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Carbon Offsets: Decarbonization or Transition-Washing?

Finance Working Paper N° 1122/2025
July 2026

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ECGI Working Paper Series in Finance

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Abstract

Using rich hand-collected data, we examine how firms use carbon offset credits issued by third-party developers to claim emission reductions. Guided by a conceptual framework, we show that following an exogenous ESG rating downgrade, firms facing greater internal abatement costs, including those with lower emissions, retire more carbon offsets rather than decarbonize in-house. Firms that lack climate-related governance mechanisms or face limited external scrutiny of climate claims strategically retire larger quantities of low-quality, inexpensive offsets. Our findings are consistent with offsets being used to outsource transition efforts as well as with the strategic use of offsets for “transition-washing” purposes.

Keywords: Carbon Offsets, Carbon Transition, Climate Change, ESG Ratings, Greenhouse Gas Emissions, Greenwashing, Transition-Washing, Voluntary Carbon Markets

JEL Classifications: D22, G15, G18, G23, G24, G30, M14

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Journal of Finance forthcoming

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Abstract

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The transition to a carbon-neutral economy has become a global policy objective that transcends national boundaries. This movement has exposed companies around the world to carbon-transition risk (see Bolton and Kacperczyk, 2025), prompting firms to commit to reducing their carbon emissions. So far, however, corporate efforts to directly reduce their emissions have fallen short of achieving near-term decarbonization (see Aldy et al., 2023; Bolton and Kacperczyk, 2023). To balance the near-term viability of businesses with their long-term net-zero transitions, carbon offsetting has emerged as a tool that enables firms to claim emission reductions achieved by other entities by purchasing and retiring carbon offset credits. Yet, despite its growing popularity, skepticism remains about the effectiveness and integrity of carbon offset projects in delivering genuine emission reductions, and little is known about how firms actually use carbon offsets.[1]

In this paper, we provide, to the best of our knowledge, the first systematic evidence characterizing why companies worldwide use carbon offsets. We assemble a novel hand-collected dataset from four major carbon registries containing detailed information on which entities retire carbon credits to offset their greenhouse gas emissions, how many credits they retire each year, and the projects from which those credits originate. We manually match these entities to publicly listed firms in the Compustat North America and Global universes. Using this dataset, we first offer a comprehensive overview of the global carbon offset market and then exploit a quasi-natural experiment, guided by a conceptual framework, to examine the incentives of publicly listed firms to use carbon offsets.

We document a diverse ecosystem of more than 3,300 carbon offset projects, including those that generate renewable energy, promote energy-efficient housing and appliances, and preserve forests and grassland. These projects are geographically dispersed, with the majority based in Asia, Africa, North America, and South America. Over 1,800 projects issue carbon credits that are purchased and retired by publicly listed firms worldwide, and 17% of them have an external rating verifying their quality, provided by one of the leading offset quality raters, BeZero Carbon. We find that publicly listed firms tend to rely more on larger, externally rated projects located in North America.

[1] In May 2024, the U.S. government announced a joint statement of policy and principles to govern the use of voluntary carbon offsets, aiming to boost confidence in this fast-growing market.

To understand firms' incentives to use carbon offsets, we consider a simple conceptual framework where firms minimize the sum of abatement costs, offsetting costs, and reputation costs of failing to mitigate emissions. Importantly, the reputation costs consist of two components: (i) costs of underperformance with respect to *perceived* unmitigated emissions, and (ii) costs associated with underinvesting in offset quality. Guided by this framework, we empirically test two main hypotheses. First, the "outsourcing hypothesis" posits that firms facing greater internal abatement costs, including those with smaller carbon footprints, use offsets more intensively to reduce their carbon emissions indirectly rather than abate their own emissions directly. Second, the "transition-washing hypothesis" posits that firms lacking governance mechanisms to monitor the credibility of their climate claims, such as board-level sustainability oversight or external regulatory pressure, strategically use cheap, low-quality offsets. Throughout the paper, we test whether firms use more carbon offsets or reduce their direct emissions, and whether they use high- or low-quality offsets when their incentives to improve ESG ratings increase, depending on their abatement costs and climate-governance mechanisms.

Several aggregate patterns provide preliminary support for our hypotheses. Consistent with the outsourcing hypothesis, we find that low-emission industries such as services and financials are highly intensive in their use of offsets relative to their modest emissions, nearly offsetting their direct emissions on a one-for-one basis. By contrast, in high-emission industries such as oil and gas, utilities, and transportation, the aggregate share of emissions offset with carbon credits is close to zero. Global aggregate trends in direct carbon emissions and offset retirements exhibit a similar pattern. Despite the rapid growth of the carbon offset market in recent years, aggregate offset retirements are still dwarfed by direct emissions. The market has also become more active in the United States, even though non-U.S. firms are far more emission-intensive.

Consistent with the transition-washing hypothesis, we find that relatively few offset projects are externally verified as high quality, and that most offset credits used by firms are strikingly cheap. To investigate whether carbon offsets serve as an effective and credible mechanism for firms' net-zero transitions, we utilize project ratings from BeZero Carbon, a leading carbon offset rating agency. BeZero employs more than 80 analysts—including climate and data scientists, geospatial experts, and financial market analysts—who collect project-level data from verified project information, extensive developer engagement, in-house geospatial tools, and peer-reviewed scientific studies. These analysts apply proprietary, sector-specific machine-learning models and manual reviews to evaluate risks to a project's climate claims. Each offset project is then assigned a letter rating similar to credit ratings issued by major agencies such as S&P or Moody's, with ratings of BBB and above (BB and below) denoting relatively high (low) quality.[2] Combining these ratings with proprietary offset pricing data, we show that low-quality credits trade at substantially lower prices. On average, publicly listed firms in our sample use low-quality offsets (below BBB rating) that are also cheaper, with 70% of retired offsets priced below $4. Interestingly, we find that internal abatement is, on average, forty times more costly than the average offset and an order of magnitude more costly than even high-quality offsets.

To formally test our hypotheses, we begin by examining cross-sectional relationships between firms' decarbonization strategies (i.e., offset usage, direct abatement, and offset quality) and proxies for abatement costs and climate governance. Consistent with the outsourcing hypothesis, firms facing higher abatement costs or operating fewer abatement projects rely more on offsets and engage in less direct abatement, with economically and statistically significant effects. In line with the transition-washing hypothesis, firms with weaker governance—those lacking a board ESG committee, board-level climate authority, or managerial climate incentives—also retire more offsets and abate less, and importantly, are significantly less likely to use high-quality, rated offsets.

To facilitate a causal interpretation of these tests, we exploit an exogenous change in companies' ESG ratings triggered by a sharp methodology revision at a leading ESG rating agency, Sustainalytics. Its widely used firm-level ESG scores underlie Morningstar's portfolio-level sustainability ratings and low-carbon designations that are heavily relied upon by mutual fund investors (see Hartzmark and Sussman, 2019; Ceccarelli et al., 2024).[3] At the end of 2018, Sustainalytics adopted a new methodology for computing these scores,

[2]Unlike issuer-paid credit ratings, which are often subject to conflicts of interest and ratings inflation (see, e.g., Becker and Milbourn, 2011; Bolton et al., 2012; Cornaggia and Cornaggia, 2013; Griffin et al., 2013), carbon ratings are typically sold via subscription to prospective buyers seeking high-quality offsets, mitigating concerns about inflated ratings due to conflicts of interest between rating agencies and project developers.

[3]Further demonstrating the prominence of Sustainalytics as an ESG rating provider, numerous studies use its ESG scores as a primary measure of firms' ESG performance (see, e.g., Berg et al., 2024, 2022; Ceccarelli et al., 2024; Christensen et al., 2022; Kim and Yoon, 2023; Rzeźnik et al., 2025; Serafeim and Yoon, 2023).

leading to an average reshuffling of within-industry ESG ranks by 20 percentiles. Following this "Sustainalytics shock," downgraded firms experienced a decline in institutional and ESG fund ownership, an increase in ESG reputation risk, more negative analyst ratings, and lower stock returns within two quarters. We also find that after the methodology change, ESG peer rankings became more sensitive to firms emission intensity. These developments likely served as an emissions salience shock, incentivizing downgraded firms to take actions aimed at improving their ESG ratings by reducing their perceived residual emissions.[4]

We then examine how firms adjust their use of carbon offsets in response to this rating shock. On average, firms offset a greater share of their emissions after experiencing an exogenous ESG rating downgrade. Subsample analyses further help delineate the economic mechanisms underlying this result. First, consistent with the outsourcing hypothesis, we find that firms facing high internal abatement costs tend to respond to an exogenous ESG ranking downgrade by relying more heavily on carbon offsets instead of reducing emissions directly. For these firms, the average downgraded company offsets an additional 41-57% of its direct emissions as of 2018, relative to non-downgraded peers. In contrast, those with lower abatement costs tend to decarbonize by reducing their own emissions directly.

Second, we show that firms tend to use more offsets after being downgraded if they lack internal climate-governance mechanisms. The effects are economically significant: among firms without board-level ESG oversight, for example, the average downgraded firm offsets an additional 16-18% of its direct emissions as of 2018, relative to non-downgraded firms. Moreover, conditional on using offsets, such firms become no more likely to use rated, high-quality offsets. Given the generally low quality of average carbon offset projects, this suggests that poorly governed firms strategically rely on cheaper, questionable offsets to boost their ESG rankings. These findings are consistent with the transition-washing hypothesis.

Also consistent with this hypothesis, we find that firms in industries with limited external scrutiny of climate claims, such as consumer-facing and service-oriented sectors, significantly increase their offset usage but do not improve offset quality. This suggests that in some sectors, offsets serve as a marketing tool to appeal to environmentally conscious consumers who cannot easily verify offset quality. In contrast, heavy emitters in highly scrutinized and regu-

[4]Although the Sustainalytics methodology change applied across all ESG pillars, our carbon-specific outcome variables are unlikely to be driven by social- or governance-related responses to the shock.

lated industries, such as fossil fuel and industrial sectors, do not increase offset use following a downgrade but become more likely to use high-quality offsets and reduce emissions directly. This pattern contradicts common criticism of heavy emitters and aligns with recent evidence that these firms actively pursue meaningful green innovation (see Cohen et al., 2025). Finally, firms in peer groups with a narrow emission gap between heavy and light emitters, where modest reductions can enhance perceived greenness, also tend to use more offsets.

Consistent with firms optimizing their decarbonization strategies to manage reputation costs after ESG rating downgrades, we find that those relying on low-quality offsets experience recoveries in both ESG ratings and institutional ownership—effects that are qualitatively similar to downgraded firms that abate emissions directly (but absent in firms that adopt neither strategy). Overall, our evidence suggests that firms may exploit carbon offsets as a cheap and convenient means to meet transition goals and enhance their within-industry ESG rankings.

Our study provides the first comprehensive characterization of corporate incentives in voluntary carbon offset markets worldwide. While a growing body of research examines corporate behavior and performance in compliance carbon markets, such as emissions trading systems (see Bartram et al., 2022; Ivanov et al., 2024; Chen, 2024; Bolton et al., 2025; Boeckx et al., 2025; Akey et al., 2025), much less is known about how firms interact with rapidly growing voluntary carbon markets (VCMs). VCMs are generally segmented from compliance markets and represent a novel component of firms' decarbonization strategies. Recent studies show that investors care about the biodiversity impacts of forestry carbon offsets, although offset projects on average do not benefit local biodiversity (see Allen et al., 2025; Zhou and Almond, 2025). Chua and She (2025) show that investors value firms' use of high-quality offsets. Berg et al. (2025) show that the transaction prices of voluntary offset credits exhibit wide systematic variation according to data from a single VCM broker-dealer. Our study fills a major gap by providing the first comprehensive analysis of firms' incentives and offset choices.

More generally, our findings shed light on how companies might cope with carbon-transition risk using various decarbonization strategies. Despite calls for net-zero transition, there is widespread criticism that carbon-heavy firms remain slow to respond (see Aldy et al., 2023; Bolton and Kacperczyk, 2025, 2023). Various frictions may affect firms' incentives or capacity to decarbonize, such as their immutable business models or financial constraints (see Bartram et al., 2022). Given these frictions, carbon offsets have been proposed as a tool to allow firms to reduce their emissions indirectly until they can take costlier steps to reduce their emissions directly. However, carbon offsets have also been scrutinized due to fraudulent or "poor quality" offset projects that generate carbon credits with questionable or unverifiable climate claims.[5] While our results partially support such skepticisms that call for improved credibility in corporate transition efforts, we further provide a holistic framework on how factors such as abatement costs, governance, and stakeholder demands can influence corporate decarbonization decisions.

Our study also contributes to the broader literature on sustainable investors and corporate policies. On the one hand, several recent studies indicate that investors care about climate risk (see Krüger et al., 2020; Bolton and Kacperczyk, 2021; Ilhan et al., 2021; Hsu et al., 2023; Seltzer et al., 2025), and that socially responsible investors are effective in changing firm behavior (see Andrikogiannopoulou et al., 2025; Dyck et al., 2019; Azar et al., 2021; Naaraayanan et al., 2021). However, there is also growing evidence of greenwashing and other distorted incentives by investors and firms (see Duchin et al., 2025; Griffin and Kruger, 2024). Several studies show that sustainable investors often do not follow through with their commitments (see Gibson et al., 2022; Liang et al., 2022; Heath et al., 2023; Kim and Yoon, 2023), or that they use ineffective strategies that fail to have meaningful impact (see Heinkel et al., 2001; Atta-Darkua et al., 2025; Hartzmark and Shue, 2023). Greenwashing has also been shown to be prevalent among ESG rating agencies (see Berg et al., 2021; Tang et al., 2025; Li et al., 2024) or in corporate syndicated lending (see Giannetti et al., 2025; Kim et al., 2025; Kacperczyk and Peydró, 2022). Adding to this literature, our findings suggest that pressure from investors and other stakeholders may push poorly governed firms to "window-dress" their emissions by using low-quality carbon offsets.

Finally, our study has important implications for policymakers and investors.[6] First, our framework highlights the importance of transparency and scrutiny around the quality of offsets, in line with increasingly standardized climate disclosure requirements.[7] Furthermore,

[5]See "The great cash-for-carbon hustle," The New Yorker (October 2023), or "Carbon credit market confidence ebbs as big names retreat," Reuters (September 2023).

[6]See "COP30: Momentum grows behind carbon markets as a climate solution", Reuters (November 2025).

[7]The European Union (EU) and the U.S. Securities and Exchange Commission (SEC) have recently passed rules requiring firms to disclose the total amount of retired offsets and the cost of retired offsets, respectively,

our findings underscore the importance of climate governance, highlighting a potential role for proactive and discerning investors as external monitors (see Hoepner et al., 2024; Li et al., 2023; Edmans et al., 2024).

I. Carbon Offsets and Voluntary Carbon Markets

A carbon offset, or carbon credit, is a transferrable financial instrument through which a buyer pays an issuer or a seller to implement an activity that reduces one metric ton of carbon dioxide equivalent (CO2e) emissions. By retiring the purchased credit, the buyer can count this reduction toward their own mitigation goals. Offsets enable organizations and individuals to compensate for their emissions by funding mitigation projects elsewhere, and are promoted as a way for high-emission firms to support the transition to a carbon-neutral economy. The Taskforce on Scaling Voluntary Carbon Markets projects that demand for offsets will increase 15-fold by 2030 and 100-fold by 2050, while Morgan Stanley estimates the voluntary market will reach about $100 billion by 2030 and $250 billion by 2050.[8]

Unlike carbon allowances, which are typically auctioned by regulatory authorities in limited quantities and subsequently traded on compliance markets such as the EU Emissions Trading System (EU ETS), voluntary carbon offsets operate without centralized, widely adopted regulatory standards governing how credits are generated, sold, or used.[9] Instead, market participants rely on an ecosystem of third-party organizations, including carbon offset registries, validation and verification bodies (VVBs) such as auditors, and project rating agencies to ensure the quality and credibility of offset projects, as well as brokers and private marketplaces/exchanges that facilitate the flow of carbon credits.

when these are material to investors (or other stakeholders in the case of the EU). However, the SEC has stopped short of mandating disclosures of the underlying offset projects or the associated developers. In May 2024, the U.S. government released a Joint Statement of Policy and new Principles for Responsible Participation in Voluntary Carbon Markets, calling for improved offset market standards and disclosures regarding offset usage. See Section I. for more details.

[8]For details, see the Taskforce on Scaling Voluntary Carbon Markets Final Report (2021) and "Where the carbon offset market is poised to surge," Morgan Stanley (April 2023).

[9]Voluntary and compliance carbon markets are largely segmented. Generally, voluntary offsets cannot be used to meet compliance standards, with few exceptions in small fractions, typically at the early stages of some compliance markets or for hard-to-abate sectors.

Figure 1 provides a simplified illustration of the carbon offset market ecosystem. Offset credits are generated by a variety of projects that prevent or remove emissions, such as those related to energy efficiency enhancements, renewable energy (e.g., solar, wind, hydro, geothermal, or biomass/biofuel), forest preservation or afforestation, organic waste management (e.g., combustion and storage of methane gas from landfills or livestock), treatment of ozone-depleting substances from industrial processes, and carbon capture and storage. These projects are implemented by developers who expect their primary source of revenue to come from the sale of carbon credits.

[Insert Figure 1 here]

Carbon offset registries, developed by governmental, non-profit, or private entities, track offset projects and verify and certify each credit issued by a registered project. They assign a serial number to every verified offset credit and "retire" the number once the credit is claimed by its owner to offset emissions, ensuring that the credit cannot be resold or reused. There are four major offset registries: the American Carbon Registry (ACR), Gold Standard (Gold), Climate Action Reserve (CAR), and Verra's Verified Carbon Standard (VCS). Each registry sets its own standards outlining the minimum requirements for eligible projects, methodologies for measuring emission reductions and credits, and credit transaction mechanisms.

Despite the role of registries in setting minimum standards, critics often note that offset projects vary widely in quality, particularly regarding the accuracy of estimated emission reductions. To enhance transparency regarding the quality of offset credits, carbon offset rating agencies, such as BeZero Carbon, Sylvera, and Calyx, assess and assign ratings to individual projects. These agencies typically operate on a subscription-based model targeting prospective carbon credit investors. The rating process generally involves assessing a project's "additionality" (i.e., the project would not have occurred without the expected sale of carbon credits), the methodology used to quantify expected emission reductions, the risk of leakage (i.e., seemingly reduced emissions might be displaced elsewhere), and the permanence of the project's impact.

In spite of the complex ecosystem of players attempting to fill the vacuum of commonly accepted rules and regulations, the general public remains skeptical about the authenticity of climate claims made by many offset projects and the purchasers of these credits. Market participants, companies in particular, have been accused of "greenwashing" for promoting their use of carbon offsets.[10] These concerns are heightened by the opacity of the carbon market, as most firms do not disclose which offsets they use or the prices paid, keeping stakeholders in the dark about the quality of their offsetting claims.

Regulators have taken notice of this criticism. The U.S. Commodity Futures Trading Commission (CFTC) created a task force to detect fraud in carbon markets in 2023, and subsequently approved final guidance in September 2024 regarding the listing of voluntary carbon credit derivative contracts.[11] In July 2023, the EU adopted sustainability reporting standards that require firms to disclose the total amount of retired offsets and related data unless climate change is immaterial. Similarly, in March 2024, the SEC adopted climate disclosure rules mandating firms to report offset-related expenditures when they are material to investors. In May 2024, the U.S. government released a Joint Statement of Policy and new Principles for Responsible Participation in Voluntary Carbon Markets, calling for stronger standards and disclosure of offset usage.[12]

II. Conceptual Framework

In this section, we develop a simple conceptual framework to motivate our hypotheses on firms' decisions to use carbon offsets. Facing demand from investors and other stakeholders to lower their carbon footprints (e.g., Krüger et al., 2020), firms are assumed to have two primary decarbonization policy choices: investing in innovative abatement technologies to reduce emissions directly or purchasing and retiring carbon offsets to reduce emissions

[10] Recent scientific research shows that offset credits from forest preservation projects, which are among the most commonly used by companies, often do not represent genuine carbon reductions (see West et al., 2020; Guizar-Coutiño et al., 2022; West et al., 2023). There is also skepticism about the additionality of offsets generated from wind farms (see Calel et al., 2025).

[11] In October 2024, the CFTC charged a carbon credit developer and several former officers with fraud for inflating the number of offsets issued for its projects. See https://www.cftc.gov/PressRoom/PressReleases/8969-24 for details.

[12] As of September 2025, several of these developments have been reversed or scaled back (e.g., the CFTC withdrew its Guidance Regarding Listing Voluntary Carbon Credit Derivative Contracts, the EU reduced offset disclosure requirements under its sustainability reporting standards, and the SEC's climate disclosure rules were suspended indefinitely), weakening incentives for firms to disclose details of their offset usage.

indirectly, together with a related decision concerning the quality or credibility of the offsets they use. We conjecture that two key frictions influence how firms make these decarbonization choices. The first arises from differences between the marginal costs of internal abatement and those of purchasing carbon offsets.[13] The second stems from informational opacity in the voluntary carbon market, discussed in Section I., where offset quality is not perfectly observable to external stakeholders and firms are not required to disclose either offset quality or purchase prices. A stylized framework illustrates how these frictions jointly shape firms' decarbonization policies.

In this framework, a representative firm optimizes its decarbonization strategy by choosing the level of direct abatement, a, the amount of carbon offsets, o, and the quality of those offsets, q, to minimize the following cost function, given an exogenous emission level, e:[14]

$$\text{argmin}_{a,o,q}\, C(a;e) + P(q)\cdot o + \lambda \cdot \phi(R) + f(G;q), \tag{1}$$

in which $a \in [0,e]$, $o \in [0,e]$, and $q \in [0,1]$, with $q = 0$ and $q = 1$ representing the lowest and highest quality, respectively. $C(a;e)$ denotes the cost of investing in abatement processes to reduce the firm's direct emissions. Abatement costs rise with the level of abatement ($C_a > 0$), and the last ton of carbon is increasingly costly to abate, such that the marginal abatement cost is higher for greater abatement levels ($C_{a,a} > 0$). By the same token, firms with lower emissions face greater marginal abatement costs than heavy emitters for a given level of abatement ($C_{a,e} < 0$).

$P(q)\cdot o$ denotes the cost of purchasing carbon offsets, where $P(q)$ is the unit price of an offset as a function of its quality. Higher-quality offsets are costlier ($P_q > 0$), a relationship we confirm empirically in Figure 2 and discuss in Section III.

$\lambda \cdot \phi(R)$ denotes the reputation cost imposed by uninformed investors and other stakeholders who penalize firms based on their *perceived* unmitigated emissions, $R = e - a - o$, which are reflected in ESG ratings widely followed by institutional investors.[15] We note that

[13] This is evidenced by Anglo American plc's 2023 sustainability report, which states: "In conjunction with technology research, we will consider carbon offsets for the residual Scope 1 emissions. This will depend on the trade-off between the economic viability of new technology... and the opportunities for carbon offsets."

[14] In Internet Appendix Section IA.I, we present a stylized framework based on specific functional forms.

[15] Through interviews with Sustainalytics, we confirm that their ESG ratings do not scrutinize firms' offset claims beyond publicly disclosed information.

perceived emissions generally differ from *true* emissions, which are given by $\hat{R} = e - a - q \cdot o$. The penalty function, ϕ, is increasing and convex in R ($\phi_R > 0$ and $\phi_{R,R} > 0$), the latter of which captures amplified reputation damage from higher *perceived* residual emissions.[16] λ is a penalty multiplier that scales reputational salience and thereby boosts decarbonization incentives. For example, a higher λ can represent an exogenous ESG rating change that highlights the firm's carbon footprint more saliently than before. Variation in λ serves as a theoretical counterpart for our empirical identification strategy using the Sustainalytics methodology change, which we discuss in Section B.[17]

$f(G; q)$ denotes penalties for using low-quality offsets, imposed by informed stakeholders, including shareholders and regulators who recognize that R differs from *true* residual emissions. G is a parameter that captures governance mechanisms that help discern offset quality, including internal mechanisms related to board-level ESG oversight (e.g., whether the board has a sustainability/ESG committee or the firm has climate-conscious policies) and external monitoring (e.g., stakeholder or regulatory scrutiny). Lower-quality offsets are penalized more ($f_q < 0$), and firms with stronger governance face higher penalties ($f_G > 0$). Moreover, we assume that stronger governance raises the marginal cost of low-quality offsets ($f_{q,G} < 0$), so the benefit of raising q is higher under stronger governance. Together, $\lambda \cdot \phi(R)$ and $f(G; q)$ describe how firms balance the "cost of perceived emission underpeformance" and the "cost of underinvesting in offset quality." The joint first order conditions with respect to the key choice variables, a, o, and q, that characterize interior

[16]Convexity implies that each additional unit of emissions attracts disproportionately more scrutiny. This means that small residual emissions may be tolerated by stakeholders (e.g., investors, customers, and regulators), but the damage to a firm's ESG rating or reputation escalates nonlinearly as R grows because it signals a greater deviation from sustainability goals or peer benchmarks.

[17]Several firms in our sample prominently highlight their Sustainalytics ESG ratings. For example, in its 2021 annual report, Novo Nordisk states: "Sustainalytics' ESG Risk Ratings score the ESG performance of more than 12,000 companies, from 'negligible' to 'severe'. Novo Nordisk ranked among the top 10% in the Industry Group 'Pharmaceuticals', with a ranking of 94 out of 1028 based on those companies reviewed." In its 2023 sustainability report, Anglo American plc similarly notes: "Sustainalytics: our overall ESG ranking improved in 2023, entrenching the company as a strong ESG performer among our international peers in the precious metals sector." However, unlike offset raters, Sustainalytics does not specialize in assessing carbon offset quality.

solutions can be written as follows. For ease of exposition, we focus on interior solutions and verify that all conditions ensuring an interior minimum are intuitively satisfied.

$$(a) : \ C_a = \lambda \cdot \phi_R \tag{2}$$

$$(o) : \ P(q) = \lambda \cdot \phi_R \tag{3}$$

$$(q) : \ P_q \cdot o = -f_q \tag{4}$$

These equations yield several intuitive implications. First, from equations (2) and (3), we obtain $C_a = P(q)$. Intuitively, both abatement and offsets reduce R by one unit, so firms use more of the cheaper option until marginal costs equalize. In other words, firms with high marginal abatement costs (C_a is higher for all a) rely more on offsets, reducing C_a until it equals $P(q)$. Likewise, low-emission firms, which face higher marginal abatement costs ($C_{a,e} < 0$), depend more on offsets for the same reason. This discussion leads to the following *"outsourcing"* hypothesis.

Hypothesis 1. *Firms with higher marginal abatement costs use more carbon offsets and engage in less direct abatement than those facing lower marginal costs.*

Second, equation (4) implies that optimal offset quality increases with governance strength, G. This is because stronger governance steepens the penalty for low-quality offsets ($f_{q,G} < 0$), thereby pushing q upward as firms invest in higher-quality, costlier offsets. In addition, for a given G, using more offsets induces firms to lower quality, because the unit price rises with q ($P_q > 0$). Therefore, conditional on using offsets, the quantity and quality of offsets are inversely related. Hence, firms with weaker governance use more, but lower-quality offsets, motivating the following *"transition-washing"* hypothesis.

Hypothesis 2. *Firms with weaker governance use more, but lower-quality offsets, and engage in less direct abatement.*

Third, equations (2) and (3) imply that when a firm's ESG rating is downgraded due to a methodology change that makes emissions more salient (i.e., λ increases), ϕ_R must fall, prompting the firm to reduce its perceived residual emissions, R. This occurs through increased abatement (a) or offsets (o), with the mix tilting toward the cheaper option until $C_a = P(q)$. This means that firms with higher abatement costs, including low-emission firms, will rely more on offsets after an ESG rating downgrade. Firms with weaker governance will also use more, lower-quality offsets rather than engage in costly abatement. The discussion motivates the following hypothesis.

Hypothesis 3. *Following an ESG rating downgrade, firms with higher (lower) marginal abatement costs increase their use of offsets (abatement). Firms with weaker (stronger) governance increase their use of lower-quality offsets (abatement).*

Finally, when λ increases, the firm mitigates the rise in the penalty, $\lambda \cdot \phi(R)$, by adjusting a and o to lower R. Hence, following an exogenous ESG rating downgrade that raises λ, the firm's ESG ranking and institutional ownership recover as it re-optimizes its decarbonization strategy to lower $\phi(R)$. As offset quality does not influence perceived residual emissions, R, the recovery occurs even as the firm uses low-quality offsets.

Hypothesis 4. *After an ESG rating downgrade, a firm's ESG ranking and institutional ownership recover when it responds by using (low-quality) offsets or by abating emissions.*

Our framework also has broader implications for voluntary carbon markets. It suggests that carbon offsets may not be utilized effectively by the heaviest emitters, therefore not contribute meaningfully to decarbonizing the aggregate economy. The framework also illustrates how market opacity can sustain a "bad equilibrium" in which some firms demand cheap, low-quality offsets for greenwashing purposes. If investors and other stakeholders continue to rely on third-party ESG ratings without scrutinizing offset quality, weak-governance firms may favor cheap, low-quality offsets over genuine decarbonization strategies. This can be socially suboptimal, even though low-quality offsets are not universally without merit and may deliver genuine emissions reductions in some cases. Suppose the minimum offset quality available to firms is so low that offsets at that level have almost no impact on true emissions. A firm with sufficiently low G would optimally choose these minimum quality offsets, which merely lower *perceived* emissions but have no effect on true emissions as they simply crowd out abatement.[18] True emissions may therefore remain higher in the presence of an opaque offset market.

[18] Internet Appendix Table IA.V and Figure IA.1 provide evidence that carbon offsetting can crowd out genuine abatement.

III. Data and Descriptive Statistics

A. Carbon Offset Projects

Our primary dataset features carbon offsets from four major carbon registries—ACR, Gold, CAR, and VCS. For each offset project, our data include information on the project's name, developer, location, and type; the year in which the project was launched; the quantity and issuance date of issued credits; and the quantity and retirement date of retired credits. Importantly, we read each entry and extract the names of firms retiring credits. We then identify each firm's GVKEY (when applicable) in the Compustat North America and Global universe. This step yields 3,353 unique projects issuing carbon offsets between 2005 and 2023, of which 1,854 involve 1,389 public firms worldwide that purchased and retired their credits.

For the offset quality analysis, we utilize project-level quality ratings from BeZero Carbon, a leading carbon credit rating agency. BeZero evaluates projects based on publicly verified information, extensive developer engagement, in-house geospatial tools, peer-reviewed scientific studies, proprietary sector-specific machine learning models, and manual investigations.[19] Each carbon offset project is assigned a letter rating indicating its quality: AAA (highest quality), AA (very high), A (high), BBB (moderate), BB (moderately low), B (low), C (very low), and D (lowest quality), similar to credit ratings assigned by S&P or Moody's.

We also obtain proprietary offset pricing data from Viridios AI (now part of Bloomberg), a major analytics and consulting firm that provided corporate solutions and asset management services in the voluntary carbon market. The provider sources market prices from numerous private exchanges on which offset credits are traded, and records either the daily average transaction price or the daily average bid-ask midpoint for each credit vintage. This dataset includes daily price snapshots for about 97% of our offset projects during the last two weeks of February 2024.

Table I describes the 1,854 projects in our main sample. The top panel shows that the four main regions hosting carbon offset projects are Asia, Africa, North America, and South America. By far, the predominant project type prevents carbon emissions by generating

[19] By contrast, ESG rating agencies (e.g., Sustainalytics) are broad-coverage generalists that evaluate firms across many ESG dimensions but lack the specialized tools needed to assess carbon offset quality.

renewable energy (e.g., solar, wind, geothermal, and hydro), followed by household & community projects (e.g., energy-efficient housing and appliances, and weatherization) and forestry-related projects (e.g., afforestation and reforestation, and avoided forest and grassland conversion). By region, Asia accounts for most renewable energy projects (84.6% of all renewable projects), Africa hosts most of the household & community projects (62.1%), and North America has the largest share of forestry projects (i.e., 46.6%).

[Insert Table I here]

Notably, information on the quality of offset projects is limited. Approximately 17% of all projects across the four registries are rated by BeZero Carbon.[20] The average (median) offset price is relatively low, at $4.2 ($3.2) per ton, with projects based in North America and Africa commanding the highest prices. The amount of carbon emissions purportedly prevented or removed by a project, measured by the number of credits issued, is heavily skewed. The average (median) project issues offset credits representing 784 (186) thousand metric tons of emissions, with projects from South America issuing the most credits.[21] A total of 1,453 million metric tons have been issued across all projects, nearly 70% of which have been retired during our sample period. The proportion of issued credits that have been retired is generally higher for earlier issuance years, a pattern that holds across all regions.

To mitigate concerns about institutional or regulatory differences across countries, we repeat the tabulation only for projects used by U.S. firms. For these 969 projects, Panel B of Internet Appendix Table IA.I reports statistics broadly consistent with those in Table I, except that U.S. firms are more heavily invested in North America-based projects than in Africa-based ones, and in forestry rather than household & community projects.[22]

[20] Internet Appendix Table IA.II documents that larger projects are more likely to be rated by BeZero, consistent with the fact that 59% of all offset credits are rated by the firm. We acknowledge that the absence of a BeZero rating is an imperfect proxy for low offset quality, although on average, unrated projects lie toward the lower end of the quality distribution.

[21] Notably, South American projects are the most likely to be rated by BeZero Carbon, with forestry & land use and renewable energy comprising the highest shares. This is consistent with Assunção et al. (2025) who show that tropical forest management in Brazil can be an important contributor to climate change mitigation.

[22] Internet Appendix Table IA.I also provides details on all 3,353 offset projects in the full sample (Panel A) and the distribution of the 1,854 projects used by global public firms across the four carbon registries (Panel C). Table IA.II also documents that publicly listed firms are more likely to select larger, rated projects, a pattern that holds similarly for all or U.S. firms.

Moreover, we observe that, among BeZero-rated offset projects, credits issued by lower-quality projects are much cheaper than those from high-quality ones. Figure 2 plots average offset prices per ton by quality rating and vintage year, revealing a clear monotonic pattern: higher-quality projects command higher prices within each vintage. For instance, for offsets with a 2020 vintage, the average price per ton for AA-rated projects is $15, almost double that of BBB-rated projects ($8). Offsets not rated by BeZero are priced near the bottom, comparable to the lowest-rated projects. The pricing spread between high- and low-rating offsets persists across issuance years.

[Insert Figure 2 here]

Among the 1,854 offset projects used by public firms, about 97% are rated below BBB or unrated. Although roughly half of all publicly listed firms that retire offset credits use at least some rated ones, the average rated project used by the average firm in our sample has a rating between BBB (moderate) and BB (moderately low). Figure 3 shows that approximately 45% (70%) of all retired offsets are priced below $2 ($4) per ton, consistent with widespread concerns that firms often rely on low-quality offsets as a cost-effective means of greenwashing. Overall, the unconditional quality of offsets used by publicly listed firms in our sample is generally low.

[Insert Figure 3 here]

B. Firm Characteristics

We collect data on firm-level carbon emissions, abatement costs, and climate-related governance mechanisms. Carbon emissions data are obtained from Trucost Environmental, a recognized provider of environmental data and analytics. We also obtain firm-level ESG ratings from Sustainalytics to exploit the agency's methodology change at the end of 2018 as our identification strategy, described in detail in Section B. Specifically, we use both the legacy ESG scores, which are within-industry ranks under the old methodology, and the new ESG risk scores from the updated methodology, which capture firms' ESG risk exposures.

To proxy for marginal abatement costs, we use survey responses from the Carbon Disclosure Project (CDP) regarding firms' voluntary investments in Scope 1 emission reductions. CDP is a nonprofit that operates a leading environmental disclosure system for companies and other entities. Our first proxy captures a firm's internal abatement cost per metric ton of emissions, calculated as the firm's voluntary abatement investment in a given year divided by its estimated total emission reduction the following year. This measure, however, is unobservable for firms that do not directly abate emissions. For these firms, we use the industry average abatement cost measure as a proxy, acknowledging that it is measured with error.[23] To address this limitation, we use an additional measure: the number of internally operated abatement projects scaled by firm assets.[24]

To measure climate-related governance mechanisms, we draw on the global BoardEx database, which provides detailed information on directors' committee assignments. We classify whether a firm has an ESG or sustainability committee based on this information. In addition, we use CDP survey questions that explicitly ask firms about their formal climate governance structures. Specifically, we construct two indicators: *Board climate authority*, which equals one if a firm's board has ultimate responsibility for climate policies, and *Managerial climate incentive*, which equals one if management is explicitly incentivized based on decarbonization performance.[25]

Finally, we obtain additional data from several sources: company accounting and stock return data from Compustat North America, Compustat Global, and the Center for Research in Security Prices (CRSP); quarterly institutional holdings from FactSet and mutual fund holdings from CRSP; ESG fund prospectuses from Morningstar; ESG-related reputational risk from RepRisk; analyst ratings and recommendations from I/B/E/S; and foreign exchange

[23]In Tables IA.IV and IA.VIII of the Internet Appendix, we provide robustness tests using firm-level abatement costs based on the subsample of firms that disclose abatement costs.

[24]The corresponding CDP Questionnaires are: "Identify the total number of projects at each stage of development" and "Provide details on the initiatives implemented in the reporting year - Voluntary/Mandatory, Investment required, Estimated annual CO_2e savings." We caveat that the number of internally operated abatement projects is itself an imperfect proxy that may partially reflect other operational considerations or equilibrium outcomes.

[25]The corresponding CDP questionnaires are: (i) "Where is the highest level of direct responsibility for climate change within your company?" (before 2018) or "Is there board-level oversight of climate-related issues within your organization?" (from 2018) and (ii) "Do you provide incentives for the management of climate change issues, including the attainment of targets?" In Internet Appendix A.2, we also provide additional details on the CDP data.

rates (USD pairs) from the Organisation for Economic Co-operation and Development and Yahoo Finance, which we use to convert local-currency metrics into U.S. dollars.

Table II reports characteristics of publicly listed firms for which Sustainalytics ESG ratings are available. For these statistics, the sample period begins in 2014, the first year for which CDP data are available. In our sample, the average (median) firm has assets of $28.6 ($4.7) billion and a market capitalization of $10.6 ($3.4) billion. The average return on assets is 3%, while the previous-year stock return averages 10%. The average firm has institutional ownership of 45% and U.S. firms account for 41% of the sample. Carbon emissions are heavily skewed. For example, the average Scope 1 emissions are 1.5 million tons, compared with a median of 0.03 million tons. Internal abatement cost is $159 per ton on average, which is forty times more costly than the average offset and an order of magnitude more costly than even high-quality offsets. About 20% of firms have a board ESG committee, and 17% provide climate-related incentives in executive compensation. Among firms that use non-zero offsets, the average firm retires 60.4 thousand tons of credits, while 55% of firms use some BeZero-rated credits.[26]

[Insert Table II here]

Figure 4 illustrates the industry distribution of public firms' carbon offsetting activities. For each Fama-French 30 industry, it reports the number of firm-year observations with non-zero offset usage, the industry's offsets-to-emissions ratio (aggregate credit retirements divided by aggregate Scope 1 emissions), and its total Scope 1 emissions. Panels A and B present the distributions for U.S. and non-U.S. firms, respectively.

[Insert Figure 4 here]

The key takeaway from Figure 4 is that many low-emission industries are surprisingly active in the carbon offset market. While high-emission industries such as utilities,

[26]Internet Appendix Table IA.III reports firm-level statistics for U.S. firms in our sample. Compared with the global sample, U.S. firms are somewhat smaller in terms of assets and have significantly higher institutional ownership, consistent with institutions being dominant players in the U.S. stock market. They emit relatively fewer emissions and face slightly higher abatement costs. Conditional on using offsets, U.S. firms on average retire larger amounts and are more likely to use rated offsets.

transportation, and energy frequently use offsets, several low-emission industries, such as services and finance, rank even higher. Notably, the intensity of offset use (i.e., the offsets-to-emissions ratio) does not align with industries' emission levels. For instance, while financial institutions offset almost all of their emissions on a one-for-one basis, energy and utility firms retire negligible amounts relative to their direct emissions. These patterns, observed similarly in both the U.S. and non-U.S. samples, are consistent with Hypothesis 1 that low-emission firms rely more on offsets because the marginal cost of offsetting is likely lower than that of direct abatement.

Figure 5 illustrates aggregate trends in offset retirements and Scope 1 emissions for U.S. and non-U.S firms over our sample period. The use of carbon offsets has grown substantially but remains small in magnitude compared to emissions. The market has also become more active in the U.S., even though non-U.S. firms are far more emission-intensive.

[Insert Figure 5 here]

IV. Empirical Results

A. *Ordinary Least Squares (OLS) Regressions*

To test Hypotheses 1 and 2, the outsourcing and transition-washing hypotheses, we begin by documenting cross-sectional associations between firms' offset usage, direct abatement, and offset quality, and explanatory variables that measure firms' internal abatement costs and climate-related governance mechanisms. Specifically, we estimate the following regression:

$$\mathit{Outcome}_{i,t} = \alpha + \beta \cdot Z_{i,t-1} + \gamma \cdot \boldsymbol{X}_{i,t-1} + \sigma_{j,t} + \epsilon_{i,t}, \tag{5}$$

in which $\mathit{Outcome}_{i,t}$, equals one of three measures for firm i in year t: (i) the quantity of retired carbon offsets scaled by the firm's Scope 1 emissions in the previous year, (ii) Scope 1 emissions scaled by their lagged value, or (iii) a dummy variable indicating whether the firm retires some BeZero-rated offset credits, conditional on retiring credits. The explanatory variable, $Z_{i,t-1}$, is either a proxy for the firm's internal abatement cost or an indicator for whether the firm has a corporate governance mechanism to monitor or discipline the quality of its offsets. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. $\sigma_{j,t}$ denote industry-by-year or year fixed effects.

Table III reports the results. As shown in column 1 of Panels A and B, firms facing higher abatement costs tend to use significantly more carbon offsets while engaging in significantly less abatement, i.e., maintaining higher levels of emissions. Similarly, column 2 reports that firms operating fewer abatement projects use more offsets (Panel A) but abate less (Panel B). In economic terms, a one standard deviation increase (decrease) in abatement costs (the number of abatement projects per unit of assets) from the mean corresponds to a seven (three) percentage point increase in offset retirements as a fraction of emissions and a one (two) percentage point increase in emissions growth.[27] These results are consistent with the hypothesis that firms facing higher marginal abatement costs rely more on carbon offsets and undertake less direct abatement.[28] Consistent with the interpretation that offsetting may crowd out abatement efforts, we find that firm-level emissions are positively associated with lagged offset usage, as reported in Table IA.V of the Internet Appendix.

[Insert Table III here]

In columns 3 to 5, the explanatory variable is one of three indicators of corporate governance mechanisms: Board ESG committee (a dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), Board climate authority (a dummy variable indicating whether the board has ultimate authority or responsibility for the firm's climate policies, from CDP), and Managerial climate incentive (a dummy variable indicating whether management receives explicit incentives tied to decarbonization, from CDP). Across all three indicators, firms lacking such governance mechanisms retire significantly more offsets (Panel A) and engage in less direct abatement, as reflected in

[27] For the number of abatement projects per unit of assets, the mean and standard deviation are 0.005 and 0.012, respectively.

[28] In Table IA.IV of the Internet Appendix, we show that our results are qualitatively robust to using firm-level abatement costs based on the subsample of firms that disclose abatement costs.

higher emissions (Panel B). The findings support the hypothesis that firms with weaker governance tend to use more offsets and abate less.[29]

In Panel C of Table III, we examine the relationship between a firm's carbon offset quality, measured by whether it uses rated offsets, and its corporate governance mechanisms. Across all three indicators of climate governance, firms lacking such mechanisms are 4.8 to 6.6 percentage points less likely to use high-quality, rated offsets, conditional on using offsets. These results are consistent with the hypothesis that firms with weaker governance tend to rely on lower-quality offsets.

B. Quasi-Experimental Evidence

B.1. Sustainalytics Rating Methodology Change

To draw causal inferences about the relationships studied in Section A., we exploit an exogenous change in firms' ESG ratings as an emissions salience shock that incentivizes firms to boost their peer rankings by reducing emissions. Specifically, we use the methodology change adopted at the end of 2018 by one of the most prominent ESG rating agencies, Sustainalytics. Sustainalytics' firm-level ESG ratings are widely used by both investors and academics (see, e.g., Berg et al., 2024, 2022; Ceccarelli et al., 2024; Christensen et al., 2022; Kim and Yoon, 2023; Rzeźnik et al., 2025; Serafeim and Yoon, 2023). For example, these firm-level ratings underlie the popular Morningstar fund-level sustainability ratings and low-carbon designations, which are used heavily by mutual fund investors (see Hartzmark and Sussman, 2019; Ceccarelli et al., 2024).

Pursuant to the methodology update, Sustainalytics started publishing new ESG risk scores in lieu of its legacy ESG scores. In contrast to the legacy scores, which measured firms' managed ESG risk exposures, the new scores capture unmanaged risk exposures. As a result, within-industry percentile rankings based on the new ESG risk scores differ considerably

[29] In Table IA.VI of the Internet Appendix, we show that these OLS results are robust to including both abatement costs and climate governance as explanatory variables in the same regressions. In Table IA.VII, we also report correlations between our abatement cost proxies and climate-related governance variables. The correlations are empirically modest (ranging from -0.004 to 0.03), suggesting that the two constructs capture meaningfully distinct dimensions of firm behavior.

from those based on the old scores. Between December 2018, when the new scores were introduced, and October 2019, when the legacy scores were discountinued, Sustainalytics reported both measures. Comparing the new and old scores for the same firm in the same month during this period, Figure 6 shows that the average magnitude of the change in within-industry ranking caused by the reshuffle is approximately 20 percentiles. By contrast, typical period-to-period changes in rankings based on either the old or new scores are much smaller, confirming that the shift in rankings resulting from the Sustainalytics methodology change was not driven by fundamentals.

[Insert Figure 6 here]

Using this shock, we identify exogenous treatment at the firm level based on whether a firm's within-industry ranking was adjusted downward at the end of 2018 as a result of Sustainalytics' methodology change.[30] Our identifying assumption is that an exogenous ESG rating downgrade increases a firm's incentive to improve its ESG rating going forward. For instance, prior studies show that institutional investors exhibit a preference for highly rated assets (see Hartzmark and Sussman, 2019; Krüger et al., 2020; Döttling and Kim, 2024). As discussed in our conceptual framework, an exogenous ESG rating downgrade likely makes a firm's emissions more salient, thereby inducing institutional investors to divest from the firm and potentially raising its cost of capital (see Ferreira and Matos, 2008). Investors may also react negatively in anticipation of ESG rating shocks impacting firms' future profits (see Derrien et al., 2025). Hence, affected firms have stronger incentives to improve their ESG ratings to retain institutional investors. We therefore examine how firms adjust their decarbonization strategies after the end of 2018, depending on whether they

[30] Ceccarelli et al. (2024) and Rzeźnik et al. (2025) also use Sustainalytics' methodology change as a shock. These studies set the event date as September 2019 when the new ESG risk scores were disseminated through Morningstar and other public sources such as Yahoo! Finance. We set the treatment date as December 2018 when institutional clients of Sustainalytics gained access to the new ESG risk scores before broader public dissemination, which we confirm via direct conversations with Sustainalytics (which has served over 1,000 institutions). Our results are qualitatively robust to using March 2019 as an alternative event date. As noted in these studies, the Sustainalytics methodology change inverted the rank ordering of firms, in that higher ESG risk scores represent weaker ESG profiles whereas higher legacy ESG scores corresponded to stronger ESG performance. We account for this inversion when computing the ranking changes caused by the conversion of legacy ESG scores to new ESG risk scores.

experienced a Sustainalytics-induced ESG rating downgrade.[31] Specifically, we estimate the following difference-in-differences (DID) specification:

$$\textit{Outcome}_{i,t} = \alpha + \beta \cdot \textit{Post}_t \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t}, \qquad (6)$$

in which $\textit{Outcome}_{i,t}$ denotes a firm's offset usage, direct abatement, or offset quality, as detailed in Section A. $\textit{Post}_t$ is a dummy variable equal to one for years after 2018, and zero otherwise. $\textit{Rating downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively, the latter of which captures time-varying industry-specific factors. We cluster standard errors at the firm level. The coefficient, β, captures the effect of an exogenous ESG rating downgrade on the firm's use of carbon offsets or internal abatement efforts.

Before analyzing offsets and abatement, we first assess the validity of our assumption that Sustainalytics' methodology change incentivized downgraded firms to boost their ESG ratings by reducing emissions. The premise of our empirical strategy is that investors and other stakeholders penalize firms that are worst-in-class in terms of their perceived unmitigated emissions, serving as an empirical counterpart to a shock to λ in our conceptual framework. We begin by documenting that, following the change, within-industry rankings based on Sustainalytics' ESG scores have become more closely linked to firms' carbon emission intensity, measured as Scope 1 emissions scaled by sales. As shown in Table IV, within-industry rankings based on the new ESG risk scores are positively and significantly associated with lagged emission intensity, whereas those based on the legacy ESG scores are not.

[Insert Table IV here]

More importantly, we test whether exogenous ESG rating downgrades elicit responses from investors and other stakeholders (see Derrien et al., 2025). To do this, we estimate the

[31] Although the Sustainalytics methodology change affected all ESG pillars, our carbon-specific outcome variables are unlikely to be driven by social- or governance-related responses to the shock.

baseline DID specification above, replacing the dependent variable with quarterly or monthly measures of market response. We report these results in Table V. Columns 1 to 5 present results for institutional ownership, ESG fund ownership, RepRisk index (higher values indicate greater media attention to a firm's ESG reputation risk), median analyst recommendations (higher values correspond to more negative recommendations), and the percentage of analysts with sell recommendations during the period covering the two quarters before and after the end of 2018.[32] Columns 6 and 7 show results for monthly stock returns, either raw or CAPM-adjusted (with beta estimated using 24-month rolling windows).

[Insert Table V here]

The coefficients on the interaction term, *Post* $\times$ *Rating downgrade*, indicate that an exogenous rating downgrade is followed by a decline in institutional ownership and ESG fund ownership, an increase in reputation risk, more negative analyst ratings, a higher percentage of analysts with sell recommendations, and lower monthly stock returns. Most of these estimates are both statistically and economically significant. For example, for downgraded firms, the marginal effects for the decrease in ESG fund ownership and the increase in reputation risk are 14.3% and 6.4% with respect to their means, respectively. This is consistent with the monitoring role played by institutions when they divest from downgraded firms (see Ferreira and Matos, 2008; Gibson et al., 2022), but it also shows that the shock has broader implications that generally heighten firms' reputational salience (i.e., an increase in λ in our conceptual framework). These tests validate our assumption that exogenously downgraded firms become incentivized to bolster their ESG ratings by offsetting or abating their emissions.

One potential concern is that by focusing on the effect of ESG rating downgrades, we may overlook any potential symmetric effect of ESG rating upgrades. However, there is good reason to assume that downgrades serve as the primary source of treatment rather than upgrades. First, the literature extensively documents institutional tendencies for investors to divest from brown firms rather than proactively invest in greener firms (see Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2021; Edmans et al., 2024; Berk and

[32]ESG funds are identified using fund names and prospectuses from Morningstar. ESG fund ownership is measured for U.S. firms only, as we rely on a mapping that links Morningstar fund identifiers to CRSP fund identifiers.

van Binsbergen, 2025). Second, it is reasonable to assume that reputation costs are convex, such that firms benefit disproportionately less from increasing emissions (i.e., spending less on abatement) when their ESG ratings are higher than from reducing emissions when their ESG ratings are lower.

B.2. Difference-in-Differences (DID) Regressions

For our main DID analysis, we begin with full sample regressions of carbon offsets reported in Table VI. Columns 1 to 3 report results for all firms, progressively adding firm fixed effects and time-varying control variables, while column 4 shows results for firms that use carbon offsets at least once during our sample period. All four specifications yield a positive and significant coefficient on the interaction term, *Post* $\times$ *Rating downgrade*, indicating that companies whose ESG ratings are exogenously downgraded as a result of Sustainalytics' methodology change became incentivized to use more carbon credits to offset their emissions. Relative to firms that do not experience a downgrade, the average downgraded firm offsets an additional 24-25% of its direct emissions as of the end of 2018. For the subset of firms that use offsets, the effect is about four times larger, suggesting that they largely achieve carbon neutrality.

[Insert Table VI here]

In Figure 7, we plot the DID dynamics from interacting the *Rating downgrade*$_i$ indicator variable with yearly dummy variables. The year 2018, or -1 relative to the treatment event in December 2018, is set as the baseline period. The pre-event coefficients are not significant, ensuring that the control and treated firms exhibit parallel trends prior to 2019. In line with our main results, we observe positive coefficients for year 0 to year +2, indicating that firms increase the usage of offsets after being downgraded.

[Insert Figure 7 here]

Abatement Cost Subsamples

Next, we use the conceptual framework in Section II. to guide our analysis of the economic channels underlying these results. To test whether firms with higher abatement costs, including low emitters, tend to rely more on offsets after an ESG rating downgrade (Hypothesis 3), we estimate the DID regression in equation (6) separately for subsamples based on proxies for firms' internal abatement costs. These proxies, measured at the end of 2018, include (i) abatement cost (firm-level abatement cost per ton from CDP, averaged across firms in the same industry), (ii) number of abatement projects per unit of assets, and (iii) Scope 1 emissions.[33] We consider two dependent variables: the quantity of carbon offsets retired and Scope 1 emissions, both scaled by the firm's 2018 Scope 1 emissions prior to the rating change.

The results are reported in Table VII. Panels A and B examine offset retirements and Scope 1 emissions as the dependent variables, respectively. Columns 1, 3, and 5 (2, 4, and 6) report results for high (low) abatement cost subsamples, defined relative to the median firm. Across all three proxies for abatement costs, firms with high internal abatement costs, including low emitters, respond to an exogenous ESG ranking downgrade primarily by using more carbon offsets rather than by directly reducing emissions. Among firms with high abatement costs, the average downgraded firm offsets an additional 41-57% of its direct emissions measured at the end of 2018, relative to non-downgraded firms. In contrast, firms with low abatement costs, including high emitters, do not increase offset retirements but instead engage in direct emission abatement. We also report p-values testing the difference in DID estimates between the high- and low-abatement cost subsamples, which are statistically significant at the 5%.[34] Overall, these results support Hypothesis 3. Further supporting the notion that offsets may be negatively associated with abatement, we show that downgraded firms that increased offset usage more than the median firm are less likely to directly reduce emissions after the shock, as reported in Figure IA.1 of the Internet Appendix.

[Insert Table VII here]

One implication of these results is that heavy-emission firms reduce their direct emissions meaningfully following ESG downgrades. Although we cannot rule out that these firms may be shifting their emissions through supply chains or asset divestments rather than

[33] In Table IA.VIII of the Internet Appendix, we show that our results are qualitatively robust to using firm-level abatement costs based on the subsample of firms that disclose abatement costs.

[34] The DID estimates across abatement cost subsamples are robust to controlling for climate governance (see Internet Appendix Table IA.IX).

genuine abatement (see Duchin et al., 2025), the results also align with recent evidence that brown firms lead most meaningful green innovations (see Cohen et al., 2025). While these firms do not use carbon offsets as their primary transition tool, consistent with Hypothesis 1 (the outsourcing hypothesis), our evidence suggests that they are more likely to invest in abatement projects than other firms.

Governance Mechanism Subsamples

In addition to abatement costs, our conceptual framework highlights a source of friction that affects the "quality" or trustworthiness of carbon offsets chosen by firms: the degree of climate-related scrutiny and governance strength in an opaque offset market.

To test Hypothesis 3 that following an ESG rating downgrade, poor-governance firms are more likely to engage in greenwashing using low-quality offsets, we estimate equation (6) for subsamples sorted by indicators of corporate governance mechanisms that monitor or discipline offset quality. Measured at the end of 2018, these indicators include Board ESG committee (dummy for whether the board has an ESG or sustainability committee, from BoardEx), Board climate authority (indicator for whether the firm's board has ultimate authority over climate policies, from CDP), and Managerial climate incentive (dummy for whether management receives explicit decarbonization-linked incentives, from CDP).

We report our results in Table VIII. As shown in Panel A, firms without climate-related governance mechanisms respond to an exogenous ESG rating downgrade primarily by using more carbon offsets rather than directly abating emissions. The estimates are economically significant: among firms lacking climate monitoring mechanisms, the average downgraded firm offsets an additional 16-18% of its direct emissions measured at the end of 2018, relative to non-downgraded firms. To conserve space, in Table IA.X of the Internet Appendix we show that poor-governance firms do not engage in direct emission abatement after being downgraded.[35]

[Insert Table VIII here]

[35] In Table IA.XI, we also show that the DID estimates across climate governance subsamples are robust to controlling for abatement costs.

More importantly, in Panel B, we test whether firms with strong versus weak governance improve the quality of their offsets when incentivized by an ESG rating downgrade.[36] This specification restricts the sample to firm-year observations with non-zero credit retirements. While Panel A shows that firms with climate-related governance mechanisms do not use more offsets, Panel B reports that they tilt toward higher-quality offsets when they do, proxied by whether the firm retires any offsets rated by BeZero. In contrast, firms without such governance mechanisms show no greater likelihood of using high-quality offsets. Given the generally low quality of the average carbon offset project (see Section A.), this suggests that poorly governed firms respond to ESG rating pressure mainly by increasing the quantity, but not the quality, of the offsets they use. The p-values testing the differences in DID estimates between the poor- and good-governance subsamples indicate that the differences are statistically significant.

These findings suggest that firms lacking climate-monitoring mechanisms are more likely to strategically use cheaper offsets with questionable climate claims to enhance their ESG rankings. A back-of-the-envelope estimate based on our estimates suggests that the cost poor-governance firms pay for this strategy is only about $43,000.[37] One may speculate that this "bad equilibrium" is sustained by the absence of regulatory frameworks that ensure transparency about the nature of offsets used by firms. Project developers are likely to cater to greenwashing buyers by supplying low-quality credits at low prices, since firms are not required to disclose these details (i.e., they can claim to have offset their emissions without revealing which offsets they used). Indeed, AA-rated offsets—the highest-rated in our sample—account for only 1.6% of all rated projects. Therefore, the voluntary offset market is an important area that can benefit from stronger disclosure requirements. However, with

[36] We use a dummy variable indicating whether the firm uses BeZero-rated offsets as the dependent variable, rather than a continuous variable, to mitigate small sample biases that arise from BeZero's limited coverage. In Table IA.X of the Internet Appendix, we also report an alternative measure of offset quality using a dummy variable indicating whether the firm retires any offset credits rated BBB or higher by BeZero.

[37] The estimate is calculated by multiplying the following three values: 18% (i.e., coefficient on the interaction term from column 1 of Table VIII, Panel A), 18,347 metric tons (the unconditional average scope 1 emissions of firms with no ESG committee as of 2018), and a carbon offset price of $13 per metric ton (i.e., dividing total voluntary carbon market value of $2 billion as of 2022 according to Morgan Stanley, by aggregate voluntary offset retirements of 155 million metric tons as of 2022 according to Bloomberg).

many regulators, including the SEC, retreating from corporate climate disclosure rules, investors continue to face persistent challenges in assessing the quality of retired offsets.[38]

Industry Subsamples

As an additional test of Hypothesis 3 that less scrutinized firms increase their use of lower-quality offsets after an ESG rating downgrade, we examine cross-industry heterogeneity in external scrutiny or regulatory pressure. Consumer-facing or service-oriented industries may face relatively limited scrutiny but often cater to consumers who are more responsive to climate-related claims (see Gargano and Rossi, 2025; Rodemeier, 2025), whereas heavy emitters in fossil fuel or industrial sectors tend to operate under closer oversight from stakeholders and regulators.

We examine this premise by estimating the DID regression in equation (6) separately for different industry subsamples. Columns 1-3 of Table IX report results for consumer-facing, finance and services, and fossil fuel and industrial firms, respectively.[39] Consistent with our conjecture, column 1 of Panel A shows a strong effect of ESG rating downgrades on carbon offset usage among consumer-facing firms, suggesting that offsets partly serve as a marketing tool to appeal to consumers who value environmental claims but cannot verify offset quality. Column 2 reports similar effects for service-oriented firms, whereas column 3 shows no comparable response among "brown" industries such as fossil fuel or industrial sectors.[40]

[Insert Table IX here]

However, Panel B reveals that consumer-facing, financial, or services firms do not improve the quality of the offsets they increasingly use, whereas fossil fuel and industrial firms shift toward higher-quality, BeZero-rated offsets.[41] These results suggest that heavy emitters in fossil fuel and industrial sectors adopt more prudent decarbonization strategies under

[38] See "SEC votes to end defense of climate disclosure rules," SEC (March 2025).

[39] Consumer-facing industries are defined as Fama-French 49 industry codes 2 to 7, 9 to 11, 33, 43 to 44, as well as SIC codes 6020, and 6320 to 6329. Finance and services include Fama-French codes 7, 33, 34, and 45 to 48; fossil fuel industries 29 to 31; and industrials 14 to 26.

[40] To conserve space, in Table IA.XII in the Internet Appendix, we report that consumer-facing and service firms do not increase direct abatement following downgrades, whereas fossil fuel and industrial firms do.

[41] Table IA.XII in the Internet Appendix confirms that our offset-quality results are robust to an alternative measure based on a dummy indicating whether a firm retires any offsets rated BBB or higher by BeZero.

pressure, either through direct abatement or by using higher-quality offsets, underscoring the role of stakeholder and regulatory scrutiny in shaping corporate climate policies.[42]

We next examine industry heterogeneity in the manipulability of peer rankings and its effect on firms' offset behavior. Columns 4 and 5 of Table IX split the sample by each firm's "industry emission gap"—the difference in emissions between the 75th and 25th percentiles of peer firms within the same industry in 2018. Firms in low-gap industries can more easily boost their relative greenness by offsetting small emission amounts. Consistent with a transition-washing channel, Panel A column 4 shows that such firms increase their offset use significantly (21% more of their 2018 emissions, significant at the 5% level), whereas column 5 shows no comparable effect for high-gap industries.[43] In Panel B, low-gap firms do not improve offset quality but expand their use of low-quality credits, whereas high-gap firms are 29 percentage points more likely to use higher-quality BeZero-rated offsets, conditional on using offsets.

B.3. Carbon Offset Usage, Abatement, and Post-Shock Recovery

A key premise of our conceptual framework, Hypothesis 4, is that firms optimize their decarbonization strategies to manage reputation costs following ESG rating downgrades. This premise motivates a direct empirical test of firms' transition-washing incentives: we examine whether treated firms' ESG rankings or ownership dynamics recover after exogenous downgrades when they rely on unrated, low-quality offsets in the post-downgrade period.

We regress these firms' within-industry percentile ESG rankings on yearly indicators, using 2018 (or year 1 relative to the treatment event in December 2018) as the baseline period. Similarly, we regress institutional or ESG fund ownership on quarterly indicators, with the last quarter of 2018 serving as the baseline. The estimated coefficients and their confidence bands are plotted in Figure 8.

[Insert Figure 8 here]

[42]As a robustness check, Table IA.XIII in the Internet Appendix shows that our results are not mechanically driven by firms' preclusion from voluntary carbon markets pursuant to their participation in mandatory Emissions Trading Systems (ETS). Similar conclusions hold when we exclude firms domiciled in countries with an ETS or offsets eligible for compliance under ETS programs such as California's Cap-and-Trade.

[43]Table IA.XII in the Internet Appendix shows the opposite for abatement.

Figure 8 illustrates that downgraded firms initially experience sharp declines in their within-industry ESG rankings and institutional/ESG fund ownership in 2019 (i.e., year 0), following Sustainalytics' methodology change at the end of 2018. In subsequent periods, firms that respond with non-rated offsets exhibit a swift recovery in both ESG rankings and institutional/ESG fund ownership. The effects appear qualitatively similar for downgraded firms that engage in above-median direct abatement rather than use offsets, as shown in Internet Appendix Figure IA.2.[44] Taken together, these results support our hypothesis that, on average, firms using low-quality offsets can effectively engage in "transition-washing," obtaining benefits comparable to direct emission abatement.

V. Conclusion

Carbon offsets allow firms to claim reductions in carbon emissions by purchasing and retiring carbon credits sold by projects or entities that reduce emissions. These instruments have been promoted as tools to help heavy-emitters transition to low-emission business models. However, they have been widely criticized for the lack of transparency around their climate claims. Using rich data on carbon offset retirements by publicly listed firms around the world, this paper documents stylized facts about the global carbon offset market and provides the first systematic analysis of why firms use carbon offsets.

We motivate our economic hypotheses using a simple conceptual framework, and test them using an exogenous shock to firms' decarbonization incentives to improve their climate reputation. When their ESG ratings are downgraded, firms with greater abatement costs use offsets more intensively to reduce their emissions while firms with lower abatement costs tend to abate their emissions directly. Furthermore, we show that low-quality offsets are used strategically by firms that lack governance mechanisms to monitor their decarbonization strategies or firms from less scrutinized industries.

[44] Panel B of Internet Appendix Figure IA.2 also shows the "counterfactual" dynamics for firms that do not respond to downgrades through either offsets or abatement. For these firms, ESG rankings and ownership do not recover after the initial shock, remaining suppressed for at least three years (for rankings) or quarters (for ownership).

Our findings have important implications for understanding and governing voluntary carbon markets. Our results indicate that offset projects used by publicly listed firms are generally of low quality and that the market sustains low prices for these offsets, an adverse selection problem that can discourage firms from using high-quality offsets. This highlights the importance of commonly adoptable rules and regulations to ensure the transparency of offset projects, while balancing potential trade-offs between the quality of offset projects and their costs. Much future work is needed to better understand how carbon offsets can facilitate the transition to a carbon neutral economy.

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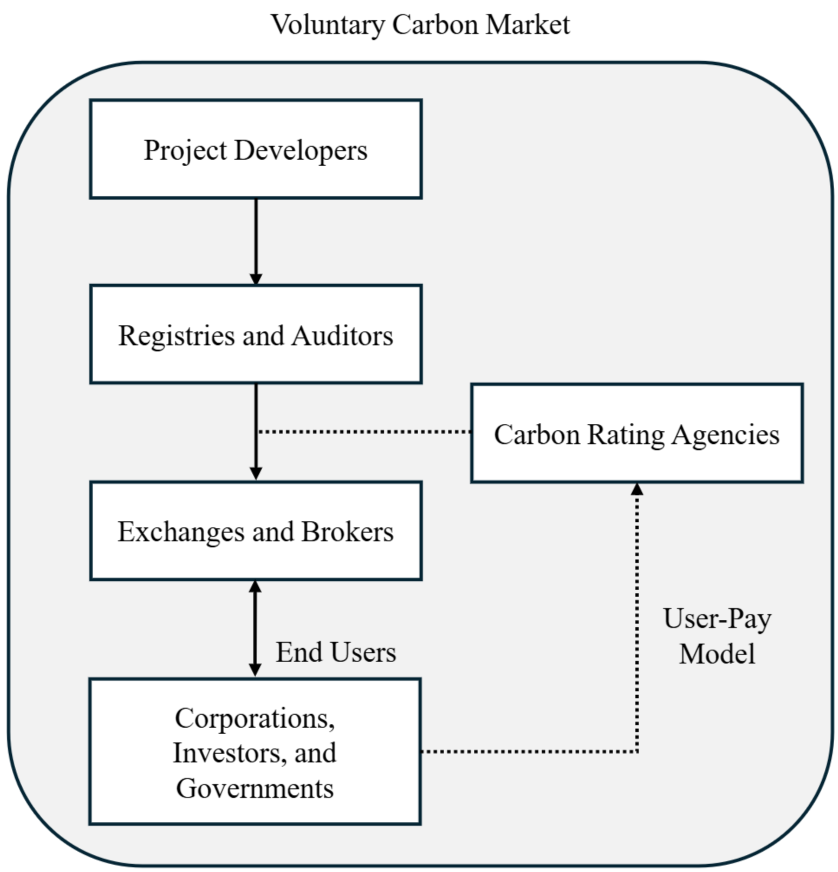

Figure 1. **Structure of the voluntary carbon offset market.** This figure illustrates the flow of carbon offset credits, depicted by solid arrows, in the ecosystem of the voluntary carbon offset market. Intermediaries, including registries, third-party auditors, brokers, and exchanges, play an important role in facilitating transactions between project developers who issue carbon offset credits and end users who purchase them. External carbon rating agencies, which typically adopt a user-pay model, also play an important role in certifying the quality of individual carbon offset projects. End users of carbon offset credits, such as corporations, investors, and governments, trade and retire credits to offset their own emissions.

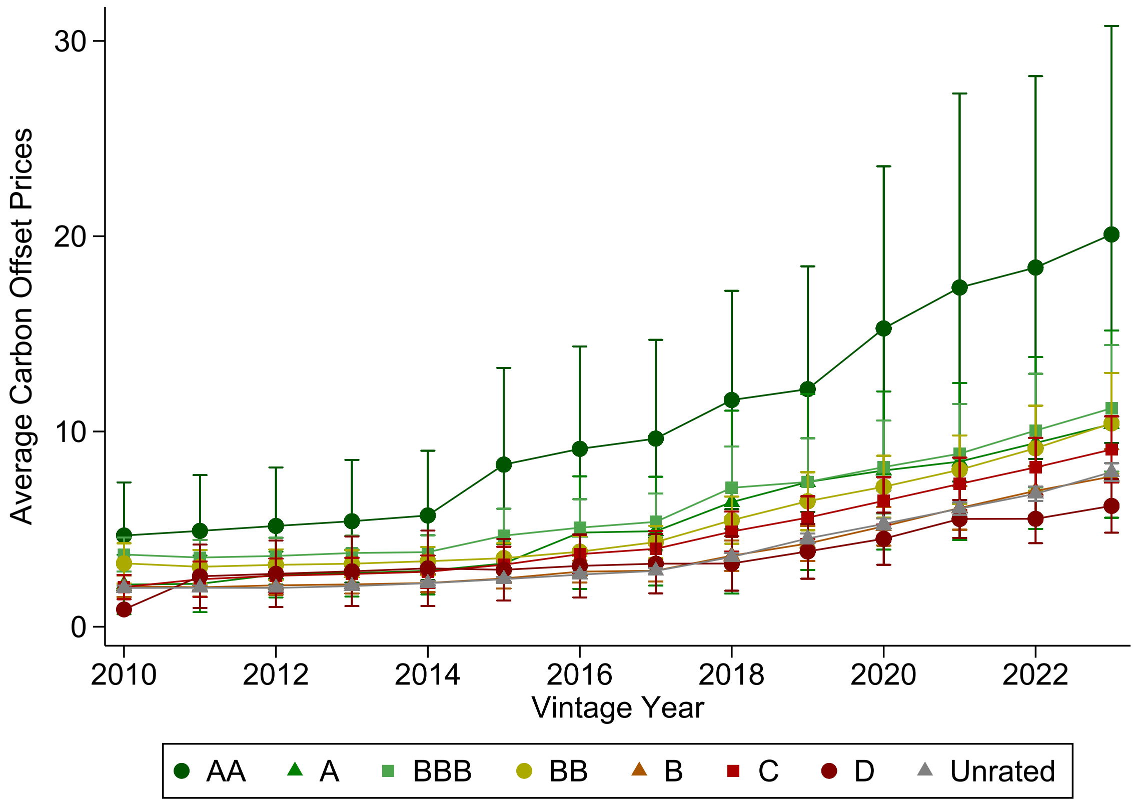

Figure 2. Average carbon offset prices by vintage and rating. For each BeZero Carbon rating group, this figure plots the average offset prices per ton across different issuance years.

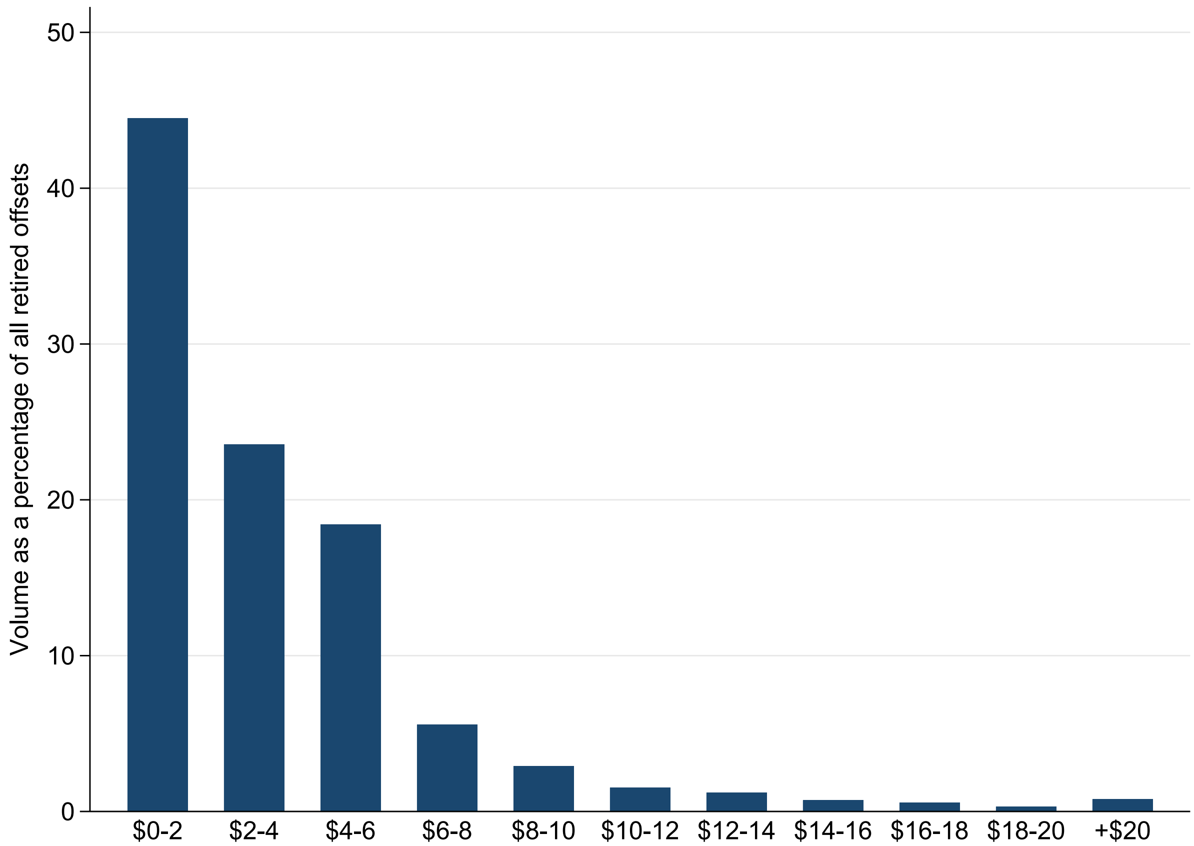

Figure 3. **Offset volume as a percentage of total retirements, by price.** This figure plots the aggregate volume of retired carbon offsets for different offset price groups as a percentage of all retired offsets. Price intervals are based on February 2024 prices and exclude the lower values. For example, $0-2 refers to prices that are greater than $0 and equal or less than $2 per ton.

Panel A: U.S. firms

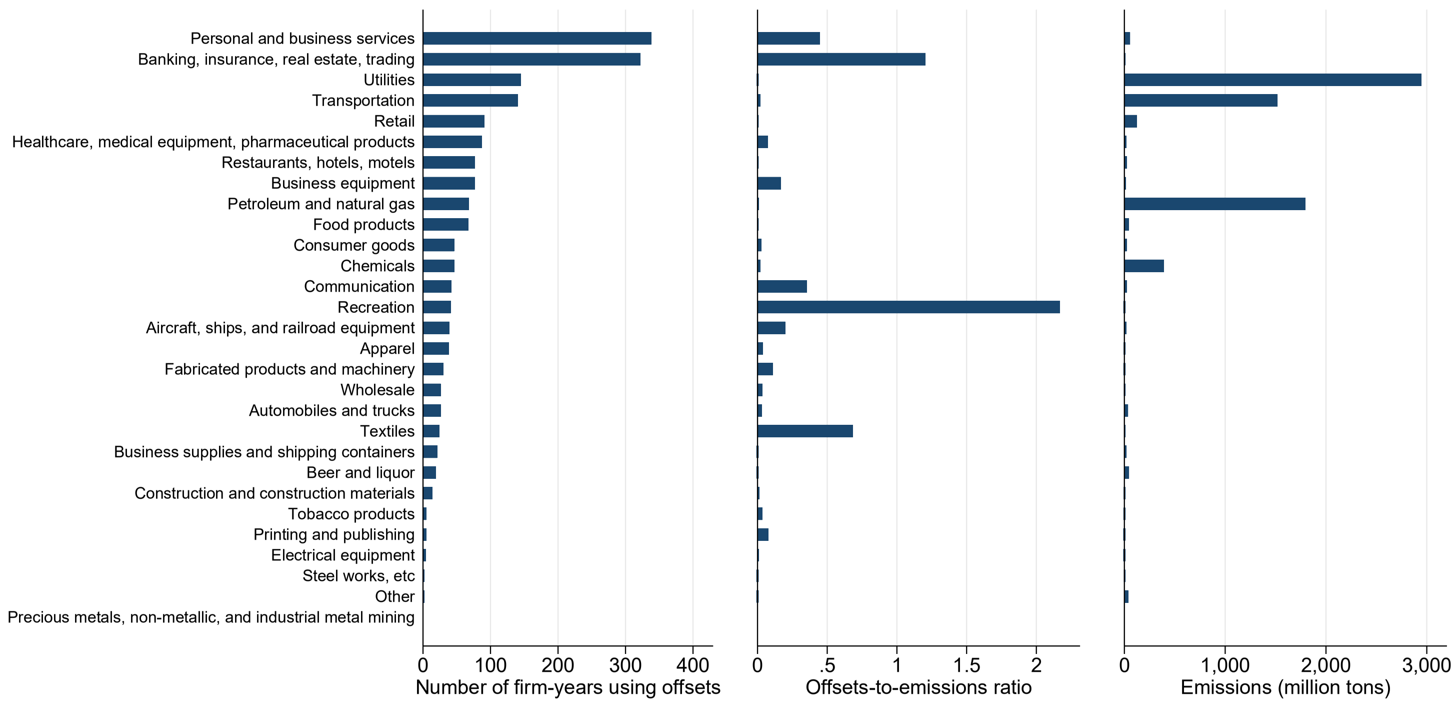

Figure 4. Industry distribution of firms that use carbon offsets. This figure plots distributions of the Fama-French 30 industries regarding the number of firm-year observations within each industry that have non-zero carbon credit retirements (left), industry-level offsets-to-emissions ratios measured as aggregate carbon credit retirements divided by aggregate Scope 1 direct emissions (middle), and industry-level aggregate Scope 1 emissions (right). Panels A and B show the distributions for the U.S. and non-U.S. firm samples, respectively.

(continued)

Panel B: Non-U.S. firms

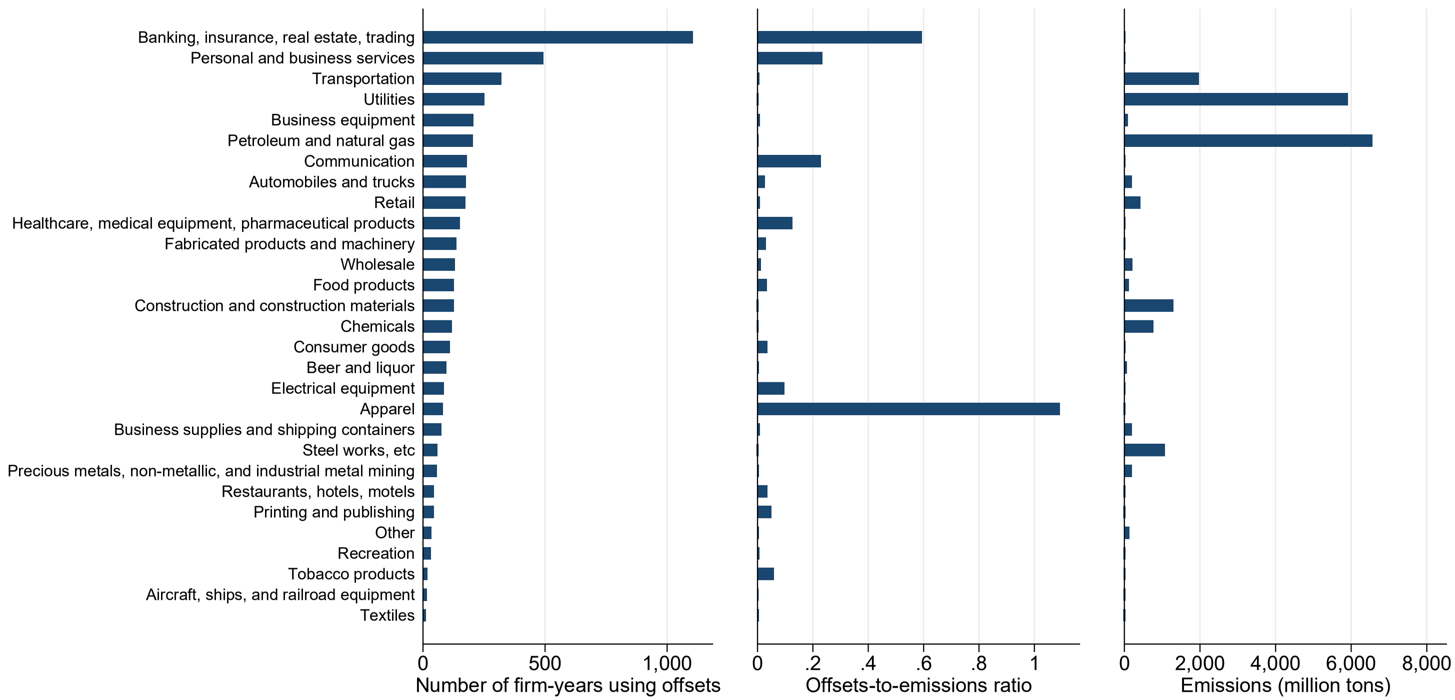

Figure 4. Industry distribution of firms that use carbon offsets (continued)

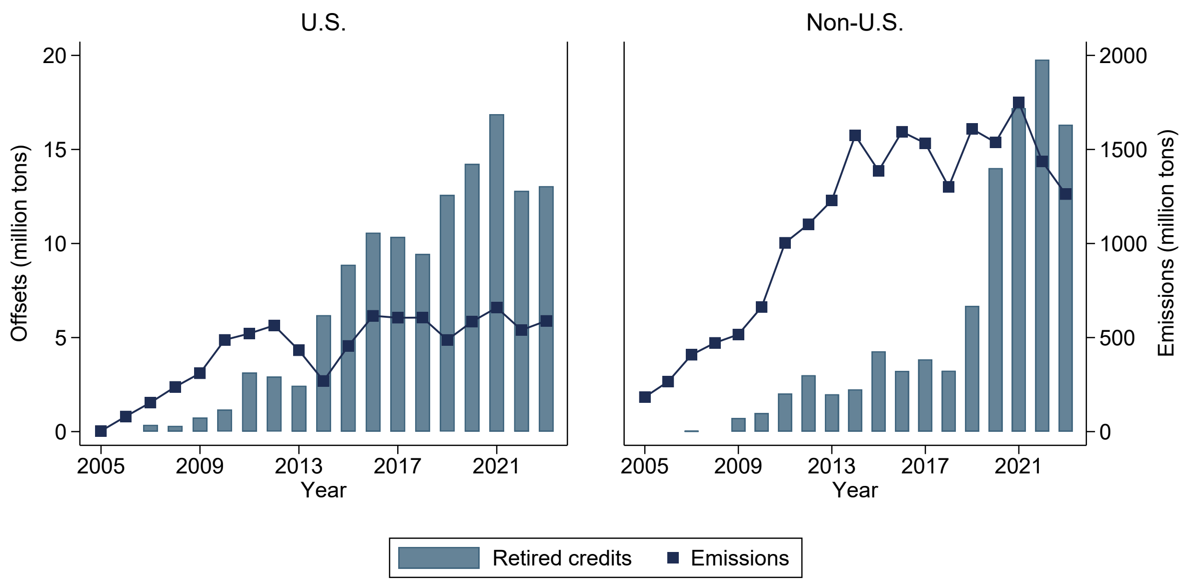

Figure 5. Aggregate carbon offset retirements and direct emissions. This figure plots annual aggregate carbon credit retirements (left axis) and aggregate Scope 1 direct emissions (right axis) for U.S. and non-U.S. firms, respectively.

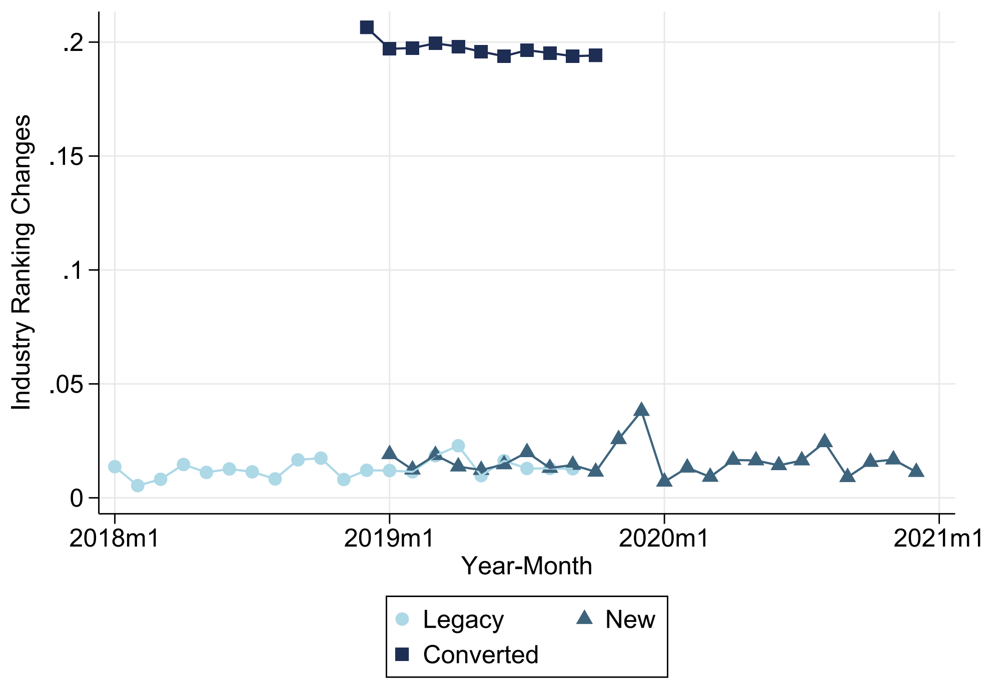

Figure 6. Ranking shifts following Sustainalytics' rating methodology change. This figure illustrates the average magnitudes of month-on-month changes in the within-industry ranking of firms based on their Sustainalytics ESG scores. The series with circle (triangle) markers are the average magnitudes of ranking changes based on the legacy ESG score (ESG risk score) measured under Sustainalytics' old (new) methodology. The series with square markers are the average magnitudes of ranking changes when comparing the new ESG risk score with the previous month's legacy ESG score for the same firm.

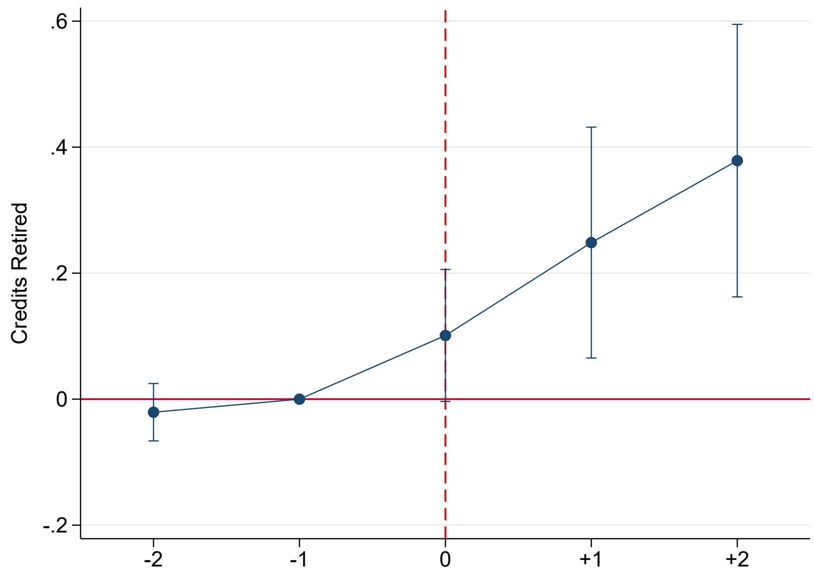

Figure 7. **Pre- and post-event differences between downgraded and control firms.** This figure plots results from an event-study regression using the Sustainalytics methodology change in December 2018 as the treatment event, where we replace the $Post$ dummy variable in equation 6 with yearly dummy variables, denoted $Pre(\text{s})(Post(\text{s}))$, which are equal to one if the observation is s years before (after) the event year 2019 and zero otherwise. The dependent variable is the quantity of carbon offset credits retired by the firm in a given year, scaled by the firm's Scope 1 carbon emissions in 2018, prior to the event. We plot the estimated coefficients on $Pre(s)(Post(s)) \times$ *Rating downgrade* along with their 90% confidence intervals. Standard errors are clustered at the firm level.

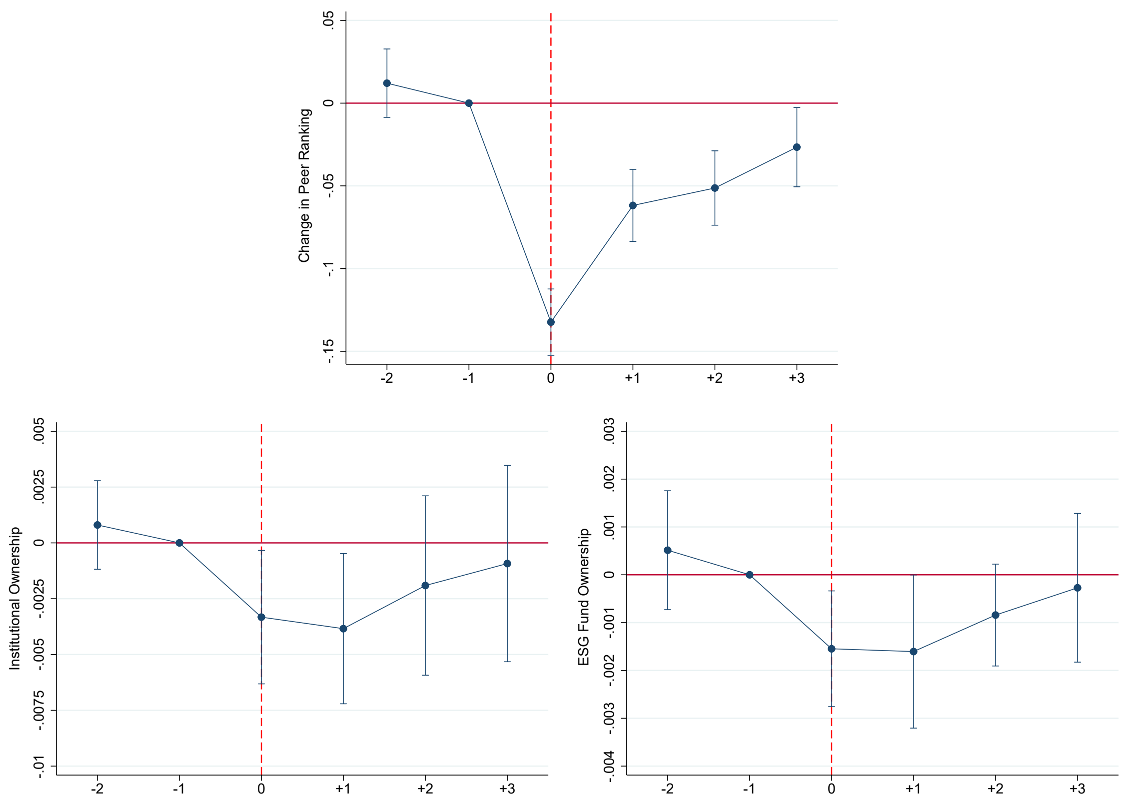

Figure 8. Carbon offset usage and post-shock recovery. This figure illustrates the post-treatment dynamics of within-industry ESG percentile rankings, institutional ownership, and ESG fund ownership for treated firms that experienced ranking downgrades following Sustainalytics' rating methodology change. The sample includes firms that responded to the downgrade by using unrated offsets. Specifically, for these subsamples, we plot the coefficients, β_s, and their 90% confidence intervals from the specification below:

$$Investor\ \ response_{i,t} = \alpha + \left(\sum_{s=-2}^{-1} \beta_s \cdot Pre(s)_t + \sum_{s=0}^{+3} \beta_s \cdot Post(s)_t \right) + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \epsilon_{i,t},$$

where *Investor response*$_{i,t}$ is: (i) within-industry ESG percentile rankings based on Sustainalytics' legacy ESG scores for 2017 and 2018, and based on the new ESG risk scores from 2019 onward after Sustainalytics changed their methodology; (ii) Insitutional ownership from FactSet; and (iii) ESG fund ownership for U.S. firms from the CRSP Mutual Fund Database and Morningstar. $Pre(s)$ ($Post(s)$) is a dummy variable equal to one if the observation is s years, or quarters for ownership dynamics, before (after) the event year 2019 and zero otherwise. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and past quarter's stock return. δ_i denotes firm fixed effects. Standard errors are clustered at the firm level.

Table I
Characteristics of Carbon Offset Projects by Region

This table reports summary statistics characterizing the distribution, types, and credit issuance/retirement activity of carbon offset projects registered on four carbon registries, ACR, Gold, CAR, and VCS. The table describes 1,854 projects that issued offset credits used by publicly listed firms included in our main sample, covering the period from 2005 through 2023. The number of offset projects is tabulated for the full sample and across geographic subsamples. The number of projects for different project types and the number of projects that are externally rated by the carbon rating agency, BeZero, are also reported separately for the full sample and across geographic subsamples. The average and median offset prices per ton (as of February 2024) are reported for our full sample and geographic subsamples. Also reported are the average, median, and total number of credits issued by projects based in each geographic region, as well as the average percentage of issued credits that are retired overall and for different credit vintage groups.

	Geographic region						
Number of projects	Full sample	Africa	Asia	Europe	North America	South America	Other
Total	1,854	307	879	33	455	168	12
Type							
Agriculture	60	1	15	4	31	9	0
Carbon capture & storage	4	0	0	0	4	0	0
Chemical processes	92	6	4	1	81	0	0
Forestry & land use	311	39	51	1	145	69	6
Household & community	377	234	116	1	17	8	1
Industrial & commercial	60	2	30	19	9	0	0
Renewable energy	733	17	620	4	20	69	3
Transportation	30	0	0	0	27	2	1
Waste management	187	8	43	3	121	11	1
Rated by BeZero Carbon	323	55	141	4	68	52	3
Average price per ton (as of February 2024)	4.2	4.8	2.2	4.2	7.7	4.1	4.5
Median price per ton (as of February 2024)	3.2	4.5	1.4	3.6	5.0	2.7	3.6
Average #credits issued (thousand tons)	783.6	745.9	832.7	352.2	446.6	1,614.9	473.5
Median #credits issued (thousand tons)	186.4	56.2	278.9	193.1	121.8	316.6	198.5
Total #credits issued (million tons)	1,452.8	229.0	731.9	11.6	203.2	271.3	5.7
Average % of credits being retired	69.9%	71.4%	66.9%	80.5%	75.2%	65.8%	85.2%
Issuance year: $\leq$2015	78.1%	87.1%	75.7%	83.3%	80.6%	73.2%	89.8%
Issuance year: 2016-2017	76.5%	81.2%	72.7%	65.4%	80.6%	75.4%	92.0%
Issuance year: 2018-2019	74.1%	75.5%	67.0%		85.2%	67.4%	
Issuance year: 2020-2021	59.2%	64.7%	53.7%	74.7%	68.8%	54.3%	32.0%
Issuance year: $\geq$2022	38.7%	31.5%	39.6%	76.9%	40.6%	40.9%	

Table II
Firm Characteristics

This table reports summary statistics for our sample of publicly listed firms for which Sustainalytics ratings are available. *q* is defined as (book value of assets – book value of equity + market value of equity – deferred taxes)/(book value of assets). *ROA* is the return on assets, defined as EBITDA/assets. *Leverage* is defined as the ratio of total debt to assets, both in book values. *Prior 12-month return* is the buy-and-hold stock return during the 12 months prior to the focal firm-year. *Institutional ownership* is the fraction of shares held by institutional investors, as reported by FactSet. *U.S. firm* equals one if a firm is domiciled in the United States and zero otherwise. Scope 1 emissions are direct greenhouse emissions. Scope 2 emissions are indirect emissions created by the production of the energy that a firm consumes. Scope 3 emissions cover emissions that a firm is indirectly responsible for up and down its value chain. *Emission intensity* equals Scope 1 emissions divided by sales. For each industry each year, we sort firms' scope 1 emissions and calculate *Industry emission gap* as the logarithm of the ratio of the 75th percentile value to the 25th percentile value. *Abatement cost* is the estimated abatement cost-per-ton extracted from CDP and averaged across firms in the same industry. For intuitive presentation, the abatement investment cost is divided by the average remaining project life. *#Abatement projects* is the number of abatement projects operated by the firm. *Board ESG committee* is a dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx. *Board climate authority* is a dummy variable indicating whether the firm's board has ultimate authority/responsibility over its climate policies, from CDP. *Managerial climate incentive* is a dummy variable indicating whether the firm gives management explicit incentives tied to decarbonization, from CDP. *Retired offsets* is the quantity of offsets retired by a firm. *Average vintage of retired offsets* is the quantity-weighted vintage of offsets retired by a firm. *Retired BeZero-rated offsets* is a dummy variable indicating whether a firm retired any offsets rated by BeZero in a given year. The averages, 25th percentiles, medians, 75th percentiles, standard deviations, and number of observations for these variables are reported.

Variable	Mean	25%	50%	75%	St. Dev.	N
Assets ($ billion)	28.57	1.64	4.70	15.39	89.02	51,057
Market capitalization ($ billion)	10.60	1.28	3.37	9.04	22.40	50,489
q	1.85	1.01	1.29	2.01	1.51	50,489
ROA	0.03	0.01	0.03	0.07	0.11	50,730
Leverage	0.27	0.10	0.24	0.39	0.20	50,899
Prior 12-month return	0.10	-0.14	0.04	0.25	0.42	42,236
Institutional ownership	0.45	0.15	0.34	0.79	0.34	41,170
U.S. firm	0.41	0.00	0.00	1.00	0.49	51,057
Scope 1 emissions (million tons)	1.46	0.00	0.03	0.19	5.73	47,090
Scope 2 emissions (million tons)	0.26	0.01	0.04	0.17	0.68	47,090
Scope 3 emissions (million tons)	1.26	0.05	0.23	0.93	3.03	47,090
Emission intensity (x1,000)	0.20	0.00	0.01	0.04	0.69	47,090
Industry emission gap	2.84	2.28	2.63	3.18	0.75	51,057
Abatement cost ($ per ton)	158.83	32.01	88.21	201.20	213.78	36,059
#Abatement projects	65.29	4.00	10.00	40.00	160.67	14,301
Board ESG committee	0.20	0.00	0.00	0.00	0.40	39,667
Board climate authority	0.18	0.00	0.00	0.00	0.38	51,057
Managerial climate incentive	0.17	0.00	0.00	0.00	0.37	51,057
Retired offsets (thousand tons)	60.44	0.06	2.10	20.00	204.38	2,402
Average vintage of retired offsets (year)	2014.98	2013.00	2015.27	2017.33	3.44	2,005
Retired BeZero-rated offsets	0.55	0.00	1.00	1.00	0.50	2,402

Table III
Ordinary Least Squares (OLS) Regressions

This table reports results from firm-year level ordinary least squares (OLS) regressions. The dependent variable is one of three variables: the quantity of carbon offset credits retired by firm i in year t (Panel A) or the firm's Scope 1 carbon emissions (Panel B), both scaled by the firm's Scope 1 emissions in the previous year, or a dummy variable indicating whether the firm retires any offset credits that are rated by BeZero conditional on retiring credits (Panel C). The independent variable is a proxy for the firm's internal abatement cost or an indicator for whether the firm has a corporate governance mechanism to monitor/discipline the quality of its offsets. Proxies for abatement costs (used in Panels A and B) include the logarithm of abatement cost (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP and averaged across firms in the same industry) and #abatement projects/assets (i.e., number of abatement projects operated by the firm scaled by its assets). Indicators of corporate governance mechanisms include: Board ESG committee (i.e., dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), Board climate authority (i.e., dummy variable indicating whether the firm's board has ultimate authority/responsibility over its climate policies, from CDP), and Managerial climate incentive (i.e., dummy variable indicating whether the firm gives management explicit incentives tied to decarbonization, from CDP). Controls include the logarithm of assets, book leverage, return on assets, and institutional ownership, all lagged by one year, as well as year or industry-by-year fixed effects. t-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Panel A. Carbon offset retirements, abatement costs, and corporate governance

	Dependent variable: Retired offsets				
	Abatement costs		Corporate governance		
	(1)	(2)	(3)	(4)	(5)
log(Abatement cost)	0.052***				
	[3.07]				
#Abatement projects/assets		-2.466**			
		[-2.12]			
Board ESG committee			-0.108**		
			[-2.01]		
Board climate authority				-0.065**	
				[-2.25]	
Managerial climate incentive					-0.055*
					[-1.85]
log(assets)	0.075***	0.066	0.109***	0.036**	0.035**
	[4.44]	[1.07]	[3.94]	[2.44]	[2.46]
Leverage	-0.075	-0.044	0.068	0.012	0.002
	[-0.58]	[-0.11]	[0.30]	[0.07]	[0.01]
ROA	0.141	-0.332	0.126	0.143	0.139
	[0.75]	[-0.45]	[0.70]	[1.03]	[1.00]
Institutional ownership	0.303***	0.207	0.118	0.151*	0.162*
	[2.65]	[1.10]	[1.26]	[1.77]	[1.85]
Year FE	Y	N	N	N	N
Industry-by-year FE	N	Y	Y	Y	Y
Observations	29,980	10,841	31,682	40,714	40,714
R-squared	0.003	0.054	0.022	0.020	0.019

(continued)

Table III
Ordinary Least Squares (OLS) Regressions (continued)

Panel B. Scope 1 emissions, abatement costs, and corporate governance					
	Dependent variable: Scope 1 emissions				
	Abatement costs		Corporate governance		
	(1)	(2)	(3)	(4)	(5)
log(Abatement cost)	0.007**				
	[2.07]				
#Abatement projects/assets		-1.244***			
		[-2.95]			
Board ESG committee			-0.052***		
			[-4.99]		
Board climate authority				-0.028***	
				[-4.03]	
Managerial climate incentive					-0.030***
					[-4.32]
log(assets)	-0.019***	-0.023***	-0.006**	-0.003	-0.003
	[-5.97]	[-3.72]	[-2.07]	[-1.50]	[-1.37]
Leverage	-0.056**	-0.047	-0.059**	-0.020	-0.019
	[-2.14]	[-0.95]	[-2.29]	[-1.16]	[-1.14]
ROA	-0.770***	0.238**	-0.613***	-0.251***	-0.252***
	[-8.54]	[2.04]	[-7.47]	[-5.06]	[-5.07]
Institutional ownership	-0.036**	0.012	-0.016	-0.003	-0.002
	[-2.43]	[0.46]	[-1.17]	[-0.30]	[-0.24]
Year FE	Y	N	N	N	N
Industry-by-year FE	N	Y	Y	Y	Y
Observations	29,941	10,872	31,643	40,472	40,472
R-squared	0.015	0.049	0.036	0.026	0.026

(continued)

Table III
Ordinary Least Squares (OLS) Regressions (continued)

Panel C. Carbon offset quality and corporate governance

	Dependent variable: **I**(Uses BeZero-rated offsets)		
	(1)	(2)	(3)
Board ESG committee	0.066**		
	[2.08]		
Board climate authority		0.048*	
		[1.65]	
Managerial climate incentive			0.062**
			[2.04]
log(assets)	-0.001	-0.005	-0.007
	[-0.10]	[-0.38]	[-0.53]
Leverage	-0.049	-0.022	-0.025
	[-0.48]	[-0.23]	[-0.26]
ROA	-0.042	-0.108	-0.115
	[-0.23]	[-0.62]	[-0.67]
Institutional ownership	0.036	-0.001	-0.000
	[0.67]	[-0.01]	[-0.00]
Industry-by-year FE	Y	Y	Y
Observations	1,878	2,102	2,102
R-squared	0.166	0.171	0.172

Table IV
Correlations Between Emissions and Sustainalytics ESG Ratings

This table reports the association between within-industry ESG percentile rankings and lagged emission intensity. Specifically, results from the following regression are reported:

$$\textit{ESGRanking}_{i,t} = \alpha + \beta \cdot \textit{Emission intensity}_{i,t-1} + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

in which within-industry ESG percentile rankings are either based on Sustainalytics' legacy ESG scores or new ESG risk scores. *Emission intensity*$_{i,t-1}$ equals scope 1 emissions scaled by sales. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1).

Rankings based on:	Legacy scores (1)	Risk scores (2)
Emission intensity	-0.028	0.383**
	[-0.25]	[2.05]
log(Assets)	0.067	-1.705***
	[0.88]	[-3.22]
Leverage	-0.645	6.426***
	[-0.99]	[4.40]
ROA	-0.000	0.167
	[-0.53]	[0.34]
Institutional ownership	-1.005	-5.060**
	[-1.07]	[-2.53]
Firm FE	Y	Y
Industry-year FE	Y	Y
Observations	21,645	24,454
R-squared	0.862	0.842

Table V
Market Response Around ESG Rating Downgrades

This table reports results from firm-quarter (columns 1 to 5) or firm-month (columns 6 and 7) difference-in-differences (DID) regressions of investor responses using the Sustainalytics methodology change as a treatment event. We estimate the regressions using a window of two quarters before and after December 2018.

$$\textit{Market response}_{i,t} = \alpha + \beta \cdot \textit{Post}_t \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

In columns 1 to 5, *Market response*$_{i,t}$ denotes quarterly institutional ownership shares (column 1), ESG fund ownership shares (column 2), reputation risk (RepRisk) index (column 3), median analyst ratings (column 4), or the percentage of analysts with sell recommendations (column 5) for firm *i* in quarter *t*. In columns 6 and 7, *Market response*$_{i,t}$ denotes the monthly stock return, measured as either the raw return or the CAPM-adjusted return and winsorized at the 1% level. Post$_t$ is a dummy variable equal to one for quarters or months after December 2018 and zero otherwise. *Rating downgrade*$_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, and return on assets. δ_i and $\sigma_{j,t}$ denote firm and industry-by-quarter fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	Dependent variable:						
	Institutional ownership	ESG fund ownership	RepRisk index	Analyst med. rating	Analyst sell %	Monthly returns: Raw	Monthly returns: CAPM-adj.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Rating downgrade	-0.003**	-0.001**	0.699***	0.058**	2.475*	-0.003*	-0.004*
	[-2.51]	[-2.52]	[2.69]	[1.99]	[1.78]	[-1.72]	[-1.67]
log(assets)	0.014***	0.001	0.745	-0.540***	-26.140***	-0.002	-0.011
	[4.29]	[1.37]	[1.03]	[-7.11]	[-7.31]	[-0.33]	[-1.62]
Leverage	-0.002	-0.003	-0.554	0.013	-1.725	0.042**	0.028
	[-0.27]	[-1.54]	[-0.31]	[0.07]	[-0.18]	[2.31]	[1.63]
ROA	0.006	-0.002*	-1.579	-0.552***	-25.675***	-0.034**	-0.035**
	[0.99]	[-1.65]	[-0.78]	[-3.11]	[-3.04]	[-2.23]	[-2.18]
Firm FE	Y	Y	Y	Y	Y	Y	Y
Industry-by-quarter FE	Y	Y	Y	Y	Y	Y	Y
Observations	15,237	8,143	13,632	12,965	12,965	49,756	49,737
R-squared	0.996	0.937	0.857	0.661	0.671	0.443	0.324

Table VI
Difference-in-Differences (DID): Carbon Offset Retirements Around ESG Rating Downgrades

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event.

$$\textit{Retired offsets}_{i,t} = \alpha + \beta \cdot \textit{Post}_t \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable is the quantity of carbon offset credits retired by firm *i* in year *t*, scaled by the firm's scope 1 carbon emissions in 2018 prior to the rating change event. $\textit{Post}_t$ is a dummy variable equal to one for years after 2018 and zero otherwise. $\textit{Rating downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. Columns 1 to 3 report results for all firms in the sample where firm fixed effects and control variables are gradually added to the regression specification, and column 4 reports results from the fully saturated model for a subsample of firms that retire offset credits at least once during the sample period. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1).

	Dependent variable: Retired offsets			
	Full sample			Firms using offsets
	(1)	(2)	(3)	(4)
Post × Rating downgrade	0.244**	0.242**	0.250**	1.128**
	[2.35]	[2.34]	[2.32]	[1.97]
Rating downgrade	-0.037			
	[-0.89]			
log(assets)			-0.044	-0.885
			[-0.17]	[-0.43]
Leverage			1.277	13.007
			[1.59]	[1.63]
ROA			0.363	6.538*
			[1.37]	[1.67]
Institutional ownership			0.293	2.502
			[1.26]	[1.40]
Firm FE	N	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y
Observations	23,419	23,304	23,222	3,956
R-squared	0.015	0.471	0.472	0.490

Table VII
Subsample Difference-in-Differences (DID): Abatement Costs

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for subsamples sorted on proxies of internal abatement costs. These proxies, measured at the end of 2018, include abatement cost (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP and averaged across firms in the same industry), #abatement projects/assets (i.e., number of abatement projects operated by the firm scaled by its assets), and Scope 1 emissions.

$$\textit{Outcome}_{i,t} = \alpha + \beta \cdot \textit{Post}_t \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable, $\textit{Outcome}_{i,t}$, is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* (Panel A) or the firm's Scope 1 carbon emissions (Panel B), both scaled by the firm's scope 1 carbon emissions in 2018 prior to the rating change event. $\textit{Post}_t$ is a dummy variable equal to one for years after 2018 and zero otherwise. $\textit{Rating downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-values from testing the statistical difference of the β coefficients between the high- and low-abatement cost subsamples are also reported.

Panel A. Carbon offset retirements						
	Dependent variable: Retired offsets					
	Abatement cost		#Abate. projects/assets		Scope 1 emissions	
	High (1)	Low (2)	Low (3)	High (4)	Low (5)	High (6)
Post × Rating downgrade	0.405**	0.026	0.569**	-0.154	0.506**	0.030
	[2.15]	[0.53]	[2.41]	[-1.18]	[2.36]	[0.85]
log(assets)	-0.451	0.082	-3.107	0.425	-0.113	0.033
	[-0.65]	[1.49]	[-1.42]	[1.28]	[-0.28]	[0.56]
Leverage	4.287*	0.033	8.571	0.569	2.034	0.032
	[1.65]	[0.28]	[1.08]	[1.34]	[1.60]	[0.46]
ROA	1.966	0.042	4.432	1.070	0.393	0.191
	[1.50]	[0.53]	[1.23]	[1.06]	[1.17]	[0.82]
Institutional ownership	0.726	-0.019	1.443	-0.641	0.665	-0.019
	[1.50]	[-0.32]	[1.10]	[-1.19]	[1.46]	[-0.25]
p-value: L > R	0.026		0.004		0.014	
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y	Y	Y
Observations	11,176	11,103	4,071	4,045	11,673	11,473
R-squared	0.453	0.742	0.431	0.783	0.474	0.512

(continued)

Table VII
Subsample Difference-in-Differences (DID): Abatement Costs (continued)

Panel B. Scope 1 emissions						
	Dependent variable: Scope 1 emissions					
	Abatement cost		#Abate. projects/assets		Scope 1 emissions	
	High (1)	Low (2)	Low (3)	High (4)	Low (5)	High (6)
Post × Rating downgrade	-0.001	-0.064**	-0.015	-0.131**	0.003	-0.048**
	[-0.04]	[-2.42]	[-0.35]	[-2.25]	[0.10]	[-2.04]
log(assets)	0.388***	0.351***	0.533***	0.158*	0.410***	0.385***
	[5.50]	[8.60]	[5.56]	[1.67]	[9.40]	[9.35]
Leverage	-0.158	0.258*	0.072	-0.836***	0.354**	-0.206**
	[-0.94]	[1.78]	[0.28]	[-2.80]	[2.44]	[-1.99]
ROA	-0.446	0.272**	-0.294	-0.064	0.182	0.114
	[-1.44]	[2.12]	[-1.27]	[-0.25]	[1.36]	[1.26]
Institutional ownership	-0.119	0.131	0.367	-1.924	0.080	-0.056
	[-0.57]	[1.11]	[1.09]	[-1.46]	[0.50]	[-0.44]
p-value: L > R	0.042		0.054		0.091	
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y	Y	Y
Observations	11,101	10,322	3,981	3,939	10,883	11,410
R-squared	0.321	0.424	0.435	0.399	0.418	0.427

Table VIII
Subsample Difference-in-Differences (DID): Corporate Governance

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for subsamples sorted on indicators for whether the firm has a corporate governance mechanism to monitor/discipline the quality of its offsets. These indicators, measured at the end of 2018, include: Board ESG committee (i.e., dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), Board climate authority (i.e., dummy variable indicating whether the firm's board has ultimate authority/responsibility over its climate policies, from CDP), and Managerial climate incentive (i.e., dummy variable indicating whether the firm gives management explicit incentives tied to decarbonization, from CDP).

$$Outcome_{i,t} = \alpha + \beta \cdot Post_t \times Rating\ downgrade_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable, $Outcome_{i,t}$, is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* scaled by the firm's Scope 1 carbon emissions in 2018 prior to the rating change event (Panel A), or a dummy variable indicating whether the firm retires any offset credits that are rated by BeZero conditional on retiring credits (Panel B). $Post_t$ is a dummy variable equal to one for years after 2018 and zero otherwise. $Rating\ downgrade_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-values from testing the statistical difference of the β coefficients between the poor- and good-governance subsamples are also reported.

Panel A. Carbon offset retirements						
	Dependent variable: Retired offsets					
	Board ESG committee		Board climate authority		Managerial climate incentive	
	No (1)	Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)
Post × Rating downgrade	0.179**	-0.026	0.170**	-0.011	0.156**	0.009
	[2.12]	[-0.30]	[2.16]	[-0.19]	[2.09]	[0.14]
log(assets)	0.089	-0.125*	0.093	-0.061	0.088	-0.052
	[0.73]	[-1.81]	[1.39]	[-0.56]	[1.34]	[-0.41]
Leverage	0.439	0.232	0.270	0.075	0.265	-0.003
	[1.26]	[1.64]	[0.89]	[0.27]	[0.90]	[-0.01]
ROA	0.315	0.292	0.297	0.224	0.306	0.152
	[0.96]	[1.56]	[1.07]	[0.65]	[1.12]	[0.37]
Institutional ownership	0.078	0.291	0.064	0.054	0.070	0.043
	[0.34]	[1.05]	[0.37]	[0.16]	[0.41]	[0.10]
p-value: L > R	0.045		0.032		0.068	
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y	Y	Y
Observations	17,855	3,444	17,422	6,108	18,010	5,520
R-squared	0.574	0.590	0.467	0.755	0.466	0.762

(continued)

Table VIII
Subsample Difference-in-Differences (DID): Corporate Governance (continued)

Panel B. Carbon offset quality						
	Dependent variable: **I**(Uses BeZero-rated credits)					
	Board ESG committee		Board climate authority		Managerial climate incentive	
	No (1)	Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)
Post × Rating downgrade	0.034	0.306**	-0.104	0.261**	-0.033	0.257**
	[0.27]	[2.10]	[-0.40]	[2.59]	[-0.17]	[2.51]
log(assets)	-0.224	0.857***	-0.524*	0.140	-0.197	0.133
	[-1.13]	[2.86]	[-1.82]	[0.63]	[-0.73]	[0.59]
Leverage	0.685	0.391	0.053	-0.353	0.083	-0.220
	[1.17]	[0.75]	[0.08]	[-0.70]	[0.13]	[-0.42]
ROA	0.359	1.705	-0.113	-0.110	-0.321	-0.085
	[0.80]	[1.17]	[-0.13]	[-0.21]	[-0.30]	[-0.16]
Institutional ownership	-0.513	-0.646	0.416	-0.711	0.534	-0.743
	[-0.98]	[-0.98]	[0.69]	[-1.00]	[0.87]	[-1.02]
p-value: L < R	0.079		0.096		0.094	
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y	Y	Y
Observations	473	202	168	513	189	492
R-squared	0.693	0.790	0.780	0.723	0.795	0.728

Table IX
Subsample Difference-in-Differences (DID): Industry Subsamples

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for non-mutually exclusive industry subsamples. Columns 1 to 3 focus on "Consumer-facing", "Finance and services", and "Fossil fuels or industrials" industries, respectively. Consumer-facing industries are defined as Fama-French 49 industry codes 2 to 7, 9 to 11, 33, 43 to 44, as well as SIC codes 6020, and 6320 to 6329. Finance and services include Fama-French codes 7, 33, 34, and 45 to 48; fossil fuel industries 29 to 31; and industrials 14 to 26. Columns 4 and 5 sort firms into industries with low or high (with respect to the median) emission gaps measured as the industry's inter-quartile range of emissions as of 2018.

$$Outcome_{i,t} = \alpha + \beta \cdot Post_t \times Rating\ downgrade_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable, $Outcome_{i,t}$, is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* scaled by the firm's Scope 1 carbon emissions in 2018 prior to the rating change event (Panel A), or a dummy variable indicating whether the firm retires any offset credits that are rated by BeZero conditional on retiring credits (Panel B). $Post_t$ is a dummy variable equal to one for years after 2018 and zero otherwise. $Rating\ downgrade_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and year (columns 1 to 3) or industry-by-year (columns 4 and 5) fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-value from testing the statistical difference of the β coefficients between the low- and high-industry emission gap subsamples (columns 4 and 5) is also reported.

Panel A. Carbon offset retirements					
	Dependent variable: Retired offsets				
	Consumer facing	Finance and services	Fossil fuels or industrials	Industry emission gap	
				Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	0.332*	0.456**	-0.039	0.208**	0.021
	[1.95]	[2.01]	[-1.16]	[1.96]	[0.34]
log(assets)	0.677	-0.877	0.076	0.158	-0.210
	[1.27]	[-0.97]	[0.93]	[0.79]	[-0.77]
Leverage	0.726	4.321	0.322	0.532	1.172
	[1.60]	[1.13]	[1.06]	[1.08]	[1.16]
ROA	0.426	1.788	-0.032	0.752	0.285
	[0.75]	[0.92]	[-0.83]	[1.25]	[0.74]
Institutional ownership	-0.248	0.697	-0.045	0.250	0.042
	[-1.06]	[1.20]	[-0.53]	[0.70]	[0.26]
p-value: L > R				0.064	
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	N
Industry-by-year FE	N	N	N	Y	Y
Observations	5,523	6,868	5,975	12,154	10,429
R-squared	0.269	0.320	0.902	0.585	0.568

(continued)

Table IX
Subsample Difference-in-Differences (DID): Industry Subsamples (continued)

Panel B. Carbon offset quality					
	Dependent variable: **I**(Uses BeZero-rated offsets)				
	Consumer	Finance and	Fossil fuels or	Industry emission gap	
	facing	services	industrials	Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	-0.026	-0.202	0.307**	0.020	0.293***
	[-0.15]	[-1.18]	[2.55]	[0.11]	[3.03]
log(assets)	0.074	-0.105	0.217	-0.122	0.202
	[0.18]	[-0.37]	[1.23]	[-0.67]	[0.89]
Leverage	-0.519	-0.056	-0.518	0.716	-0.283
	[-0.72]	[-0.08]	[-0.58]	[1.59]	[-0.61]
ROA	-0.840	-0.213	-0.303	0.653	0.342
	[-0.61]	[-0.14]	[-0.42]	[1.17]	[0.54]
Institutional ownership	-2.452	0.150	0.043	-1.162**	-0.166
	[-1.63]	[0.18]	[0.08]	[-2.40]	[-0.30]
p-value: L $<$ R				0.093	
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	N
Industry-by-year FE	N	N	N	Y	Y
Observations	203	241	235	282	444
R-squared	0.609	0.537	0.689	0.743	0.707

Internet Appendix

to "*Carbon Offsets: Decarbonization or Transition-Washing?*"

by

Sehoon Kim, Tao Li, and Yanbin Wu

IA.I Framework with Example Functional Specification

This section provides an example of specific functional forms incorporated into our conceptual framework in Section II. For simplicity, we assume the following functional forms:

$$C(a;e) = \tfrac{1}{2}\kappa(e)a^2, \quad P(q) = p_0 + p_1 q, \quad \lambda\phi(R) = \tfrac{1}{2}\lambda R^2, \quad f(G;q) = \tfrac{1}{2}G(1-q)^2$$

where $\kappa(e) = \kappa_0 - \kappa_1 e$.[45] The joint first order conditions with respect to the key choice variables, a, o, and q, that characterize interior solutions can be written as follows. For ease of exposition, we focus on interior solutions and verify that all conditions ensuring an interior minimum are intuitively satisfied.

$$\begin{aligned} (a) &: \ \kappa a = \lambda \cdot R \\ (o) &: \ P(q) = \lambda \cdot R \\ (q) &: \ p_1 \cdot o = G(1-q) \end{aligned}$$

Based on these FOCs, the closed form solutions for the optimums can be derived as:

$$a^* = \frac{\mu}{\kappa(e)}, \quad o^* = e - \mu\left(\frac{1}{\kappa(e)} + \frac{1}{\lambda}\right), \quad q^* = \frac{\mu - p_0}{p_1}$$

where μ $(= C_a = P(q) = \lambda \cdot R)$ serves as the common marginal mitigation price, or internal shadow carbon price, such that[46]

$$\mu = \frac{G(p_0 + p_1) - p_1^2 e}{G - p_1^2\left(\frac{1}{\kappa(e)} + \frac{1}{\lambda}\right)}$$

[45] Assume that $p_0 > 0$ and $p_1 > 0$. Also assume $\kappa(e) > 0$, $\kappa_0 > 0$, and $\kappa_1 > 0$.

[46] μ must be positive. This condition is satisfied if $\frac{G}{p_1} - \frac{p_1}{p_0+p_1}e > 0$ and $\frac{G}{p_1} - p_1\left(\frac{1}{\kappa(e)} + \frac{1}{\lambda}\right) > 0$. The first condition means that the penalty for using the lowest-quality offsets relative to the cost savings this would achieve (call this term "relative penalty") should be greater than the cost savings by offsetting all of the firm's emissions using the lowest-quality offsets relative to the cost of offsetting all emissions using the highest-quality offsets. The second condition means that the "relative penalty" should be greater than the sum of two ratios of the marginal cost saving from using the lowest-quality offset: one ratio relative to marginal abatement costs, and another ratio relative to how important the penalties on nominal residual emissions are. These are sensible conditions, because firms would always use low-quality offsets if the cost-cutting benefit of doing so were too great and G were too small, resulting in a corner solution where G does not affect the firm's choice.

The model generates comparative statics that guide many of our empirical analyses:

1. Greater marginal abatement costs (i.e., higher $\kappa(e)$, which in part can be due to low emissions) shrinks μ, leading to less internal abatement and conversely more offsets.[47]

2. Better governance (i.e., higher G) generally increases μ (if $e > (p_0 + p_1)(\frac{1}{\kappa} + \frac{1}{\lambda})$), corresponding to greater abatement, less offsets, and higher offset quality.

3. An ESG rating downgrade that makes the firm's emissions more salient (i.e., higher λ) decreases μ, which lowers abatement while increasing the use of low-quality offsets.

IA.II Additional Data Details

A. Carbon Offset Projects

We compile our voluntary carbon offsets dataset from four carbon registries: American Carbon Registry (ACR), the Gold Standard (Gold), the Climate Action Reserve (CAR), and Verra's Verified Carbon Standard (VCS). Collectively, these registries account for the majority of activity in the voluntary carbon market during our sample period and serve as the central repositories for certifying, issuing, and retiring carbon credits worldwide. Each registry maintains publicly accessible online databases that provides detailed information on offset projects and their associated credit retirements. The data were downloaded directly from the respective registry websites in December 2023. The registries assign unique project identification numbers to each offset project upon registration, enabling precise tracking of credit issuance and retirement. Our raw dataset encompasses all offset projects and their credit retirements from each registry's inception through the end of 2023.

For each project, the dataset contains information including: (i) project name and a unique identifier; (ii) project developer identity; (iii) geographic location (country and, where available, subnational region); (iv) project type and carbon reduction methodologies; (v) quantities and vintage years of issued credits; and (vii) detailed credit retirement

[47]Although the absolute levels of a^* and o^* are ambiguously related to e, a^*/e (o^*/e) increases (decreases) with e as long as $\partial\mu/\partial e$ is negative, in other words, the shadow cost of total mitigation is a decreasing function of e.

records including retirement dates, quantities, and beneficiaries (when disclosed). After standardizing and merging data from the four registries into a single comprehensive dataset, our consolidated dataset comprises more than 336,100 entries of voluntary carbon credit retirement records from 2005 through 2023. Table IA.I in the Internet Appendix provides comprehensive summary statistics on the distribution of offsets projects. The dataset includes 3,353 unique offset projects that have issued over 1.7 billion metric tons of carbon credits. The average project size is approximately 501,000 metric tons of issued credits, with a median size of 102,000 metric tons. The projects are geographically diverse, spanning 126 countries across six continents, and cover a wide range of project types including forestry and land use (12%), household and community (26%), and renewable energy (40%). The projects also vary in terms of their vintage years, with some dating back to the early 2010s and others being more recent.

To identify publicly listed firms that retire carbon credits, we first extract the names of the entities that retire credits from the retirement beneficiary/notes fields in the retirement records. These fields often contain the name of the firm or organization that has retired the credits, along with additional notes or comments about the retirement. We then use a combination of automated text-matching algorithms and manual verification to match these names with a comprehensive list of publicly listed firms worldwide, based on the Compustat Global and North America databases. We employ fuzzy string matching techniques to account for variations in naming conventions, abbreviations, and potential typographical errors in the retirement records. This process involves manual review for any similarity match between the names in the retirement records and those in the Compustat databases. If the recorded retirement beneficiary is a non-listed subsidiary of another publicly listed firm, we assign the publicly traded parent company as the retirement beneficiary. If the subsidiary itself is a publicly traded firm, it is considered the retirement beneficiary.

It is possible that some firms choose not to disclose their identities when retiring carbon credits; in such cases, these entities do not appear in the retirement beneficiary/notes fields of our dataset and therefore cannot be linked to publicly listed firms. We verify whether the total number of credits retired by a randomly chosen firm in a given year, as recorded by the registries, generally aligns with the amounts disclosed in the firm's ESG/sustainability report (if available), and we find that they are mostly in alignment. The composition of our sample of offset projects is also corroborated by emerging studies in the literature. For example, Berg et al. (2025), who study voluntary carbon credit transactions using proprietary data from a single VCM broker-dealer, report distributions across project types, registries, and geographic regions that are identical or similar to ours. Finally, to further ensure data quality, we cross-verify our manually identified project-firm matches with an alternative commercial database on voluntary carbon markets, Allied Offsets, which was established during our study. This verification step helps to minimize data errors.

B. Carbon Disclosure Project (CDP)

As described in the paper, we use CDP data to obtain measures of firms' internal abatement costs and climate-related governance mechanisms. CDP solicits responses from firms through annual questionnaires that cover a wide range of environmental topics, including greenhouse gas emissions, climate change risks and opportunities, and sustainability initiatives. The questionnaires are designed to capture both quantitative data (e.g., emission levels, abatement costs) and qualitative information (e.g., governance structures, climate strategies). CDP has established rigorous verification processes to ensure the accuracy and reliability of self-reported data. Firms are encouraged to provide detailed explanations for their responses, and CDP conducts follow-up inquiries to clarify any ambiguities or inconsistencies. CDP covers over 23,000 private and publicly listed companies worldwide as of 2023. We focus on publicly listed firms and use survey responses available from 2013 to 2022. We merge CDP data with our main sample using ISINs, which are linked to each firm's unique CDP account number.

IA.III Additional Results

This section reports additional summary statistics and analyses pertaining to alternative measures, subsamples, and specifications.

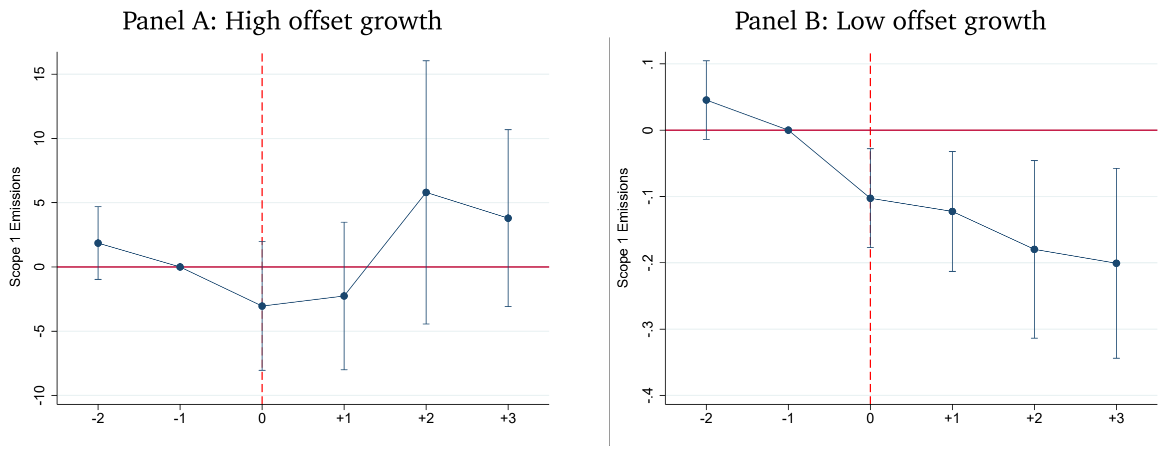

Figure IA.1. Carbon offset usage and emissions dynamics. This figure illustrates the post-treatment dynamics of Scope 1 emissions, scaled by 2018 emissions, for treated firms that experienced ranking downgrades following Sustainalytics' rating methodology change. Panel A (Panel B) shows emissions dynamics for the subsample of firms that responded to the downgrade by increasing their offset usage more (less) than the median firm. Specifically, for these subsamples, we plot the coefficients, β_s, and their 90% confidence intervals from the specification below:

$$Scope\ \ 1\ \ emissions_{i,t} = \alpha + \left(\sum_{s=-2}^{-1} \beta_s \cdot Pre(s)_t + \sum_{s=0}^{+3} \beta_s \cdot Post(s)_t \right) + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \epsilon_{i,t},$$

where $Pre(s)$ ($Post(s)$) is a dummy variable equal to one if the observation is s years before (after) the event year 2019 and zero otherwise. Offset growth is measured as the change in average offset retirements during the post-period compared to the pre-period, scaled by 2018 emissions. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and past quarter's stock return. δ_i denotes firm fixed effects. Standard errors are clustered at the firm level.

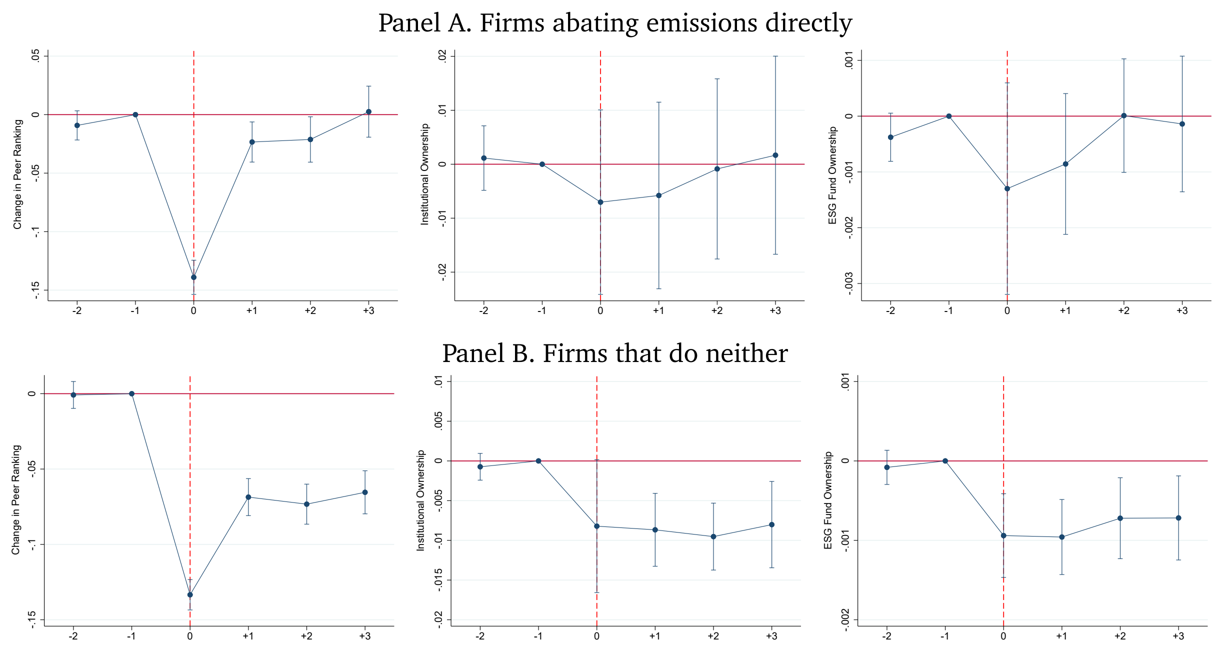

Figure IA.2. **Counterfactual post-shock recoveries.** This figure illustrates the post-treatment dynamics of within-industry ESG percentile rankings, institutional ownership, and ESG fund ownership for treated firms that experienced ranking downgrades following Sustainalytics' rating methodology change. The sample includes firms that responded to the downgrade by abating their emissions directly, defined as having average post-period emissions at least 25% lower than average pre-period emissions (Panel A), and firms that did not respond by offsetting or abating emissions (Panel B). Specifically, for these subsamples, we plot the coefficients, β_s, and their 90% confidence intervals from the specification below:

$$Investor\ \ response_{i,t} = \alpha + \left(\sum_{s=-2}^{-1} \beta_s \cdot Pre(s)_t + \sum_{s=0}^{+3} \beta_s \cdot Post(s)_t \right) + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \epsilon_{i,t},$$

where *Investor response*$_{i,t}$ is: (i) within-industry ESG percentile rankings based on Sustainalytics' legacy ESG scores for 2017 and 2018, and based on the new ESG risk scores from 2019 onward after Sustainalytics changed their methodology; (ii) Insitutional ownership from FactSet; and (iii) ESG fund ownership for U.S. firms from the CRSP Mutual Fund Database and Morningstar. $Pre(s)$ ($Post(s)$) is a dummy variable equal to one if the observation is s years before (after) the event year 2019 and zero otherwise. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and past quarter's stock return. δ_i denotes firm fixed effects. Standard errors are clustered at the firm level.

Table IA.I
Characteristics of Carbon Offset Projects by Region and Carbon Registry

This table reports summary statistics characterizing the distribution, types, and credit issuance/retirement activity of all carbon offset projects registered on four carbon registries, ACR, Gold, CAR, and VCS. Panel A summarizes all 3,353 projects. Panel B describes a subset of 969 projects that issue offset credits used by publicly listed firms in the U.S. Panel C describes 1,854 projects that issue offset credits used by publicly listed firms included in our main sample. In Panels A and B, the number of offset projects is tabulated for the full sample and across geographic subsamples. The number of projects for different project types and the number of projects that are externally rated by the carbon rating agency, BeZero, are also reported separately for the full sample and across geographic subsamples. The average and median offset prices per ton (as of February 2024) are reported for our full sample and geographic subsamples. Also reported are the average, median, and total number of credits issued by projects based in each geographic region, as well as the average percentage of issued credits that are retired overall and for different credit vintage groups. In Panel C, the number of offset projects is tabulated for the full sample and across each of the four registries. The number of projects in different geographic regions and project types as well as the number of projects that are externally rated by the carbon rating agency, BeZero, are also reported separately for the full sample and across registry subsamples. The average and median offset prices per ton (as of February 2024) are reported for the full sample and each carbon registry. Also reported are the average, median, and total number of credits issued by projects on each registry, as well as the average percentage of issued credits that are retired overall and for different credit vintage groups.

Panel A: All projects

		Geographic region					
Number of projects	Full sample	Africa	Asia	Europe	North America	South America	Other
Total	3,353	662	1,714	59	659	245	14
Type							
Agriculture	132	1	49	6	60	16	0
Carbon capture & storage	4	0	0	0	4	0	0
Chemical processes	119	8	7	1	103	0	0
Forestry & land use	398	50	62	1	194	84	7
Household & community	873	544	285	1	29	13	1
Industrial & commercial	158	3	87	41	25	3	0
Renewable energy	1,330	43	1,130	6	36	109	3
Transportation	43	0	2	0	36	3	2
Waste management	296	13	92	3	172	17	1
Rated by BeZero Carbon	411	79	191	5	78	55	3
Average price per ton (as of February 2024)	4.2	5	2.3	4.3	7.7	3.9	4.2
Median price per ton (as of February 2024)	3.5	4.9	1.5	3.6	4.9	2.5	3.6
Average #credits issued (thousand tons)	501.6	392.4	511.3	274.5	360.6	1,168.2	411.1
Median #credits issued (thousand tons)	102.4	43.4	140.1	141.7	89.8	199.4	173.4
Total #credits issued (million tons)	1,681.9	259.8	876.4	16.2	237.6	286.2	5.8
Average % of credits being retired	66.0%	66.4%	62.5%	82.6%	73.2%	65.6%	86.7%
Issuance year: ≤2015	77.5%	88.7%	74.8%	85.3%	80.4%	75.1%	90.9%
Issuance year: 2016-2017	76.1%	81.3%	71.6%	65.4%	82.0%	71.7%	92.0%
Issuance year: 2018-2019	73.9%	76.2%	67.6%		85.5%	63.3%	
Issuance year: 2020-2021	56.4%	64.1%	49.3%	64.4%	64.0%	50.3%	32.0%
Issuance year: ≥2022	35.9%	40.5%	32.6%	76.9%	34.9%	40.3%	89.8%

(continued)

Table IA.I
Characteristics of Carbon Offset Projects by Region and Carbon Registry (continued)

Panel B: Projects used by publicly listed firms in the *U.S.*

	Geographic region						
Number of projects	Full sample	Africa	Asia	Europe	North America	South America	Other
Total	969	106	393	9	356	97	8
Type							
Agriculture	32	1	5	4	16	6	0
Carbon capture & storage	4	0	0	0	4	0	0
Chemical processes	66	1	2	1	62	0	0
Forestry & land use	217	24	27	0	114	48	4
Household & community	130	70	43	0	13	4	0
Industrial & commercial	24	0	17	0	7	0	0
Renewable energy	344	8	281	2	15	35	3
Transportation	22	0	0	0	20	1	1
Waste management	130	2	18	2	105	3	0
Rated by BeZero Carbon	232	34	90	4	62	39	3
Average price per ton (as of February 2024)	4.6	5.2	2.0	4.2	7.5	3.6	4.8
Median price per ton (as of February 2024)	3.4	4.7	1.2	3.6	5.0	2.5	2.6
Average #credits issued (thousand tons)	1,182.6	1,620.3	1,344.2	510.7	524.7	2,568.8	668.5
Median #credits issued (thousand tons)	299.8	143.2	446.3	397.7	160.2	544.3	430
Total #credits issued (million tons)	1,145.9	171.8	528.3	4.6	186.8	249.2	5.3
Average % of credits being retired	72.0%	74.4%	69.3%	61.4%	75.1%	68.8%	81.5%
Issuance year: $\leq$2015	80.1%	85.3%	78.7%	61.2%	82.1%	74.2%	88.0%
Issuance year: 2016-2017	76.8%	77.6%	77.0%	65.4%	78.1%	74.0%	92.0%
Issuance year: 2018-2019	75.2%	82.4%	66.4%		83.8%	71.4%	
Issuance year: 2020-2021	59.9%	65.9%	53.5%	58.0%	68.2%	53.1%	32.0%
Issuance year: $\geq$2022	36.2%	32.2%	32.9%	53.7%	37.0%	48.0%	

(continued)

Table IA.I
Characteristics of Carbon Offset Projects by Region and Carbon Registry (continued)

Panel C: Projects used by publicly listed firms

	Carbon registries				
Number of projects	Full sample	ACR	CAR	Gold	VCS
Total	1,854	152	212	587	903
Geography					
Africa	307	0	0	226	81
Asia	879	2	0	316	561
Europe	33	1	0	5	27
North America	455	147	212	18	78
South America	168	2	0	17	149
Other	12	0	0	5	7
Type					
Agriculture	60	4	23	2	31
Carbon capture & storage	4	3	0	0	1
Chemical processes	92	70	12	0	10
Forestry & land use	311	35	91	10	175
Household & community	377	0	0	341	36
Industrial & commercial	60	2	0	4	54
Renewable energy	733	2	0	209	522
Transportation	30	26	0	1	3
Waste management	187	10	86	20	71
Rated by BeZero Carbon	323	28	19	59	217
Average price per ton (as of February 2024)	4.2	6.0	9.9	3.8	2.8
Median price per ton (as of February 2024)	3.2	4.5	6.5	3.9	1.5
Average #credits issued (thousand tons)	783.6	471.1	348.8	363.9	1,211.0
Median #credits issued (thousand tons)	186.4	124.8	85.1	91.1	332.5
Total #credits issued (million tons)	1,452.8	71.6	73.9	213.6	1,093.5
Average % of credits being retired	69.9%	65.5%	80.6%	69.7%	68.4%
Issuance year: $\leq$2015	78.1%	75.7%	80.1%	82.2%	76.4%
Issuance year: 2016-2017	76.5%	97.7%	69.9%	77.5%	73.6%
Issuance year: 2018-2019	74.1%	86.9%	88.6%	73.8%	64.9%
Issuance year: 2020-2021	59.2%	67.0%	74.6%	57.3%	56.0%
Issuance year: $\geq$2022	38.7%	40.2%	38.3%	37.6%	38.7%

Table IA.II
Which Carbon Offset Projects are Rated and Used by Firms?

This table reports offset project-level regression results from linear probability models. The dependent variable is an indicator variable equal to one if a project issues credits rated by BeZero (columns 1 and 2) or retired by publicly listed firms (all firms in columns 3 and 4, and U.S. firms in columns 5 and 6) and zero otherwise. The independent variables include the logarithm of total credits issued by the project and dummy variables indicating different project types (with carbon capture & storage and transportation projects as the baseline group). Columns 3 to 6 further include a dummy variable indicating whether the project is rated by BeZero. Columns 1, 3, and 5 control for fixed effects corresponding to the project's age group, registry, and geographic region. Columns 2, 4, and 6 include dummy variables indicating the project's geographic region (baseline group consists of projects based in Asia), and drops geographic region fixed effects. Standard errors are clustered at the project-age level and the associated t-statistics are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1).

	Dependent variable:					
	I(Rated by BeZero)		**I**(Used by publicly listed firms)		**I**(Used by publicly listed firms in U.S.)	
	(1)	(2)	(3)	(4)	(5)	(6)
log(#credits issued)	0.053***	0.053***	0.092***	0.092***	0.079***	0.079***
	[11.22]	[11.22]	[13.89]	[13.89]	[12.43]	[12.43]
Forestry & land use	0.033	0.033	-0.034	-0.034	-0.007	-0.007
	[0.73]	[0.73]	[-0.31]	[-0.31]	[-0.09]	[-0.09]
Renewable energy	-0.218***	-0.218***	-0.173	-0.173	-0.100*	-0.100*
	[-4.27]	[-4.27]	[-1.61]	[-1.61]	[-1.87]	[-1.87]
Household & community	-0.203***	-0.203***	-0.198	-0.198	-0.077	-0.077
	[-3.13]	[-3.13]	[-1.68]	[-1.68]	[-1.20]	[-1.20]
Agriculture	-0.089	-0.089	-0.220	-0.220	-0.156	-0.156
	[-1.63]	[-1.63]	[-1.65]	[-1.65]	[-1.57]	[-1.57]
Chemical processes	-0.174***	-0.174***	-0.110	-0.110	-0.145	-0.145
	[-3.51]	[-3.51]	[-0.96]	[-0.96]	[-1.62]	[-1.62]
Industrial & commercial	-0.144**	-0.144**	-0.398***	-0.398***	-0.258***	-0.258***
	[-2.53]	[-2.53]	[-2.91]	[-2.91]	[-4.12]	[-4.12]
Waste management	-0.155***	-0.155***	-0.203*	-0.203*	-0.110*	-0.110*
	[-3.12]	[-3.12]	[-1.95]	[-1.95]	[-1.76]	[-1.76]
Rated by BeZero			0.080***	0.080***	0.165***	0.165***
			[2.73]	[2.73]	[6.40]	[6.40]
Africa based		0.028		0.033		0.005
		[0.92]		[0.61]		[0.18]
Europe based		-0.017		0.203***		0.049
		[-0.20]		[3.02]		[0.67]
North America based		-0.014		0.119***		0.245***
		[-0.56]		[3.20]		[6.97]
South America based		0.003		0.103**		0.094**
		[0.11]		[2.79]		[2.73]
Other regions		0.005		0.253**		0.261***
		[0.04]		[2.50]		[3.18]
Project age FE	Y	Y	Y	Y	Y	Y
Registry FE	Y	Y	Y	Y	Y	Y
Geographic region FE	Y	N	Y	N	Y	N
Observations	3,353	3,353	3,353	3,353	3,353	3,353
R-squared	0.193	0.193	0.230	0.230	0.268	0.268
% (Dep. variable=1)			55.3%	55.3%	28.9%	28.9%

Table IA.III
U.S. Firm Characteristics

This table reports summary statistics for our sample of publicly listed firms domiciled in the U.S. for which Sustainalytics ratings are available. *q* is defined as (book value of assets – book value of equity + market value of equity – deferred taxes)/(book value of assets). *ROA* is the return on assets, defined as EBITDA/assets. *Leverage* is defined as the ratio of total debt to assets, both in book values. *Prior 12-month return* is the buy-and-hold stock return during the 12 months prior to the focal firm-year. *Institutional ownership* is the fraction of shares held by institutional investors, as reported by FactSet. *U.S. firm* equals one if a firm is domiciled in the United States and zero otherwise. Scope 1 emissions are direct greenhouse emissions. Scope 2 emissions are indirect emissions created by the production of the energy that a firm consumes. Scope 3 emissions cover emissions that a firm is indirectly responsible for up and down its value chain. *Emission intensity* equals Scope 1 emissions divided by sales. For each industry each year, we sort firms' scope 1 emissions and calculate *Industry emission gap* as the logarithm of the ratio of the 75th percentile value to the 25th percentile value. *Abatement cost* is the estimated abatement cost-per-ton extracted from CDP and averaged across firms in the same industry. *#Abatement projects* is the number of abatement projects operated by the firm. *Board ESG committee* is a dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx. *Board climate authority* is a dummy variable indicating whether the firm's board has ultimate authority/responsibility over its climate policies, from CDP. *Managerial climate incentive* is a dummy variable indicating whether the firm gives management explicit incentives tied to decarbonization, from CDP. *Retired offsets* is the quantity of offsets retired by a firm. *Average vintage of retired offsets* is the quantity-weighted vintage of offsets retired by a firm. *Retired BeZero-rated offsets* is a dummy variable indicating whether a firm retired any offsets rated by BeZero in a given year. The averages, 25th percentiles, medians, 75th percentiles, standard deviations, and number of observations for these variables are reported.

Variable	Mean	25%	50%	75%	St. Dev.	N
Assets ($ billion)	14.85	0.99	3.08	9.86	37.93	20,820
Market capitalization ($ billion)	11.89	0.80	2.44	7.96	30.26	20,615
q	2.10	1.08	1.47	2.32	2.00	20,820
ROA	0.02	0.00	0.03	0.07	0.15	20,770
Leverage	0.30	0.09	0.27	0.44	0.26	20,820
Prior 12-month return	0.11	-0.12	0.08	0.29	0.40	16,549
Institutional ownership	0.80	0.70	0.86	0.96	0.21	16,101
Scope 1 emissions (million tons)	0.85	0.00	0.02	0.10	3.72	17,787
Scope 2 emissions (million tons)	0.19	0.01	0.03	0.10	0.54	17,787
Scope 3 emissions (million tons)	0.90	0.03	0.14	0.62	2.24	17,787
Emission intensity (x1,000)	0.13	0.00	0.01	0.03	0.45	17,787
Industry emission gap	2.79	2.29	2.62	3.08	0.71	20,820
Abatement cost ($ per ton)	166.88	32.01	92.44	211.42	227.52	14,483
#Abatement projects	72.33	3.00	11.00	50.00	166.92	3,567
Board ESG committee	0.12	0.00	0.00	0.00	0.33	19,882
Board climate authority	0.10	0.00	0.00	0.00	0.29	20,820
Managerial climate incentive	0.10	0.00	0.00	0.00	0.30	20,820
Retired offsets (thousand tons)	79.91	0.12	3.04	33.00	231.37	754
Average vintage of retired offsets (year)	2015.08	2013.00	2015.31	2017.80	3.68	681
Retired BeZero-rated offsets	0.56	0.00	1.00	1.00	0.50	754

Table IA.IV
Ordinary Least Squares (OLS) Regressions: Firm-Level Abatement Costs

This table reports results from firm-year level ordinary least squares (OLS) regressions. The dependent variable is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* (column 1) or the firm's Scope 1 carbon emissions (column 2), both scaled by the firm's Scope 1 emissions in the previous year. The independent variable is the logarithm of abatement cost (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP). Controls include the logarithm of assets, book leverage, return on assets, and institutional ownership, all lagged by one year, as well as industry-by-year fixed effects. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	Dependent variables:	
	Retired offsets	Scope 1 emissions
	(1)	(2)
log(abatement cost)	0.017**	0.004**
	[1.97]	[2.12]
log(assets)	-0.001	-0.020***
	[-0.03]	[-3.05]
Leverage	-0.006	0.047
	[-0.03]	[0.94]
ROA	-0.861	0.215**
	[-0.97]	[2.03]
Institutional ownership	0.271	0.017
	[1.25]	[0.64]
Industry-by-year FE	Y	Y
Observations	7,862	7,859
R-squared	0.050	0.047

Table IA.V
Ordinary Least Squares (OLS) Regressions of Emissions on Offsets

This table reports results from firm-year level ordinary least squares (OLS) regressions. The dependent variable is the firm's Scope 1 carbon emissions, scaled by the firm's Scope 1 emissions in the previous year. The independent variable is the lagged quantity of carbon offset credits retired by firm *i* in year *t-1*, scaled by the firm's Scope 1 emissions in year *t-2*. Controls include the logarithm of assets, book leverage, return on assets, and institutional ownership, all lagged by one year, as well as firm, year, or industry-by-year fixed effects. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1).

	Dependent variables: Scope 1 emissions		
	(1)	(2)	(3)
Lagged retired offsets	0.092**	0.083*	0.120**
	[2.02]	[1.85]	[2.11]
log(assets)	-0.016***	-0.010***	-0.093***
	[-6.38]	[-3.64]	[-4.96]
Leverage	-0.033	-0.047**	-0.054
	[-1.60]	[-2.03]	[-0.77]
ROA	-0.650***	-0.567***	-0.705***
	[-8.82]	[-7.98]	[-6.23]
Institutional ownership	-0.046***	-0.034***	0.012
	[-3.95]	[-2.77]	[0.25]
Firm FE	N	N	Y
Year FE	Y	N	N
Industry-by-year FE	N	Y	Y
Observations	44,695	44,067	44,005
R-squared	0.012	0.027	0.139

Table IA.VI
Ordinary Least Squares (OLS) Regressions: Cross-Controlled Specifications

This table reports results from firm-year level ordinary least squares (OLS) regressions that include both abatement costs and an indicator for climate governance as independent variables. The dependent variable is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* (columns 1 and 2) or the firm's Scope 1 carbon emissions (columns 3 and 4), both scaled by the firm's Scope 1 emissions in the previous year. The independent variables are the logarithm of abatement cost (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP and averaged across firms in the same industry) or #abatement projects/assets (i.e., number of abatement projects operated by the firm scaled by its assets), and Board ESG committee (i.e., dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), all lagged by one year. Controls include the logarithm of assets, book leverage, return on assets, and institutional ownership, all lagged by one year, as well as year or industry-by-year fixed effects. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	Dependent variables:			
	Retired offsets		Scope 1 emissions	
	(1)	(2)	(3)	(4)
log(abatement cost)	0.052***		0.008**	
	[3.00]		[2.31]	
#Abatement projects/assets		-6.462**		-1.611***
		[-2.31]		[-3.45]
Board ESG committee	-0.123**	-0.379**	-0.037***	-0.025*
	[-2.23]	[-2.29]	[-3.25]	[-1.87]
log(assets)	0.084***	0.052	-0.015***	-0.021***
	[4.33]	[0.43]	[-4.49]	[-3.33]
Leverage	-0.094	1.494	-0.051*	-0.033
	[-0.72]	[1.13]	[-1.87]	[-0.61]
ROA	0.138	-0.477	-0.840***	0.195
	[0.73]	[-0.47]	[-8.41]	[1.50]
Institutional ownership	0.204*	0.407	-0.004	0.015
	[1.91]	[1.06]	[-0.27]	[0.61]
Year FE	Y	N	Y	N
Industry-by-year FE	N	Y	N	Y
Observations	23,479	8,780	23,401	8,771
R-squared	0.004	0.062	0.022	0.054

Table IA.VII
Correlations

This table reports pairwise correlations between the logarithm of abatement cost (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP and averaged across firms in the same industry), #Abatement projects (i.e., number of abatement projects operated by the firm), Board ESG committee (i.e., dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), Board climate authority (i.e., dummy variable indicating whether the firm's board has ultimate authority/responsibility over its climate policies, from CDP), Managerial climate incentive (i.e., dummy variable indicating whether the firm gives management explicit incentives tied to decarbonization, from CDP), the logarithm of assets, book leverage, return on assets, and institutional ownership. For its correlations with other abatement cost and climate governance variables, #Abatement projects are scaled by assets.

	log(abatement cost)	#Abatement projects	Board ESG committee	Board climate authority	Managerial climate incentive
#Abatement projects	-0.162				
Board ESG committee	-0.023	-0.027			
Board climate authority	-0.004	0.029	0.167		
Managerial climate incentive	-0.006	0.023	0.191	0.788	
log(assets)	0.135	0.196	0.163	0.298	0.340
Leverage	0.016	0.004	0.040	-0.022	-0.011
ROA	-0.062	-0.010	0.036	0.048	0.051
Institutional ownership	-0.054	-0.003	-0.091	-0.060	-0.049

Table IA.VIII
Subsample Difference-in-Differences (DID): Firm-Level Abatement Costs

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for subsamples sorted on internal abatement cost estimates, measured at the end of 2018 (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP).

$$\mathit{Outcome}_{i,t} = \alpha + \beta \cdot \mathit{Post}_t \times \mathit{Rating\ downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable, $\mathit{Outcome}_{i,t}$, is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* (columns 1 and 2) or the firm's Scope 1 carbon emissions (columns 3 and 4), both scaled by the firm's scope 1 carbon emissions in 2018 prior to the rating change event. Post_t is a dummy variable equal to one for years after 2018 and zero otherwise. $\mathit{Rating\ downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-values from testing the statistical difference of the β coefficients between the high- and low-abatement cost subsamples are also reported.

	Dependent variables:			
	Retired offsets		Scope 1 emissions	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Post × Rating downgrade	0.187*	-0.008	0.012	-0.063*
	[1.65]	[-0.44]	[0.11]	[-1.92]
log(assets)	0.284	0.028	1.074**	0.345***
	[0.67]	[1.12]	[2.02]	[5.84]
Leverage	0.657	0.212	-1.527	-0.235
	[0.84]	[1.40]	[-0.78]	[-1.21]
ROA	1.869	0.130	-1.031	0.182
	[1.23]	[0.94]	[-0.63]	[1.07]
Institutional ownership	-0.205	0.028	0.789	-0.388
	[-0.47]	[0.46]	[1.22]	[-1.15]
p-value: L > R	0.045		0.255	
Firm FE	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y
Observations	2,634	2,650	2,645	2,595
R-squared	0.477	0.671	0.458	0.530

Table IA.IX
Abatement Cost Subsample DID Controlling for Climate Governance

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for subsamples sorted on internal abatement cost estimates measured at the end of 2018 (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP and averaged across firms in the same industry), while also controlling for climate governance.

$$\mathit{Outcome}_{i,t} = \alpha + \beta \cdot \mathit{Post}_t \times \mathit{Rating\ downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable, $\mathit{Outcome}_{i,t}$, is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* (columns 1 and 2) or the firm's Scope 1 carbon emissions (columns 3 and 4), both scaled by the firm's scope 1 carbon emissions in 2018 prior to the rating change event. Post_t is a dummy variable equal to one for years after 2018 and zero otherwise. $\mathit{Rating\ downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including Board ESG committee (i.e., dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-values from testing the statistical difference of the β coefficients between the high- and low-abatement cost subsamples are also reported.

	Dependent variables:			
	Retired offsets		Scope 1 emissions	
Abatement cost:	High (1)	Low (2)	High (3)	Low (4)
Post × Rating downgrade	0.457**	0.036	-0.038	-0.187**
	[2.05]	[1.07]	[-0.57]	[-2.13]
Board ESG committee	-0.036	-0.099*	-0.164	-0.039
	[-0.11]	[-1.65]	[-0.56]	[-0.17]
log(assets)	-0.537	-0.015	0.706***	0.747***
	[-0.61]	[-1.02]	[5.39]	[5.40]
Leverage	4.908	-0.080	-0.748**	0.107
	[1.54]	[-1.05]	[-2.41]	[0.37]
ROA	2.168	-0.005	-0.708**	-0.682
	[1.36]	[-0.19]	[-2.44]	[-1.33]
Institutional ownership	0.701	-0.008	0.238	-0.061
	[1.31]	[-0.13]	[1.01]	[-0.13]
p-value: L > R	0.031		0.088	
Firm FE	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y
Observations	8,934	8,833	8,925	8,809
R-squared	0.514	0.498	0.436	0.407

Table IA.X
Subsample Difference-in-Differences (DID): Corporate Governance

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for subsamples sorted on indicators for whether the firm has a corporate governance mechanism to monitor/discipline the quality of its offsets. These indicators, measured at the end of 2018, include: Board ESG committee (i.e., dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), Board climate authority (i.e., dummy variable indicating whether the firm's board has ultimate authority/responsibility over its climate policies, from CDP), and Managerial climate incentive (i.e., dummy variable indicating whether the firm gives management explicit incentives tied to decarbonization, from CDP).

$$\textit{Outcome}_{i,t} = \alpha + \beta \cdot \textit{Post}_t \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable, $\textit{Outcome}_{i,t}$, is one of two variables: firm *i*'s Scope 1 carbon emissions in year *t* scaled by the firm's Scope 1 emissions in 2018 prior to the rating change event (Panel A), or a dummy variable indicating whether the firm retires any offset credits with a BeZero rating of BBB or higher conditional on retiring credits (Panel B). $\textit{Post}_t$ is a dummy variable equal to one for years after 2018 and zero otherwise. $\textit{Rating downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-values from testing the statistical difference of the β coefficients between the poor- and good-governance subsamples are also reported.

Panel A. Scope 1 emissions

	Dependent variable: Scope 1 emissions					
	Board ESG committee		Board climate authority		Managerial climate incentive	
	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Post $\times$ Rating downgrade	-0.026	-0.221**	0.028	-0.124**	0.049	-0.181***
	[-0.67]	[-2.44]	[0.83]	[-2.28]	[1.44]	[-3.54]
log(assets)	0.557***	0.707***	0.471***	0.440***	0.467***	0.481***
	[8.61]	[3.44]	[8.61]	[3.71]	[8.65]	[3.72]
Leverage	-0.021	-1.254**	0.048	-0.292	0.023	-0.288
	[-0.12]	[-2.52]	[0.32]	[-0.90]	[0.15]	[-0.85]
ROA	-0.090	-0.025	0.130	-0.034	0.119	-0.152
	[-0.46]	[-0.06]	[0.89]	[-0.12]	[0.83]	[-0.54]
Institutional ownership	-0.079	0.134	-0.059	-0.242	-0.075	0.015
	[-0.48]	[0.27]	[-0.43]	[-0.52]	[-0.55]	[0.03]
p-value: L > R	0.024		0.009		0.000	
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y	Y	Y
Observations	17,855	3,446	17,290	6,110	17,871	5,527
R-squared	0.436	0.476	0.446	0.423	0.445	0.434

(continued)

Table IA.X
Subsample Difference-in-Differences (DID): Corporate Governance (continued)

Panel B. Carbon offset quality						
	Dependent variable: **I**(Uses highly rated credits)					
	Board ESG committee		Board climate authority		Managerial climate incentive	
	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Rating downgrade	-0.061	0.149*	-0.076	0.159**	-0.100	0.156**
	[-0.66]	[1.73]	[-1.20]	[2.20]	[-1.50]	[2.13]
log(assets)	0.015	-0.127	-0.283	0.046	-0.137	0.042
	[0.11]	[-0.26]	[-1.25]	[0.32]	[-0.70]	[0.29]
Leverage	0.165	0.699	-0.150	0.116	-0.210	0.128
	[0.51]	[0.83]	[-0.30]	[0.27]	[-0.49]	[0.30]
ROA	0.417	2.011	-0.494	-0.315	-0.084	-0.305
	[1.65]	[1.51]	[-0.61]	[-0.54]	[-0.12]	[-0.50]
Institutional ownership	-0.385	0.333	-0.113	0.429	-0.324	0.419
	[-1.08]	[0.62]	[-0.26]	[0.90]	[-0.84]	[0.86]
p-value: L < R	0.048		0.007		0.005	
Firm FE	Y	Y	Y	Y	Y	Y
Industry-by-year FE	Y	Y	Y	Y	Y	Y
Observations	473	202	168	513	189	492
R-squared	0.731	0.801	0.865	0.771	0.858	0.759

Table IA.XI
Climate Governance Subsample DID Controlling for Abatement Costs

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for subsamples sorted on an indicator for whether the firm has a Board ESG committee measured at the end of 2018 (i.e., dummy variable indicating whether the firm's board has an ESG or sustainability committee, from BoardEx), while also controlling for abatement costs.

$$\textit{Outcome}_{i,t} = \alpha + \beta \cdot \textit{Post}_t \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_t + \epsilon_{i,t},$$

The dependent variable, $\textit{Outcome}_{i,t}$, is one of two variables: the quantity of carbon offset credits retired by firm *i* in year *t* (columns 1 and 2) or the firm's Scope 1 carbon emissions (columns 3 and 4), both scaled by the firm's scope 1 carbon emissions in 2018 prior to the rating change event. $\textit{Post}_t$ is a dummy variable equal to one for years after 2018 and zero otherwise. $\textit{Rating downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of abatement costs (i.e., firm-level estimates of abatement cost-per-ton extracted from CDP and averaged across firms in the same industry), the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and σ_t denote firm and year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-values from testing the statistical difference of the β coefficients between the poor- and good-governance subsamples are also reported.

	Dependent variables:			
	Retired offsets		Scope 1 emissions	
Board ESG committee:	No (1)	Yes (2)	No (3)	Yes (4)
Post × Rating downgrade	0.152**	-0.032	-0.012	-0.155**
	[2.01]	[-0.49]	[-0.34]	[-1.98]
log(Abatement cost)	0.030	0.089	0.047	0.055
	[0.65]	[1.54]	[1.35]	[1.04]
log(assets)	0.038	-1.681	0.522***	0.784***
	[0.27]	[-1.12]	[6.38]	[3.95]
Leverage	0.332	5.396	-0.172	-0.942**
	[1.04]	[1.20]	[-0.91]	[-2.37]
ROA	0.282	3.153	-0.225	0.086
	[1.45]	[1.15]	[-1.17]	[0.20]
Institutional ownership	-0.089	1.881	-0.020	0.575
	[-0.53]	[1.62]	[-0.10]	[1.00]
p-value: L > R	0.033		0.048	
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	13,840	2,696	13,842	2,697
R-squared	0.585	0.540	0.543	0.566

Table IA.XII
Subsample Difference-in-Differences (DID): Industry Subsamples

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for non-mutually exclusive industry subsamples. Columns 1 to 3 focus on "Consumer-facing", "Finance and services", and "Fossil fuels or industrials" industries, respectively. Consumer-facing industries are defined as Fama-French 49 industry codes 2 to 7, 9 to 11, 33, 43 to 44, as well as SIC codes 6020, and 6320 to 6329. Finance and services include Fama-French codes 7, 33, 34, and 45 to 48; fossil fuel industries 29 to 31; and industrials 14 to 26. Columns 4 and 5 sort firms into industries with low or high (with respect to the median) emission gaps measured as the industry's inter-quartile range of emissions as of 2018.

$$\mathit{Outcome}_{i,t} = \alpha + \beta \cdot \mathit{Post}_t \times \mathit{Rating\ downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable, $\mathit{Outcome}_{i,t}$, is one of two variables: firm *i*'s Scope 1 carbon emissions in year *t* scaled by the firm's Scope 1 emissions in 2018 prior to the rating change event (Panel A), or a dummy variable indicating whether the firm retires any offset credits with a BeZero rating of BBB or higher conditional on retiring credits (Panel B). Post_t is a dummy variable equal to one for years after 2018 and zero otherwise. $\mathit{Rating\ downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and year (columns 1 to 3) or industry-by-year (columns 4 and 5) fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1). p-value from testing the statistical difference of the β coefficients between the low- and high-industry emission gap subsamples (columns 4 and 5) is also reported.

Panel A. Scope 1 emissions

	Dependent variable: Scope 1 emissions				
	Consumer facing	Finance and services	Fossil fuels or industrials	Industry emission gap	
				Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	-0.017	-0.033	-0.179*	-0.068	-0.190***
	[-0.18]	[-0.30]	[-1.85]	[-1.56]	[-4.50]
log(assets)	1.040***	0.650***	0.823***	0.616***	0.517***
	[3.82]	[4.39]	[3.14]	[7.20]	[6.35]
Leverage	-1.018***	-1.224***	-0.774	-0.690***	0.573**
	[-2.84]	[-2.88]	[-1.13]	[-3.84]	[2.41]
ROA	-0.227	-0.222	-0.590	-0.274	0.314
	[-0.53]	[-0.46]	[-1.24]	[-1.07]	[1.50]
Institutional ownership	-0.860	0.039	-0.129	-0.226	-0.006
	[-1.43]	[0.11]	[-0.37]	[-1.09]	[-0.03]
p-value: L > R				0.022	
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	N
Industry-by-year FE	N	N	N	Y	Y
Observations	5,523	6,868	5,975	12,154	10,393
R-squared	0.378	0.385	0.440	0.419	0.474

(continued)

Table IA.XII
Subsample Difference-in-Differences (DID): Industry Subsamples (continued)

Panel B. Carbon offset quality

	Dependent variable: **I**(Uses highly rated credits)				
	Consumer	Finance and	Fossil fuels or	Industry emission gap	
	facing	services	industrials	Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	-0.002	-0.082	0.224**	-0.105	0.143**
	[-0.01]	[-0.77]	[2.37]	[-0.58]	[2.22]
log(assets)	-0.171	-0.020	0.089	0.105	0.078
	[-0.62]	[-0.22]	[0.76]	[0.65]	[0.65]
Leverage	-0.701	0.126	0.138	0.307	0.263
	[-1.37]	[0.43]	[0.19]	[0.74]	[0.83]
ROA	-0.014	-1.287*	0.044	-0.364	0.233
	[-0.01]	[-1.86]	[0.06]	[-0.59]	[0.49]
Institutional ownership	0.264	0.388	-0.300	-0.609	-0.271
	[0.45]	[1.22]	[-0.63]	[-1.10]	[-1.01]
p-value: L $<$ R				0.099	
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	N
Industry-by-year FE	N	N	N	Y	Y
Observations	203	241	235	282	444
R-squared	0.695	0.643	0.756	0.666	0.789

Table IA.XIII
Ruling Out Confounding Effects of ETS

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event, estimated separately for subsamples of firms (or offsets) depending on whether they are covered by mandatory emissions trading systems (ETS). Column 1 drops firms domiciled in countries with an ETS (i.e., European Union, United Kingdom, Iceland, Norway, South Korea, and China). Column 2 further excludes ETS-eligible offsets (e.g., ARB or CORSIA eligible) when computing firm-level credit retirements. Column 3 focuses on the subsample of firms domiciled in countries with an ETS.

$$\textit{Retired offsets}_{i,t} = \alpha + \beta \cdot \textit{Post}_t \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

The dependent variable is the quantity of carbon offset credits retired by firm *i* in year *t*, scaled by the firm's Scope 1 carbon emissions in 2018 prior to the rating change event. $\textit{Post}_t$ is a dummy variable equal to one for years after 2018 and zero otherwise. $\textit{Rating downgrade}_i$ is a dummy variable indicating whether firm *i* experienced a within-industry ranking downgrade because of the Sustainalytics methodology change at the end of 2018. $\boldsymbol{X}_{i,t-1}$ denotes a vector of lagged firm control variables, including the logarithm of assets, book leverage, return on assets, and institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. *t*-statistics from standard errors adjusted for clustering at the firm level are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1).

	Dependent variable: Retired offsets		
	No-ETS countries		ETS countries
	All offsets	Drop ETS-eligible offsets	All offsets
	(1)	(2)	(3)
Post × Rating downgrade	0.267**	0.264**	0.078
	[2.09]	[2.06]	[0.59]
log(assets)	-0.040	-0.042	-0.059
	[-0.13]	[-0.13]	[-0.32]
Leverage	1.279	1.283	0.419
	[1.47]	[1.47]	[1.07]
ROA	0.257	0.255	0.646
	[0.87]	[0.86]	[1.63]
Institutional ownership	0.294	0.299	0.387
	[0.99]	[1.00]	[0.82]
Firm FE	Y	Y	Y
Industry-by-year FE	Y	Y	Y
Observations	18,610	18,610	4,941
R-squared	0.498	0.495	0.291

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