Carbon Offsets:
Decarbonization or Transition-Washing?

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Abstract

Using rich hand-collected data, we examine how corporations use carbon offset credits issued by third-party developers to claim emission reductions. Larger firms with higher institutional ownership and net-zero commitments tend to use offsets. However, offsets are used intensively in low-emission industries. After an exogenous ESG rating downgrade, triggered by a leading ESG rating agency's methodology change, low-emission firms retire larger quantities of cheap, low-quality offsets while heavy emitters decarbonize more in-house. Our findings are consistent with a separating equilibrium where firms choose whether to outsource their transition efforts, but also with firms using offsets strategically for certification and ranking benefits.

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1. Introduction

The transition to a carbon-neutral economy has become a global policy objective transcending national boundaries. This movement has exposed companies around the world to carbon-transition risk (see Bolton and Kacperczyk, 2023a), pushing firms to commit to reducing their carbon emissions. So far, however, corporate efforts to directly reduce their emissions have fallen short of achieving decarbonization in the near future (see Aldy, Bolton, Halem, and Kacperczyk, 2023; Bolton and Kacperczyk, 2023b). To bridge the near-term viability of businesses and their long-term net-zero transitions, carbon offsetting has emerged as a tool that enables firms to claim emission reductions achieved by other entities as their own by purchasing and retiring carbon offset credits. However, there is much skepticism regarding the effectiveness and quality of carbon offset projects in terms of their ability to reduce carbon emissions, yet very little understanding of how companies use carbon offsets.[1]

In this paper, we provide the first systematic evidence, to our knowledge, characterizing why companies around the world use carbon offsets. We use a novel hand-collected dataset that contains rich information about which entities retire carbon credits to offset their greenhouse gas emissions, how many credits they retire in a given year, and which carbon offset projects those credits originate from. We manually match the entities in this dataset to publicly listed firms around the world covered in the Compustat North America and Global universe. Using this data, we first provide a comprehensive analysis of the current landscape of the global carbon offset market, and then use a quasi-natural experiment to study the incentives of publicly listed firms to use carbon offsets.

We document an ecosystem of a variety of carbon offset projects, such as those generating renewable energy, contributing to energy-efficient housing and appliances, and preserving forests and grassland. These projects are geographically dispersed around the world, the majority of them based in Asia, Africa, North America, and South America. However, only a fraction of these projects have an external rating that provides verification of their quality (i.e., 10% of nearly three thousand projects). About half of all projects issue carbon credits that are purchased and retired by publicly listed firms around the world,

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

which tend to rely more on larger projects with external quality ratings located in North America. We also find that among publicly listed companies, firms that are larger, more valuable, and have higher institutional ownership are more likely to use carbon offsets. These firms are also more likely to have stated net-zero commitments. This is consistent with carbon offsets being a tool for often-scrutinized firms to achieve carbon-transition goals without incurring the large costs associated with reducing emissions directly.

To understand the incentives of firms to use carbon offsets, we consider two non-mutually exclusive economic hypotheses. The first is an "outsourcing hypothesis," which is consistent with a separating equilibrium: Firms with smaller carbon footprints use offsets more intensively to reduce their carbon emissions indirectly due to lower marginal costs associated with offsetting compared to reducing emissions directly through abatement investments and innovations, while heavy-emission firms are more likely to reduce their emissions in-house. The second is a "certification hypothesis," where firms care about their credentials with outside stakeholders and use offsets strategically to signal their commitment to reducing their carbon footprints. These hypotheses motivate a set of empirical tests. Specifically, we test whether firms use more carbon offsets when they face greater needs to improve their ESG ratings, when they have a larger carbon footprint, or when it is easier to improve ESG ratings. We also conduct additional tests to examine how these firms change their direct emissions and whether offsetting firms use carbon credits issued by high- or low-quality offset projects.

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, almost offsetting their direct emissions one-for-one. In contrast, the aggregate share of direct emissions that are offset using carbon credits is close to zero in high-emission industries such as oil and gas, utilities, or transportation. Global aggregate trends of direct carbon emissions and carbon offset retirements also 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. Similar to the industry patterns, twice as many carbon credits have been retired by U.S. firms over the past two decades, despite the fact that firms in the rest of the world have generated twice as more direct emissions. Also consistent with the certification hypothesis, we find that relatively few offset projects are externally verified as having high quality, and that most offset credits used by firms are strikingly cheap.

To facilitate a causal interpretation of tests regarding our hypotheses, we exploit an exogenous change in companies' ESG ratings triggered by a sharp rating methodology change at a leading ESG rating agency, Sustainalytics. Its widely used firm-level ESG scores underlie the Morningstar portfolio-level sustainability ratings and low-carbon designations that are heavily used by mutual fund investors (see Hartzmark and Sussman, 2019; Ceccarelli, Ramelli, and Wagner, 2024).[2] At the end of 2018, Sustainalytics adopted a new methodology for computing these scores that created an average within-industry ESG rank reshuffle of 20 percentiles. We find that after this "Sustainalytics shock," institutional ownership, ownership by foreign institutions in particular, declined for firms that were downgraded pursuant to the methodology change. We also find that the ESG ratings became more sensitive to firms' emission intensity after the methodology change. These changes were likely to incentivize downgraded firms to make efforts to reduce their emissions to retain institutional investors, which could lower these firms' costs of capital (see Ferreira and Matos, 2008).

We then examine how firms use carbon offsets in response to this "rating shock." Consistent with the strategic role of carbon offsets, firms offset more of their emissions using carbon credits after experiencing an exogenous ESG rating downgrade. Two subsample analyses further support this interpretation. First, we find that firms with ex-ante lower emissions use more carbon offsets following the Sustainalytics shock. This indicates that firms that are already closer to achieving net-zero status are more likely to use a modest quantity of offsets to achieve this salient milestone that could help boost their ESG ratings. Second, firms are more likely to use offsets after being downgraded if they belong to industries with little within-industry cross-sectional variation in emissions. In these industries where the "emission gap" between heavy and light emitters is small, a modest reduction in emissions can easily make a firm appear greener than its peers. In contrast, high-emission firms in industries with high-emission gaps do not use more carbon offsets but rather reduce their scope 1 emissions directly, following an ESG rating downgrade. Such

[2] Further demonstrating the popularity and importance of Sustainalytics as an ESG rating firm, many other studies in the literature use their ESG scores as one of the main ESG performance metrics of interest (see, e.g., Berg, Kölbel, Pavlova, and Rigobon, 2023; Berg, Kölbel, and Rigobon, 2022; Ceccarelli, Evans, Glossner, Homanen, and Luu, 2024; Christensen, Serafeim, and Sikochi, 2022; Kim and Yoon, 2023; Rzeźnik, Hanley, and Pelizzon, 2022; Serafeim and Yoon, 2023).

evidence again supports the outsourcing hypothesis and contradicts the notion that carbon offsets can help high-emission firms transition to low-carbon business models. Rather, carbon offsets are used strategically by firms that are already close to meeting their net-zero targets or by firms that can easily improve their within-industry ESG rankings with a small emission reduction. Consistent with such certification benefits, we indeed find that firms who increased the use of offsets more sharply than the median firm enjoyed a quicker recovery in their within-industry ESG rankings after the downgrade.

To further investigate whether carbon offsets are likely to be an effective and credible net-zero transition mechanism used by firms, we utilize offset project ratings provided by a prominent carbon offset rating agency, BeZero Carbon. BeZero employs 70+ analysts, including climate and data scientists, geospatial experts, and financial market analysts, to collect project-level data based on verified project information, extensive developer engagement, in-house geospatial tools, and peer-reviewed scientific studies. The analysts then use proprietary sector-specific machine learning models and manual investigations to assess the risks to a project's climate claims. Finally, each carbon offset project is assigned a letter rating similar to credit ratings assigned by major rating agencies such as S&P or Moody's, with ratings of BBB and above (BB and below) indicating relatively high (low) quality.[3]

Using this data, we examine whether firms become more or less likely to use high-quality offset projects *conditional on using offsets*, following the Sustainalytics shock. We find that low-emission firms in low-gap industries become no more likely to use high-quality offsets. This indicates that they use more low-quality offsets, given that the average quality of projects used by publicly listed firms is moderately low. On the other hand, although high-emission firms in high-gap industries do not use significantly more offsets following a rating downgrade, they become more likely to use high-quality ones. This contradicts popular criticism often levied on heavy-emission firms regarding their transition efforts and is consistent with recent evidence that these firms are quite active in conducting meaningful green innovation (see Cohen, Gurun, and Nguyen, 2023).

[3] Unlike issuer-paid credit ratings that are often subject to conflicts of interest and ratings inflation (see, e.g., Becker and Milbourn, 2011; Bolton, freixas, and Shapiro, 2012; Cornaggia and Cornaggia, 2013; Griffin, Nickerson, and Tang, 2013), carbon offset ratings are typically sold via a subscription model to prospective buyers who value high-quality offsets. This likely mitigates concerns that offset ratings may be inflated due to potential conflicts of interest between offset rating agencies and project developers.

Moreover, using proprietary offset pricing data, we demonstrate that low-quality offset credits command substantially lower prices. Conditional on project ratings, offsets issued in earlier years, which firms heavily use, are also cheaper. Altogether, our findings support the notion that low-emission firms are more likely to utilize offsets to reduce their carbon footprints indirectly, while high-emission firms tend to reduce emissions directly. Our evidence also suggests that low-emission firms, which are already close to net-zero targets, exploit carbon offsets as a cheap and easy way to meet transition objectives, thereby boosting their within-industry ESG rankings.

By characterizing corporate incentives in the carbon offsets market, our findings contribute to understanding how companies cope with carbon-transition risk. While firms are increasingly committed to reducing emissions, many companies that most need to reduce their emissions remain slow to respond to calls for net-zero transition (see Aldy et al., 2023; Bolton and Kacperczyk, 2023a,b). Moreover, firms that are financially incapable of investing in reducing their direct emissions may choose to operate in regions where they face less regulatory pressure (see Bartram, Hou, and Kim, 2022). Given the tension between the societal objective of carbon neutrality and the short-term transition costs to firms, carbon offsets have been promoted as an affordable intermediate tool to allow firms to reduce their emissions *indirectly* until they become ready to take costlier longer-term 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 on the basis that they effectively reduce equivalent amounts of emissions, when in truth they do not or cannot be verified that they do.[4] Our results support this skepticism and call for solutions to improve the transparency of carbon offsets, and in turn the credibility of corporate transition efforts.

Our study also contributes to the climate finance literature that examines the impact of sustainable investing. To date, evidence on the impact of ESG investing on corporate behavior remains decidedly mixed. On the one hand, recent studies indicate that investors care about carbon-transition risk and climate-regulatory risk (see Krueger, Sautner, and Starks, 2020; Bolton and Kacperczyk, 2021; Ilhan, Sautner, and Vilkov, 2021; Hsu, Li, and Tsou, 2023; Seltzer, Starks, and Zhu, 2023). Some studies argue that socially responsible

[4]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).

investors are effective in changing firm behavior (see Dyck, Lins, Roth, and Wagner, 2019; Azar, Duro, Kadach, and Ormazabal, 2021; Naaraayanan, Sachdeva, and Sharma, 2021).

However, a growing literature documents widespread evidence of greenwashing by investors and firms (see Andrikogiannopoulou, Krueger, Mitali, and Papakonstantinou, 2023; Duchin, Gao, and Xu, 2023; Griffin and Kruger, 2024). Several studies show that sustainable investors often do not follow through with their commitments (see Gibson, Glossner, Krueger, Matos, and Steffen, 2022; Liang, Sun, and Teo, 2022; Heath, Macciocchi, Michaely, and Ringgenberg, 2023; Kim and Yoon, 2023), or that they use ineffective strategies that fail to have meaningful impact (see Heinkel, Kraus, and Zechner, 2001; Atta-Darkua, Glossner, Krueger, and Matos, 2023; Hartzmark and Shue, 2023). Greenwashing is not only a concern among funds, but also among ESG rating agencies (see Berg, Fabisik, and Sautner, 2021; Tang, Yan, and Yao, 2022; Li, Lou, and Zhang, 2023) or commercial banks and their borrowers (see Giannetti, Jasova, Loumioti, and Mendicino, 2023; Kim, Kumar, Lee, and Oh, 2023). For example, pressure from committed banks might push brown borrowers to engage in more greenwashing (see Kacperczyk and Peydró, 2022). Adding texture to this literature, our findings suggest that short-term pressure from investors and other stakeholders may have the perverse effect of pushing firms to "window-dress" their emissions by using low-quality carbon offsets.

One potential solution to improve the transparency of the carbon offset market and prevent "transition-washing" is to set up rules and regulations that govern standardized methodologies for determining how carbon credits can be issued.[5] A minimalist approach may involve requiring firms to disclose the amount and cost of retired offsets as well as the *source* of such offsets, in addition to the increasingly standardized climate disclosure requirements.[6] Indeed, our analysis suggests that the absence of these requirements may sustain the demand for low-quality offsets and the supply that caters to such demand.

[5] See "How do carbon offsets factor into UN COP28 climate talks?", Reuters (November 2023).

[6] 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, 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 2. for more details.

A more discerned approach to sustainable investing may also be helpful in making carbon offsets a more effective tool for transitioning to a carbon-free economy. For instance, sustainable investors might be more selective in supporting firms' environmental and social (E&S) policies (see, e.g., Li, Naaraayanan, and Sachdeva, 2023). Sustainable investors might also take a more nuanced approach to providing firms with capital conditional on tangible and credible abatement efforts, rather than pursue blanket divestment strategies (see Edmans, Levit, and Schneemeier, 2023).

2. Carbon Offsets and Voluntary Carbon Markets

As nations and corporations increasingly commit to combating climate change, carbon markets are often purported as instrumental in achieving net-zero carbon emissions by 2050, as mandated by the 2015 Paris Agreement. While governmental mandates, such as the EU Emissions Trading System (ETS) or the California Cap-and-Trade Program, operate regulated compliance carbon markets, companies around the world are increasingly turning to voluntary carbon markets to proactively offset their emissions.

A carbon offset, or carbon credit, is a transferrable financial instrument where the purchaser pays the seller or issuer to implement an activity that reduces a metric ton of carbon dioxide equivalent (CO2e) or other greenhouse gas emissions. The purchaser can claim this reduction toward their own carbon mitigation goals by retiring the purchased credit and "offsetting" their own emissions by the amount of emissions reduced by the project that generated the credit. The primary purpose of carbon offsets is to enable organizations and individuals to compensate for their emissions by investing in mitigation projects elsewhere. As such, these instruments have been widely promoted as a way for heavy-emission firms to contribute to the transition toward a carbon-neutral economy. According to the Taskforce on Scaling Voluntary Carbon Markets, demand for carbon offsets is expected to rise by a factor of 15 by 2030 and by a factor of 100 by 2050.[7] Accounting for higher carbon prices due to increased demand in the future, Morgan Stanley forecasts that the voluntary offset market will grow to about \$100 billion by 2030 and to around \$250 billion by 2050.[8]

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

Carbon offset credits are generated from 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, or carbon capture and storage. These projects are implemented by project developers who expect their primary source of revenue to come from the sale of carbon credits.

Unlike carbon allowances, which are typically auctioned by regulatory authorities in limited quantity and thereafter traded on compliance markets such as the EU ETS, voluntary carbon offsets lack centralized and widely adopted regulatory standards governing the criteria for how projects generate credits or how those credits are sold and used.[9] Instead, market participants rely on an ecosystem of third-party organizations consisting of 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.

Carbon offset registries, developed by various governmental, non-profit, or private entities, play a critical role in creating a credible environment for offset markets. These registries track offset projects, verifying and certifying each offset credit that is issued by a registered project. They assign serial numbers to each verified offset credit and "retires" the serial number when the credit is claimed by its owner to offset emissions, so that it cannot be resold or reused. Each registry sets its own standards outlining the minimum requirements for eligible projects, methodologies for the measurement of emission reductions and credits, and credit transaction mechanisms. 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). These registries maintain publicly available information of the projects that meet their standards and the credits that are issued or retired.

[9] As such, voluntary and compliance carbon markets are largely segmented. Generally, voluntary offsets cannot be used to meet compliance standards, and vice versa. However, there have been some exceptions in the early stages of some compliance markets. Until 2015, the California Air Resource Board (CARB) had allowed the use of certain voluntary offsets in the California Cap-and-Trade program, if they satisfied specific quantification methodologies and restrictions under the Early Action Offset Program. Until 2020, the EU ETS had also allowed limited use of offsets that follow the regulatory offset mechanisms under the Kyoto Protocol. None of the offset retirements in our sample are related to these regulatory programs.

Despite the role of registries in setting minimum standards, critics often point out that offset projects vary widely in their quality in terms of the accuracy of their estimated impact on reducing emissions. To provide transparency to the quality of offset credits generated by various projects, carbon offset rating agencies, such as BeZero, Sylvera, or Calyx, assess and assign ratings to offset projects, often aiming to profit from subscriptions by prospective investors in carbon credits who value this information. The rating process typically involves assessing the project's "additionality" (i.e., the carbon offset project would not have occurred without the expected sale of carbon credits), its methodology for quantifying and estimating expected emission reductions, the risk of leakage (i.e., seemingly reduced emissions might simply be pushed elsewhere), and the permanence of the project's impact.

Financial institutions are also increasingly participating in all aspects of carbon offset markets as investors, traders, advisors, brokers, exchange or marketplace operators, project financiers, project developers, or writers of carbon offset derivatives and other related financial products.[10] Figure 1 shows a simplified illustration of the carbon offset market ecosystem.

[Insert Figure 1 here]

Despite the complex ecosystem of players that exist 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 offset credits. Market participants, companies in particular, have been accused of "transition-washing" for promoting their use of carbon offsets. This is corroborated by recent scientific research showing that offset credits from forest preservation projects, which are among the most commonly used by companies, do not represent genuine carbon reductions (see West, Börner, Sills, and Kontoleon, 2020; Guizar-Coutiño, Jones, Balmford, Carmenta, and Coomes, 2022; West, Wunder, Sills, Börner, Rifai, Neidermeier, and Kontoleon, 2023).

Regulators have also taken notice of this criticism. After creating an environmental task force focused on detecting fraud in carbon markets in June 2023, the U.S. Commodity Futures Trading Commission (CFTC) issued a proposed guidance in December 2023

[10] Major banks such as Goldman Sachs, JPMorgan Chase, Citigroup, and Barclays are building their carbon trading or financing operations.

regarding the listing of voluntary carbon credit derivative contracts, which aims to "shape standards in support of [market] integrity." In July 2023, the EU adopted sustainability reporting standards that require firms to disclose the total amount of retired offsets and certain disaggregated data related to these offsets, unless climate change is not material to the firm or its stakeholders according to a formal and detailed assessment. In March 2024, the SEC similarly adopted corporate climate disclosure rules, requiring that firms report expenditures related to carbon offsets when they are material to investors. The SEC, however, stopped short of mandating disclosures of the underlying offset projects or the associated developers, limiting the usefulness of these disclosures for gauging the quality of retired offsets. In its latest acknowledgment of the importance of transparency in this market, in May 2024, the U.S. government released a Joint Statement of Policy and new Principles for Responsible Participation in Voluntary Carbon Markets. The statement calls for improved offset market standards and disclosures regarding offset usage to better enable stakeholders to assess the quality and trustworthiness of carbon offsets.

In addition to greenwashing concerns, there is also widespread concern that these instruments may discourage high-emitting entities (e.g., fossil-fuel firms) from transitioning to less carbon-intensive practices.

3. Hypothesis Development

In this section, we utilize a simple conceptual framework to develop our hypotheses on firms' decisions to use carbon offsets. Facing demand from investors and other stakeholders to lower their carbon footprints (e.g., Krueger et al., 2020), corporations are assumed to have two choices: purchasing and retiring carbon offsets to reduce emissions indirectly, or developing innovative abatement technologies to reduce emissions directly. Because the supply of carbon offsets is relatively inelastic, purchasing carbon offsets incurs increasing marginal costs—it entails minimal fixed costs but variable costs that rise quickly with the quantity of emissions to be offset.[11] On the contrary, abatement technologies (e.g., equipping oil and

[11] According to Carbon Direct, the global issuance of offsets in 2022 was only 278 million tons, a fraction of the combined carbon footprint of Fortune 500 companies.

gas processes with carbon capture, utilization and storage technologies) exhibit relatively flat marginal costs due to substantial initial fixed costs and small variable costs afterwards.

Under this framework, offsetting is likely to be an optimal choice for low-emission firms while technological innovation will likely be optimal for heavy-emission firms, assuming that the marginal benefit of reducing an additional metric ton of emissions is relatively constant.[12] In other words, we conjecture a separating equilibrium where heavy-emission firms reduce their emissions in-house, whereas low-emission firms outsource the reduction to offset project developers. This suggests that while carbon offsets by themselves may not generate a sufficient impact to transition the aggregate economy to net-zero carbon, a relatively small carbon offset market that serves light-emission firms may be socially optimal if project developers genuinely reduce emissions at a lower marginal cost. Our intuition contradicts propositions that carbon offsets are especially useful for fossil fuel firms because they have greater carbon footprints to reduce while their business models make it difficult to reduce emissions directly in a short period of time. This motivates our first hypothesis that offsets are *unlikely* to be used intensively by firms whose transition efforts would have the most impact on transitioning the aggregate economy to net-zero carbon, because outsourcing such efforts to offset projects is not cost-efficient for these firms (i.e., the "outsourcing hypothesis").

However, an offset market catering to light emitters can be socially suboptimal due to information asymmetry stemming from various sources of market opacity, including the lack of regulatory frameworks, the inconsistency of standards set by carbon registries, and the lack of widespread availability of carbon project ratings. These factors may help sustain a "bad equilibrium" where low-quality offsets are consistently cheaper, as project developers cater to firms that demand these offsets for transition-washing purposes. Moreover, given informational frictions in assessing firms' carbon footprints, investors and other stakeholders continue to rely on third-party ESG ratings. These ratings typically do not disambiguate the quality of offsets used by firms, rewarding firms with low reported emissions. Therefore, firms that choose to use offsets have an incentive to use cheap, low-quality offsets to reduce their emissions and boost their ESG ratings. This motivates our second hypothesis that

[12]The marginal costs of using carbon offsets are small for low-emission firms because small purchases are unlikely to affect the price of offsets. However, large purchases by heavy-emission firms would lead to an equilibrium offset price that likely exceeds the marginal costs of reducing emissions in-house.

(low-emission) firms strategically use carbon offsets to obtain certification or ESG ranking benefits cheaply (i.e., the "certification hypothesis").

We note that these two hypotheses are not mutually exclusive—the notion that the marginal cost function of offsetting emissions may discourage heavy-emission firms from using carbon offsets is largely unrelated to firms' greenwashing or certification incentives. Therefore, rather than attempting to rule in one hypothesis while ruling out the other, we explore both hypotheses by documenting a broad set of empirical facts. We first characterize the global carbon offset market and investigate which industries and countries are especially active in this market. We then examine whether exogenous ESG ranking downgrades incentivize firms to reduce their emissions, and which firms use carbon offsets to achieve this goal. Specifically, we test whether light-emission firms use more carbon offsets than heavy-emission firms, and whether they use offsets when it is easier to improve their within-industry rankings by reducing only a small quantity of emissions. We also examine whether firms tend to use cheaper, lower-quality offsets as an indication of transition-washing.

4. Data

This study draws data from several sources. Our primary dataset features carbon offsets from four major carbon registries, ACR, Gold, CAR, and VCS. For each unique offset project, our data include information on project name, developer, and location, project type (e.g., forestry and land use, renewable energy, or waste management), year in which the project was launched, the quantity of issued offset credits and issuance date, and the quantity of retired credits and retirement date. In addition, ACR, CAR, and Gold attach a note for each retirement, which includes information on the entity that retires offset credits from the registry. VCS explicitly discloses the retirement entity under "retirement beneficiary."

As of December 2022, our combined carbon offsets dataset includes nearly 279,000 entries of voluntary carbon credit retirement records from 2005 through 2021. To identify publicly listed firms around the world, we manually read each entry and extract the firm names. We then identify each firm's GVKEY in the Compustat North America and Global universe. This step yields 866 unique public corporations from 46 countries.[13]

We also obtain data on firm-level ESG ratings from Sustainalytics to exploit the methodology change adopted by the rating agency at the end of 2018 as our identification strategy, which we explain in more detail in Section 5. We obtain both the legacy ESG scores measured according to the old methodology, which are within-industry ranks, and the new ESG risk scores corresponding to the updated methodology, which represent ESG risk exposures. In addition, we complement our analysis of corporate offset usage with similar analysis of corporate carbon emissions by incorporating firm-level scope 1 emissions data obtained from Trucost Environmental.

We also utilize project-level quality rating data from one of the leading carbon credit rating agencies, BeZero Carbon. BeZero employs over 70 analysts consisting of climate and data scientists, geospatial experts, and financial market analysts. These analysts collect and analyze project-level data based on publicly verified project information, extensive developer engagement, in-house geospatial tools, peer-reviewed scientific studies, proprietary sector-specific machine learning models, and manual investigations. After assessing the credibility and risks to a project's climate claims, 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). These ratings are available for a subset of our sample of offset projects.

In addition, we obtain proprietary pricing data for carbon offsets from a leading analytics and consulting firm that provides corporate solutions and asset management services in the voluntary offset 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 offset credit issued in different vintage years. This dataset includes daily price snapshots for about 86% of our sample of offset projects during the last two weeks of February 2024.

[13] It is possible that some firms may choose not to disclose their identities when retiring carbon credits, in which case the retirement entities will not appear under retirement beneficiary/notes in our dataset. In these cases, the credit retirements will not be linked to publicly listed firms by our identification procedure. However, we find that the total number of credits retired by a firm in a given year, as recorded by the registries, is generally consistent with that disclosed in the firm's sustainability report (if available).

We obtain additional data from the following sources: stock information from the Center in Research for Security Prices (for U.S. firms), Compustat North America (for Canadian firms), and Compustat Global (for non-U.S. and non-Canadian firms), company accounting data from Compustat North America and Global, quarterly institutional holdings from FactSet Ownership, information on firms' net-zero commitments from Net Zero Track, and foreign exchange rates (USD pairs) from the Organisation for Economic Co-operation and Development and Yahoo Finance. We use foreign exchange rates to convert local-currency accounting metrics to USD ones.

5. Current Landscape of Corporate Carbon Offsets

5.1. Characteristics of Carbon Offset Projects Around the World

Using our novel data, we start by providing the first comprehensive characterization of the global carbon offset market. Table 1 characterizes the distribution and types of all carbon offset projects from the four carbon registries: ACR, Gold, CAR, and VCS. Panel A summarizes all 2,916 projects, and Panel B describes the subset of 1,413 projects issuing offset credits that are used by 866 publicly listed firms around the world included in our main sample.

[Insert Table 1 here]

Panel A shows that the top four geographies that host carbon offset projects are Asia, Africa, North America, and South America. By far, the predominant type of carbon offset projects prevent carbon emissions by generating renewable energy (e.g., solar, wind, geothermal, and hydro), with household & community (e.g., energy-efficient housing and appliances, and weatherization) and forestry-related projects (e.g., afforestation and reforestation, and avoided forest and grassland conversion) being the second and third most common, respectively. In particular, Asia is home to the most renewable energy projects (85.2% of all renewable projects), Africa hosts most of the household & community projects (65.3% of all household & community projects), and North America is populated with the most forest preservation projects (i.e., 40.3% of all forestry projects).

Notably, information on the quality of offset projects is limited. Approximately 10% of all projects from the four registries are rated by BeZero Carbon. The average (median) price per ton for offsets is relatively low, at $3.6 ($2.7), with projects based in North America and Africa commanding the highest prices. The amount of carbon emissions purportedly prevented or removed by a project, as measured by the number of credits issued, is heavily skewed. The average (median) project issues offset credits representing 524 (108) thousand metric tons of emissions, with projects from South America issuing the most credits. A total of 1,529 million metric tons have been issued across all projects, nearly 68% of which have been retired during our sample period. The percentage of issued credits that have been retired is generally higher for credits issued in earlier years, relative to those issued in more recent years.[14] This pattern holds for all regions.

Panel B of Table 1 reports statistics for the subset of projects whose credits have been retired by publicly listed firms. While these projects represent slightly less than half of the full universe of offset projects, the distribution of these projects across geographies and project types is similar to the overall sample. This points to the generalizability of our analyses that focus on publicly listed firms. However, the statistics also highlight some important aspects of project selection by publicly listed firms. Unsurprisingly, publicly listed firms are more likely to use rated projects (approximately 16% of the projects are rated by BeZero vs. 10% for the full sample) and larger projects (the average project issues credits worth 877 thousand metric tons vs. 524 for the full sample). Publicly listed firms also marginally over-weight projects that are based in North America (24% vs. 19% for the full sample) and those specializing in forestry and land use (15% vs. 11% for the full sample).

This project selection pattern by publicly listed firms is also confirmed in regression analysis that further controls for project characteristics as well as fixed effects corresponding to a project's age group, registry, and geographic region. Table 2 reports these project-level regressions where the dependent variable is a dummy variable indicating whether an offset project is used by publicly listed firms.

[Insert Table 2 here]

[14]One potential reason is that older vintage credits are cheaper than younger vintage credits, as we detail later in Figure 7.

Consistent with the summary statistics reported in Table 1, project size, measured by the quantity of credits issued by a project, is positively associated with the likelihood of the project being used by publicly listed firms. The estimate is significant at the 1% level in the full sample and across most geographic subsamples. Interestingly, credits issued by projects related to forestry activities or other land use restrictions are 16.8 percentage points more likely to be retired by public firms (25.2 percentage points more likely among projects in Asia). Given that the unconditional probability of a project being used by public firms is 48.5%, this marginal effect is substantial. Such popularity of deforestation-prevention projects has raised concerns about greenwashing, as scientific research suggests that forestry offset projects do not prevent or reduce emissions as much as providers claim (see West et al., 2023; Wyburd and Dufrasne, 2023). For example, West et al. (2023) find that 94% of the credits from 26 major deforestation-prevention projects do not represent real reductions in carbon emissions.

In addition, projects rated by BeZero Carbon, a leading carbon credit rating agency, are 10.5 percentage points more likely to be used by public firms (significant at the 1% level). This suggests that these third-party ratings likely convey valuable signals regarding project quality. The effect is strongest among projects launched in North America. Lastly, public firms are 15.1 percentage points more likely to purchase carbon credits issued by projects based in North America, relative to other regions, suggesting that North American projects are perceived as having higher quality.

In Appendix Table A.1, we also report a breakdown of offset projects across the four carbon registries. It is evident that ACR and CAR feature only projects based in North America, while projects based in Asia and Africa are most popular on the Gold and VCS registries. The statistics also indicate that VCS is the largest registry, accounting for nearly 55% of all projects and 76% of all carbon credits issued, while ACR is the smallest registry. The average size of VCS projects is also significantly larger than that of projects on the other registries.

5.2. Which Publicly Listed Firms Use Carbon Offsets?

Table 3 reports summary statistics for our sample of publicly listed firms for which Sustainalytics ESG ratings are available. We present information on firm fundamentals such as total assets, market capitalization, book-to-market (B/M) ratio, Tobin's q, return-on-assets (ROA), leverage, prior 12-month returns, dividend yield, institutional ownership, and a dummy variable indicating whether the firm is domiciled in the U.S. We also report carbon emissions (scope 1, 2, and 3), scope 1 emission intensity (emissions divided by sales), industry emissions gap (within-industry interquartile range of scope 1 emissions), a dummy variable indicating whether a firm is committed to a net-zero target, offset credit retirements, and the quantity-weighted vintage of retired offsets. The averages, medians, and standard deviations of these variables are shown separately for firms that use offsets during our sample period and firms that do not. The differences in means between the two groups of firms and the corresponding t-statistics are also reported.

[Insert Table 3 here]

Companies that retire carbon credits are disproportionately larger, measured by asset size and market capitalization. These firms also have greater institutional ownership, suggesting that firms use offsets to pander to institutional investors who aim to "green" their portfolios via allocation (see Atta-Darkua et al., 2023) or engagement (see Naaraayanan et al., 2021; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2023). In addition, firms using carbon offsets are more likely to be domiciled in the U.S., which likely reflects the fact that the U.S. lacks a national mandatory carbon market. Therefore, U.S. firms, unlike those in the EU, rely more on voluntary carbon markets. Not surprisingly, firms that have made a net-zero commitment are more likely to tap the voluntary carbon market.

Figure 2 illustrates the industry distribution of publicly listed firms in terms of their carbon offsetting activities. For each Fama-French 30 industry over our sample period, the figure reports the number of firm-year observations with non-zero offset usage, the industry's aggregate credit retirements divided by its aggregate scope 1 emissions (i.e., offsets-to-emissions ratio), and the industry's aggregate scope 1 emissions. Panels A and B illustrate industry distributions for U.S. and non-U.S. firms, respectively.

[Insert Figure 2 here]

The key takeaway from Figure 2 is that many low-emission industries are surprisingly active in the carbon offset market. While high-emission industries such as utilities, transportation, and energy rank highly in terms of how often firms use offsets, several low-emission industries such as services and finance rank even higher at the top. Notably, the intensity with which industries offset their emissions (i.e., the relative quantity of credit retirements) does not align with the magnitude of emissions in each industry. For instance, while banks and other financial institutions offset almost every unit of their emissions on a one-for-one basis, the quantity of offset credits retired by energy or utilities firms are almost negligible compared to their direct emissions. This is true for both the U.S. and non-U.S. samples. These patterns are consistent with our outsourcing hypothesis that low-emission firms are more likely to utilize offsets to reduce their carbon footprints indirectly due to lower marginal costs associated with offsetting compared to reducing emissions directly.

[Insert Figure 3 here]

Figure 3 illustrates the aggregate trends in offset credit retirements and scope 1 emissions over our sample period for U.S. and non-U.S. firms. The figure shows that the use of carbon offsets has grown substantially but remains small in magnitude compared to emissions. Moreover, the carbon offset market has become more active in the U.S., despite the fact that non-U.S. firms are substantially more emission-intensive. Together, the aggregate statistics throughout this section provide preliminary support for our hypotheses regarding the choice made by high- and low-emission firms to outsource their transition efforts and the incentives of firms that use offsets heavily.

6. Why Do Firms Use Carbon Offsets?

6.1. Quasi-Experimental Evidence from Sustainalytics' Rating Changes

To test our hypotheses, we exploit an exogenous change in firm-level ESG ratings as a shock to firms' incentives to boost their within-industry rankings. Namely, we use the methodology change adopted at the end of 2018 by one of the most prominent ESG rating agencies, Sustainalytics. The ESG ratings published by Sustainalytics are widely used by investors and academics (see, e.g., Berg et al., 2023, 2022; Ceccarelli et al., 2024; Christensen et al., 2022;

Kim and Yoon, 2023; Rzeźnik et al., 2022; Serafeim and Yoon, 2023). For example, these firm-level ratings are the building blocks that underlie the popular Morningstar fund-level sustainability ratings and low-carbon designations that are heavily used 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 their legacy ESG scores. In contrast to the legacy ESG scores that measured firms' managed ESG risk exposures, the new ESG risk scores measure unmanaged risk exposures. As such, the within-industry percentile rankings based on the new ESG risk scores are considerably different from those based on the old ESG scores. After issuing the new ESG risk scores in December 2018, Sustainalytics also continued to publish the legacy ESG scores until October 2019 when they were discontinued. Based on a comparison of the new and old scores for the same firm in the same month during this time, Figure 4 shows that the average magnitude of the change in within-industry ranking caused by the reshuffle is approximately 20 percentiles. In contrast, the magnitude of the period-by-period changes in rankings based on either the old or new scores are much smaller, confirming that the shift in rankings caused by the Sustainalytics methodology change is not driven by fundamentals.[15]

[Insert Figure 4 here]

Using this shock, we identify exogenous treatment to a firm based on whether its within-industry ranking was adjusted downward at the end of 2018 as a result of Sustainalytics' methodology change. Our underlying assumption for using this setting to test our hypotheses is that an exogenous ESG rating downgrade will positively affect the firm's incentive to improve its ESG rating going forward. For instance, previous studies show that institutional investors exhibit a preference to invest in highly rated assets (see Hartzmark and Sussman, 2019; Krueger et al., 2020; Döttling and Kim, 2022). An exogenous ESG rating downgrade may cause institutional investors to divest from the firm, potentially raising its cost of capital (see Ferreira and Matos, 2008). Thereafter, firms will have an incentive to improve their ESG ratings to retain their institutional investors. Therefore, we examine whether

[15] As emphasized by Ceccarelli et al. (2024) and Rzeźnik et al. (2022), 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.

firms increase their use of carbon offsets after the end of 2018, depending on whether they were treated by the Sustainalytics ESG rating downgrade.[16] Specifically, we estimate the following difference-in-differences (DID) specification:

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

in which $\mathit{Offsets}_{i,t}$ denotes 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. 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 log of assets, book leverage, and return on assets. 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.

6.1.1. Exogenous Downgrades and Firms' Incentives

Before we analyze offsets, we first examine the validity of our underlying assumption that Sustainalytics' methodology change incentivized downgraded firms to boost their ESG ratings. We begin by testing whether exogenous ESG rating downgrades affect firms' institutional ownership. To do this, we estimate the baseline DID specification above by replacing the dependent variable with quarterly institutional ownership. We report these results in

[16] Ceccarelli et al. (2024) and Rzeźnik et al. (2022) also use Sustainalytics' methodology change as a shock. While they 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 use December 2018 as the treatment date. The reason is two-fold. First, unlike these studies that focus on mutual fund managers whose portfolio ratings are disseminated by Morningstar or retail investors who rely on public sources such as Yahoo! Finance, our mechanism is through the response of institutional investors who are the primary clients of Sustainalytics, which has served over 1,000 institutions. Because Sustainalytics' clients had access to the new ESG risk scores as soon as the rating agency implemented the methodology change before broader public dissemination, we use the actual time of the methodology change as the event date. Our rationale is corroborated by direct conversations with Sustainalytics. Our results are qualitatively robust to using March 2019 as an alternative event date.

Table 4, which shows the results for overall, foreign, and domestic institutional ownership during the period spanning two quarters before and after the end of 2018. Our results show that an exogenous rating downgrade is followed by a decline in overall and foreign institutional ownership, indicated by coefficients on the interaction term, *Post* $\times$ *Rating downgrade*. This is consistent with the monitoring role played by institutions, especially foreign institutions, when they divest from downgraded firms (see Ferreira and Matos, 2008). In contrast, we find no effect for domestic institutional ownership. One explanation for this might be that domestic institutions have closer relationships with the firms they invest in (see Gillan and Starks, 2003). These results are also consistent with Gibson et al. (2022) who find that non-U.S. institutions tend to tilt their portfolios away from stocks with low ESG scores, in line with the social norms of their countries (see Liang and Renneboog, 2017).

[Insert Table 4 here]

Moreover, we find that after the methodology change, Sustainalytics' ESG ratings have become much more closely linked to the firm's carbon emission intensity, measured as scope 1 emissions scaled by sales. As shown in Table 5, the new ESG risk score is positively and significantly associated with lagged emission intensity, whereas the legacy ESG score was not. This further validates our assumption that exogenously downgraded firms should become incentivized to bolster their ratings by offsetting their emissions.

[Insert Table 5 here]

6.1.2. Main Results

The results of our main regression analyses of carbon offsets are reported in Table 6. Panel A reports the results for all firms, and Panel B shows results for the subset of firms that use carbon offsets at least once during our sample period. In both panels, the first column reports a positive and significant coefficient on the interaction term, *Post* $\times$ *Rating downgrade*, indicating that companies whose ESG rankings were exogenously downgraded as a result of Sustainalytics' methodology change became incentivized to use more carbon credits to offset their own emissions. Relative to firms that do not experience an ESG rating downgrade, the average downgraded firm offsets an additional 21.7% of its direct emissions measured at the end of 2018. For the subset of firms that use offsets, the effect is four times larger, indicating that they largely achieve carbon neutrality. This result is consistent with the certification hypothesis, where firms use offsets to achieve milestone targets that may help improve their third-party ESG ratings.

[Insert Table 6 here]

To further highlight firms' certification incentives, we split the sample based on the amount of firms' direct emissions as of 2018 prior to the rating shock. We then test how exogenous downgrades affect offset usage by below-median and above-median emission firms separately. If firms use offsets primarily for certification purposes, low-emission firms should find offsetting attractive as they are already close to achieving net-zero targets and could easily do so by offsetting a small quantity of emissions. Column 2 shows that rating downgrades cause below-median firms to use significantly more offsets (offsetting an additional 45% of their 2018 emissions, significant at the 5% level), whereas column 3 shows that above-median firms remain unaffected. Contrary to the notion that offsets can help the transition of heavy-emission firms, these results indicate that low-emission firms that are already close to achieving carbon neutrality use more offsets in response to rating shocks. This is more consistent with firms using offsets as a cheap and easy way of achieving a salient goal that is close at hand to impress stakeholders, rather than as a serious effort to reduce large-scale emissions. Indeed, a back-of-the-envelope estimate based on these results suggests that the cost low-emission firms pay for this strategy is only about $41,000.[17]

Alternatively, we split the sample with respect to the firm's "industry emission gap," defined as the difference in emissions between the 75th and 25th percentiles of peer firms in the same industry as of 2018. Firms in industries with narrow emission gaps could achieve disproportionate improvements in their within-industry greenness rankings by offsetting a small amount of emissions. Indeed, consistent with a certification channel, column 4

[17]The estimate is calculated by multiplying the following three values: 45% (i.e., coefficient on the interaction term from column 2 of Table 6), 7,010 metric tons (i.e., unconditional average scope 1 emissions of low-emission firms 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).

of Table 6 shows that firms in low-gap industries increase their use of offsets significantly (offsetting 33% more of their 2018 emissions, significant at the 5% level), whereas column 5 shows that firms in high-gap industries do not.

Overall, these results suggest that firms use carbon offsets as a means of "transition-dressing" when they face an incentive to improve their ESG rankings. To further corroborate this interpretation, we also examine firms' scope 1 direct emissions around the rating shocks. The results are reported in Table 7. In contrast to their offsetting behavior, low-emission firms or firms in low-gap industries do not reduce their direct emissions in response to rating downgrades. In other words, their use of carbon credits to offset their emissions indirectly does not align with their efforts to reduce emissions directly.

[Insert Table 7 here]

Notably, while high-emission firms or firms in high-gap industries do not use offsets to boost their ratings, they significantly reduce their direct scope 1 emissions (by 6.5% or 7.3%, respectively, both significant at the 5% level). This indicates that third-party ESG ratings help discipline corporate emissions where it matters: Heavy-emission firms take action to reduce their emissions when their ratings are at risk. However, carbon offsets are not heavily used for this purpose. Such evidence supports our outsourcing hypothesis, which is consistent with a separating equilibrium: Firms with smaller carbon footprints use offsets more intensively to reduce their carbon emissions while heavy-emission firms are more likely to reduce their emissions directly.

6.1.3. Parallel Trends

The key identifying assumption in our DID model is that the treatment group (i.e., downgraded firms) would have exhibited trends that are similar to those of the control group in the absence of rating downgrades. Although the parallel trend assumption is not directly testable, we demonstrate parallel trends in the pre-event period. Specifically, we regress *Offsets*$_{i,t}$ on yearly indicator variables, interacted with the *Rating downgrade*$_i$ indicator, and plot the coefficients along with their confidence intervals in Figure 5. The year 2018, or -1 relative to the treatment event in December 2018, is set as the baseline period. 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. However, none of the pre-event coefficients are significant, suggesting that the control and treated firms do not exhibit any meaningful differences prior to 2019.[18]

[Insert Figure 5 here]

6.1.4. Carbon Offset Usage and Post-Shock ESG Rating Recovery

As an additional corroboration of the certification hypothesis, we provide evidence of the treated firms' ESG ranking dynamics after exogenous downgrades, depending on how many more offset credits they use compared to before the shock. We consider two subsets downgraded firms: "high or low offset growth" firms. We measure offset usage intensity as offset retirements scaled by scope 1 emissions as of 2018, and define offset growth for each treated firm as the difference between the average offset usage intensity in the post- and pre-treatment periods. We then sort firms into high or low groups based on whether their offset growth is higher or lower than the median firm's. For these subsamples, we regress their within-industry percentile ESG rankings on yearly dummy variables and plot the associated coefficients along with their confidence bands in Figure 6. The rankings are based on the legacy ESG scores prior to the methodology change and the new ESG risk scores thereafter.

[Insert Figure 6 here]

Panels A and B of Figure 6 clearly show that treated firms—high and low offset growth firms alike—experienced sharp declines in their within-industry rankings in 2019 (i.e., year 0), after Sustainalytics changed their ESG rating methodology at the end of 2018. In the following years, high offset growth firms on average enjoyed a swifter recovery in their ESG rankings than low offset growth firms. This difference is also evident when we pool the sub-samples together and interact the time dummies with a high offset growth dummy instead. Panel C shows that while the ESG rankings of high and low offset growth firms dropped in parallel during 2019, the rankings of high offset growth firms increased at a faster rate

[18] In Appendix Figure A.1, we also demonstrate parallel trends for scope 1 emissions in the pre-event period.

than low offset growth firms in the two years after 2019. Consistent with the certification hypothesis, this result illustrates that firms that used offsets more intensively following a downgrade were indeed able to boost their ESG rankings more effectively thereafter.

6.2. Quality of Carbon Offset Projects

An important question about the carbon offset market is whether firms use high-quality carbon offsets. To measure the quality of carbon offset projects, we rely on project quality ratings assigned by BeZero Carbon, one of the leading offset rating agencies. Under BeZero's rating system, projects are rated on a scale from AAA (highest quality) to D (lowest quality), similar to credit ratings assigned by S&P or Moody's.

A major difference between offset ratings and credit ratings is that, unlike issuer-paid credit ratings that 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 offset ratings are typically sold to prospective buyers who value high-quality offsets. This likely mitigates concerns that offset ratings may be inflated due to ties between offset rating agencies and project developers.

Although only 10% of all offset projects are rated by BeZero (see Table 1), roughly half of all publicly listed firms that retire offset credits use at least some that are rated. Conditional on being rated by BeZero, the average offset project used by the average publicly listed firm in our sample has a rating between BBB (moderate) and BB (moderately low), consistent with widespread concerns that firms might often use low-quality offsets.

Given the low quality of the average carbon offset project, we test whether firms tilt toward using higher or lower quality offsets when they are incentivized to improve their within-industry ESG rankings. We re-estimate the DID specification in equation 1 using a dummy variable indicating whether the firm retires a high- or low-quality offset credit in a given year as the dependent variable. Each year, we classify firms based on whether they use BeZero-rated or non-rated offsets, or alternatively, high- (BBB or higher) or low-rating (BB or lower, or non-rated) offsets. We use an indicator variable as the dependent variable, rather than a continuous quantity variable, to mitigate small sample biases that might arise from the fact that BeZero covers a relatively small fraction of all offset credits. This specification also constrains the sample to firm-year observations with non-zero credit retirements.

The results are reported in Table 8. Panel A presents results using the dependent variable indicating whether the firm uses at least some BeZero-rated offsets or only non-rated offsets, and Panel B shows results based on the dependent variable indicating whether the firm uses high- or low-rating offsets. In both panels, we report results for the full sample and subsamples sorted with respect to the median firm's scope 1 emissions or industry emission gap.

[Insert Table 8 here]

As shown in Table 8, following an exogenous ESG ranking downgrade, low-emission firms and firms in low-gap industries become no more likely to use high-quality offsets than before, conditional on using offsets. The coefficient on the interaction term, *Post* $\times$ *Rating downgrade*, is insignificant in columns 2 and 4. Coupled with our findings reported in Table 6 that such firms use larger quantities of offsets, these results indicate that low-emission firms in low-gap industries respond to ESG ranking downgrades by using more of the same low-quality offsets that they had used ex-ante.

On the other hand, Table 8 indicates that high-emission firms or firms in high-gap industries become more likely to use higher quality offsets than before following an ESG ranking downgrade (see columns 3 and 5), although they do not necessarily use offsets in greater quantities (see Table 6 above). For example, the coefficient on the interaction term in column 3 of Panel A indicates a 24 percentage point increase in the likelihood of using BeZero-rated offsets, conditional on the firm using offsets. Considering that the unconditional probability of using any BeZero-rated credits is 62%, the marginal effect is substantial. The marginal effect is similarly large when we examine the likelihood of using high- or low-rating projects, as shown in Panel B. Together with the fact that these firms directly reduce their emissions after ESG ranking downgrades (see Table 7 above), these results indicate that heavy-emission firms in industries with extreme polluters exhibit more responsible behavior when their ESG ratings indicate the need for citizenship and action. This contrasts with popular criticism often levied on these firms regarding their transition efforts and is consistent with recent evidence that brown firms conduct most of the meaningful green innovation activities (see Cohen et al., 2023). While these firms do not use carbon offsets as the primary tool for their transition efforts, consistent with our outsourcing hypothesis, our evidence suggests that they choose offset projects more prudently than other firms do.

6.3. The Cost of Carbon Offsets

Our results reported in Section 6.2. lead to a natural question: do firms engaged in transition-washing use lower-quality offsets that are cheaper? To examine this question, we obtain pricing information for carbon offsets from a leading analytics and consulting firm that provides corporate solutions and asset management services in the voluntary offset market. The data 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 offset credit issued in different vintage years. From this provider, we obtain a proprietary dataset that includes daily price snapshots for about 86% of our sample of offset projects during the last two weeks of February 2024.

We first average the daily snapshots at the project-vintage year level before merging the pricing data with project-level quality ratings assigned by BeZero Carbon. For each rating group, we plot in Figure 7 the average offset prices per ton across different vintage years.

[Insert Figure 7 here]

Figure 7 reveals two important patterns. First, offset credits that are issued more recently command higher prices, consistent with growing demand and improving standards in the voluntary offset market. Second, offset credits issued by poor-quality projects are much cheaper than high-quality ones. From AA to D ratings, average carbon offset prices are generally decreasing, conditional on the vintage year. Offsets that are not rated by BeZero are also priced nearly at the bottom, similar to offsets with the lowest ratings. While we caveat that the time stamps for our pricing data are not aligned with our sample period, these patterns are consistent with the idea that low-quality offsets provide firms a cost-effective means of transition-washing.

From a regulatory standpoint, it is also noteworthy that the pricing spread between high- and low-rating offsets is persistent across issuance years, despite the fact that low-quality offsets enjoy robust demand by firms (among the 1,413 offset projects used by public firms, about 97% are rated below BBB or unrated). Highlighting such demand for cheap offsets, Figure 8 strikingly shows that more than 50% (70%) of all retired offsets are priced below $2 ($4) per ton.

[Insert Figure 8 here]

Overall, the evidence presented in Sections 6.2. and 6.3. is consistent with the certification hypothesis that (low-emission) firms strategically use carbon offsets to obtain ESG rating benefits cheaply. One may speculate that this "bad equilibrium" is sustained by the absence of a regulatory framework that ensures transparency and accountability. Project developers are likely to cater to transition-washing buyers by supplying low-quality credits at a low price, given that firms are not required to disclose these details. Indeed, AA-rated offsets, which receive the highest rating, make up only 1.6% of all rated projects in our sample. Therefore, the voluntary offset market is an important area that can benefit from stronger disclosure requirements. Although the SEC's newly adopted corporate climate disclosure rules require that firms report expenditures related to carbon offsets when they are material to investors, it remains difficult for investors to infer the quality of retired offsets from these disclosures.[19]

7. Conclusion

Carbon offsets allow firms to claim reductions in carbon emissions by purchasing and retiring carbon credits sold by projects or entities that achieve those reductions. These instruments have been promoted as tools that can be effective at helping heavy-emission firms transition to low-emission business models. However, they have also been criticized for the lack of transparency regarding whether a firm might falsely claim emission reductions that would have occurred irrespective of its offset credit purchase, or how accurate an offset project's estimated impact might be.

[19] See "The enhancement and standardization of climate-related disclosures: Final rules," SEC (March 2024).

Based on rich data on carbon offsets collected from carbon registries and manually linked with firm financial information, this paper documents stylized facts about the global carbon offset market and provides the first systematic analysis of why firms use carbon offsets. We find evidence of a separating equilibrium, where firms with smaller carbon footprints use offsets more intensively to reduce their emissions indirectly while heavy emitters tend to reduce their footprints directly. Furthermore, we show that offsets are often used strategically by firms that are already positioned close to achieving these targets or in industries where it is easier to boost their ESG rankings relative to their peers. When facing an exogenous shock to their incentives to boost rankings, firms with low emissions in industries with narrow cross-peer emission gaps become more likely to use offsets whereas heavy-emission firms in large-gap industries do not. Moreover, firms that strategically increase the use of offsets do so by retiring credits from low-quality offset projects, which command lower prices and therefore provide a cost-effective way of transition-washing.

Overall, our evidence does not support the purported idea that carbon offsets can be effective at facilitating net-zero transitions by heavy-emission firms. While we find some evidence that heavy-emission firms can be incentivized to use high-quality offsets than low-quality ones, we do not find evidence that these firms would use such "good" offsets in large enough quantities to meaningfully reduce their net emissions.

Our findings that carbon offsets are often used strategically for certification and ranking purposes have important implications for understanding the current state of the carbon offset market and designing future policies and regulations around it. Our results suggest that the quality of projects generating the credits being used is low and that the market currently sustains low prices for these offsets. This likely discourages the use of high-quality offsets by firms that are under the most pressure from investors and other stakeholders to take serious steps to reduce their emissions. This highlights the importance of commonly adoptable rules and regulations that can ensure the transparency of offset projects. However, such policies must also consider potential trade-offs between the authenticity of offset projects, the prices those projects' carbon credits would command, and the costs firms would need to bear to use them for their transition goals. Much future work is needed to understand whether and how to regulate the carbon offset market so that it facilitates an effective 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.

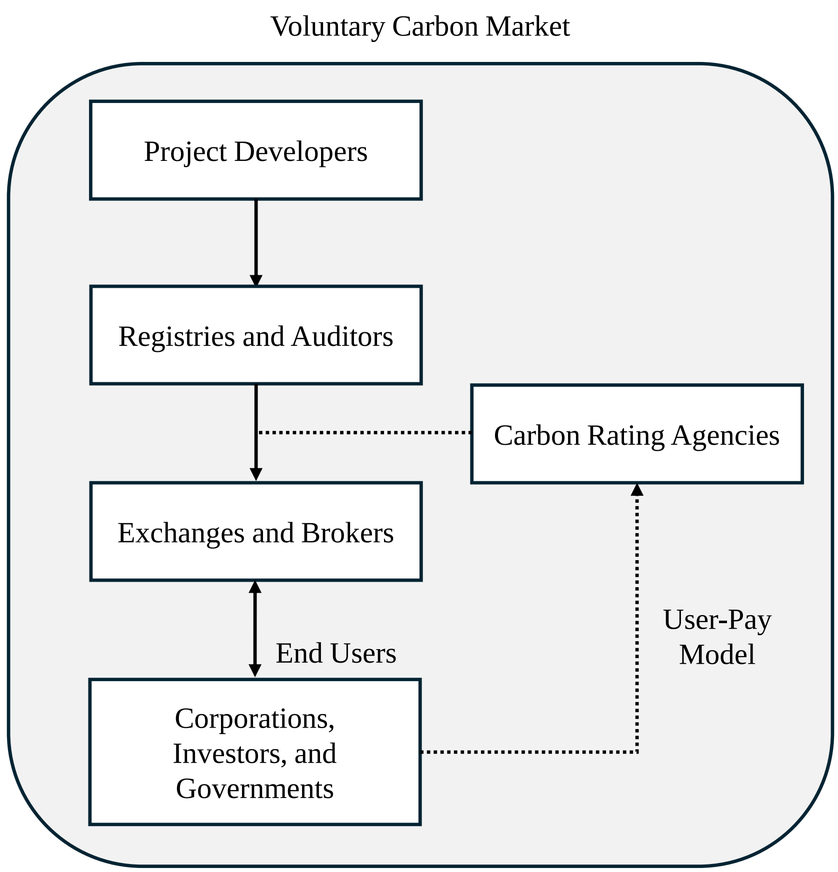
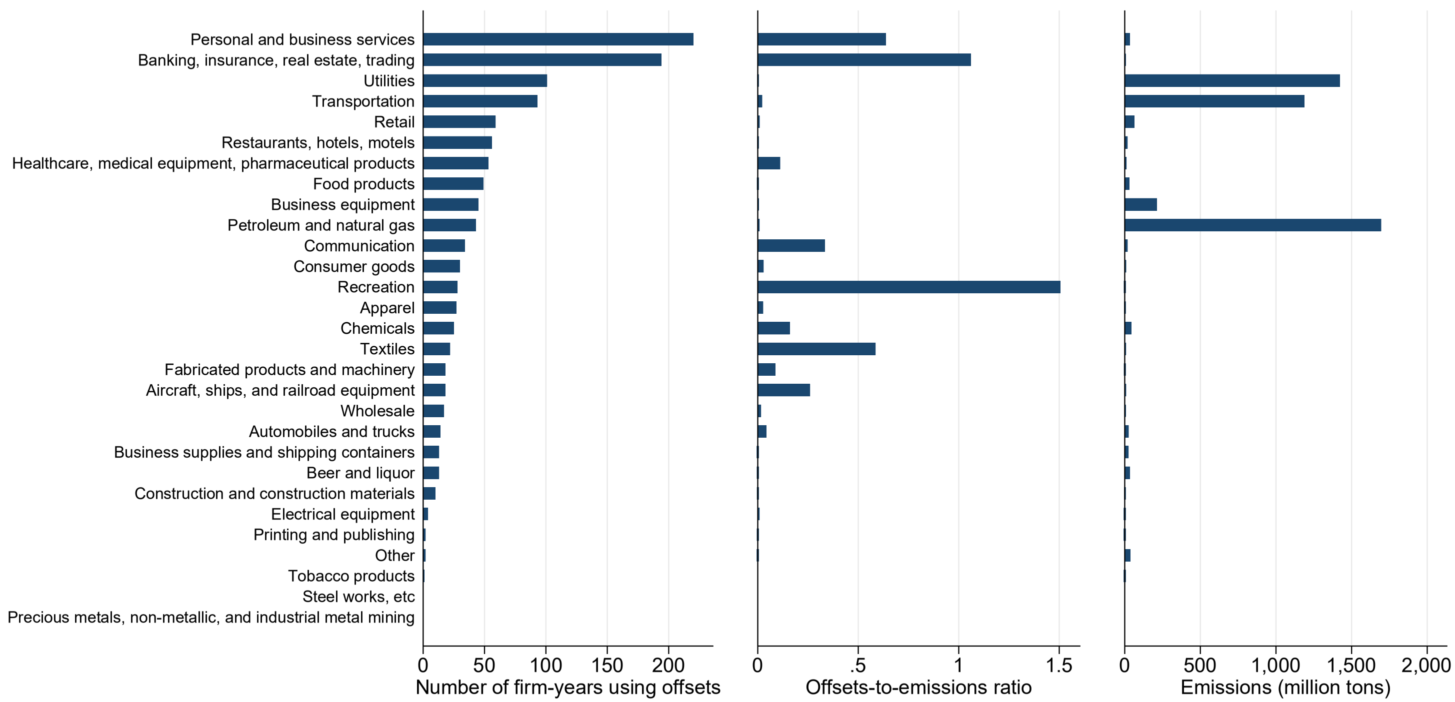


Figure 2. Industry Distribution of Firms that Use Carbon Offsets

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.

Panel A: U.S. firms



(continued)

Figure 2. Industry Distribution of Firms that Use Carbon Offsets (continued)

Panel B: Non-U.S. firms

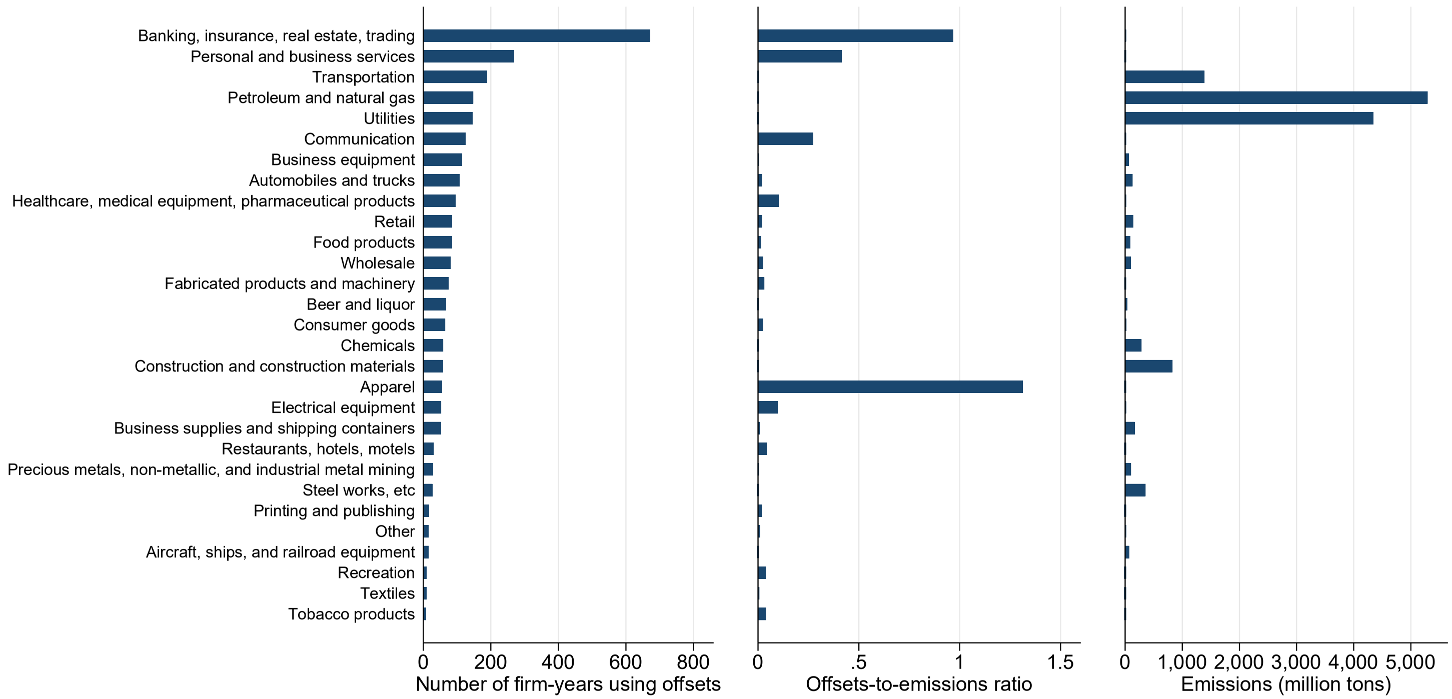


Figure 3. Aggregate Carbon Offset Retirements and Direct Emissions

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.

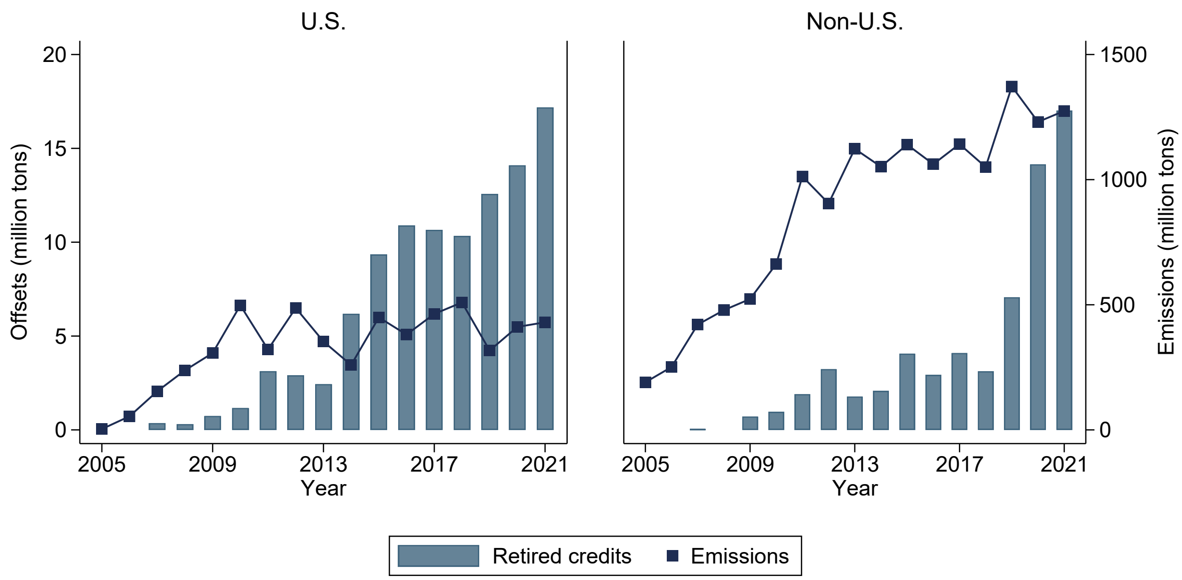


Figure 4. Ranking Shifts Following Sustainalytics' Rating Methodology Change

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.

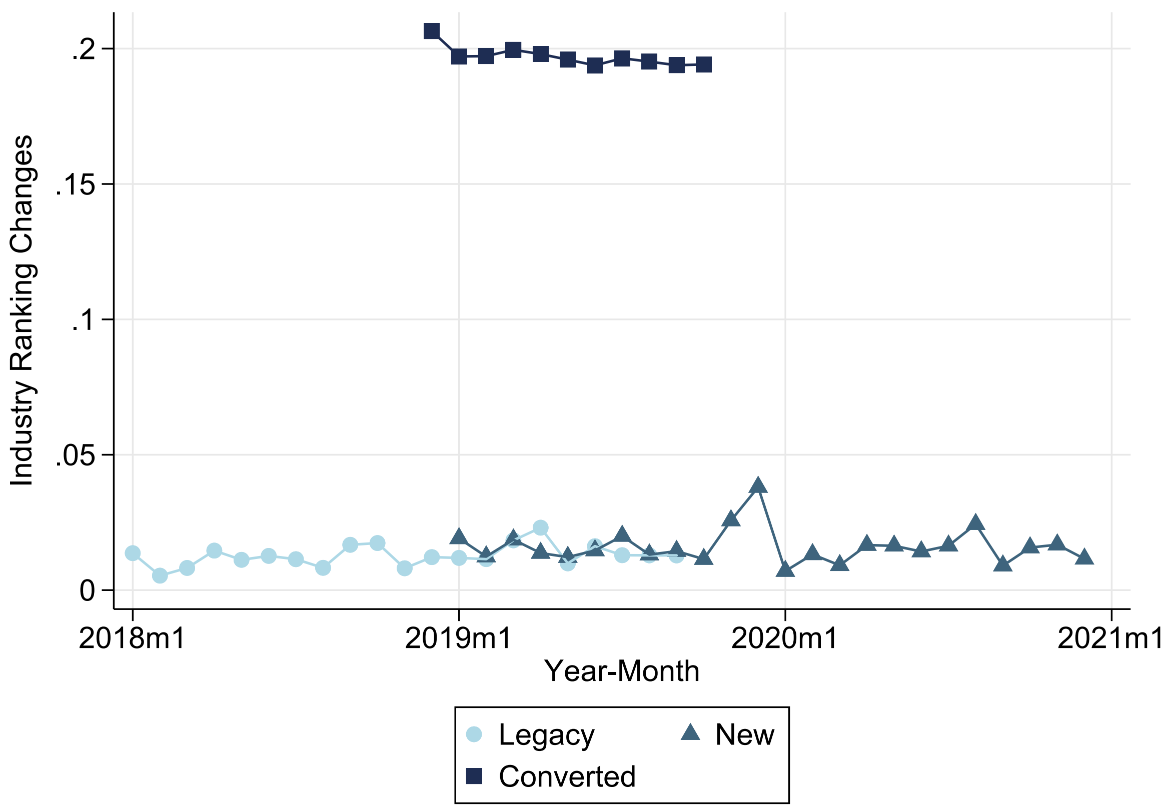


Figure 5. Pre- and Post-Event Differences Between Downgraded and Control Firms

This figure plots results from the following event-study regression using the Sustainalytics methodology change in December 2018 as the treatment event:

$$\mathit{Offsets}_{i,t} = \alpha + \left(\sum_{s=-2}^{-1} \beta_s \cdot Pre(s)_t + \sum_{s=0}^{+2} \beta_s \cdot Post(s)_t \right) \times \mathit{Rating\ downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

in which $\mathit{Offsets}_{i,t}$ denotes 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 event. 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. $\mathit{Rating\ downgrade}_i$ 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. We plot the estimated coefficients, β_s, along with their 90% confidence intervals. Standard errors are clustered at the firm level.

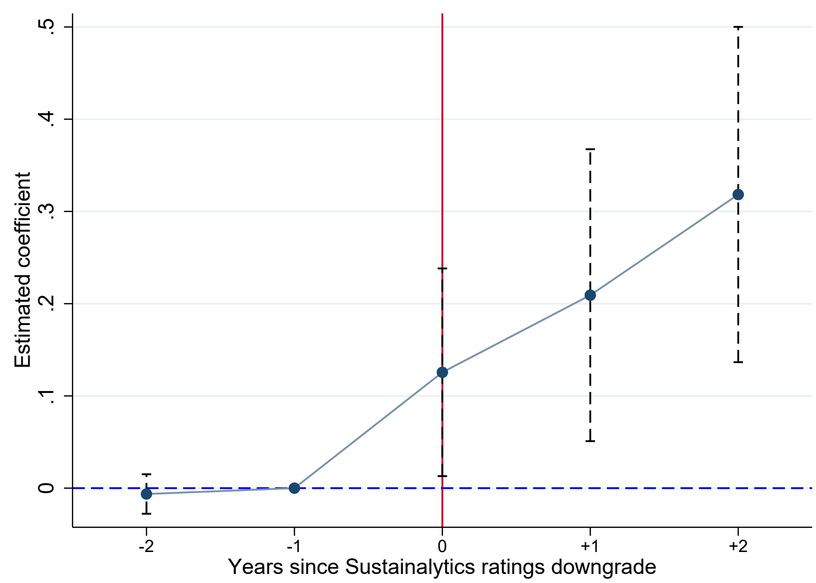


Figure 6. Carbon Offset Usage and Post-Shock ESG Rating Recovery

This figure illustrates the post-treatment dynamics of within-industry ESG percentile rankings for treated firms that experienced ranking downgrades following Sustainalytics' rating methodology change. In Panels A and B, we consider two subsets of treated firms separately: "high (low) offset growth" firms whose growth in offset usage intensity (i.e., offset retirements scaled by 2018 emissions) from the pre-treatment period to the post-treatment period is more (less) than the median firm's. Specifically, for these subsamples, we plot the coefficients, β_s, and their 90% confidence intervals from the specification below:

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

in which within-industry ESG percentile rankings are 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. $Pre(\mathrm{s})(Post(\mathrm{s}))$ 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 institutional ownership. δ_i and $\sigma_{j,t}$ denote firm and industry-by-year fixed effects, respectively. Standard errors are clustered at the firm level. In Panel C, we pool the high and low offset growth subsamples and plot the coefficients on the interaction terms between the time dummies and an indicator for high offset growth firms.

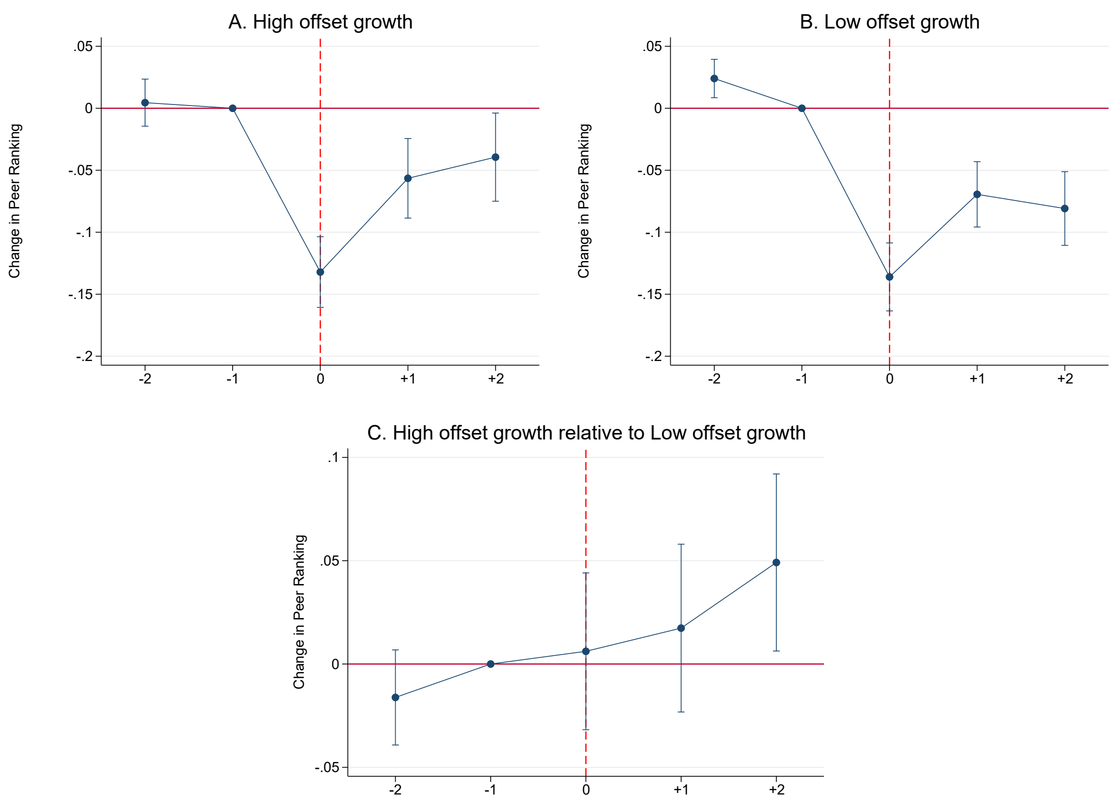


Figure 7. Average Carbon Offset Prices by Vintage and Rating

For each BeZero Carbon rating group, this figure plots the average offset prices per ton across different issuance years.

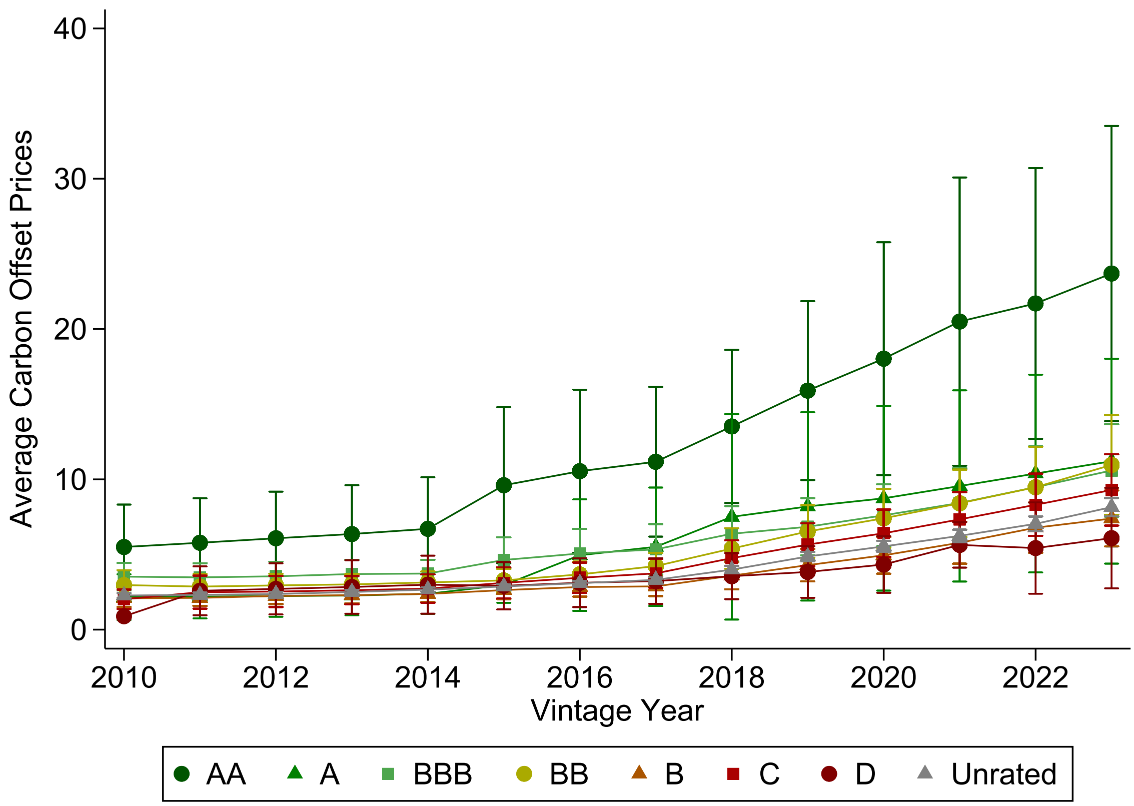


Figure 8. Offset Volume as a Percentage of All Retired Offsets by Price

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.

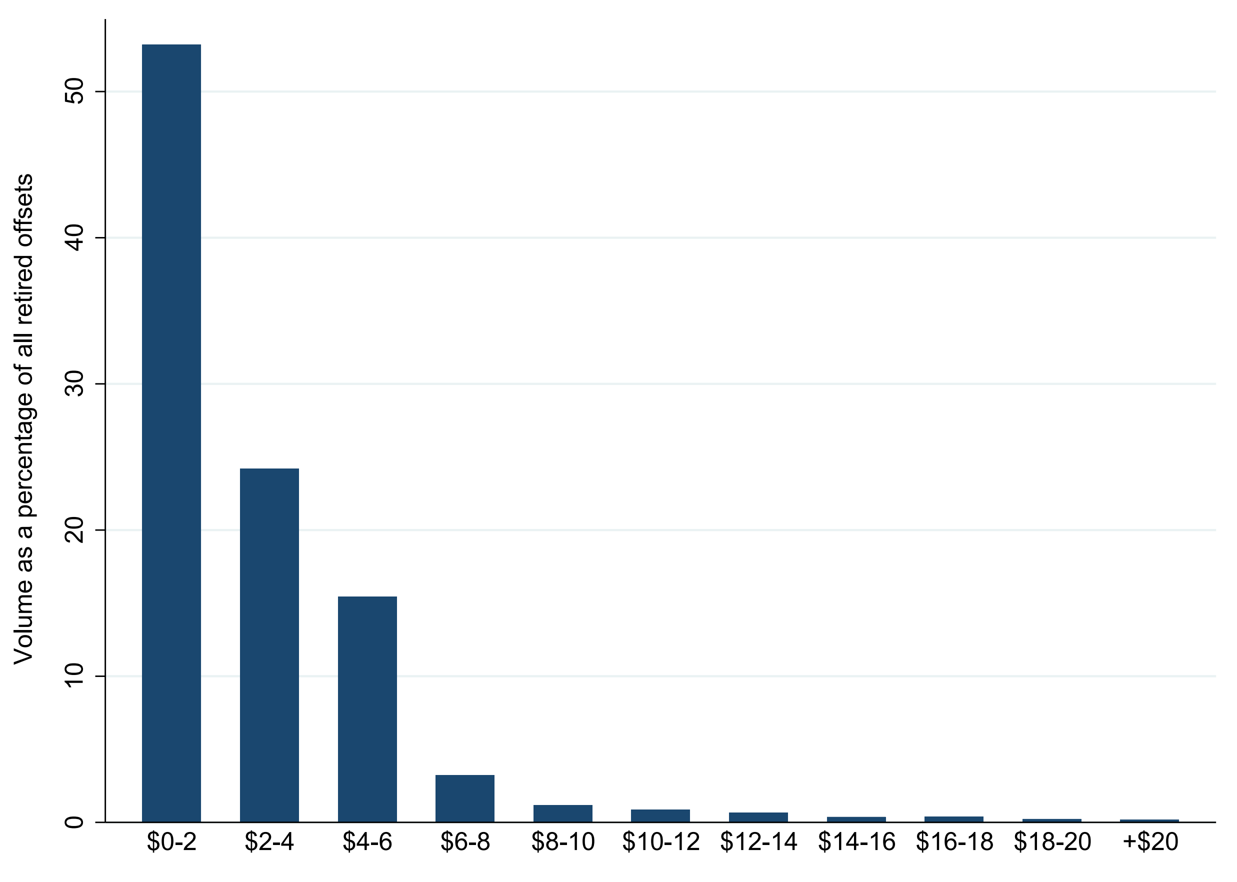


Table 1. Characteristics of Carbon Offset Projects by Region

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 2,916 projects, and Panel B describes a subset of 1,413 projects that issue offset credits used by publicly listed firms included in our main sample. In each panel, 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.

Panel A: All projects

	Geographic region						
Number of projects	Full sample	Africa	Asia	Europe	North America	South America	Other
Total	2,916	530	1,541	54	545	232	14
Type							
Agriculture	117	1	37	6	59	14	0
Carbon capture & storage	3	0	0	0	3	0	0
Chemical processes	82	8	4	0	70	0	0
Forestry & land use	320	50	58	1	129	75	7
Household & community	632	413	184	1	20	13	1
Industrial & commercial	156	3	85	40	25	3	0
Renewable energy	1,276	42	1,087	4	33	107	3
Transportation	43	0	2	0	36	3	2
Waste management	287	13	84	2	170	17	1
Rated by BeZero Carbon	304	51	152	5	52	41	3
Average price per ton (as of February 2024)	3.6	4.7	2.0	4.0	6.4	3.7	4.6
Median price per ton (as of February 2024)	2.7	4.6	1.3	3.5	4.5	2.4	3.6
Average #credits issued (thousand tons)	524.2	423.7	525.7	279.7	390.5	1,126.4	333.0
Median #credits issued (thousand tons)	108.1	39.6	149.7	151.1	111.0	179.1	173.4
Total #credits issued (million tons)	1,528.6	224.6	810.1	15.1	212.8	261.3	4.7
Average % of credits being retired	67.9%	69.8%	64.6%	80.7%	75.0%	65.1%	86.3%
Issuance year: $\leq$2015	77.0%	87.1%	74.2%	85.9%	80.4%	73.9%	90.5%
Issuance year: 2016	77.3%	80.9%	73.9%	58.6%	82.1%	67.0%	92.0%
Issuance year: 2017	74.7%	82.9%	72.8%	68.6%	73.1%	72.5%	
Issuance year: 2018	71.3%	74.7%	64.5%		78.7%	61.1%	
Issuance year: 2019	70.0%	73.8%	67.9%		78.0%	59.1%	
Issuance year: $\geq$2020	45.1%	54.6%	39.7%	42.5%	47.8%	40.0%	60.5%

(continued)

Table 1. Characteristics of Carbon Offset Projects by Region (continued)

Panel B: Projects used by publicly listed firms

	Geographic region						
Number of projects	Full sample	Africa	Asia	Europe	North America	South America	Other
Total	1,413	220	689	24	333	135	12
Type							
Agriculture	44	1	8	2	26	7	0
Carbon capture & storage	3	0	0	0	3	0	0
Chemical processes	48	1	2	0	45	0	0
Forestry & land use	218	34	38	1	83	56	6
Household & community	278	166	90	0	13	8	1
Industrial & commercial	53	1	26	17	9	0	0
Renewable energy	585	12	495	2	18	55	3
Transportation	30	0	0	0	27	2	1
Waste management	154	5	30	2	109	7	1
Rated by BeZero Carbon	229	35	106	2	48	35	3
Average price per ton (as of February 2024)	3.6	4.5	2.0	4.6	6.0	3.7	4.9
Median price per ton (as of February 2024)	2.7	4.2	1.3	3.5	4.5	2.4	3.7
Average #credits issued (thousand tons)	876.7	848.2	912.9	398.5	519.3	1,748.7	382.4
Median #credits issued (thousand tons)	194.9	53.5	296.6	348.1	160.9	305.3	198.5
Total #credits issued (million tons)	1,238.8	186.6	629.0	9.6	172.9	236.1	4.6
Average % of credits being retired	73.2%	76.8%	71.4%	81.6%	75.0%	69.0%	84.9%
Issuance year: $\leq$2015	78.8%	85.0%	76.9%	87.4%	80.9%	73.1%	89.5%
Issuance year: 2016	79.8%	81.3%	77.9%	58.6%	82.3%	79.4%	92.0%
Issuance year: 2017	73.0%	82.7%	72.5%	68.6%	66.2%	72.8%	
Issuance year: 2018	67.9%	72.2%	66.7%		65.8%	51.7%	
Issuance year: 2019	69.8%	73.5%	65.4%		76.0%	67.9%	
Issuance year: $\geq$2020	54.0%	57.5%	55.3%	51.2%	49.0%	53.9%	31.3%

Table 2. Which Carbon Offset Projects do Publicly Listed Firms Use?

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 retired by publicly listed firms and zero otherwise. The independent variables include the logarithm of total credits issued by the project, dummy variables indicating whether the project generates credits through forest preservation and land use restrictions or through renewable energy generation, and a dummy variable indicating whether the project is rated by BeZero. Column 1 further controls for fixed effects corresponding to the project's age group, registry, and geographic region. Column 2 includes dummy variables indicating whether the project is based in North America or Europe, and drops geographic region fixed effects. Columns 3 to 8 report results for geographic region subsamples and further drop the North America and Europe dummy variables. Standard errors are clustered at the project-age level and the associated t-statistics are reported in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	Full sample		Africa	Asia	Europe	North America	South America	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(#credits issued)	0.085***	0.084***	0.079***	0.107***	0.212**	0.052***	0.076***	0.157
	[12.43]	[12.31]	[4.23]	[10.64]	[2.85]	[3.32]	[4.17]	[0.46]
Forestry & land use	0.168***	0.192***	0.141	0.252**		0.135*	0.068	
	[4.83]	[5.46]	[1.22]	[2.72]		[1.98]	[0.81]	
Renewable energy	0.028	0.007	-0.064	0.056	-1.092***	0.019	-0.053	-0.035
	[1.00]	[0.26]	[-0.73]	[1.30]	[-4.04]	[0.20]	[-0.62]	[-0.46]
Rated by BeZero	0.105***	0.106***	0.034	0.067	-0.293	0.220***	0.145**	
	[4.04]	[4.02]	[0.48]	[1.38]	[-0.95]	[4.82]	[2.13]	
North America based		0.151***						
		[3.24]						
Europe based		-0.024						
		[-0.62]						
Project age FE	Y	Y	Y	Y	Y	Y	Y	Y
Registry FE	Y	Y	Y	Y	Y	Y	Y	Y
Geographic region FE	Y	N	N	N	N	N	N	N
Observations	2,916	2,916	530	1,541	54	545	232	14
R-squared	0.204	0.199	0.314	0.186	0.280	0.196	0.291	0.831
% (Dependent variable = 1)	48.5%	48.5%	41.5%	44.7%	44.4%	61.1%	58.2%	85.7%

Table 3. Characteristics of Publicly Listed Firms that Use Offsets

This table reports summary statistics for our sample of publicly listed firms for which Sustainalytics ratings are available. *B/M* is the book-to-market ratio, defined as (book value of equity)/(market value of equity). 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, all in book values. *Prior 12-month return* is the buy-and-hold stock return during the 12 months prior to the focal firm-year. *Dividend yield* equals (common dividends + preferred dividends)/(market value of common stock + book value of preferred). *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. *Net-zero commitment* equals one once a firm commits to a net-zero target and zero otherwise. *Vintage of retired offsets* is the quantity-weighted vintage of retired offsets by a firm. The averages, medians, and standard deviations of these variables are shown separately for firms that use offsets during our sample period and firms that do not. The differences in means between the two groups of firms and the corresponding t-statistics are also reported.

	Firm-years with offset usage			Firm-years without offset usage				
	Average	Median	Std. Dev.	Average	Median	Std. Dev.	Avg. Diff.	t-stat.
Assets ($billion)	47.94	35.86	39.91	15.99	5.30	24.66	31.95	49.56
Market capitalization ($billion)	26.27	22.05	23.97	8.14	3.75	11.89	18.13	57.27
B/M	0.66	0.55	0.57	0.67	0.52	0.70	-0.01	-0.48
q	1.80	1.18	1.61	1.77	1.28	1.52	0.02	0.60
ROA	0.10	0.09	0.08	0.10	0.10	0.11	-0.01	-1.86
Leverage	0.27	0.26	0.19	0.26	0.24	0.20	0.02	3.15
Prior 12-month return	0.13	0.09	0.45	0.16	0.07	0.62	-0.03	-1.69
Dividend yield	0.02	0.02	0.03	0.02	0.02	0.03	0.004	5.57
Institutional ownership	0.47	0.38	0.30	0.41	0.28	0.33	0.06	6.87
U.S. firm	0.37	0.00	0.48	0.31	0.00	0.46	0.06	5.14
Scope 1 emissions (million tons)	3.41	0.08	8.35	1.67	0.04	5.68	1.74	12.11
Scope 2 emissions (million tons)	0.64	0.17	1.00	0.26	0.05	0.59	0.38	25.24
Scope 3 emissions (million tons)	2.53	2.22	1.90	1.25	0.42	1.63	1.28	31.28
Emission intensity ($\times$1,000)	0.19	0.01	0.56	0.27	0.02	0.86	-0.07	-3.03
Industry emission gap	2.61	2.43	0.73	2.45	2.28	0.70	0.15	8.75
Net-zero commitment	0.24	0	0.43	0.12	0	0.33	0.11	11.68
Retired offsets (thousand tons)	140.10	6.29	904.21					
Vintage of retired offsets (year)	2012.95	2013	3.63					
Observations	1,639			49,362				

Table 4. Institutional Ownership Around the Sustainalytics Methodology Change

This table reports results from the following firm-quarter difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event. We estimate the regressions using a window of two quarters before and after December 2018. The regressions are estimated for all institutional ownership, foreign institutional ownership, and domestic institutional ownership, respectively:

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

in which $IO_{i,t}$ denotes the institutional ownership share of firm *i* in year *t*. 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 past quarter's stock return. 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:	IO		Foreign IO		Domestic IO	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Rating downgrade	-0.003**	-0.003**	-0.003***	-0.003***	-0.000	0.000
	[-2.41]	[-2.24]	[-3.35]	[-3.32]	[-0.17]	[0.28]
log(assets)	0.010	0.007	0.005*	0.003	0.004	0.004
	[0.90]	[0.87]	[1.83]	[1.31]	[0.45]	[0.49]
Leverage	-0.001	-0.009	-0.005	-0.003	0.004	-0.007
	[-0.05]	[-0.51]	[-0.94]	[-0.60]	[0.18]	[-0.38]
ROA	-0.081	-0.071	-0.026**	-0.024**	-0.056	-0.047
	[-0.96]	[-1.04]	[-2.14]	[-2.18]	[-0.72]	[-0.75]
Past quarter stock return		0.007***		-0.003***		0.010***
		[3.50]		[-2.76]		[5.67]
Firm FE	Y	Y	Y	Y	Y	Y
Industry-quarter FE	Y	Y	Y	Y	Y	Y
Observations	13,036	11,714	13,036	11,714	13,036	11,714
R-squared	0.996	0.997	0.993	0.990	0.997	0.998

Table 5. 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. $\textit{Emission intensity}_{i,t-1}$ 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	Risk scores
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 6. Carbon Offset Retirements Around the Sustainalytics Methodology Change

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event. Panel A reports results for all firms in the sample, and Panel B reports results for a subsample of firms that retire offset credits at least once during the sample period. In each panel, the regressions are run on the full sample (column 1), separately for subsamples of low-emission and high-emission firms sorted with respect to the median firm's emissions as of 2018 (columns 2-3), and separately for subsamples of firms in industries with low or high emission gaps measured as the industry's inter-quartile range of emissions as of 2018 (columns 4-5):

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

in which $\mathit{Offsets}_{i,t}$ denotes 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. 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).

Panel A: All firms

	Full sample	Emissions as of 2018		Industry gap as of 2018	
		Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	0.217**	0.446**	0.028	0.325**	0.092
	[2.31]	[2.22]	[1.02]	[2.08]	[1.04]
log(assets)	0.003	-0.001	0.012	0.116	-0.100
	[0.04]	[-0.01]	[1.22]	[1.27]	[-0.90]
Leverage	1.248*	2.037*	0.072	1.204	1.264
	[1.74]	[1.68]	[1.30]	[1.47]	[1.08]
ROA	0.502*	0.714	0.160	1.370	0.260
	[1.68]	[1.41]	[0.86]	[1.30]	[1.11]
Institutional ownership	0.179	0.308	0.081	0.501	-0.204
	[0.67]	[0.55]	[1.25]	[1.15]	[-0.79]
Firm FE	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y
Observations	24,749	11,830	12,914	13,144	11,583
R-squared	0.494	0.496	0.500	0.519	0.426

(continued)

Table 6. Carbon Offset Retirements Around the Sustainalytics Methodology Change (continued)

Panel B: Firms that use offsets at least once

	Full sample	Emissions as of 2018		Industry gap as of 2018	
		Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	1.017**	2.497**	0.094	1.582*	0.396
	[2.11]	[2.21]	[0.69]	[1.94]	[0.79]
log(assets)	0.083	0.061	0.031	0.602	-0.329
	[0.31]	[0.06]	[1.21]	[1.50]	[-0.86]
Leverage	13.801*	24.774*	0.590*	11.095	20.015
	[1.87]	[1.87]	[1.71]	[1.57]	[1.24]
ROA	18.503**	28.506*	0.811	28.713*	8.529
	[2.10]	[1.86]	[0.59]	[1.75]	[1.50]
Institutional ownership	-3.423	-9.058	0.682	-0.416	-5.100
	[-1.33]	[-1.52]	[1.26]	[-0.12]	[-1.29]
Firm FE	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y
Observations	3,292	1,559	1,721	1,665	1,619
R-squared	0.521	0.534	0.561	0.548	0.456

Table 7. Direct Carbon Emissions Around the Sustainalytics Methodology Change

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event. The regressions are run on the full sample (column 1), separately for subsamples of low-emission and high-emission firms sorted with respect to the median firm's emissions as of 2018 (columns 2-3), and separately for subsamples of firms in industries with low or high emission gaps measured as the industry's inter-quartile range of emissions as of 2018 (columns 4-5):

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

in which $\textit{Log(emissions)}_{i,t}$ denotes the logarithm of direct scope 1 emissions of firm i in year t. $\textit{Post}_t$ 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).

	Full sample	Emissions as of 2018		Industry gap as of 2018	
		Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	-0.057***	-0.025	-0.065**	-0.043	-0.073**
	[-2.64]	[-0.73]	[-2.41]	[-1.44]	[-2.33]
log(assets)	0.113***	0.193***	0.065***	0.128***	0.106***
	[6.75]	[5.33]	[4.08]	[4.85]	[4.82]
Leverage	0.115	0.320**	-0.248	-0.170	0.400**
	[0.98]	[2.25]	[-1.30]	[-1.30]	[2.02]
ROA	0.280**	0.297	0.105	0.336	0.271*
	[2.17]	[1.40]	[0.92]	[1.46]	[1.75]
Institutional ownership	0.313***	0.402***	0.176	0.258**	0.383**
	[3.01]	[2.67]	[1.23]	[1.96]	[2.35]
Firm FE	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y
Observations	24,710	11,791	12,914	13,115	11,573
R-squared	0.967	0.886	0.949	0.943	0.976

Table 8. Quality of Carbon Offsets Conditional on Using Offsets

This table reports results from the following firm-year difference-in-differences (DID) regressions using the Sustainalytics methodology change as a treatment event. The regressions are estimated on the sample of firm-year observations with non-zero offset credit retirements. Results are reported for the full sample (column 1), separately for subsamples of low-emission and high-emission firms sorted with respect to the median firm's emissions as of 2018 (columns 2-3), and separately for subsamples of firms in industries with low or high emission gaps measured as the industry's inter-quartile range of emissions as of 2018 (columns 4-5):

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

in which $\mathbf{I}\textit{(offset quality)}_{i,t}$ denotes one of the two dummy variables indicating whether firm *i* retires good-quality offset credits in year *t*, conditional on retiring any offset credits. Panel A reports results from using a dummy variable indicating whether the firm retires any offset credits that are rated by BeZero. Panel B reports results from using a dummy variable indicating whether the firm retires any offset credits with a BeZero rating of BBB or higher. $\textit{Post}_t$ 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).

Panel A: BeZero-rated offset credits

	Full sample	Emissions as of 2018		Industry gap as of 2018	
		Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	0.200**	0.115	0.241**	-0.154	0.312**
	[1.99]	[0.68]	[2.08]	[-0.92]	[2.54]
log(assets)	0.013	0.394	-0.011	-0.039	0.054
	[0.36]	[1.49]	[-0.33]	[-0.95]	[1.19]
Leverage	0.065	-0.018	0.956*	0.566	-0.473
	[0.13]	[-0.04]	[1.77]	[1.10]	[-0.71]
ROA	0.534	1.064	0.839	-0.142	1.173
	[0.85]	[0.77]	[1.07]	[-0.13]	[1.30]
Institutional ownership	0.451	2.573**	0.221	0.368	0.214
	[0.82]	[2.47]	[0.31]	[0.24]	[0.36]
Firm FE	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y
Observations	602	163	394	264	333
R-squared	0.710	0.822	0.733	0.730	0.711
% (Dependent variable = 1)	61.6%	59.6%	62.0%	62.5%	61.0%

(continued)

Table 8. Quality of Carbon Offsets Conditional on Using Offsets (continued)

Panel B: Offset credits with BeZero rating of BBB or higher

	Full sample	Emissions as of 2018		Industry gap as of 2018	
		Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
Post × Rating downgrade	0.120*	-0.082	0.168**	-0.051	0.184***
	[1.71]	[-0.65]	[2.28]	[-0.33]	[2.60]
log(assets)	-0.006	0.162	-0.023	0.008	-0.027
	[-0.40]	[1.03]	[-1.48]	[0.33]	[-1.12]
Leverage	0.126	0.342	0.775*	0.256	0.064
	[0.45]	[0.79]	[1.76]	[0.69]	[0.17]
ROA	1.561*	5.068***	0.490	2.709**	0.081
	[1.91]	[4.44]	[0.60]	[2.31]	[0.08]
Institutional ownership	-0.565	-0.304	-0.477	-1.302	-0.104
	[-1.30]	[-0.51]	[-0.87]	[-1.33]	[-0.24]
Firm FE	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y
Observations	602	163	394	264	333
R-squared	0.799	0.823	0.824	0.763	0.834
% (Dependent variable = 1)	27.4%	33.3%	25.8%	25.4%	28.8%

Internet Appendix

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

by

Sehoon Kim, Tao Li, and Yanbin Wu

Figure A.1. Pre- and Post-Event Differences Between Downgraded and Control Firms

This figure plots results from the following event-study regression using the Sustainalytics methodology change in December 2018 as the treatment event:

$$\textit{Log(emissions)}_{i,t} = \alpha + \left(\sum_{s=-2}^{-1} \beta_s \cdot Pre(s)_t + \sum_{s=0}^{+2} \beta_s \cdot Post(s)_t \right) \times \textit{Rating downgrade}_i + \gamma \cdot \boldsymbol{X}_{i,t-1} + \delta_i + \sigma_{j,t} + \epsilon_{i,t},$$

in which $\textit{Log(emissions)}_{i,t}$ denotes the logarithm of direct scope 1 emissions of firm *i* in year *t*. $Pre(\mathrm{s})(Post(\mathrm{s}))$ is a dummy variable equal to one if the observation is s years before (after) the event year 2019 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. We show the estimated coefficients on "Years since Sustainalytics ratings downgrade" along with the 90% confidence intervals.

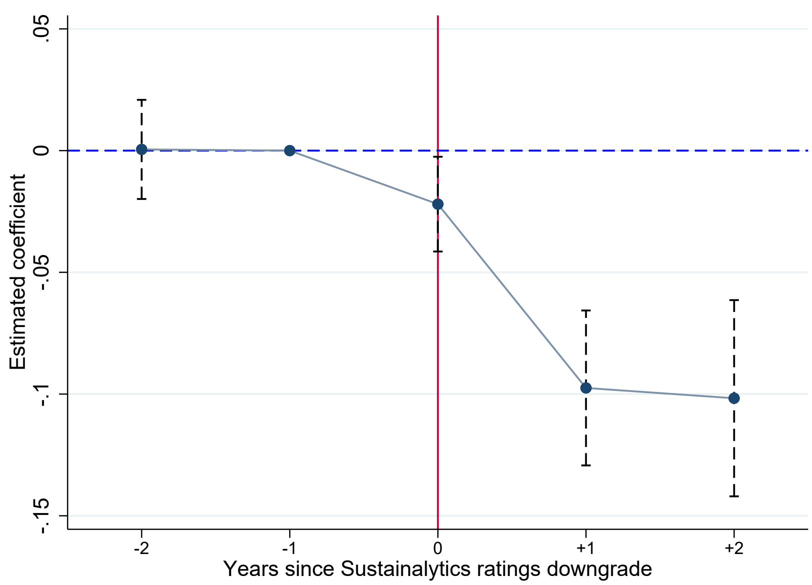


Table A.1. Characteristics of Carbon Offset Projects by Carbon Registry

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 2,916 projects, and Panel B describes a subset of 1,413 projects that issue offset credits used by publicly listed firms included in our main sample. In each panel, 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

	Carbon registries				
Number of projects	Full sample	ACR	CAR	Gold	VCS
Total	2,916	148	253	916	1,599
Geography					
Africa	530	0	0	405	125
Asia	1,541	0	0	453	1,088
Europe	54	0	0	4	50
North America	545	143	253	23	126
South America	232	5	0	26	201
Other	14	0	0	5	9
Type					
Agriculture	117	6	43	12	56
Carbon capture & storage	3	3	0	0	0
Chemical processes	82	48	19	0	15
Forestry & land use	320	35	70	21	194
Household & community	632	0	0	572	60
Industrial & commercial	156	6	0	9	141
Renewable energy	1,276	2	0	271	1,003
Transportation	43	36	0	1	6
Waste management	287	12	121	30	124
Rated by BeZero Carbon	304	22	12	62	208
Average price per ton (as of February 2024)	3.6	5.5	7.6	3.9	2.4
Median price per ton (as of February 2024)	2.7	3.6	5.0	4.0	1.3
Average #credits issued (thousand tons)	524.2	440.2	340.4	238	725
Median #credits issued (thousand tons)	108.1	110.6	107.8	49.2	165.7
Total #credits issued (million tons)	1,528.6	65.2	86.1	218	1,159.3
Average % of credits being retired	67.9%	65.6%	81.2%	69.0%	65.5%
Issuance year: $\leq$2015	77.0%	77.6%	83.1%	81.1%	74.7%
Issuance year: 2016	77.3%3	93.9%	73.9%	81.2%	67.1%
Issuance year: 2017	74.7%	100.0%	68.2%	83.2%	67.0%
Issuance year: 2018	71.3%	79.4%	80.3%	71.2%	65.0%
Issuance year: 2019	70.0%	79.1%	79.9%	73.0%	65.1%
Issuance year: $\geq$2020	45.1%	42.5%	58.6%	51.9%	39.0%

(continued)

Table A.1. Characteristics of Carbon Offset Projects by Carbon Registry (continued)

Panel B: Projects used by publicly listed firms

Number of projects	Carbon registries				
	Full sample	ACR	CAR	Gold	VCS
Total	1,413	102	147	447	717
Geography					
Africa	220	0	0	165	55
Asia	689	0	0	243	446
Europe	24	0	0	3	21
North America	333	101	147	15	70
South America	135	1	0	16	118
Other	12	0	0	5	7
Type					
Agriculture	44	2	21	1	20
Carbon capture & storage	3	3	0	0	0
Chemical processes	48	31	12	0	5
Forestry & land use	218	28	37	13	140
Household & community	278	0	0	261	17
Industrial & commercial	53	2	0	3	48
Renewable energy	585	1	0	154	430
Transportation	30	27	0	1	2
Waste management	154	8	77	14	55
Rated by BeZero Carbon	229	19	11	41	158
Average price per ton (as of February 2024)	3.6	5.6	6.9	3.6	2.6
Median price per ton (as of February 2024)	2.7	3.4	4.6	3.7	1.3
Average #credits issued (thousand tons)	876.7	516.9	447.6	374.2	1,329.2
Median #credits issued (thousand tons)	194.9	104.4	160.4	80.8	339.8
Total #credits issued (million tons)	1,238.8	52.7	65.8	167.2	953.0
Average % of credits being retired	73.2%	68.1%	78.7%	76.0%	71.0%
Issuance year: $\leq$2015	78.8%	77.2%	81.1%	82.6%	76.9%
Issuance year: 2016	79.8%	91.1%	56.0%	81.5%	74.7%
Issuance year: 2017	73.0%	100.0%	64.2%	80.8%	66.8%
Issuance year: 2018	67.9%	67.0%	71.5%	68.6%	65.1%
Issuance year: 2019	69.8%	77.4%	83.1%	75.2%	63.1%
Issuance year: $\geq$2020	54.0%	52.0%	27.4%	59.2%	52.0%

Table A.2. Which Carbon Offset Projects do Public Firms Use? By Carbon Registry

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 retired by publicly listed firms and zero otherwise. The independent variables include the logarithm of total credits issued by the project, dummy variables indicating whether the project generates credits through forest preservation and land use restrictions or through renewable energy generation, and a dummy variable indicating whether the project is rated by BeZero. Column 1 further controls for fixed effects corresponding to the project's age group, registry, and geographic region. Column 2 includes dummy variables indicating whether the project is based in North America or Europe, and drops geographic region fixed effects. Columns 3 to 8 report results for registry subsamples for which we drop registry fixed effects. In columns 3 to 8, we also add back geographic region fixed effects and drop the North America and Europe dummy variables. *t*-statistics from robust standard errors are reported in brackets (*** p<0.01, ** p<0.05, * p<0.1).

	Full sample		ACR	CAR	Gold	VCS
	(1)	(2)	(3)	(4)	(5)	(6)
log(#credits issued)	0.085***	0.084***	0.028	0.064**	0.078***	0.105***
	[12.43]	[12.31]	[1.21]	[2.27]	[7.66]	[15.14]
Forestry & land use	0.168***	0.192***	0.189**	0.236	0.376***	0.105
	[4.83]	[5.46]	[2.53]	[1.48]	[3.99]	[1.58]
Renewable energy	0.028	0.007	0.620**		0.007	0.048
	[1.00]	[0.26]	[2.65]		[0.10]	[1.43]
Rated by BeZero	0.105***	0.106***	0.154	0.176**	0.058	0.108***
	[4.04]	[4.02]	[1.29]	[2.24]	[0.74]	[4.27]
North America based		0.151***				
		[3.24]				
Europe based		-0.024				
		[-0.62]				
Project age FE	Y	Y	Y	Y	Y	Y
Registry FE	Y	Y	N	N	N	N
Geographic region FE	Y	N	Y	Y	Y	Y
Observations	2,916	2,916	148	253	916	1,599
R-squared	0.204	0.199	0.311	0.252	0.231	0.230
% (Dependent variable = 1)	48.5%	48.5%	68.9%	58.1%	48.8%	44.8%