}(1 + R_{m,t+k}) \tag{3}$$

BHAR is calculated as the compounded stock return over a given horizon minus the compounded market return over the same period, as shown in the equation above, where $R_{i,t}$ denotes the return of stock i in month t, and $R_{m,t}$ represents the market return in month t. In the regression analysis, we include lagged stock returns to control for momentum and reversal effects. By further controlling for a range of firm characteristics, we mitigate concerns that differences in stock performance between engaged and non-engaged firms are simply driven by the asset manager's propensity to engage with firms that are more or less likely to perform well.

Table 8 presents the regression results. After controlling for firm characteristics, past returns, and industry-by-month and country-by-month fixed effects, we find that engaged firms outperform non-engaged firms in the months following the engagement. The outperformance grows as we extend the time horizon and becomes statistically significant when the period reaches nine months. This pattern is consistent with the idea that it may take time for the market to learn engagement-related information or for the engagement itself to begin having an effect, especially since one engagement typically lasts for several months. The magnitude is also economically meaningful. Column (4) shows that engaged firms outperform non-engaged firms by 3.9 percentage points over the twelve months following engagement. Taken together, the results suggest that engagement is indeed associated with improved firm value.

6.2 ESG Performance

The improvement in firm value may result from either an increased cash flow or a reduced discount rate. Previous research suggests that enhanced ESG performance could be the underlying mechanism through which engagement leads to higher firm value, as it could be associated with both an increased cash flow and a reduced discount rate. For example, previous research

suggests that a better ESG performance could lead to a higher cash flow by increasing firm sales. This is because customers have been found to prefer products by firms with better ESG performance (Duan et al., 2024; Houston et al., 2024). ESG performance could also lower firm discount rate by attracting investors with sustainability preferences. This channel has been illustrated by both theoretical models (e.g., Pástor et al., 2021; Luo and Balvers, 2017) and empirical studies (e.g., Hong and Kacperczyk, 2009; Chava, 2014; Eskildsen et al., 2024).

To understand how engagement improves firm value, we first examine whether engagement leads to better ESG performance. We use external, perception-based ESG performance measures from the FactSet Truvalue SASB Scores dataset. These scores are constructed using machine learning and natural language processing techniques that analyze the semantic content of millions of third-party media articles related to firms' ESG practices. Compared to traditional ESG ratings from various data vendors, Truvalue offers higher-frequency measures that capture real-time changes in ESG performance. Its reliance on external media sources enhances objectivity, expands firm coverage, and avoids the well-documented inconsistencies across ESG ratings (Berg et al., 2022). In contrast to incident data from RepRisk, which primarily captures negative events, Truvalue incorporates both positive and negative ESG events, enabling a more comprehensive assessment of public discourse around a firm's ESG performance. This distinction is important because engagement may generate favorable media coverage that would be missed by negative-event-only datasets like RepRisk.

We focus on two ESG performance metrics provided by Truvalue. The first is the overall sentiment score, which reflects performance across all 26 ESG issues defined by SASB. The second is the material sentiment score, which captures performance on ESG issues identified by SASB as financially material for a firm's specific industry. Table 9 presents the results. Panel A reports the effect of engagement on overall sentiment, while Panel B shows the results for material sentiment. We find that engagement does not significantly affect overall sentiment but does lead to a significant improvement in material sentiment. For example, Column (8) shows that, twelve months after engagement, the material sentiment score for engaged firms increases by 2.2 percentage points more than for matched non-engaged firms. This suggests that engagement is particularly effective in improving ESG performance on financially material issues, supporting the idea that enhanced ESG performance is the channel through which engagement improves firm value.

6.3 Cash Flow vs. Discount Rate

We next examine whether the improvement in firm value stems from a higher cash flow or a lower discount rate. To assess the cash flow channel, we focus on firm sales. Table 10 shows that engaged firms experience stronger sales growth in the years following engagement. The effects are also economically meaningful. Columns (1) to (3) indicate that engaged firms exhibit sales growth that is 2.5, 4.6, and 6.3 percentage points higher than matched firms in the engagement year, the first year after engagement, and the second year after engagement, respectively. These correspond to 18%, 33%, and 45% of the sample mean of sales growth (14%). These findings suggest that part of the improvement in firm value following engagement may be driven by enhanced firm cash flows.

To assess the discount rate channel, we focus on firm implied cost of capital (ICC). Specifically, we analyze ICC measures calculated based on four different models: Gebhardt et al. (2001) (ICC_GLS), Claus and Thomas (2001) (ICC_CT), Easton (2004) (ICC_PEG), and Ohlson and Juettner-Nauroth (2005) (ICC_OJ). For each measure, we compare the percentage change in ICC for engaged firms over various post-engagement horizons, relative to matched non-engaged firms. Table 11 presents the results. Across all four ICC measures and time windows, we find no evidence that engagement leads to a greater reduction in ICC for engaged firms.

Although we find no direct evidence supporting the discount rate channel, we further examine whether engagement affects a firm's ownership base. Following Ilhan et al. (2023), we construct three measures of socially responsible institutional ownership. The first, *Universal Inst. Own.*, refers to ownership by universal investors, defined as those who hold the largest number of portfolio stocks (top 1% across all institutions at the end of a given quarter). Universal investors are considered socially responsible because their broad holdings make them more exposed to externalities, thereby giving them stronger incentives to internalize ESG risks. The second measure, *Stewardship Inst. Own*, captures ownership by institutions based in countries that passed any stewardship codes, which aim to promote responsible investing practices. The third, *High-Norm Inst. Own*, reflects ownership by institutions headquartered in countries with an above-median Environmental Performance Index score, used by Dyck et al. (2019) as a proxy for stronger environmental norms.

Table 12 presents the results. We find that engagement is associated with a greater increase in overall institutional ownership. According to Column (4), institutional ownership in

engaged firms rises by an additional 1.5 percentage points relative to non-engaged firms four quarters after engagement. We also observe a stronger increase in socially responsible ownership. For example, Column (8) shows that *Universal Inst.Own.* increases by 3 percentage points more for engaged firms, while Column (16) shows a 2-percentage-point greater increase in *High-NormInst. Own.* These findings indicate that engagement does attract more institutional investors, particularly those with a stronger focus on sustainability. However, the magnitude of these increases may not be sufficient to significantly reduce the firm's cost of capital. Taken together, the evidence suggests that improved cash flow, rather than a reduced discount rate, is the primary channel through which engagement enhances firm value.

7 Conclusion

This paper provides new evidence on the triggers and motivations of ESG engagement by institutional investors. Using a proprietary dataset of ESG engagements from a European asset manager, we show that both firms' own ESG incidents and those of their suppliers are key triggers for engagement. We further demonstrate that engagement decisions are shaped by both financial and non-financial considerations, with reputational concerns representing a key non-financial motivation. Finally, we show that engagement enhances firm value, primarily through improved cash flows, potentially driven by better ESG performance.

While prior research on ESG engagement has largely focused on its outcomes, our study contributes by examining the underlying motivations for institutional investor engagement. By documenting the spillover effects of supplier incidents, we add to the growing body of work highlighting the importance of supply chain ESG issues and provide new evidence on how investor pressure can shape firm behavior beyond a company's own operations. We also extend existing research on the consequences of ESG engagement by identifying the specific channels through which engagement enhances firm value.

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8 Figures

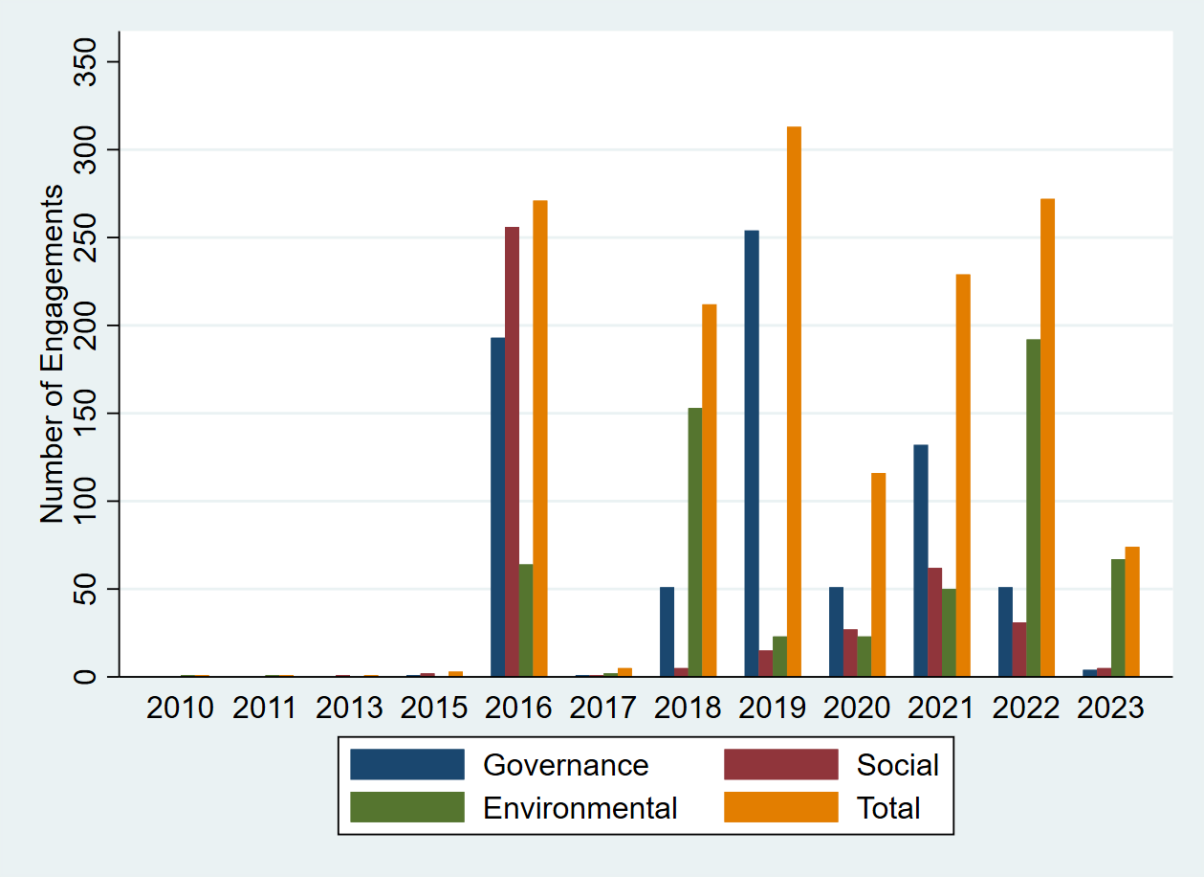
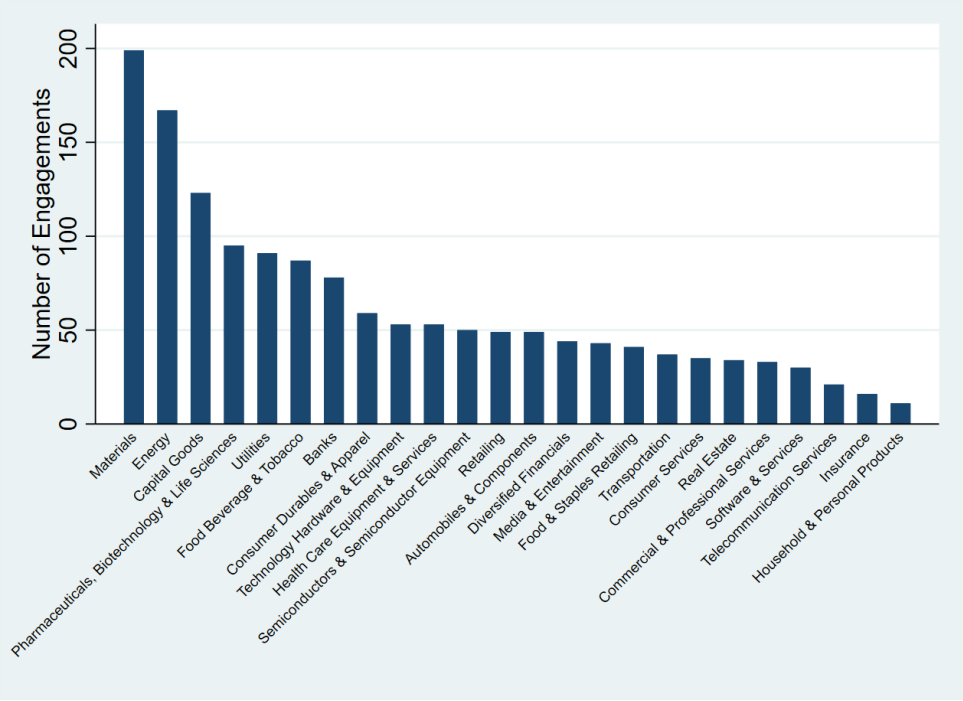
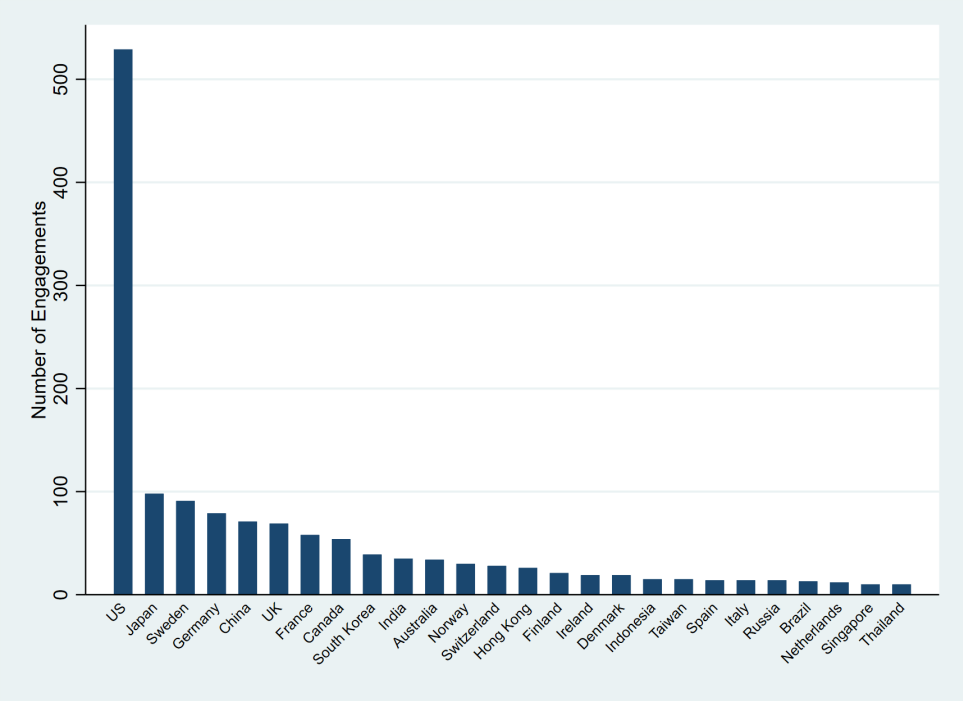


Figure 1: **Number of Engagements by Year.** This figure plots the number of engagement records initiated each year, disaggregated by environmental, social, and governance categories.



(a) **Number of Engagements by Industry (GICS2).**



(b) **Number of Engagements by Country or Region.**

Figure 2: **Number of Engagements by Industry and Country/Region.** Figure 2a shows the number of engagement records by GICS industry group. Figure 2b shows the number of engagement records by headquarters country or region, including only those with at least 10 engagements.

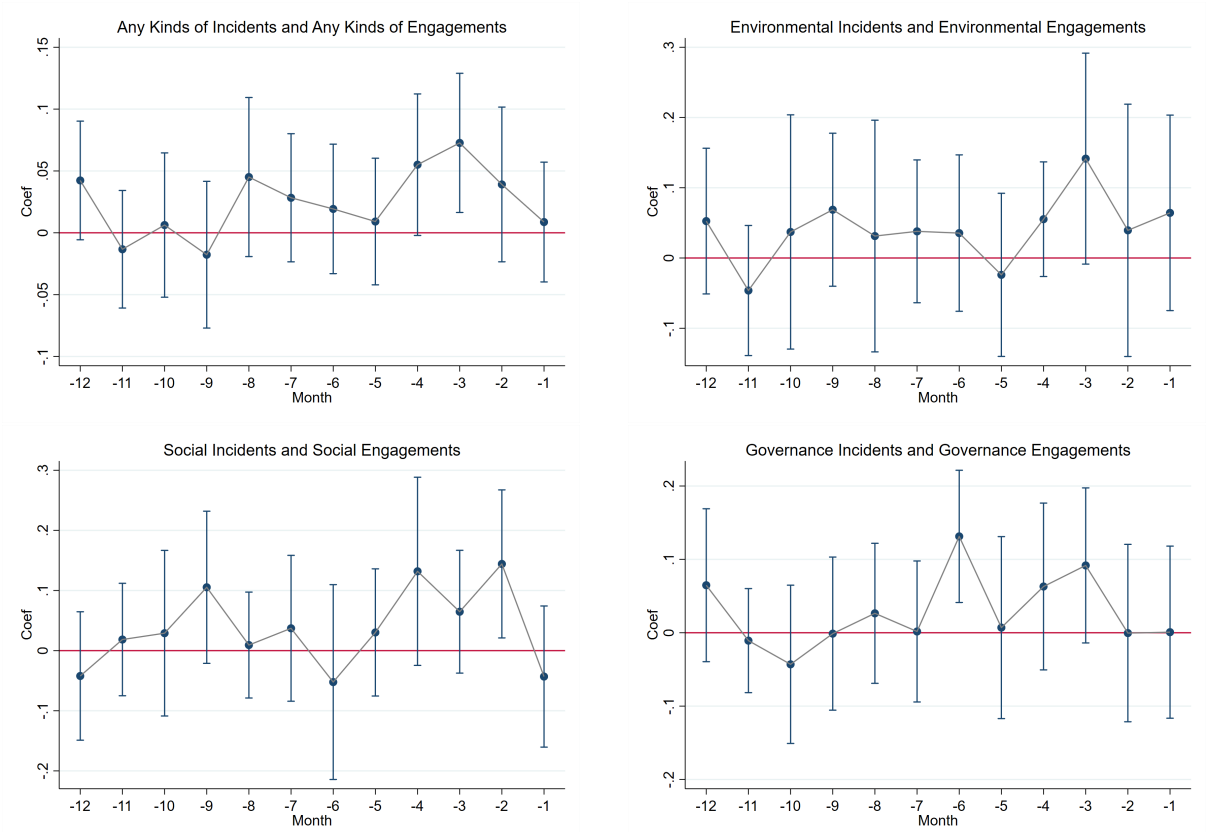


Figure 3: **ESG Incidents and Engagement Probability: Dynamic Effects.** This figure plots the point estimates of the coefficients β_1^k, where $k = -1, -2, \ldots, -12$, along with their 95% confidence intervals, from the following model: $Engagement_{i,t} = \beta_0 + \sum_{k=-12}^{-1} \beta_1^k \cdot Number\ of\ Incidents_{i,t+k} + \boldsymbol{\beta}_2 \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t}$. The dependent variable, $Engagement_{i,t}$, is a dummy equal to 1 if firm i was engaged in month t, and 0 otherwise. The key independent variables, $Number\ of\ Incidents_{i,t+k}$, are defined as the logarithm of one plus the number of ESG incidents in month $t+k$. $\boldsymbol{X}_{i,t-1}$ includes *Size*, *Market-to-Book Ratio*, *Tobin's Q*, *Sales Growth*, *ROA*, *Leverage*, *Cash Holdings*, and *Capital Expenditures* measured at the end of the last fiscal year, as well as *Institutional Ownership* and *Asset Manager Ownership* measured at the end of the last quarter, all relative to month t. Control variables are defined as in Table 3. The model includes industry-by-month fixed effects ($\lambda_{j,t}$) and country-by-month fixed effects ($\eta_{c,t}$). Standard errors are clustered at the industry-by-month level.

9 Tables

	count	mean	sd	p25	p50	p75	min	max
Internal	1,498	0.3965	0.49	0.00	0.00	1.00	0.00	1.00
Successful	1,498	0.3725	0.48	0.00	0.00	1.00	0.00	1.00
Number of Engagement Actions	1,498	1.4319	1.08	1.00	1.00	2.00	0.00	14.00
Months btw. Creation & Last Action	1,291	14.8544	20.84	0.00	3.00	20.00	0.00	117.00
Approach: Meeting	1,498	0.0247	0.16	0.00	0.00	0.00	0.00	1.00
Approach: Conference	1,498	0.0007	0.03	0.00	0.00	0.00	0.00	1.00
Approach: Site visit	1,498	0.0027	0.05	0.00	0.00	0.00	0.00	1.00
Approach: Phone call	1,498	0.0327	0.18	0.00	0.00	0.00	0.00	1.00
Approach: Letter	1,498	0.4713	0.50	0.00	0.00	1.00	0.00	1.00
Approach: E-mail	1,498	0.1248	0.33	0.00	0.00	0.00	0.00	1.00
Approach: Shareholder voting	1,498	0.0013	0.04	0.00	0.00	0.00	0.00	1.00
Approach: Digital meeting	1,498	0.2069	0.41	0.00	0.00	0.00	0.00	1.00
Approach: Shareholder resolution	1,498	0.0020	0.04	0.00	0.00	0.00	0.00	1.00
Approach: Other	1,498	0.2377	0.43	0.00	0.00	0.00	0.00	1.00
Contact: CEO	1,498	0.0234	0.15	0.00	0.00	0.00	0.00	1.00
Contact: CFO	1,498	0.0033	0.06	0.00	0.00	0.00	0.00	1.00
Contact: CSR	1,498	0.0053	0.07	0.00	0.00	0.00	0.00	1.00
Contact: IR	1,498	0.0327	0.18	0.00	0.00	0.00	0.00	1.00
Contact: Board	1,498	0.0033	0.06	0.00	0.00	0.00	0.00	1.00
Contact: Senior management	1,498	0.0040	0.06	0.00	0.00	0.00	0.00	1.00
Contact: Operational management	1,498	0.0007	0.03	0.00	0.00	0.00	0.00	1.00
Contact: Sustainability dept.	1,498	0.0100	0.10	0.00	0.00	0.00	0.00	1.00
Contact: Human Resources	1,498	0.0007	0.03	0.00	0.00	0.00	0.00	1.00
Contact: Corporate secretary	1,498	0.0020	0.04	0.00	0.00	0.00	0.00	1.00

Table 1: **Engagement Characteristics.** This table reports summary statistics of engagement characteristics.

Panel A: Key Regression Variables

	count	mean	sd	p25	p50	p75	min	max
Engagement	5,630	0.2144	0.41	0.00	0.00	0.00	0.00	1.00
Ln Own Incidents in [-3, -1]	5,630	0.4917	0.77	0.00	0.00	0.69	0.00	3.26
Ln Own E Incidents in [-3, -1]	5,630	0.2013	0.47	0.00	0.00	0.00	0.00	2.20
Ln Own S Incidents in [-3, -1]	5,630	0.2921	0.58	0.00	0.00	0.00	0.00	2.64
Ln Own G Incidents in [-3, -1]	5,630	0.2516	0.52	0.00	0.00	0.00	0.00	2.48
Ln Customer Incidents in [-3, -1]	2,947	1.5186	1.07	0.69	1.49	2.25	0.00	3.97
Ln Customer E Incidents in [-3, -1]	2,947	0.7974	0.86	0.00	0.62	1.27	0.00	3.74
Ln Customer S Incidents in [-3, -1]	2,947	1.0040	0.87	0.22	0.92	1.58	0.00	3.25
Ln Customer G Incidents in [-3, -1]	2,947	0.9321	0.81	0.18	0.79	1.46	0.00	2.94
Ln Supplier Incidents in [-3, -1]	2,482	1.3062	1.12	0.29	1.16	2.08	0.00	4.40
Ln Supplier E Incidents in [-3, -1]	2,482	0.6137	0.75	0.00	0.32	1.08	0.00	2.94
Ln Supplier S Incidents in [-3, -1]	2,482	0.8939	0.93	0.00	0.69	1.39	0.00	3.77
Ln Supplier G Incidents in [-3, -1]	2,482	0.8217	0.84	0.00	0.69	1.34	0.00	3.31
Size	5,630	8.9888	1.55	8.15	9.06	9.95	4.23	13.36
Market-to-book	5,630	4.9694	7.49	1.59	2.68	4.90	0.33	53.20
Tobin's Q	5,630	3.0190	3.14	1.32	1.89	3.34	0.59	18.73
Sales Growth	5,630	0.1400	0.28	0.01	0.08	0.19	-0.40	1.67
ROA	5,630	0.1278	0.08	0.08	0.12	0.16	-0.13	0.39
Leverage	5,630	0.3930	0.23	0.23	0.39	0.56	0.00	0.91
Cash Holding	5,630	0.1347	0.14	0.04	0.09	0.18	0.00	0.68
Capital Expenditure	5,630	0.0444	0.04	0.02	0.03	0.06	0.00	0.19
Institutional Own.	5,630	0.5917	0.30	0.32	0.66	0.86	0.03	1.00
Asset Manager Own.	5,630	0.0033	0.01	0.00	0.00	0.00	0.00	0.07
Ret in -1M	5,180	-0.0069	0.11	-0.07	-0.01	0.05	-0.51	0.85
Ret in [-12M, -1M]	5,098	0.0961	0.42	-0.17	0.03	0.26	-0.90	4.34
Ln Article Number	5,607	3.2928	1.73	2.06	3.27	4.45	0.00	7.67

Panel B: Engagement Outcomes

	count	mean	sd	p25	p50	p75	min	max
BHAR [1M, 3M]	5,155	-0.0004	0.16	-0.09	-0.01	0.08	-0.71	2.71
BHAR [1M, 6M]	5,110	0.0095	0.23	-0.12	-0.01	0.11	-0.86	3.11
BHAR [1M, 9M]	5,083	0.0043	0.28	-0.16	-0.02	0.14	-0.82	4.64
BHAR [1M, 12M]	4,898	0.0007	0.34	-0.20	-0.04	0.16	-1.20	5.33
ΔSales_0Y	5,450	0.1184	0.24	-0.00	0.07	0.18	-0.40	1.24
ΔSales_1Y	4,991	0.1969	0.40	-0.01	0.11	0.30	-0.65	2.08
ΔSales_2Y	3,961	0.2596	0.49	0.00	0.16	0.40	-0.63	2.87
ΔICC_GLS_3M	3,823	0.0167	0.16	-0.07	-0.00	0.09	-0.33	0.83
ΔICC_GLS_6M	3,470	0.0288	0.27	-0.11	0.00	0.12	-0.59	1.43
ΔICC_GLS_9M	3,089	0.0420	0.30	-0.12	0.01	0.15	-0.64	1.40
ΔICC_GLS_12M	3,001	0.0239	0.32	-0.15	-0.02	0.14	-0.67	1.42
ΔICC_PEG_3M	2,381	0.0092	0.20	-0.10	-0.01	0.10	-0.52	0.79
ΔICC_PEG_6M	2,177	0.0072	0.25	-0.15	-0.02	0.11	-0.53	0.90
ΔICC_PEG_9M	1,951	0.0088	0.28	-0.17	-0.02	0.15	-0.57	0.98
ΔICC_PEG_12M	1,861	-0.0075	0.29	-0.19	-0.03	0.12	-0.62	1.15
ΔICC_CT_3M	2,670	0.0256	0.27	-0.14	-0.01	0.15	-0.63	1.25
ΔICC_CT_6M	2,430	0.0330	0.38	-0.20	-0.03	0.18	-0.67	1.79
ΔICC_CT_9M	2,205	0.0466	0.44	-0.23	-0.00	0.21	-0.75	2.06
ΔICC_CT_12M	2,149	0.0430	0.49	-0.27	-0.02	0.23	-0.74	2.24
ΔICC_OJ_3M	2,254	0.0072	0.19	-0.10	-0.01	0.10	-0.44	0.64
ΔICC_OJ_6M	2,068	0.0181	0.27	-0.14	-0.01	0.14	-0.51	1.19
ΔICC_OJ_9M	1,858	0.0301	0.31	-0.17	-0.00	0.17	-0.59	1.37
ΔICC_OJ_12M	1,768	0.0310	0.36	-0.19	-0.00	0.16	-0.66	1.76
ΔInstitutional Own._1Q	4,843	0.0106	0.09	-0.02	0.01	0.04	-0.32	0.44
ΔInstitutional Own._2Q	4,698	0.0107	0.11	-0.03	0.01	0.04	-0.35	0.48
ΔInstitutional Own._3Q	4,289	0.0163	0.14	-0.03	0.01	0.05	-0.44	0.64
ΔInstitutional Own._4Q	4,126	0.0161	0.16	-0.04	0.01	0.06	-0.52	0.76
ΔUniversal Inst. Own._1Q	4,819	0.0353	0.17	-0.03	0.01	0.07	-0.41	1.09
ΔUniversal Inst. Own._2Q	4,679	0.0544	0.21	-0.03	0.03	0.10	-0.42	1.30
ΔUniversal Inst. Own._3Q	4,274	0.0860	0.28	-0.03	0.04	0.14	-0.53	1.80
ΔUniversal Inst. Own._4Q	4,113	0.0999	0.30	-0.02	0.06	0.16	-0.57	1.72
ΔStewardship Inst. Own._1Q	4,814	0.0870	0.36	-0.02	0.01	0.06	-0.43	2.53
ΔStewardship Inst. Own._2Q	4,669	0.1041	0.43	-0.02	0.02	0.08	-0.45	3.23
ΔStewardship Inst. Own._3Q	4,260	0.1676	0.68	-0.03	0.02	0.12	-0.58	5.38
ΔStewardship Inst. Own._4Q	4,101	1.8654	4.62	-0.02	0.04	0.50	-0.55	25.03
ΔHigh-Norm Inst. Own._1Q	4,843	0.0098	0.10	-0.02	0.01	0.04	-0.35	0.52
ΔHigh-Norm Inst. Own._2Q	4,698	0.0112	0.12	-0.03	0.01	0.04	-0.39	0.58
ΔHigh-Norm Inst. Own._3Q	4,289	0.0155	0.15	-0.03	0.01	0.05	-0.52	0.71
ΔHigh-Norm Inst. Own._4Q	4,126	0.0157	0.17	-0.04	0.01	0.06	-0.57	0.82
ΔOverall ESG Sentiment_3M	5,127	0.0050	0.08	-0.03	0.00	0.04	-0.20	0.29
ΔOverall ESG Sentiment_6M	5,088	0.0133	0.12	-0.04	0.01	0.06	-0.33	0.46
ΔOverall ESG Sentiment_9M	5,066	0.0205	0.14	-0.05	0.01	0.08	-0.37	0.61
ΔOverall ESG Sentiment_12M	5,040	0.0262	0.16	-0.06	0.01	0.10	-0.40	0.72
ΔMaterial ESG Sentiment_3M	5,046	0.0023	0.08	-0.04	0.00	0.04	-0.26	0.28
ΔMaterial ESG Sentiment_6M	5,007	0.0101	0.12	-0.05	0.00	0.06	-0.34	0.47
ΔMaterial ESG Sentiment_9M	4,986	0.0170	0.15	-0.06	0.01	0.08	-0.40	0.59
ΔMaterial ESG Sentiment_12M	4,960	0.0256	0.18	-0.07	0.01	0.09	-0.40	0.74

Table 2: **Summary Statistics.** This table reports summary statistics for the key regression variables and engagement outcomes. Please refer to Table 3 and the relevant regression tables for detailed variable definitions.

	Any Kinds	Environmental	Social	Governance
	(1)	(2)	(3)	(4)
Ln Own Incidents in [-3, -1]	0.135***			
	(0.016)			
Ln Own E Incidents in [-3, -1]		0.213***		
		(0.038)		
Ln Own S Incidents in [-3, -1]			0.195***	
			(0.043)	
Ln Own G Incidents in [-3, -1]				0.118***
				(0.028)
Size	0.135***	0.139***	0.143***	0.170***
	(0.011)	(0.018)	(0.021)	(0.015)
Market-to-book	0.003**	0.005	0.002	0.006**
	(0.002)	(0.004)	(0.003)	(0.002)
Tobin's Q	0.011**	-0.005	0.014	0.014**
	(0.005)	(0.010)	(0.010)	(0.006)
Sales Growth	-0.003	-0.025	-0.029	0.043
	(0.029)	(0.032)	(0.069)	(0.042)
ROA	0.342**	0.370	0.266	0.342**
	(0.165)	(0.283)	(0.244)	(0.170)
Leverage	-0.215***	-0.125*	-0.207*	-0.325***
	(0.051)	(0.069)	(0.121)	(0.068)
Cash Holding	0.031	0.012	0.135	0.107
	(0.054)	(0.097)	(0.101)	(0.073)
Capital Expenditure	0.548*	0.524	0.448	0.786**
	(0.323)	(0.625)	(0.541)	(0.343)
Institutional Own.	-0.012	0.041	-0.061	-0.015
	(0.043)	(0.057)	(0.090)	(0.068)
Asset Manager Own.	9.601***	9.815***	1.226	11.057***
	(1.198)	(2.318)	(2.082)	(1.435)
Industry × Month FE	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓
Observations	5,630	2,128	1,555	2,836
R^2	0.32	0.35	0.33	0.32

Table 3: **ESG Incidents and Engagement Probability: Main Results.** This table reports the effects of ESG incidents on engagement probability. The dependent variable is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own Incidents in [-3, -1]* is the logarithm of one plus the number of ESG incidents within the past three months. *Ln Own E Incidents in [-3, -1]*, *Ln Own S Incidents in [-3, -1]*, and *Ln Own G Incidents in [-3, -1]* are the logarithm of one plus the number of environmental, social, and governance incidents within the past three months, respectively. *Size* is defined as ln(1 + Total Assets (USD)). *Market-to-book* is market capitalization divided by total common equity. *Tobin's Q* is the sum of market capitalization and total debt, divided by the sum of total common equity and total debt, where total debt is the sum of debt in current liabilities and total long-term debt. *Sales Growth* is sales in year t over sales in year $t-1$. *ROA* is earnings before interest over total assets. *Leverage* is total debt over the sum of total debt and total common equity. *Cash Holding* is cash and short-term investments over total assets. *Capital Expenditures* is capital expenditures over total assets. *Institutional Own.* is institutional ownership. *Asset Manager Own.* is the ownership by the asset manager. Column (1) uses the full sample of engagements, regardless of category. Columns (2) focuses on environmental engagements, Columns (3) examines social engagements, and Columns (4) analyzes governance engagements. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

	Environmental	Social	Governance
	(1)	(2)	(3)
Ln Own E Incidents in [-3, -1]	0.206***	0.063	0.113**
	(0.050)	(0.086)	(0.053)
Ln Own S Incidents in [-3, -1]	-0.006	0.163***	0.051
	(0.041)	(0.057)	(0.037)
Ln Own G Incidents in [-3, -1]	0.029	-0.002	0.042
	(0.048)	(0.051)	(0.035)
Size	0.136***	0.141***	0.159***
	(0.021)	(0.024)	(0.016)
Market-to-book	0.005	0.002	0.005**
	(0.004)	(0.003)	(0.002)
Tobin's Q	-0.006	0.014	0.014**
	(0.010)	(0.010)	(0.006)
Sales Growth	-0.023	-0.026	0.049
	(0.032)	(0.072)	(0.043)
ROA	0.369	0.267	0.319*
	(0.283)	(0.248)	(0.177)
Leverage	-0.123*	-0.202	-0.300***
	(0.070)	(0.122)	(0.070)
Cash Holding	0.012	0.131	0.091
	(0.099)	(0.103)	(0.074)
Capital Expenditure	0.562	0.430	0.672*
	(0.659)	(0.562)	(0.382)
Institutional Own.	0.044	-0.062	0.003
	(0.057)	(0.089)	(0.065)
Asset Manager Own.	9.715***	1.188	10.996***
	(2.305)	(2.104)	(1.396)
Industry × Month FE	✓	✓	✓
Country × Month FE	✓	✓	✓
Observations	2,128	1,555	2,836
R^2	0.35	0.33	0.33

Table 4: **ESG Incidents and Engagement Probability: Combined Model.** This table reports the effects of ESG incidents on engagement probability using a combined model. The dependent variable is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own E Incidents in [-3, -1]*, *Ln Own S Incidents in [-3, -1]*, and *Ln Own G Incidents in [-3, -1]* are the logarithm of one plus the number of environmental, social, and governance incidents within the past three months, respectively. Control variables are defined as in Table 3. Column (1) focuses on environmental engagements, Column (2) examines social engagements, and Column (3) analyzes governance engagements. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

	Any Kinds	Environmental	Social	Governance
	(1)	(2)	(3)	(4)
Ln Own Incidents in [-3, -1] $^{CAR<0}$	0.111***			
	(0.022)			
Ln Own Incidents in [-3, -1] $^{CAR\geq 0}$	0.078***			
	(0.020)			
Ln Own E Incidents in [-3, -1] $^{CAR<0}$		0.192***		
		(0.032)		
Ln Own E Incidents in [-3, -1] $^{CAR\geq 0}$		0.120**		
		(0.057)		
Ln Own S Incidents in [-3, -1] $^{CAR<0}$			0.125**	
			(0.048)	
Ln Own S Incidents in [-3, -1] $^{CAR\geq 0}$			0.129**	
			(0.055)	
Ln Own G Incidents in [-3, -1] $^{CAR<0}$				0.058*
				(0.034)
Ln Own G Incidents in [-3, -1] $^{CAR\geq 0}$				0.116***
				(0.036)
Size	0.136***	0.144***	0.151***	0.171***
	(0.012)	(0.017)	(0.020)	(0.015)
Market-to-book	0.003**	0.005	0.002	0.006**
	(0.002)	(0.004)	(0.003)	(0.002)
Tobin's Q	0.011**	-0.005	0.014	0.014**
	(0.005)	(0.010)	(0.010)	(0.006)
Sales Growth	0.003	-0.021	-0.015	0.042
	(0.030)	(0.033)	(0.072)	(0.042)
ROA	0.335**	0.352	0.300	0.342**
	(0.167)	(0.287)	(0.257)	(0.169)
Leverage	-0.208***	-0.128*	-0.196	-0.317***
	(0.051)	(0.070)	(0.125)	(0.068)
Cash Holding	0.035	0.021	0.144	0.108
	(0.054)	(0.094)	(0.103)	(0.073)
Capital Expenditure	0.503	0.544	0.415	0.752**
	(0.328)	(0.629)	(0.563)	(0.341)
Institutional Own.	-0.008	0.037	-0.067	-0.012
	(0.043)	(0.059)	(0.089)	(0.067)
Asset Manager Own.	9.580***	9.989***	1.280	11.066***
	(1.189)	(2.281)	(2.078)	(1.433)
Industry × Month FE	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓
Observations	5,630	2,128	1,555	2,836
R^2	0.32	0.35	0.32	0.32

Table 5: **ESG Incidents and Engagement Probability: Financial Impact of ESG Incidents.** This table reports the effects of incidents with negative and non-negative CARs. The dependent variable is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. Ln Own Incidents in [-3, -1]$^{CAR<0}$ is the logarithm of one plus the number of ESG incidents with a negative CAR within the past three months. Ln Own Incidents in [-3, -1]$^{CAR\geq 0}$ is the logarithm of one plus the number of ESG incidents with a non-negative CAR within the past three months. Ln Own E Incidents in [-3, -1]$^{CAR<0}$, Ln Own E Incidents in [-3, -1]$^{CAR\geq 0}$, Ln Own S Incidents in [-3, -1]$^{CAR<0}$, Ln Own S Incidents in [-3, -1]$^{CAR\geq 0}$, Ln Own G Incidents in [-3, -1]$^{CAR<0}$, and Ln Own G Incidents in [-3, -1]$^{CAR\geq 0}$ are defined in the same way, restricted to environmental, social, or governance incidents, respectively. Control variables are defined as in Table 3. Column (1) uses the full sample of engagements, regardless of category. Column (2) focuses on environmental engagements, Column (3) examines social engagements, and Column (4) analyzes governance engagements. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

Panel A: Firm Size

	Any Kinds	Environmental	Social	Governance
	(1)	(2)	(3)	(4)
Ln Own Incidents in [-3, -1] × Size	0.034***			
	(0.007)			
Ln Own E Incidents in [-3, -1] × Size		0.060***		
		(0.016)		
Ln Own S Incidents in [-3, -1] × Size			0.028	
			(0.018)	
Ln Own G Incidents in [-3, -1] × Size				0.040***
				(0.013)
Industry × Month FE	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓
Control Variables	Yes	Yes	Yes	Yes
Observations	5,630	2,128	1,555	2,836
R^2	0.33	0.36	0.34	0.33

Panel B: Article Number

	Any Kinds	Environmental	Social	Governance
	(1)	(2)	(3)	(4)
Ln Own Incidents in [-3, -1] × Ln Article Number	0.027***			
	(0.006)			
Ln Own E Incidents in [-3, -1] × Ln Article Number		0.046***		
		(0.016)		
Ln Own S Incidents in [-3, -1] × Ln Article Number			0.016	
			(0.012)	
Ln Own G Incidents in [-3, -1] × Ln Article Number				0.037***
				(0.009)
Industry × Month FE	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓
Control Variables	Yes	Yes	Yes	Yes
Observations	5,607	2,125	1,549	2,822
R^2	0.33	0.36	0.35	0.33

Table 6: **ESG Incidents and Engagement Probability: Firm Size and Media Exposure.** This table reports the heterogeneous effects of ESG incidents on engagement probability across firm size and firm media exposure. The dependent variable is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own Incidents in [-3, -1]* is the logarithm of one plus the number of ESG incidents within the past three months. *Ln Own E Incidents in [-3, -1]*, *Ln Own S Incidents in [-3, -1]*, and *Ln Own G Incidents in [-3, -1]* are the logarithm of one plus the number of environmental, social, and governance incidents within the past three months, respectively. *Size* is defined as ln(1 + Total Assets (USD)). *Ln Article Number* is the logarithm of one plus the average number of ESG-related articles a firm received annually between 2007 and 2022. Control variables are defined as in Table 3. Column (1) uses the full sample of engagements, regardless of category. Column (2) focuses on environmental engagements, Column (3) examines social engagements, and Column (4) analyzes governance engagements. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

Panel A: Supplier Incidents

	Any Kinds	Environmental	Social	Governance
	(1)	(2)	(3)	(4)
Ln Supplier Incidents in [-3, -1]	0.028**			
	(0.012)			
Ln Supplier E Incidents in [-3, -1]		0.082***		
		(0.025)		
Ln Supplier S Incidents in [-3, -1]			-0.022	
			(0.031)	
Ln Supplier G Incidents in [-3, -1]				0.024
				(0.019)
Industry × Month FE	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓
Control Variables	Yes	Yes	Yes	Yes
Own Incidents	Yes	Yes	Yes	Yes
Observations	2,391	900	626	1,210
R^2	0.42	0.47	0.45	0.42

Panel B: Customer Incidents

	Any Kinds	Environmental	Social	Governance
	(1)	(2)	(3)	(4)
Ln Customer Incidents in [-3, -1]	0.003			
	(0.009)			
Ln Customer E Incidents in [-3, -1]		-0.011		
		(0.022)		
Ln Customer S Incidents in [-3, -1]			-0.021	
			(0.016)	
Ln Customer G Incidents in [-3, -1]				-0.007
				(0.016)
Industry × Month FE	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓
Control Variables	Yes	Yes	Yes	Yes
Own Incidents	Yes	Yes	Yes	Yes
Observations	2,875	1,177	750	1,358
R^2	0.40	0.43	0.38	0.38

Table 7: **Supply Chain Incidents and Engagement Probability.** This table reports the effects of supply chain ESG incidents on engagement probability. The dependent variable is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Supplier Incidents in [-3, -1]* is the logarithm of one plus the average number of ESG incidents involving a firm's suppliers over the past three months. *Ln Supplier E Incidents in [-3, -1]*, *Ln Supplier S Incidents in [-3, -1]*, and *Ln Supplier G Incidents in [-3, -1]* are the logarithm of one plus the average number of suppliers' environmental, social, and governance incidents within the past three months, respectively. *Ln Customer Incidents in [-3, -1]*, *Ln Customer E Incidents in [-3, -1]*, *Ln Customer S Incidents in [-3, -1]*, and *Ln Customer G Incidents in [-3, -1]* are the logarithm of one plus the average number of customers' ESG, environmental, social, and governance incidents within the past three months, respectively. Numbers of firm own incidents and control variables are defined as in Table 3. Column (1) uses the full sample of engagements, regardless of category. Column (2) focuses on environmental engagements, Column (3) examines social engagements, and Column (4) analyzes governance engagements. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

	(1) BHAR [1M, 3M]	(2) BHAR [1M, 6M]	(3) BHAR [1M, 9M]	(4) BHAR [1M, 12M]
Engagement	0.013	0.016	0.024*	0.039**
	(0.009)	(0.011)	(0.013)	(0.018)
Size	-0.010**	-0.004	-0.002	-0.014
	(0.004)	(0.006)	(0.009)	(0.010)
Market-to-book	0.001	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.003)
Tobin's Q	-0.002	0.001	-0.001	-0.001
	(0.003)	(0.004)	(0.004)	(0.005)
Sales Growth	-0.034*	-0.061***	-0.094***	-0.090***
	(0.019)	(0.020)	(0.021)	(0.026)
ROA	-0.138	-0.017	0.068	-0.005
	(0.103)	(0.122)	(0.142)	(0.191)
Leverage	-0.028	-0.031	-0.019	0.017
	(0.034)	(0.036)	(0.049)	(0.062)
Cash Holding	-0.048	-0.042	0.011	0.092
	(0.033)	(0.053)	(0.068)	(0.114)
Capital Expenditure	0.163	-0.122	-0.130	-0.099
	(0.147)	(0.187)	(0.214)	(0.273)
Institutional Own.	-0.012	-0.034	-0.060	-0.052
	(0.024)	(0.042)	(0.050)	(0.071)
Asset Manager Own.	-0.547	0.069	0.402	1.124
	(0.653)	(0.661)	(0.728)	(1.122)
Ret in -1M	0.049	0.071	0.072	-0.079
	(0.038)	(0.073)	(0.095)	(0.106)
Ret in [-12M, -1M]	-0.007	-0.005	-0.016	-0.053*
	(0.018)	(0.024)	(0.028)	(0.029)
Ln Own Incidents in [-3, -1]	0.009	0.008	0.004	0.011
	(0.009)	(0.011)	(0.012)	(0.012)
Industry × Month FE	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓
Observations	5,050	5,019	4,992	4,806
R^2	0.28	0.28	0.28	0.29

Table 8: **Engagement and Buy-and-hold Abnormal Returns.** This table reports the effects of ESG engagement on buy-and-hold abnormal returns (BHAR): $\textit{BHAR[1M, TM]}_{i,t} = \beta_0 + \beta_1 \cdot \textit{Engagement}_{i,t} + \boldsymbol{\beta_2} \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t}$. The sample includes each engagement observation and its matched non-engaged firms. The dependent variables are BHARs measured over different horizons following month t: $\textit{BHAR[1M, TM]}_{i,t} = \prod_{k=1}^{T}\left(1 + R_{i,t+k}\right) - \prod_{k=1}^{T}\left(1 + R_{m,t+k}\right)$, where $R_{i,t}$ is the return of stock i in month t, and $R_{m,t}$ is the market return in month t. *Engagement* is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own Incidents in [-3, -1]* is the logarithm of one plus the number of ESG incidents that occurred within the past three months. *Ret in -1M* is the stock return in the previous month. $\textit{Ret in [-12M, -1M]}_{i,t} = \prod_{k=-12}^{-1}\left(1 + R_{i,t+k}\right) - 1$. Other control variables are defined as in Table 3. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

	ΔOverall ESG Sentiment				ΔMaterial ESG Sentiment			
	(1) 3M	(2) 6M	(3) 9M	(4) 12M	(5) 3M	(6) 6M	(7) 9M	(8) 12M
Engagement	0.007*	0.007	0.007	0.010	0.015***	0.014*	0.016*	0.022*
	(0.004)	(0.006)	(0.007)	(0.009)	(0.005)	(0.008)	(0.009)	(0.011)
Size	-0.005**	-0.007**	-0.009**	-0.009*	-0.006*	-0.008*	-0.009*	-0.008
	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)	(0.006)
Market-to-book	-0.000	-0.001*	-0.001	-0.000	-0.001	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Tobin's Q	-0.000	0.000	-0.001	-0.002	0.000	0.000	-0.001	-0.003
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)
Sales Growth	-0.001	0.005	0.005	0.006	-0.005	0.002	0.006	0.004
	(0.009)	(0.010)	(0.012)	(0.014)	(0.009)	(0.009)	(0.013)	(0.020)
ROA	0.015	0.001	-0.035	-0.053	-0.014	-0.043	-0.021	0.001
	(0.027)	(0.055)	(0.076)	(0.089)	(0.029)	(0.044)	(0.064)	(0.080)
Leverage	-0.005	0.005	-0.023	-0.032	-0.007	-0.003	-0.007	0.006
	(0.014)	(0.018)	(0.023)	(0.028)	(0.014)	(0.021)	(0.028)	(0.034)
Cash Holding	0.005	-0.004	-0.025	-0.020	-0.020	-0.049	-0.039	-0.003
	(0.022)	(0.035)	(0.048)	(0.048)	(0.021)	(0.039)	(0.055)	(0.065)
Capital Expenditure	0.060	-0.021	-0.083	-0.079	-0.096	-0.192**	-0.203*	-0.109
	(0.062)	(0.069)	(0.088)	(0.118)	(0.060)	(0.091)	(0.108)	(0.132)
Institutional Own.	-0.001	-0.014	-0.015	-0.011	-0.003	-0.016	-0.030	-0.026
	(0.013)	(0.019)	(0.021)	(0.023)	(0.016)	(0.021)	(0.022)	(0.024)
Asset Manager Own.	0.365	0.737*	0.588	0.309	-0.325	-0.075	-0.125	-0.535
	(0.285)	(0.380)	(0.479)	(0.591)	(0.331)	(0.387)	(0.521)	(0.614)
Ln Own Incidents in [-3, -1]	0.002	0.003	0.001	-0.006	0.002	0.005	-0.001	-0.014*
	(0.003)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.008)
Industry × Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,106	5,067	5,046	5,020	5,020	4,981	4,961	4,935
R^2	0.16	0.16	0.17	0.17	0.16	0.17	0.16	0.16

Table 9: **Engagement and ESG Sentiment.** This table reports the effects of ESG engagement on ESG sentiment measures: $\Delta ESG\ Sentiment_{i,t}^{TM} = \beta_0 + \beta_1 \cdot Engagement_{i,t} + \boldsymbol{\beta_2} \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t}$. The sample includes each engagement observation and its matched non-engaged firms. The dependent variables in Columns (1), (2), (3), and (4) are the ratio changes in *Overall ESG Sentiment* at the end of months 3, 6, 9, and 12 following the engagement month, relative to its value at the end of the month prior to engagement: $\Delta Overall\ ESG\ Sentiment_t^{TM} = (Overall\ Insight\ Score_{i,t+T} - Overall\ Insight\ Score_{i,t-1})/Overall\ Insight\ Score_{i,t-1}$. The dependent variables in Columns (5), (6), (7), and (8) are the ratio changes in *Material ESG Sentiment*, calculated in the same way. The *Overall ESG Sentiment* and *Material ESG Sentiment* are *Insight* scores obtained from the FactSet Truvalue SASB Scores database. These scores are generated by analyzing the semantic content of external reports related to a firm's ESG issues, using machine learning and natural language processing techniques. Values range from 0 to 100, where 50 indicates neutral sentiment, and higher values reflect more positive sentiment. The *Overall ESG Sentiment* reflects all 26 ESG issues outlined by SASB, while the *Material ESG Sentiment* focuses only on ESG issues deemed financially material to the firm's industry by SASB. *Engagement* is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own Incidents in [-3, -1]* is the logarithm of one plus the number of ESG incidents within the past three months. Other control variables are defined as in Table 3. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

	(1) ΔSales_0Y	(2) ΔSales_1Y	(3) ΔSales_2Y
Engagement	0.025**	0.046**	0.063**
	(0.012)	(0.020)	(0.029)
Size	-0.019***	-0.044***	-0.056***
	(0.005)	(0.012)	(0.017)
Market-to-book	0.000	0.003	0.001
	(0.001)	(0.002)	(0.004)
Tobin's Q	0.010***	0.009	0.024***
	(0.003)	(0.006)	(0.009)
Sales Growth	0.208***	0.085	0.154*
	(0.030)	(0.058)	(0.078)
ROA	-0.685***	-1.176***	-1.013***
	(0.087)	(0.177)	(0.284)
Leverage	-0.049*	-0.190**	-0.206*
	(0.028)	(0.076)	(0.112)
Cash Holding	-0.055	-0.011	0.017
	(0.051)	(0.092)	(0.125)
Capital Expenditure	0.736***	0.927***	0.732
	(0.231)	(0.314)	(0.459)
Institutional Own.	-0.020	0.109*	0.126
	(0.043)	(0.059)	(0.091)
Asset Manager Own.	-0.732	-3.012***	-4.736***
	(0.662)	(0.948)	(1.605)
Ln Own Incidents in [-3, -1]	0.001	-0.004	-0.013
	(0.008)	(0.014)	(0.020)
Industry × Month FE	✓	✓	✓
Country × Month FE	✓	✓	✓
Observations	5,446	4,986	3,958
R^2	0.47	0.39	0.37

Table 10: **Engagement and Cash Flow.** This table reports the effects of ESG engagement on cash flow measures: $\Delta Cash\ Flow_{i,t}^{TY} = \beta_0 + \beta_1 \cdot Engagement_{i,t} + \boldsymbol{\beta_2} \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t}$. The sample includes each engagement observation and its matched non-engaged firms. The dependent variables in Columns (1), (2), and (3) are the ratio changes in *Sales* at the end of years 0, 1, and 2 following the engagement year, relative to its absolute value at the end of the previous year: $\Delta Sales_{i,t}^{TY} = (Sales_{i,t+T} - Sales_{i,t-1})/|Sales_{i,t-1}|$. *Engagement* is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own Incidents in [-3, -1]* is the logarithm of one plus the number of ESG incidents within the past three months. Other control variables are defined as in Table 3. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

	ΔICC_GLS				ΔICC_PEG				ΔICC_CT				ΔICC_OJ			
	(1) 3M	(2) 6M	(3) 9M	(4) 12M	(5) 3M	(6) 6M	(7) 9M	(8) 12M	(9) 3M	(10) 6M	(11) 9M	(12) 12M	(13) 3M	(14) 6M	(15) 9M	(16) 12M
Engagement	-0.009	-0.014	-0.021	-0.002	-0.010	-0.010	-0.000	0.019	-0.018	-0.031	0.007	0.030	-0.015	-0.003	0.007	0.025
	(0.009)	(0.017)	(0.021)	(0.025)	(0.017)	(0.022)	(0.022)	(0.024)	(0.018)	(0.030)	(0.034)	(0.038)	(0.015)	(0.022)	(0.022)	(0.025)
Size	-0.005	-0.003	-0.018*	-0.012	-0.006	-0.006	0.001	-0.013	-0.001	0.042**	0.027	0.008	-0.006	0.020	0.015	0.011
	(0.006)	(0.009)	(0.009)	(0.010)	(0.013)	(0.014)	(0.012)	(0.015)	(0.015)	(0.021)	(0.026)	(0.026)	(0.011)	(0.014)	(0.019)	(0.017)
Market-to-book	-0.000	-0.000	-0.002	-0.001	-0.001	-0.001	-0.001	-0.002	0.001	-0.000	-0.000	-0.002	-0.000	-0.001	-0.002	-0.002
	(0.001)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Tobin's Q	0.010***	0.013**	0.019***	0.018**	0.004	0.010	0.002	0.006	0.006	0.006	0.008	0.016	0.003	0.011*	0.006	0.010
	(0.003)	(0.006)	(0.007)	(0.008)	(0.003)	(0.007)	(0.005)	(0.006)	(0.005)	(0.009)	(0.009)	(0.010)	(0.003)	(0.007)	(0.007)	(0.008)
Sales Growth	0.031*	0.058	0.147***	0.169***	0.040	-0.114*	-0.070	-0.099	0.009	-0.002	-0.020	-0.089	0.080	-0.097*	-0.068	-0.129
	(0.018)	(0.046)	(0.047)	(0.048)	(0.060)	(0.060)	(0.066)	(0.082)	(0.040)	(0.066)	(0.089)	(0.114)	(0.059)	(0.058)	(0.078)	(0.111)
ROA	-0.156	-0.172	-0.449**	-0.478***	-0.272	-0.522**	-0.476**	-0.495*	-0.563*	-0.496	-0.728**	-0.941***	-0.247	-0.559**	-0.645**	-0.762**
	(0.095)	(0.145)	(0.193)	(0.178)	(0.165)	(0.256)	(0.240)	(0.258)	(0.298)	(0.313)	(0.289)	(0.305)	(0.155)	(0.281)	(0.263)	(0.298)
Leverage	0.100	0.135	0.060	0.035	0.059	0.018	-0.022	-0.007	-0.008	-0.071	-0.146	-0.072	0.033	0.034	-0.004	-0.022
	(0.063)	(0.090)	(0.061)	(0.072)	(0.036)	(0.053)	(0.073)	(0.066)	(0.051)	(0.091)	(0.091)	(0.098)	(0.039)	(0.076)	(0.079)	(0.078)
Cash Holding	0.029	0.071	-0.025	-0.046	-0.042	-0.050	0.004	0.010	0.003	0.083	0.091	0.136	-0.048	-0.005	0.068	0.071
	(0.054)	(0.096)	(0.077)	(0.080)	(0.060)	(0.081)	(0.077)	(0.086)	(0.067)	(0.110)	(0.118)	(0.134)	(0.056)	(0.097)	(0.099)	(0.124)
Capital Expenditure	0.048	-0.382	-0.301	-0.319	0.384	0.334	0.756*	0.451	0.426	0.194	-0.178	0.246	0.313	0.251	0.712	0.481
	(0.149)	(0.276)	(0.278)	(0.241)	(0.300)	(0.384)	(0.419)	(0.414)	(0.380)	(0.478)	(0.545)	(0.503)	(0.253)	(0.422)	(0.466)	(0.515)
Institutional Own.	0.026	0.023	-0.061	-0.017	0.031	0.094	0.147**	0.139	0.084	0.159**	0.090	0.001	0.035	0.057	0.087	0.118
	(0.026)	(0.046)	(0.058)	(0.050)	(0.057)	(0.080)	(0.064)	(0.092)	(0.062)	(0.072)	(0.076)	(0.096)	(0.052)	(0.075)	(0.064)	(0.097)
Asset Manager Own.	-0.175	-0.367	0.855	0.626	-1.348	-1.354	-2.007	-1.401	0.142	-1.463	-1.377	-0.610	-0.104	-1.103	-1.499	-0.039
	(0.724)	(1.046)	(1.141)	(1.299)	(1.213)	(1.574)	(1.913)	(2.302)	(1.544)	(2.291)	(2.982)	(3.620)	(1.123)	(1.775)	(2.138)	(2.484)
Ln Own Incidents in [-3, -1]	0.014	0.021	0.035*	0.030	0.022	0.019	0.016	0.017	0.022	-0.011	-0.014	-0.010	0.025	-0.010	-0.014	-0.017
	(0.010)	(0.018)	(0.021)	(0.024)	(0.020)	(0.024)	(0.022)	(0.025)	(0.016)	(0.024)	(0.025)	(0.027)	(0.017)	(0.025)	(0.027)	(0.031)
Industry × Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,770	3,418	3,042	2,954	2,310	2,109	1,888	1,796	2,593	2,354	2,131	2,080	2,185	2,001	1,791	1,701
R^2	0.41	0.31	0.37	0.39	0.36	0.34	0.39	0.39	0.45	0.42	0.46	0.46	0.42	0.35	0.40	0.40

Table 11: **Engagement and ICC.** This table reports the effects of ESG engagement on firm implied cost of capital (ICC): $\Delta ICC_{i,t}^{TM} = \beta_0 + \beta_1 \cdot Engagement_{i,t} + \boldsymbol{\beta_2} \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t}$. The sample includes each engagement observation and its matched non-engaged firms. The dependent variables in Columns (1), (2), (3), (4) are the ratio changes in *ICC_GLS* in months 3, 6, 9, and 12 following the engagement month, relative to its value in the month prior to engagement: $\Delta ICC_GLS_t^{TM} = (ICC_GLS_{i,t+T} - ICC_GLS_{i,t-1})/ICC_GLS_{i,t-1}$. The dependent variables in Columns (5), (6), (7), and (8) are the ratio changes in *ICC_PEG*. The dependent variables in Columns (9), (10), (11), and (12) are the ratio changes in *ICC_PEG*. The dependent variables in Columns (13), (14), (15), and (16) are the ratio changes in *ICC_OJ*. *ICC_GLS*, *ICC_CT*, *ICC_PEG*, and *ICC_OJ* are ICC measures calculated using four commonly used models: Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005), respectively. *Engagement* is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own Incidents in [-3, -1]* is the logarithm of one plus the number of ESG incidents within the past three months. Other control variables are defined as in Table 3. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

	ΔInstitutional Own.				ΔUniversal Inst. Own.				ΔStewardship Inst. Own.				ΔHigh-Norm Inst. Own.			
	(1) 1Q	(2) 2Q	(3) 3Q	(4) 4Q	(5) 1Q	(6) 2Q	(7) 3Q	(8) 4Q	(9) 1Q	(10) 2Q	(11) 3Q	(12) 4Q	(13) 1Q	(14) 2Q	(15) 3Q	(16) 4Q
Engagement	0.005	0.007	0.014**	0.015*	0.007	0.006	0.031*	0.028**	-0.004	0.005	-0.002	0.203	0.009**	0.013**	0.019**	0.019*
	(0.004)	(0.005)	(0.006)	(0.009)	(0.010)	(0.011)	(0.016)	(0.014)	(0.012)	(0.016)	(0.023)	(0.216)	(0.004)	(0.005)	(0.008)	(0.010)
Size	-0.005*	-0.000	0.001	-0.002	-0.012**	-0.015**	-0.028***	-0.026**	-0.030***	-0.045***	-0.086***	-0.488**	-0.007**	-0.005	-0.006	-0.008
	(0.003)	(0.003)	(0.005)	(0.006)	(0.005)	(0.006)	(0.010)	(0.011)	(0.008)	(0.012)	(0.023)	(0.190)	(0.003)	(0.004)	(0.006)	(0.007)
Market-to-book	-0.001	-0.001	-0.001	-0.002*	-0.001	-0.002*	-0.003*	-0.003**	-0.000	-0.001	-0.003	-0.038	-0.001	-0.001	-0.002*	-0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.025)	(0.000)	(0.001)	(0.001)	(0.001)
Tobin's Q	0.001	0.002*	0.003	0.003	0.005**	0.005**	0.005	0.006	-0.001	-0.002	-0.003	-0.037	0.002*	0.002	0.004	0.005
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.065)	(0.001)	(0.002)	(0.003)	(0.003)
Sales Growth	-0.009	-0.011	-0.010	-0.013	-0.056***	-0.062***	-0.051	-0.061	-0.025	-0.034	-0.087	0.604	-0.015	-0.013	-0.014	-0.018
	(0.008)	(0.010)	(0.016)	(0.019)	(0.018)	(0.022)	(0.036)	(0.041)	(0.022)	(0.026)	(0.053)	(0.369)	(0.009)	(0.011)	(0.018)	(0.020)
ROA	-0.017	-0.048	0.016	0.073	-0.004	-0.019	-0.000	0.059	-0.100	-0.202	-0.194	-0.499	-0.021	-0.054	0.008	0.056
	(0.032)	(0.035)	(0.049)	(0.052)	(0.054)	(0.068)	(0.101)	(0.104)	(0.095)	(0.136)	(0.184)	(1.309)	(0.035)	(0.040)	(0.052)	(0.062)
Leverage	0.009	-0.004	0.010	0.018	0.045**	0.056*	0.075	0.083*	0.041*	0.088**	0.210***	0.723	0.005	-0.001	0.017	0.030
	(0.010)	(0.013)	(0.018)	(0.025)	(0.020)	(0.031)	(0.048)	(0.046)	(0.025)	(0.040)	(0.066)	(0.469)	(0.011)	(0.013)	(0.020)	(0.025)
Cash Holding	0.004	-0.006	0.028	0.032	-0.046	-0.056	-0.066	-0.086	-0.016	-0.049	-0.058	-1.792	-0.016	-0.019	-0.015	-0.013
	(0.016)	(0.020)	(0.028)	(0.032)	(0.032)	(0.040)	(0.048)	(0.060)	(0.056)	(0.057)	(0.090)	(1.118)	(0.022)	(0.027)	(0.042)	(0.045)
Capital Expenditure	-0.106	-0.182**	-0.265**	-0.221**	-0.295**	-0.329*	-0.597***	-0.536***	0.159	0.184	0.165	-0.237	-0.119*	-0.145**	-0.299***	-0.189
	(0.066)	(0.074)	(0.116)	(0.105)	(0.121)	(0.167)	(0.202)	(0.198)	(0.251)	(0.323)	(0.407)	(1.705)	(0.064)	(0.072)	(0.108)	(0.115)
Institutional Own.	-0.076***	-0.095***	-0.141***	-0.163***	-0.093***	-0.123***	-0.171***	-0.162***	-0.184***	-0.261***	-0.431***	-1.358	-0.067***	-0.089***	-0.121***	-0.147***
	(0.017)	(0.023)	(0.034)	(0.035)	(0.029)	(0.037)	(0.047)	(0.048)	(0.058)	(0.077)	(0.135)	(0.935)	(0.019)	(0.025)	(0.035)	(0.037)
Asset Manager Own.	-0.545*	-0.796**	-1.025**	-0.987	-0.580	-1.231	-2.939**	-3.807*	2.222	2.710	4.361	4.160	-0.720**	-1.108***	-1.391**	-1.320*
	(0.299)	(0.329)	(0.493)	(0.636)	(0.669)	(1.018)	(1.461)	(2.017)	(1.596)	(2.065)	(2.896)	(8.497)	(0.311)	(0.357)	(0.540)	(0.688)
Ln Own Incidents in [-3, -1]	0.002	0.001	-0.002	-0.007	0.002	0.006	0.007	-0.001	0.011	0.015*	0.039**	0.051	0.002	0.002	0.001	-0.004
	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.009)	(0.009)	(0.007)	(0.009)	(0.017)	(0.140)	(0.004)	(0.004)	(0.006)	(0.006)
Industry × Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country × Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,842	4,697	4,288	4,124	4,818	4,678	4,273	4,111	4,813	4,668	4,259	4,099	4,842	4,697	4,288	4,124
R^2	0.21	0.20	0.21	0.24	0.27	0.23	0.26	0.26	0.61	0.57	0.56	0.78	0.21	0.21	0.21	0.23

Table 12: **Engagement and Institutional Ownership.** This table reports the effects of ESG engagement on institutional and socially responsible institutional ownership: $\Delta Ownership_{i,t}^{TQ} = \beta_0 + \beta_1 \cdot Engagement_{i,t} + \boldsymbol{\beta_2} \cdot \boldsymbol{X}_{i,t-1} + \lambda_{j,t} + \eta_{c,t} + \varepsilon_{i,t}$. The sample includes each engagement observation and its matched non-engaged firms. The dependent variables in Columns (1), (2), (3), (4) are the ratio changes in *Institutional Own.* at the end of quarters 1, 2, 3, and 4 following the engagement quarter, relative to its value at the end of the quarter prior to engagement: $\Delta Institutional\ Own._t^{TQ} = (Institutional\ Own._{i,t+T} - Institutional\ Own._{i,t-1})/Institutional\ Own._{i,t-1}$. The dependent variables in Columns (5), (6), (7), and (8) are the ratio changes in *Universal Inst. Own.* The dependent variables in Columns (9), (10), (11), and (12) are the ratio changes in *Stewardship Inst. Own.*. The dependent variables in Columns (13), (14), (15), and (16) are the ratio changes in *High-Norm Inst. Own. Universal Inst. Own.* refers to ownership by investors whose portfolios include the largest number of stocks (top 1% across all institutions at the end of a given quarter). *Stewardship Inst. Own* is the ownership by institutions based in countries that passed any stewardship codes. *High-Norm Inst. Own* is the ownership by institutions headquartered in countries with an above-median Environmental Performance Index score. *Engagement* is a dummy that equals 1 if a firm was engaged in a given month and 0 otherwise. *Ln Own Incidents in [-3, -1]* is the logarithm of one plus the number of ESG incidents within the past three months. Other control variables are defined as in Table 3. Standard errors clustered at the industry-by-month level are reported in parentheses. * p<.10; ** p<.05; *** p<.01.

A Summary Statistics of the Engagement Data

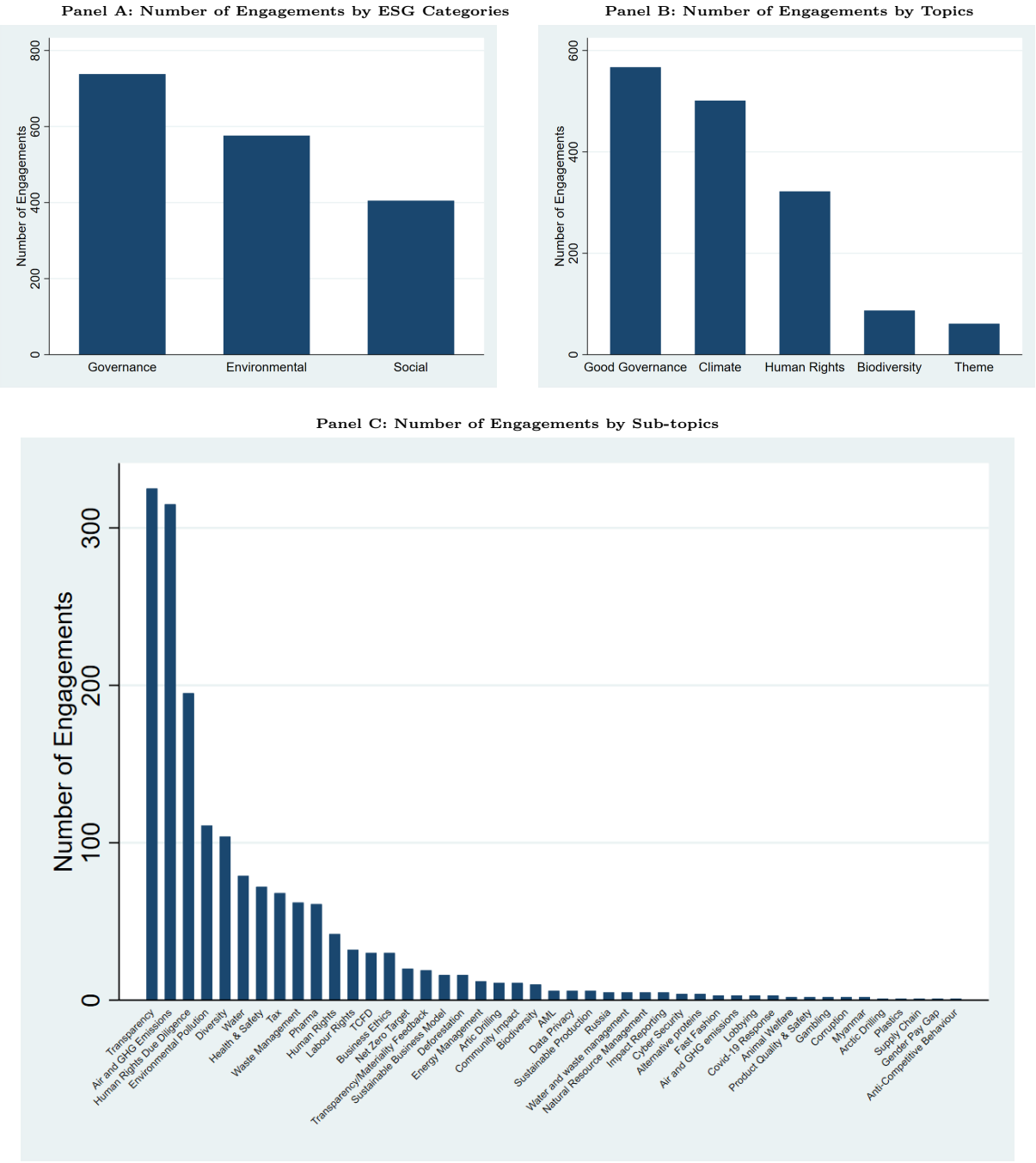


Figure IA.1: **Number of Engagements by ESG Categories, Topics, and Sub-topics.** This figure plots the number of engagement records by the ESG categories, topics, and sub-topics recorded for each engagement.

B Economic Significance of Main Results

	Any Kinds	Environmental	Social	Governance
	(1)	(2)	(3)	(4)
Ln Own Incidents in [-3, -1]	48.39%			
Ln Own E Incidents in [-3, -1]		46.98%		
Ln Own S Incidents in [-3, -1]			53.21%	
Ln Own G Incidents in [-3, -1]				28.95%
Size	97.65%	100.55%	103.44%	122.97%
Market-to-book	10.50%	17.49%	7.00%	20.99%
Tobin's Q	16.13%	-7.33%	20.53%	20.53%
Sales Growth	-0.39%	-3.24%	-3.75%	5.57%
ROA	12.67%	13.71%	9.86%	12.67%
Leverage	-22.91%	-13.32%	-22.05%	-34.63%
Cash Holding	2.07%	0.80%	9.02%	7.15%
Capital Expenditure	9.60%	9.18%	7.85%	13.77%
Institutional Own.	-1.67%	5.71%	-8.49%	-2.09%
Asset Manager Own.	41.68%	42.61%	5.32%	48.00%

Table IA.1: **ESG Incidents and Engagement Probability: Economic Significance.** The table reports the economic significance of each variable, based on the estimates from Table 3. Economic significance is calculated as the estimated coefficient multiplied by the standard deviation of the variable, divided by the mean value of engagement.