Corporate Carbon Divestitures and Green Reinvestment:

The Role of Capital Reallocation and Investor Engagement

Tobi Oladiran[1]

Yale School of Management

August 2026

Abstract

A central concern in the corporate green transition is *asset reshuffling*: carbon-intensive public firms may sell "dirty" assets to private owners, reducing their reported carbon exposure without reducing emissions from the transferred assets. This paper examines whether divesting firms subsequently reallocate capital toward green productive capacity, a margin that is central to assessing the broader emissions consequences of corporate divestiture. Using plant-level data and patent-level measures of green innovation, I find that firms exiting brown generation expand green physical assets, primarily through greenfield construction, but do not increase green patenting. I then examine investor engagement as a mechanism shaping capital reallocation. Exploiting the rule-based construction of the Climate Action 100+ Focus List, I show that engagement shifts corporate investment away from brown and toward green capacity. Finally, I combine seller reallocation, buyer investment, plant operation, and retirement responses in a counterfactual emissions-accounting framework. The results suggest that the environmental consequences of divestiture depend not only on the ownership and operation of transferred assets, but also on the subsequent investment decisions of sellers and buyers.

[1]Yale School of Management. I thank seminar participants at Yale for helpful comments. All errors are my own.

1 Introduction

The corporate green transition increasingly operates through asset markets. Environmental pressure may induce carbon-intensive firms to sell polluting assets rather than reduce emissions at those assets. If the assets are acquired by owners subject to weaker environmental scrutiny, divestiture can reduce the seller's reported carbon footprint without reducing emissions in the atmosphere. Existing evidence supports this concern. Duchin et al. (2025) show that industrial plants sold by public firms continue to emit after sale, even as sellers receive higher ESG ratings and favorable stock-market responses. Berg et al. (2026) document a global reallocation of carbon-intensive assets toward less-scrutinized owners and estimate that divestitures have shifted hundreds of millions of tonnes of CO_2e since the Paris Agreement. The resulting concern is that divestiture may transfer carbon exposure across owners rather than reduce global emissions.

This paper argues that an ownership-based view of divestiture is incomplete. A sale changes not only who owns and operates a carbon-intensive asset, but also the seller's balance sheet and subsequent investment opportunities. The ownership margin determines the future operation of the divested asset. The capital-redeployment margin determines how the seller reallocates capital after the sale. If sellers use divestiture proceeds or freed-up balance-sheet capacity to build green generation, divestiture may accelerate the transition toward a lower-carbon capital stock even if the transferred asset continues to emit. If, instead, sellers reinvest in other brown activities, retain the proceeds, or distribute them to shareholders, divestiture primarily reallocates carbon exposure across firms. I examine this capital-redeployment margin.

BP's sale of its Alaska upstream business to privately held Hilcorp Alaska illustrates both margins. BP sold the business for $5.6 billion as part of its two-year, $10 billion divestment program (BP, 2019, 2020). BP presented divestment as part of its decarbonization strategy. Between its 2019 baseline and 2021, BP's reported Scope 1 and 2 emissions fell from 54.4 to 35.6 $MtCO_2e$, a decline of 18.8 $MtCO_2e$, or 35%. BP attributed 14.7 $MtCO_2e$—approximately 78% of this reduction—to divestments. Over 2020–2021, divestments accounted for 9.3 $MtCO_2e$ of BP's reported emissions reduction, including the sale of its Alaska operations (BP, 2021). The transaction therefore materially reduced BP's reported emissions while generating substantial financial resources. BP also stated that its divestment program would support investment in low-carbon businesses and accelerate its transition strategy (BP, 2021). This case motivates the paper's central question: when firms divest carbon-intensive assets, do they subsequently build green productive capacity?

I study this question in the global power sector, where generating assets, ownership histories, technologies, capacity, and emissions are observable at the physical-asset level. I construct a panel of 80,291 power plants and 164,070 generating units with complete ownership histories from S&P Global, covering 28,007 ultimate-parent firms. I classify generating units as green or brown according to generation technology and link plant-level ownership and asset characteristics to unit-level CO_2 emissions and net generation, firm-level green and non-green patent applications from Moody's Orbis, and firm-level emissions data from CDP and Trucost. The final analysis sample contains 1,997 consolidated energy and utility firms. Of these, 198 firms fully exit brown generating capacity between 2014 and 2023; I compare them with 1,478 firms that retain brown capacity. Table A1 details the sample construction.

My first analysis provides descriptive evidence on firms' investment patterns around brown-asset divestitures. Because firms do not divest brown assets at random, I do not interpret these estimates causally. I estimate stacked difference-in-differences models with firm-by-cohort and year-by-cohort fixed effects, comparing divesters with firms that have not yet divested. I find that brown-asset divestitures are followed by substantial expansion in green physical assets. Following a full exit from brown generation, a divester's green-capacity share rises by 5.1 percentage points, and the firm builds approximately 46 MW more green capacity per year. Divesters' green-capacity stocks rise by 370 MW, while their brown-capacity stocks decline by 751 MW. The increase in green capacity primarily reflects greenfield construction rather than acquisitions of operating green assets. Thus, post-divestment patterns are consistent not only with the transfer of existing brown assets across owners, but also with an expansion of low-carbon generating capacity.

The post-divestment shift is concentrated in physical assets rather than green technological innovation. Green patent applications do not increase after divestiture; instead, they decline by 0.28 log points. Divesting firms therefore expand green generating assets without becoming more active green technology innovators. Taken together, these descriptive findings motivate the capital-redeployment margin: firms that exit brown generation subsequently reorient their installed capital toward green generation.

I next examine whether investor engagement shapes this reallocation of real investment. Berg et al. (2026) show that investor engagement affects firms' divestiture activity. I ask whether engagement also affects the allocation of investment between green and brown capacity. I study Climate Action 100+ (CA100+), an investor coalition that began engaging the world's largest corporate greenhouse-gas emitters in late 2017. Its principal Focus List was constructed from a ranking of firms' 2015 Scope 1–3 emissions. I exclude

the separately investor-nominated "+ List" firms from the main analysis.

I use two complementary empirical approaches. First, I compare CA100+ targets with non-target firms matched on pre-engagement Scope 1 and 2 emissions. Second, I exploit Focus List assignment around a reconstructed emissions-ranking cutoff in a fuzzy regression-discontinuity design, alongside local difference-in-differences specifications within narrow rank windows around the cutoff. The setting is informative because Focus List assignment depends partly on modeled Scope 3 emissions, which are substantially less consistent across data providers than Scope 1 and 2 emissions (Table 4). Moreover, firms could neither select into nor opt out of Focus List membership.

The evidence indicates that engagement shifts real investment away from brown and toward green capacity. Relative to firms matched on 2015 Scope 1 and 2 emissions, CA100+ targets build approximately 131 MW more green capacity per year after 2017; the corresponding estimate relative to all non-targets is 78 MW. At the Focus List cutoff, fuzzy-RD estimates imply economically large, though imprecisely estimated, increases in green construction and consistently show reductions in brown construction of 165–272 MW per year. Local difference-in-differences estimates near the cutoff yield a similar pattern: engaged firms build 108–211 MW more green capacity annually and reduce brown construction by 147–198 MW annually. Engagement also increases the green share of new construction and the ratio of green to brown investment. Investor engagement therefore affects not only whether firms shed carbon-intensive assets, but also the composition of their subsequent real investment.

Finally, I quantify the net emissions implications of divestiture using a counterfactual accounting framework that compares emissions in a world with divestiture to emissions in a world without the transaction. The framework distinguishes five channels. First, divestiture may affect the survival of the sold plant if sellers and buyers differ in their retirement policies. Second, conditional on continued operation, it may affect the plant's generation, emissions intensity, and total emissions. Third, divestiture may be associated with sellers' subsequent construction of green capacity. Fourth, buyers may reduce green investment because they acquire an existing brown asset. Fifth, buyers may substitute acquired brown assets for new brown capacity that they would otherwise have built.

The evidence does not support the view that sales systematically prolong the life of divested plants or cause them to emit more intensively. Sold brown plants retire sooner: their annual retirement hazard rises by 1.07 percentage points relative to matched never-sold plants, from a control-group baseline of 0.60% (Table 9). Conditional on remaining in operation, sold plants experience no statistically detectable change in total CO_2 emissions.

Generation rises modestly, but emissions intensity falls, leaving total emissions essentially unchanged (Table 10). This finding is consistent with Duchin et al. (2025): a change in ownership need not reduce emissions at a transferred asset while it continues to operate.

I also find no evidence that buyers finance acquisitions by reducing green investment or by substituting acquired plants for new brown capacity. To the contrary, buyers increase green construction by 26.8 MW per year, while their brown construction does not change significantly (Table 11). Combining these buyer-side patterns with sellers' post-divestment green construction, plant-operation effects, and earlier retirements, I translate capacity changes into emissions using technology- and location-specific generation and emissions factors. The resulting five-year net emissions effect is -297 $MtCO_2$ for the 198 treated divesters. The estimate is driven principally by sellers' incremental green construction, which accounts for 247 $MtCO_2$ of avoided emissions. Earlier retirements of sold plants and buyers' additional green construction provide further reductions, partly offset by the positive but statistically insignificant estimate for buyers' brown construction.

The paper contributes to three related literatures: asset-market reallocation and pollution, investor voice and exit, and corporate investment in the low-carbon transition. Its central contribution is to show that the climate consequences of carbon-intensive asset sales depend not only on the subsequent operation of transferred assets, but also on the investment responses of both parties to the transaction.

First, the paper contributes to research on asset markets as a mechanism through which firms respond to environmental pressure. Existing work emphasizes that environmental regulation, investor scrutiny, and climate-related pressure can change the ownership of polluting assets without necessarily changing their operation. Duchin et al. (2025) show that plants divested by public firms continue to pollute after acquisition by buyers subject to weaker oversight, even as sellers receive higher ESG ratings and favorable market responses. Berg et al. (2026) document a global reallocation of carbon-intensive assets toward less-scrutinized owners and show that investor pressure affects firms' divestiture decisions. Related work examines the effects of ownership, organizational structure, financing constraints, and regulation on pollution and environmental liability (Shive and Forster, 2020; Bellon, 2025; Akey and Appel, 2021; Xu and Kim, 2022; Bartram et al., 2022; Ben-David et al., 2021; Dai et al., 2021).

This literature has focused primarily on ownership and operation of the transferred asset. I add the capital-redeployment margin. A sale changes not only who owns a brown asset, but also the seller's subsequent investment opportunities. Using plant-level ownership and capacity data, I show descriptively that firms exiting brown generation

expand green capacity through greenfield construction rather than acquisitions of existing green assets. I also examine whether buyers' acquisitions displace investment in new green or brown capacity. I find no evidence of green crowd-out or brown substitution; instead, buyers increase green construction. Assessing divestiture therefore requires tracking the real investment choices of both sellers and buyers, rather than considering only emissions from the sold asset.

Second, the paper contributes to the literature on investor voice, exit, and their interaction. A central question in this literature is whether investors can improve firms' environmental performance through direct engagement, divestment, or the credible threat of divestment. On the voice side, growing evidence shows that environmentally motivated institutional investors can affect corporate environmental outcomes. Firms with greater ownership by institutions from countries with stronger social norms exhibit better environmental performance (Dyck et al., 2019); mechanically induced increases in index-fund ownership are associated with improved environmental outcomes (Chen et al., 2020); and ownership by large asset managers predicts subsequent carbon-emissions reductions (Azar et al., 2021).

Engagement appears to be an important mechanism. Institutional investors often influence firms through private engagement rather than public confrontation (McCahery et al., 2016), and investors view engagement as a more effective response to climate risk than divestment (Krueger et al., 2020). Successful ESG engagements by individual investors, coordinated investor groups, and public campaigns have been linked to improved firm performance, lower downside risk, and reductions in toxic releases and carbon emissions (Dimson et al., 2015; Barko et al., 2022; Hoepner et al., 2024; Dimson et al., 2026; Naaraayanan et al., 2026). Kahn et al. (2023) provide direct evidence that emissions decline when green public pension funds increase their ownership stakes.

Exit provides a distinct disciplinary mechanism. Carbon-intensive firms face higher expected financing costs when investors demand compensation for carbon risk (Bolton and Kacperczyk, 2021, 2023), and the prospect of losing environmentally sensitive investors may influence managerial choices. Gantchev et al. (2022) show that environmental and social incidents trigger exit by E&S-conscious institutions and that exposed firms subsequently improve their E&S policies. Yet the effects of actual divestment remain theoretically and empirically ambiguous. Asset-price effects may be limited when capital supply is elastic or divesting investors represent a small share of the market (Heinkel et al., 2001; Broccardo et al., 2022; Berk and van Binsbergen, 2025). Moreover, higher financing costs for brown firms may induce greater carbon intensity if transition investment is costly

(Hartzmark and Shue, 2023).

I extend this literature by showing that engagement affects not only divestment decisions, but also the composition of subsequent real investment. Exploiting the rule-based construction of the CA100+ Focus List, I find that engaged firms build more green capacity and reduce brown construction. These results identify a real-investment mechanism through which investor engagement can shape firms' transition strategies.

Third, the paper contributes to research on corporate adjustment to climate risk and the low-carbon transition. This literature examines how climate risk, environmental regulation, technological change, and changing investor preferences affect corporate investment, employment, technology adoption, and innovation. For example, Sautner et al. (2023) show that firms more exposed to climate change expand employment in disruptive green technologies and increase green patenting. More generally, transition-risk research emphasizes that changes in the expected returns to carbon-intensive assets can induce firms to reallocate resources toward lower-carbon activities.

A central empirical challenge is measuring real green investment consistently across firms. Corporate disclosures often combine renewable generation, clean technology, energy efficiency, pollution abatement, and other environmental activities into heterogeneous and non-comparable categories. Researchers therefore often use green patents as a standardized proxy for transition effort (e.g., Sautner et al., 2023; Pupo and D'Ambrosio, 2026). Patents measure technological invention, however, rather than the deployment of green productive capital. Firms can transition by adopting and scaling existing technologies without undertaking substantial in-house innovation.

This paper provides a direct measure of investment in green productive assets. Using unit-level ownership and technology data, I observe the construction, acquisition, and retirement of green and brown generating capacity. I can therefore distinguish greenfield construction, which expands the stock of low-carbon generation, from acquisitions of existing green assets, which primarily reallocate ownership. I also distinguish physical-capital deployment from technological innovation. The evidence shows that divesting firms, and especially engaged firms, expand green generating capacity without increasing green patenting. Corporate transition can therefore occur through the reallocation of productive capital toward existing green technologies, even without an increase in green innovation.

The remainder of the paper is organized as follows. Section I describes the data and defines the main variables. Section II examines post-divestment investment patterns by sellers, including green productive assets and green technology. Section III investi-

gates whether investor engagement affects firms' allocation of investment between green and brown assets, as well as green technological innovation. Section IV presents the net-emissions accounting framework and evaluates its component channels. Section V concludes.

2 Data and Measurement

Directly observing the green component of corporate investment is difficult. Firms have only recently begun to disclose green and non-green investment breakdowns, historical disclosures are limited, and reported categories are not standardized across firms. For example, Shell reports investment in "Renewables and Energy Solutions," whereas BP reports investment in "Gas & low carbon energy."[2] I therefore measure real investment using physical generating assets and their underlying technologies, for which classifications are standardized and ownership histories are available over a long horizon. The trade-off is scope: because this approach requires observable ownership of physical generation assets, the analysis is limited to energy and utility firms.

I complement this measure of investment in productive capital with a measure of green technological innovation based on patent filings. I classify a patent as green if at least one of its Cooperative Patent Classification (CPC) codes falls within the Y02 or Y04 climate-mitigation taxonomy. This measure captures firms' development of climate-related technologies, whereas the asset-based measures capture the construction, acquisition, and ownership of green generating capacity. The distinction allows me to assess whether divestiture and investor engagement affect the deployment of existing green technologies, the invention of new green technologies, or both.

2.1 Asset-Level Data

I obtain global asset-level data from S&P Global, covering 1858–2025. The data are reported at both the power-plant and generating-unit levels. Ownership information is available at the plant level and records 184,026 plant–owner links,[3] including ownership

[2] See Shell plc, *Annual Report 2025*, available at https://www.shell.com/investors/results-and-reporting/annual-report/_jcr_content/root/main/section/promo/links/item0.stream/1774544186011/5727c329a58b5eb7a54442c0a03f562a5aef1159/shell-annual-report-2025-interactive.pdf; and BP p.l.c., *Annual Report and Form 20-F 2025*, available at https://www.bp.com/api/files/6cqieuqhq4no/master/33M2iHp8A6d07McKzKqLNP/12b5d4eccb4e02093d1ad9efc0d6a746/bp-annual-report-and-form-20f-2025.pdf.

[3] I exclude ownership records with a reported operating stake of zero.

start and end dates, operating stakes, plant operators, direct owners, and ultimate-parent owners. I use unit-level data to measure nameplate capacity, generation technology, in-service year, and retirement year. Nameplate capacity is the maximum electricity output that a unit can produce under normal operating conditions. Measuring capacity at the unit level is important because it permits the identification of capacity additions, expansions, and retirements.

I classify generating units as *green* or *brown* according to their reported generation technology. Green technologies include solar, wind, hydraulic turbines, nuclear, geothermal, batteries and other storage, and fuel cells. Brown technologies include steam turbines, gas turbines, combined-cycle units, internal-combustion units, and integrated-gasification units. I exclude units whose technology is unclassified or reported as "other"; these account for approximately 0.1% of total capacity.

I merge unit-level capacity and technology information with plant-level ownership records to construct a firm–plant–year panel. For each firm-year, I measure stake-weighted green and brown capacity, capacity entries and exits, and the decomposition of capacity changes into greenfield construction, expansions, acquisitions, divestitures, and retirements. The raw panel contains 3.04 million firm–plant–year observations for 27,944 ultimate-parent firms and 80,160 plants over 1858–2025.

Sample construction. I construct the analysis sample in three steps. First, I link each ultimate parent to its ultimate-ultimate parent—the highest entity in the corporate hierarchy reported by S&P Global—and map the raw GICS classifications of both entities into 15 broad industry groups: utilities; oil and gas; mining and metals; industrials; autos; transport; agriculture; real estate; financials; technology; healthcare; consumer; media and telecommunications; business services; and other. I retain a firm if either its own industry group or that of its ultimate-ultimate parent falls within one of six energy-relevant groups: utilities, including independent power producers and renewable electricity; oil and gas, including coal; mining and metals; industrials; autos; and transport. This screen removes financial, real-estate, technology, and other non-industrial owners and leaves 16,408 firms.

Second, I consolidate subsidiaries into their energy-relevant ultimate-ultimate parent. Specifically, when a subsidiary's ultimate-ultimate parent is also classified in an energy-relevant industry, I sum all capacity stocks and flow measures across the parent and its subsidiaries in each year. Thus, a utility holding company and its operating subsidiaries are treated as a single firm. This procedure absorbs 1,974 subsidiaries and leaves 14,434

entities; 1,300 of the absorbed subsidiaries roll into parents that remain in the final sample.

Third, I retain entities whose stake-weighted brown capacity exceeds 100 MW in at least one year. I retain all observations for qualifying firms, including years in which their brown capacity falls below this threshold, so that each firm's time series remains intact. This is the most restrictive screen: it removes 12,437 small entities and yields a final sample of 1,997 firms. These firms hold ownership stakes in 37,905 plants and 85,287 generating units, representing approximately one-half of the plants in the ownership panel. Appendix Table A1 reports the number of firms remaining after each stage of the sample construction.

2.2 Patent Data

I obtain patent data from the Moody's Orbis Intellectual Property (Orbis IP) database, using the version downloaded on October 7, 2025. The database covers the period from 1980 through 2025 and includes 171 million patent-header records, 588 million patent–CPC classification records, 203 million patent–firm matching records, and approximately 3 million company-header records. Patent headers provide the patent filing, or application, date; CPC classifications are used to identify climate-related technologies; and the patent–firm matching data link patents to firms through Bureau van Dijk (BvD) identifiers. The timing of the data download is important because patent applications are published with a delay. As a result, the most recent years in the data mechanically understate patenting activity, particularly for applications that have not yet been published (Hegde et al., 2023). To mitigate this publication-lag concern, I restrict the patent analysis to applications filed on or before December 2022.

I classify patents using the Cooperative Patent Classification (CPC) system, jointly developed by the European Patent Office and the U.S. Patent and Trademark Office. The CPC climate-mitigation taxonomy identifies relevant technologies through the Y02 and Y04S classification codes and can be applied retrospectively to earlier patent documents.[4] Because a patent may be assigned multiple CPC codes, I classify a patent as green if at least one of its CPC codes belongs to the Y02/Y04 climate-mitigation taxonomy. I classify all remaining patents as non-green. Using the BvD-identifier crosswalk, I aggregate patent filings to the firm-year level. The resulting sample includes 98,289 patenting firms over 1980–2024, with 2.7 million green and 19.8 million non-green patent filings. Among the 1,997 firms in the energy-asset panel, 510 can be linked to a BvD identifier and file at

[4]The Cooperative Patent Classification system was jointly introduced by the EPO and USPTO in January 2013.

least one patent. I measure green innovation in year t as the number of green patent applications filed by firm i in that year. Appendix Table A2 reports the composition of green patents across the Y02/Y04 climate-technology classifications.

2.3 Engagement Data

I identify firms targeted by Climate Action 100+ (CA100+), a major investor-led coalition that coordinates engagement with large corporate greenhouse-gas emitters. I distinguish between firms on the initiative's initial, rule-based focus list and firms added through discretionary selection. The initial focus list contains 100 companies selected according to CA100+'s published mechanical rules (hereafter, "CA100-main"). The discretionary list contains 61 additional companies selected outside these rule-based criteria (hereafter, "CA61").

I obtain the initial list of 100 focus companies from the appendix to the Corporate Governance Committee and Board of Investments meeting materials published by the Los Angeles County Employees Retirement Association (LACERA) on June 13, 2018.[5] I obtain the list of discretionary additions from the 2019 CA100+ Progress Report.[6]

I match both lists to the 1,997 energy panel using firm names and corporate-parent information. The panel contains observed power-plant assets for 70 of the 100 firms on the rule-based focus list and for 29 of the 61 discretionary additions. Thus, the asset-level data cover 99 of the 161 firms identified across the two CA100+ lists.

2.4 Other Data

Plant-level emissions and generation. I obtain unit-level carbon dioxide (CO_2) emissions, measured in metric tons, and net electricity generation, measured in MWh, from S&P Global for 2005–2025. S&P Global reports these operating data only for U.S. plants; accordingly, the analysis of plant-level emissions and generation is restricted to the United States. I also obtain unit-level capacity factors and heat rates for U.S. generating units.

Firm-level emissions. I obtain firm-level Scope 1, Scope 2, and Scope 3 emissions from the Carbon Disclosure Project (CDP). CDP maintains one of the world's largest

[5] https://www.lacera.gov/sites/default/files/assets/documents/board/2018/boi/corp_gov/2018-06-13_corp_gov_agnd.pdf

[6] https://www.climateaction100.org/wp-content/uploads/2020/10/English-Progress-Report-2019.pdf

repositories of self-reported corporate environmental information.[7] I additionally obtain Scope 1, Scope 2, and Scope 3 emissions from Trucost, a third-party provider with broad global coverage that supplements disclosed emissions with model-based estimates for non-disclosing firms (Aswani et al., 2024).[8] I use the comparison between CDP and Trucost to assess measurement differences across emissions sources, with particular attention to the greater uncertainty surrounding Scope 3 emissions.

Other firm characteristics. I obtain additional firm-level characteristics from S&P Global, including financial and industry information used in the empirical analysis.

2.5 Summary Statistics

Table 1 reports summary statistics for the variables used in the analysis. Panel A describes the annual firm-year capacity panel for the 1,997 energy firms. The central variables are firms' stake-weighted capacity stocks, separated into green and brown capacity, and the annual flows that change those stocks: capacity built (greenfield construction and expansions of plants already held by the firm), capacity acquired from other owners, capacity divested to other owners, and capacity retired.

The mean firm holds 2,504 MW of generating capacity, whereas the median holds 414 MW. The mean exceeds the 75th percentile (1,320 MW), indicating that the distribution of capacity is strongly right-skewed. Brown capacity represents 72% of mean capacity, or 1,806 of 2,504 MW. At the median, a firm holds 349 MW of brown capacity and no green capacity. Accordingly, many firm-years have no green generating assets: the green share of capacity is 0.12 on average but zero at the median. Averaged across all firm-years, firms build approximately twice as much brown as green capacity each year (57 versus 27 MW). Brown capacity exits the portfolio through divestitures and retirements in broadly similar amounts, averaging 14 and 17 MW per year, respectively. Overall, the capacity stock is large, highly skewed, and predominantly brown.

Panel B reports summary statistics for green innovation, measured using green patent filings. Patent activity is similarly skewed. Among the 510 energy-panel firms that are matched to a BvD identifier and file at least one patent, the median firm files two patents per year, compared with a mean of 221. The average green share of patent filings, calculated among firm-years with at least one filing, is 0.32.

[7] For further information, see https://www.cdp.net/en/data.

[8] For a description of the Trucost environmental methodology, see https://assets.marketplace.spglobal.com/SupportLinks/Trucost_Environmental_Methodology_FAQ_document-4e47c3d4-d9d1-462b-9f2c-cd4c7530daa7.pdf.

Panel C describes the plant-year panel for U.S. plants with observed generation. The median plant generates 486 GWh annually and emits 343 thousand metric tons of CO_2, corresponding to a median emissions intensity of 0.93 tCO_2/MWh. The median capacity factor is 0.49, and the median heat rate is 11,793 Btu/kWh.

Panel D reports the corresponding capacity and patent measures for the 99 Climate Action 100+ (CA100+) target firms in the energy panel. These firms are substantially larger than the typical firm in the full sample and are more active in both capacity construction and patenting. The median CA100+ target holds 2,283 MW of capacity—more than five times the full-sample median of 414 MW—and has an average green capacity share of 0.18, compared with 0.12 in the full sample. CA100+ firms build green and brown capacity at similar average rates, 169 and 151 MW per year, respectively, compared with 27 and 57 MW for all energy-panel firms. Conditional on building capacity, the median CA100+ firm's new capacity is predominantly green: its median green share of new construction is 0.78, compared with 0.14 for the full sample. Nevertheless, brown capacity remains the majority of the typical target's installed capacity. CA100+ firms are also more active green innovators. The median target files 25 patents per year, including seven green patents, compared with two total patents and zero green patents for the median patenting firm in the full energy-panel sample.

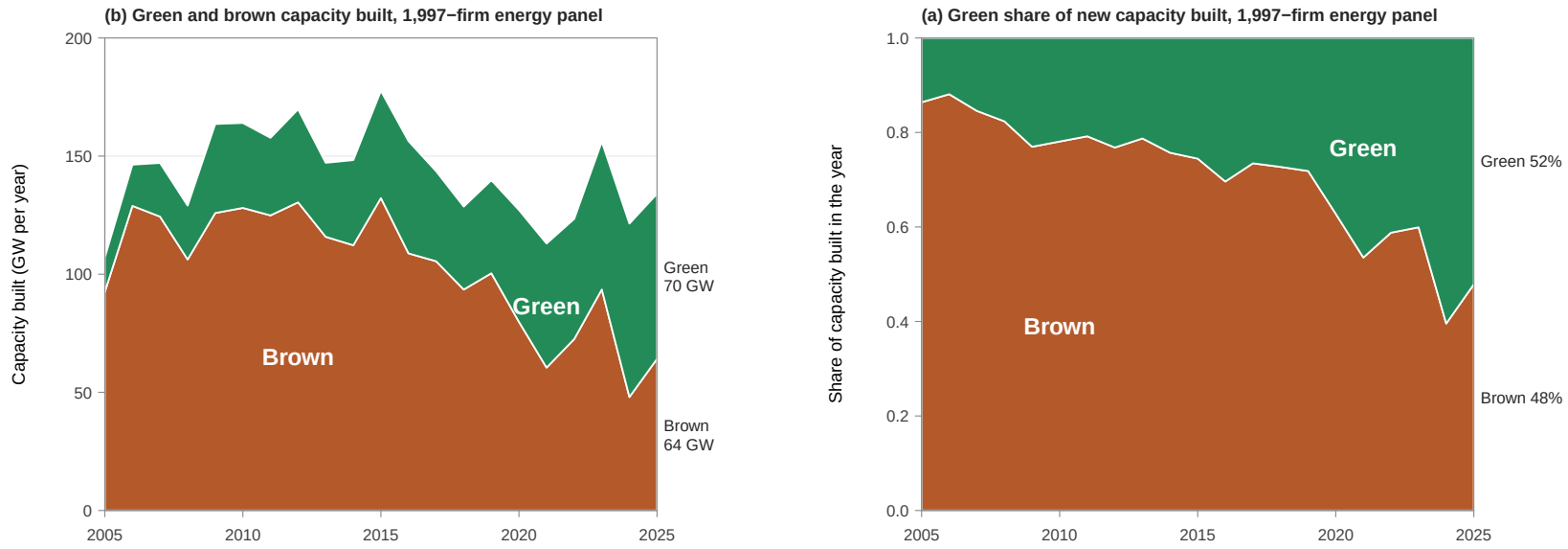
Figure 1 tracks annual new capacity built by the 1,997 analysis-sample firms from 2005 through 2025. New capacity includes greenfield construction and expansions of existing plants, but excludes acquisitions. Total annual construction remains within approximately 110 to 180 GW over the period, while its composition changes markedly. Brown construction dominates in the first decade, peaking at 132 GW in 2015, before falling by roughly one-half to 64 GW in 2025. By contrast, green construction rises from 15 GW in 2005 to 70 GW in 2025 and exceeds brown construction for the first time in 2024. The green share of new capacity consequently increases in three stages: from 14% in 2005, to roughly one-quarter by 2015, and to 52% in 2025. Thus, the sector's observed construction flow shifts from predominantly brown to predominantly green only in the final two years of the sample.

Figure 2 plots the green share of annual patent filings for patenting energy-panel firms from 2005 through 2022. This share more than doubles over the sample period, increasing from 16% to 38%. The increase is not monotonic. The green share rises to 26% by 2011, declines to 22% by 2016 as non-green patenting grows more quickly, and then increases sharply after 2017. The acceleration in the post-2017 period coincides with the post-Paris period in which the divestiture and investor-engagement events studied in the paper occur.

Table 1
Summary Statistics

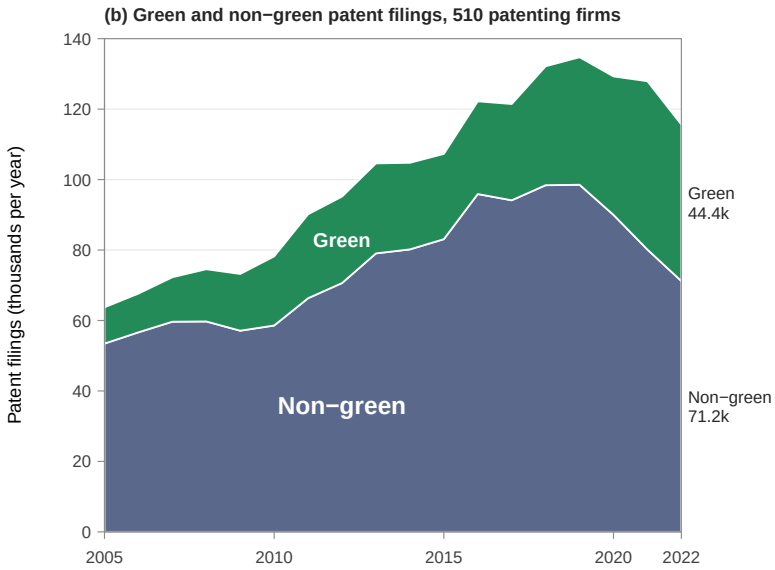
This table reports summary statistics. Panel A covers the annual firm-level panel of 1,997 energy firms over 2010–2025. Capacity is measured in stake-weighted nameplate MW; *green* capacity includes solar, wind, hydro, nuclear, geothermal, storage, and fuel cells, while *brown* capacity includes fossil technologies. Divestitures, retirements, construction (including greenfield projects and expansions), and acquisitions are annual capacity flows. Panel B covers 510 energy firms with patent filings during 2010–2022, using Moody's Orbis data. Green patents contain at least one Y02/Y04 CPC code; non-filing years are coded as zero, and the green share is defined only for filing years. Panel C covers U.S. power plants with S&P Global data over 2010–2025. Generation and CO_2 emissions are aggregated across units; capacity factors and heat rates are weighted by capacity and generation, respectively. Panel D reports the capacity and patent measures for the 99 Climate Action 100+ targets in the energy panel (70 rule-based and 29 discretionary).

	N	Mean	Median	SD	P25	P75
Panel A. Firm-level sample: capacity (energy-panel firms, 2010–2025)						
Total capacity (MW)	28,408	2,504.2	414.0	8,626.0	168.3	1,320.0
Green capacity (MW)	28,408	698.2	0.0	3,869.4	0.0	62.2
Brown capacity (MW)	28,408	1,806.1	349.3	6,094.3	150.4	1,077.3
Green share of capacity	27,846	0.12	0.00	0.24	0.00	0.10
Brown capacity divested (MW/yr)	28,408	14.3	0.0	235.9	0.0	0.0
Brown capacity retired (MW/yr)	28,408	17.3	0.0	142.5	0.0	0.0
New green capacity built (MW/yr)	28,408	27.1	0.0	190.2	0.0	0.0
New brown capacity built (MW/yr)	28,408	56.9	0.0	311.4	0.0	0.0
Green share of new build (builder-years)	6,759	0.45	0.14	0.47	0.00	1.00
Green capacity acquired (MW/yr)	28,408	4.6	0.0	173.6	0.0	0.0
Brown capacity acquired (MW/yr)	28,408	15.6	0.0	332.7	0.0	0.0
Panel B. Firm-level sample: patents (patenting energy-panel firms, 2010–2022)						
Total patent filings (per year)	6,630	220.7	2.0	873.4	0.0	34.0
Green patent filings (per year)	6,630	59.9	0.0	321.7	0.0	8.0
Non-green patent filings (per year)	6,630	160.8	1.0	644.7	0.0	22.0
Green share of filings (filing years)	3,821	0.32	0.20	0.34	0.00	0.52
Panel C. Plant-level sample: U.S. plants with measured generation (2010–2025)						
Net generation (GWh/yr)	23,183	2,167.8	486.4	3,745.8	110.1	2,661.0
CO_2 emissions (kt/yr)	22,018	1,405.7	342.9	2,626.6	45.0	1,518.2
Emission intensity (tCO_2/MWh)	13,883	1.19	0.93	5.91	0.49	1.18
Capacity factor (0–1)	23,138	0.46	0.49	0.28	0.23	0.68
Heat rate (Btu/kWh)	16,959	14,270	11,793	6,368	10,804	14,868
Panel D. Climate Action 100+ targets (99 firms)						
Total capacity (MW)	1,581	11,487.2	2,283.4	21,641.0	422.4	9,581.1
Green capacity (MW)	1,581	4,116.3	109.6	12,510.9	0.0	2,232.6
Brown capacity (MW)	1,581	7,371.0	1,784.2	12,445.9	289.4	7,495.4
Green share of capacity	1,580	0.18	0.07	0.24	0.00	0.29
New green capacity built (MW/yr)	1,581	169.2	0.0	538.3	0.0	58.5
New brown capacity built (MW/yr)	1,581	150.5	0.0	499.6	0.0	12.5
Green share of new build (builder-years)	821	0.57	0.78	0.45	0.00	1.00
Total patent filings (per year)	1,105	507.0	25.0	1,098.7	0.0	425.0
Green patent filings (per year)	1,105	128.8	7.0	285.5	0.0	83.0
Non-green patent filings (per year)	1,105	378.2	12.0	897.0	0.0	348.0

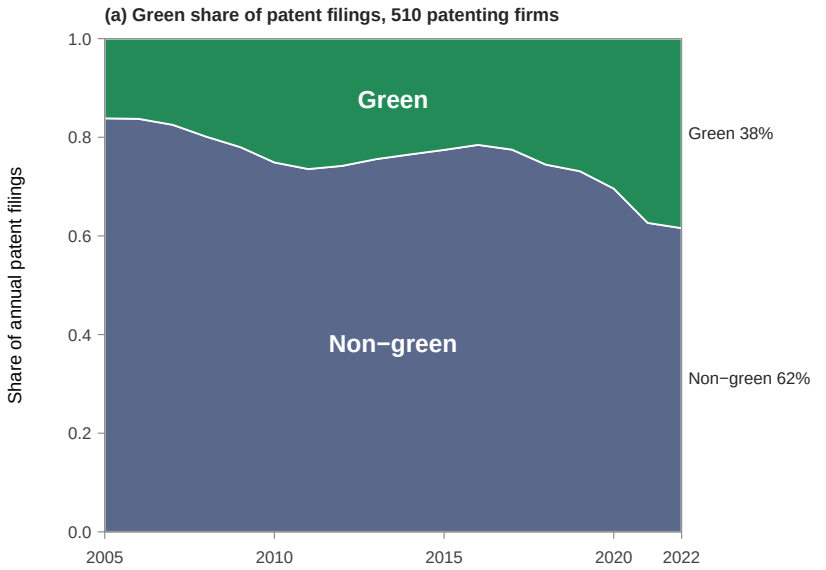


(a) New capacity (GW) *(b) Green share of new capacity*

Figure 1: New-capacity composition of the energy panel, 2005–2025. Stake-weighted new generating capacity of the 1,997 consolidated firms in the analysis sample, by technology classification (green: solar, wind, hydro, nuclear, geothermal, storage, fuel cell; brown: steam turbine, gas turbine, combined cycle, internal combustion, integrated gasification). Each plant's nameplate capacity is allocated to its owners in proportion to their ownership stakes. Panel (a) shows capacity in gigawatts, with green stacked on brown; panel (b) shows the green share of total capacity.



(a) Patent filings



(b) Green share of patent filings

Figure 2: Patent filings by energy-panel firms, 2005–2023. Panel (a) reports annual patent filings by the 510 energy-panel firms linked to Orbis that file at least one patent. Panel (b) reports the share of those annual filings classified as green, defined as having at least one CPC code in the Y02/Y04 climate-mitigation taxonomy. Patent filings are aggregated across each firm's linked BvD identifiers.

3 Capital Reallocation after Divestment

This section examines whether firms that divest brown generating assets subsequently reallocate investment toward green physical capital and green technology. I first document the mechanisms through which generating capacity leaves and enters divesting firms. I then test whether divesting firms increase their investment in green capacity and green innovation following a brown-asset divestiture.

3.1 How Capacity Leaves and Enters Divesting Firms

Generating capacity can leave a firm through either a change in ownership or a physical retirement. First, a firm may divest an ownership stake in an operating plant. A divestiture is a *full exit* if the firm's ownership stake falls from a positive value to zero, and a *partial exit* if its stake declines but remains positive. Second, a generating unit may be retired while the firm continues to own the plant. The first mechanism reallocates an existing asset across owners, whereas the second removes physical capacity from the capital stock.

On the other hand, capacity can enter a firm's portfolio through construction, expansion, or acquisition. I define greenfield construction as capacity that enters service in a plant's first operating year. An expansion is capacity from new units added after a plant has begun operating, provided that the firm was already an owner of the plant. Finally, an acquisition occurs when a firm gains an ownership stake in an existing operating plant. Construction and expansions increase the physical capital stock, while acquisitions represent transfers of existing assets between owners.

The treated sample consists of firms that hold brown capacity in 2013 and experience their first full exit from a brown plant between 2014 and 2023. For each firm, the event year is the first year in this interval in which the firm fully divests at least one brown plant. Plant retirement does not trigger the event because it removes capacity rather than transferring ownership, and partial sales do not trigger the event because the firm retains an ownership stake. This definition produces a sample of 198 treated divesting firms.

Table 2 reports how brown capacity leaves these firms after their event and how the same firms add capacity over the corresponding event-year-to-2025 windows. The table shows that divestitures primarily reallocate ownership rather than retire brown physical capital. Of the 421.8 GW of brown capacity removed from treated firms' portfolios, 269.3 GW (64%) leaves through full-exit sales and a further 17.0 GW (4%) through partial sales. Only 135.5 GW (32%) is retired. Thus, for each gigawatt of brown capacity

Table 2

Sources of Brown-Capacity Reductions and Subsequent Capacity Additions

This table decomposes brown-capacity reductions among the 198 treated divesters following their first full-exit divestiture. Values are stake-weighted GW, cumulated from the event year through 2025 for events occurring between 2014 and 2023. Panel A decomposes brown capacity removed into full-exit sales (the firm's stake falls to zero), partial sales (the firm retains a positive stake), and retirements. Panel B reports green and brown capacity added by the same firms over the corresponding event windows through greenfield construction, expansion of existing plants, and acquisitions. Sales and acquisitions reallocate existing assets across owners, whereas construction and retirement alter the physical capital stock.

Panel A. Sources of brown-capacity reductions

	Capacity (GW)	Share of total removed
Full-exit sales (stake $\rightarrow$ 0)	269.3	64%
Partial sales (positive stake retained)	17.0	4%
Retirements	135.5	32%
Total brown capacity removed	421.8	100%

Panel B. Capacity additions by the same firms (GW)

	Green	Brown
Greenfield construction	201.6	78.6
Expansion of existing plants	32.8	22.4
Acquisitions	43.7	83.5
Total capacity added	278.2	184.5

retired, approximately two gigawatts are transferred to another owner.

Treated firms add more green than brown capacity following divestment. They add 278.2 GW of green capacity, compared with 184.5 GW of brown capacity. Green additions are predominantly newly constructed capacity: 201.6 GW is greenfield construction and 32.8 GW is expansion at plants the firms already own, while 43.7 GW is acquired from other owners. By contrast, acquisitions account for a substantial share of brown additions: treated firms acquire 83.5 GW of existing brown capacity, nearly one-half of their total brown additions. Notably, greenfield green construction alone (201.6 GW) exceeds all brown additions combined (184.5 GW).

These descriptive patterns establish two facts. First, the ownership channel is quantitatively dominant on the brown-capacity removal margin: divestiture usually transfers assets to other owners rather than shutting them down. Second, the subsequent addition margin is tilted toward green capacity, particularly newly built green capacity. The following analysis examines whether these patterns reflect a change in divesting firms' investment choices relative to the control group.

3.2 Do Firms Invest in Green after Divesting Brown Assets?

I next examine whether firms reallocate capital toward green assets and technologies after divesting brown generating assets. Following a divestiture, a firm may expand its green generating portfolio, reinvest in other carbon-intensive activities, retain the proceeds as cash, or distribute them to shareholders. I examine whether divesting firms differentially increase green capacity construction and green technological innovation, relative to comparable firms that do not divest brown plants.

I estimate a stacked difference-in-differences specification around each divestment cohort. For each event year $g \in \{2014, \ldots, 2023\}$, I form a stack containing firms whose first full-exit divestiture of a brown plant occurs in year g and clean controls, observed from event time -3 through $+5$. I begin the event window in 2014 so that divestiture events are plausibly related to the period of increased investor pressure documented by Berg et al. (2026). I estimate:

$$Y_{i,t,g} = \beta \, \text{Divested}_{i,g} \times \text{Post}_{t,g} + \alpha_{i,g} + \lambda_{t,g} + \varepsilon_{i,t,g}, \tag{1}$$

where $\alpha_{i,g}$ and $\lambda_{t,g}$ denote firm-by-cohort and year-by-cohort fixed effects, respectively. Standard errors are clustered at the firm level. $\text{Divested}_{i,g}$ equals one for firms whose first full-exit divestiture occurs in cohort year g, and $\text{Post}_{t,g}$ equals one in the event year and subsequent years. The stacked design ensures that already-treated firms are not used as controls for later-treated firms (Goodman-Bacon, 2021). I assess robustness using conventional two-way fixed-effects specifications and a matched-control sample.

The outcome $Y_{i,t,g}$ is one of several measures of firms' physical-capital and innovation choices: the green share of installed capacity; annual green or brown capacity built; year-end green or brown capacity stocks; the green share of newly built capacity; or green, non-green, and total patent filings. Thus, β measures the post-divestment change for divesting firms relative to clean controls, after accounting for firm and calendar-year effects within each cohort stack.

Table 3 reports the baseline estimates. Panel A considers physical-capital reallocation. Following a full-exit divestiture, treated firms increase their green capacity share by 5.1 percentage points. They build an additional 46 MW of green capacity per year, through greenfield construction and expansions of plants they already own, with no statistically detectable increase in new brown capacity. At the same time, their brown capacity stock falls by approximately 751 MW, while their green capacity stock rises by approximately 370 MW. Thus, divesting firms become greener partly because they shed brown capacity,

but also because they undertake additional green construction. Divestment is therefore associated with a shift in the composition of treated firms' aggregate generating-capacity portfolios toward green assets.

Panel B considers green technological innovation, measured by patent filings. The estimates do not indicate a corresponding increase in green patenting. Instead, green patent filings decline after divestment: the coefficient on the inverse-hyperbolic-sine transformation of green filings is -0.276. Non-green and total patent filings also decline, with coefficients of -0.217 and -0.259, respectively. The green share of patent filings is economically and statistically unchanged. Because the inverse-hyperbolic-sine transformation approximates the logarithm for larger values, these estimates are consistent with declines of roughly 24–26% in filing activity, although the exact percentage interpretation depends on the level of patenting. Taken together, the results suggest that divesting firms shift their physical capital toward green generation, but do not exhibit a complementary increase in green technology development.

3.2.1 Dynamic Pattern of Green Construction around Divestiture

I next examine the timing of green capacity construction relative to a firm's first full-exit divestiture. I estimate the dynamic version of equation (1):

$$\text{NewGreen}_{i,t,g} = \sum_{\substack{k=-3 \\ k\neq -1}}^{5} \beta_k \, \text{Divested}_{i,g} \times \mathbf{1}\{t - g = k\} + \alpha_{i,g} + \lambda_{t,g} + \varepsilon_{i,t,g}. \tag{2}$$

Here, $\text{NewGreen}_{i,t,g}$ is the stake-weighted green capacity, measured in MW, that firm i brings online in year t within cohort-g stack through greenfield construction. $\text{Divested}_{i,g}$ equals one for firms whose first full-exit sale of a brown plant occurs in year g and zero for clean controls. The indicator $\mathbf{1}\{t - g = k\}$ denotes event time k, ranging from three years before to five years after divestment. The specification includes firm-by-cohort and year-by-cohort fixed effects, and standard errors are clustered by firm. Event year -1 is omitted, so each coefficient β_k measures the difference in green construction between divesters and controls at event time k, relative to the corresponding difference one year before divestment.

Figure 3 presents the resulting event-study estimates. There is no evidence that future divesters were systematically building more green capacity than clean controls before the sale: the coefficients in event years -3 and -2 are small relative to their standard errors and are not statistically distinguishable from zero. Green construction rises at the time

Table 3
Capital Reallocation and Innovation after Divestment

This table reports estimates from the stacked difference-in-differences specification in equation (1). For each divestment cohort from 2014 to 2023, a stack includes firms whose first full-exit sale of a brown plant occurs in that year and all clean controls, observed from event time −3 through +5. The coefficient on Divested × Post measures the post-divestment change for divesters relative to clean controls. All specifications include firm-by-cohort and year-by-cohort fixed effects, and standard errors are clustered by firm. Panel A reports capacity outcomes through 2025 for the 198 treated divesters and 1,478 clean controls in the energy panel. Built capacity is cumulative from the event year and includes greenfield construction and expansions. Panel B reports patent outcomes through 2023 for firms with at least one patent filing during the sample period. Patent data are from Moody's Orbis; green patents contain at least one CPC code in the Y02/Y04 taxonomy. Non-filing years for patenting firms are coded as zero. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Capacity reallocation

Dep. var.:	Green share (0–1) (1)	Tot. built green (MW) (2)	Tot. built brown (MW) (3)	Green stock (MW) (4)	Brown stock (MW) (5)
Divested × Post	0.051***	46.0**	−17.4	370.0***	−751.3***
	(0.012)	(19.5)	(16.5)	(123.7)	(179.3)
Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Observations	118,786	118,867	118,867	118,867	118,867
Adj. R^2	0.959	0.478	0.439	0.988	0.990

Panel B. Patent filings

Dep. var.:	Green patents (asinh) (1)	Non-green patents (asinh) (2)	Total patents (asinh) (3)	Green share (0–1) (4)
Divested × Post	−0.276***	−0.217*	−0.259**	0.000
	(0.104)	(0.112)	(0.112)	(0.039)
Firm × Cohort FE	Yes	Yes	Yes	Yes
Year × Cohort FE	Yes	Yes	Yes	Yes
Observations	23,480	23,480	23,480	14,478
Adj. R^2	0.875	0.911	0.910	0.456

of divestment. In the event year, divesters bring online approximately 59 MW more green capacity than controls, relative to the year before divestment (95% confidence interval: 15 to 103 MW). The differential remains positive in year +1 at 33 MW, is imprecisely estimated in years +2 and +3, and increases to approximately 71 MW in year +4 and 57 MW in year +5.

The dynamic pattern is consistent with green construction following, rather than preceding, brown-asset divestiture. These estimates are descriptive rather than causal: they characterize the evolution of capital reallocation among divesting firms relative to clean controls, but may also reflect other changes that coincide with firms' divestiture decisions.

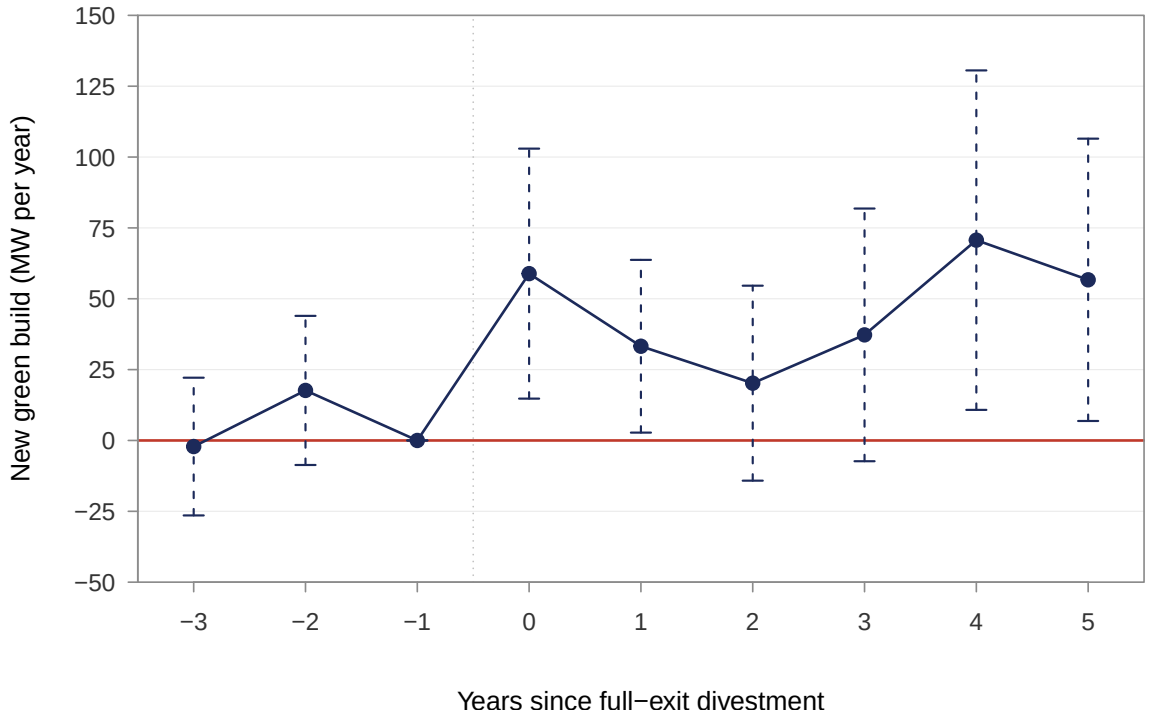


Figure 3: Greenfield green-capacity additions around full-exit divestitures. This figure reports estimates from a dynamic stacked difference-in-differences specification based on equation (1). The outcome is a firm's annual stake-weighted MW of green capacity—solar, wind, hydro, nuclear, geothermal, storage, and fuel cells—entering service through greenfield construction. The specification interacts the *Divested* indicator with event-time indicators spanning three years before through five years after a firm's first full-exit sale of a brown power plant. Event year −1 is omitted; thus, each coefficient measures the difference between divesters and clean controls in a given event year, relative to the year before divestment. Each divestiture cohort forms a separate stack comprising firms that first fully divest in that year and all clean controls. The regression includes firm-by-cohort and year-by-cohort fixed effects. The sample comprises 198 treated divesters and 1,478 clean controls from the 1,997-firm energy panel. Vertical dashed lines denote 95% confidence intervals based on standard errors clustered by firm; the horizontal red line denotes zero.

4 Investors' Engagement as a Mechanism

The preceding section shows that firms that divest brown generating assets subsequently shift their physical-capital portfolios toward green assets. This section examines whether investor engagement is a mechanism that induces such green investment. Berg et al. (2026) shows that investor engagement increases firms' propensity to divest brown assets. I examine whether the same engagement pressure also affects firms' allocation of capital toward green productive assets.

I proceed in three steps. First, I describe the institutional setting of Climate Action 100+ (CA100+) and the selection process that determines the initiative's initial target list. Second, I present a difference-in-differences design comparing CA100+ targets with comparable non-target firms. Third, I supplement the baseline matched difference-in-differences estimates with a fuzzy regression discontinuity design and a local difference-in-differences design based on firms close to the initial selection threshold.

4.1 Institutional Setting and Identification

Launched in December 2017, Climate Action 100+ (CA100+) is the largest investor coalition focused on corporate climate action (Climate Action 100+, 2021). The coalition grew from 225 investor signatories representing approximately $26 trillion in assets under management in 2017 to a peak of 727 signatories representing $68 trillion in 2022. Its objective is to coordinate institutional-investor engagement with major corporate greenhouse-gas emitters on climate governance, emissions reductions, and climate-related financial disclosure (Climate Action 100+, 2021). Figure C1 documents the growth of the coalition over time.

CA100+ engagement is organized around a *focus list* of target companies. The construction of this list provides the basis for the empirical design. According to the coalition's methodology (Climate Action 100+, 2023), the initial list was constructed mechanically. CA100+ began with the MSCI All Country World Index (ACWI) universe, retained the 1,000 largest companies by market capitalization, ranked these companies by total Scope 1, Scope 2, and Scope 3 greenhouse-gas emissions using 2015 CDP data, and selected the top 100 firms. I refer to these rule-based targets as *CA100-main*. Companies did not self-select into this list and could not opt out.

In addition to the 100 rule-based targets, CA100+ compiled a discretionary "+ list" of 61 firms. These firms were selected through an investor risk-perception survey in which signatories nominated companies that they viewed as financially material to their

portfolios, subject to regional voting. I refer to this discretionary group as *CA61*. Because its selection is not determined by the rule-based emissions ranking, I exclude CA61 firms from the main analysis and report results for this group separately in the Appendix.

Two features of the rule-based selection process motivate its use as a source of quasi-experimental variation. First, the emissions-based ranking contains measurement noise. The CA100-main ranking is based on total greenhouse-gas emissions, including Scope 3 emissions. Scope 3 emissions are particularly difficult to measure consistently because they require value-chain information and depend on reporting boundaries and estimation assumptions. Further, differences between self-reported disclosures and model-based estimates can generate substantial variation in measured emissions across data providers.

Table 4 illustrates this issue by comparing CDP-reported 2015 emissions with Trucost estimates for firms observed in both sources. Agreement is high for directly measured or more standardized emissions: the rank correlations between CDP and Trucost are 0.96 for Scope 1 emissions and 0.91 for Scope 2 emissions. In contrast, the rank correlation for Scope 3 emissions is only 0.58. The median Trucost Scope 3 estimate is 44% of the CDP estimate, only 5% of firms have estimates within 25% across the two sources, and Trucost estimates are less than one-half of CDP values for 52% of firms. Consequently, firms near the CA100-main selection cutoff may be assigned different ranks owing to measurement differences in total emissions, especially Scope 3 emissions.

Second, absolute emissions need not predict a firm's incentives or capacity to invest in green productive assets. Total emissions measure the scale of a firm's carbon footprint, rather than its cost of abatement, access to financing, technology set, or expected returns to green investment. The CA100+ selection rule was designed to identify firms with substantial climate footprints, not firms that are especially likely to undertake green capital investment. Firms with similar total emissions may therefore have very different opportunities or incentives to decarbonize, whereas firms with different absolute emissions may face similar green-investment opportunities.

Table 4
Agreement Between CDP and Trucost 2015 Emissions Estimates by Scope
This table compares 2015 firm-level emissions reported to CDP with Trucost's modeled 2015 estimates for energy-panel firms observed in both sources. CA61 firms are excluded. A firm is included in a row when both providers report a positive value for the relevant scope; CDP Scope 3 equals the sum of categories calculated by the firm. *Rank correlation* is Spearman's correlation; *correlation of logs* is Pearson's correlation between natural logarithms; and *median Trucost / CDP* is the median ratio of the two estimates. *Within ±25%* is the share of firms for which the Trucost estimate is within 25% of the CDP estimate, and *Trucost below half of CDP* is the share for which the Trucost estimate is less than one-half of the CDP estimate. The number of CA100-main targets is reported in parentheses.

	Firms (targets)	Rank correlation	Correlation of logs	Median Trucost / CDP	Within ±25%	Trucost below half of CDP
Scope 1	147 (43)	0.96	0.87	1.00	83%	1%
Scope 2 (location-based)	144 (42)	0.91	0.88	1.00	75%	5%
Scope 1+2	147 (43)	0.95	0.92	1.00	82%	1%
Scope 3	126 (39)	0.58	0.55	0.44	5%	52%
Scope 1+2+3	147 (43)	0.79	0.76	0.89	31%	32%

4.2 Estimation Design

I first estimate a difference-in-differences specification comparing CA100-main target firms with non-target firms that are similar in industry, size, and Scope 1 and Scope 2 emissions. CA61 firms are excluded from this main comparison because their selection was discretionary. I estimate:

$$Y_{it} = \beta \, \text{Member}_i \times \text{Post}_t + \gamma_i + \mu_t + \varepsilon_{it}, \tag{3}$$

where Y_{it} is an outcome measuring firm i's green or brown productive assets, capacity additions, or green innovation in year t. Member_i equals one if firm i is included in the CA100-main list, and Post_t equals one from 2018 onward, following the initiative's December 2017 launch. The specification includes firm fixed effects, γ_i, and year fixed effects, μ_t, and standard errors are clustered by firm. The coefficient β measures the differential change in the outcome for CA100-main targets after the launch of CA100+, relative to comparable non-target firms.

The analysis covers 2010–2025. Of the 1,997 firms in the energy-asset panel, 70 CA100-main firms and 29 CA61 firms have observed power-plant assets. The main matched difference-in-differences sample compares the 70 CA100-main firms with non-target firms

and excludes the 29 CA61 firms.

The baseline design relies on comparisons between observably similar target and non-target firms. I therefore use two complementary approaches that exploit the rule-based nature of the initial focus-list selection. First, I implement a fuzzy regression discontinuity design around the initial emissions-ranking threshold. Because the observed ranking is measured with error and target assignment may not be perfectly determined by the reconstructed cutoff, this design estimates the effect of CA100-main membership using threshold eligibility as an instrument for treatment. Second, I estimate a local difference-in-differences specification using firms near the selection cutoff. This approach limits the comparison to firms with similar emissions rankings and reduces reliance on extrapolation from firms with substantially different emissions profiles. Together, these approaches provide complementary evidence on whether investor engagement induces investment in green productive assets.

4.3 Engagement and Green Investment

This section presents evidence on the relationship between CA100+ engagement and firms' investment in green productive assets. I report results from three complementary designs: a matched difference-in-differences design, a local fuzzy regression discontinuity (RD) design exploiting the focus-list selection threshold, and a local difference-in-differences design comparing firms near that threshold. Across these approaches, CA100-main targets increase green capacity construction after the December 2017 launch of CA100+. The evidence also indicates that engagement shifts new investment away from brown and toward green generating capacity.

4.3.1 Matched Difference-in-Differences Estimates

The baseline analysis matches CA100-main targets to pure non-members using log 2015 Scope 1+2 emissions. Because the analysis sample is restricted to energy-relevant industries, this procedure compares firms with similar direct emissions exposure within the energy sector. Matching is performed with replacement, and control firms are weighted by the number of target–control matches in the subsequent regressions.

Table 5 assesses covariate balance using averages over 2013–2015, before the launch of CA100+. The matched sample is well balanced on pre-treatment Scope 1+2 emissions, total generating capacity, capacity-portfolio composition, green-capacity construction, and pre-treatment green-capacity growth. For example, average log Scope 1+2 emissions are

virtually identical for targets and matched controls (17.14 versus 17.12), and the normalized difference is 0.02. Targets and controls also do not differ significantly in total capacity, green capacity share, green construction, or green-capacity growth before treatment.

However, matching on Scope 1+2 emissions alone does not balance all firm characteristics. CA100-main targets are larger in terms of assets and revenue, have lower debt-to-assets ratios, and have higher return on assets than their matched controls. These differences motivate the alternative matching specifications below, which additionally match firms on size, leverage, investment, portfolio composition, and pre-treatment green-capacity growth.

Figure 4 plots the dynamic difference-in-differences estimates for annual green capacity construction in the baseline matched sample. The coefficients measure the difference between CA100-main targets and matched controls in each year relative to 2017, the year in which CA100+ was launched. The pre-2017 coefficients do not show a systematic difference between targets and controls and are jointly indistinguishable from zero ($p = 0.30$). Following the launch, the estimated gap in green construction becomes positive and generally increases over time. The target-control differential reaches 156 MW in 2022, 143 MW in 2024, and 233 MW in 2025; the estimates for 2022, 2024, and 2025 are individually statistically significant at the 5% level. This pattern is consistent with CA100-main targets increasing green construction relative to otherwise similar non-members after the initiative's launch.

Table 6 reports the corresponding average post-2017 estimates under alternative matching specifications. Panel A presents the baseline match on log Scope 1+2 emissions. Relative to matched controls, CA100-main targets increase their green capacity share by 2.0 percentage points and build an additional 131 MW of green capacity annually. The green share of new construction increases by 17.6 percentage points, while the log ratio of green to brown construction rises by 1.04. Brown construction does not increase significantly in this specification.

Panels B and C account for the observable imbalances identified in Table 5. Panel B additionally matches on log revenue and debt-to-assets, while Panel C matches on six pre-treatment characteristics: log Scope 1+2 emissions, log revenue, debt-to-assets, capital expenditures relative to assets, the green share of capacity, and green-capacity growth during 2013–2015. The central result remains. In the most demanding matching specification in Panel C, targets build 75 MW more green capacity annually than matched controls after 2017. Their green share of new construction rises by 20.3 percentage points, and the log ratio of green to brown construction rises by 0.85. Across all three panels,

the evidence points to a post-engagement shift in targets' new investment toward green capacity.

Table 7 examines green technology outcomes. In contrast to the physical-capital results, the estimates do not show an increase in green patenting by CA100-main targets. In the baseline matched sample, targets experience significant declines in green, non-green, and total patent filings relative to matched controls, while the green share of filings is unchanged. The decline in total filings remains statistically significant in the alternative matching specifications, and the green-patent coefficient is negative in each specification, although it is imprecisely estimated in Panel B. Thus, the evidence indicates a shift toward green *physical* investment rather than an increase in green technological innovation.

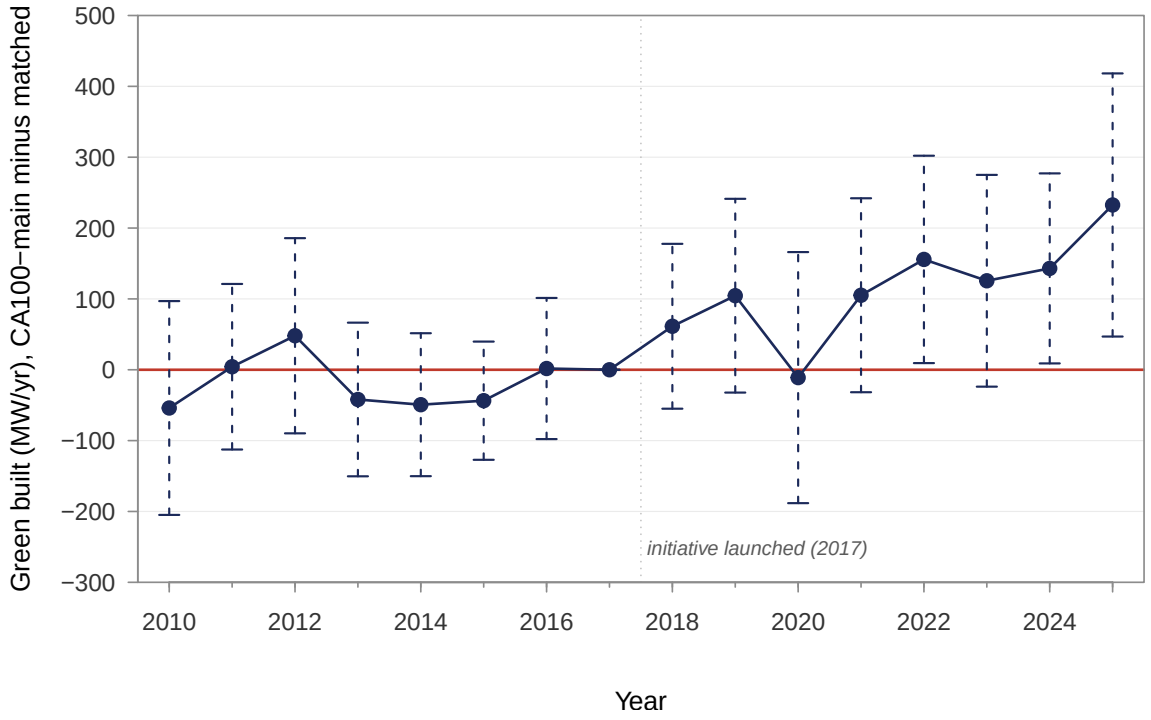


Figure 4: Green construction by CA100-main targets relative to matched controls. This figure reports event-study estimates for the difference in annual stake-weighted megawatts of green capacity built by the 65 rule-based CA100-main targets and pure non-member controls. Targets are matched with replacement on log 2015 Scope 1+2 emissions; controls are weighted by the number of target–control pairings. Coefficients are relative to 2017, the year Climate Action 100+ launched, indicated by the dotted vertical line. Each point is a coefficient from a weighted regression with firm and year fixed effects, estimated over 2010–2025. Vertical dashed lines denote 95% confidence intervals based on standard errors clustered by firm; the red horizontal line marks zero. The pre-2017 coefficients are jointly indistinguishable from zero ($p = 0.30$). Post-2017 estimates increase to 143 MW in 2024 and 233 MW in 2025.

Table 5

Firm Characteristics of CA100-Main Targets and Matched Controls: 2013–2015 Averages

This table compares CA100-main targets with their matched pure non-member controls matched with replacement on log 2015 Scope 1+2 emissions. Controls are weighted by the number of times they are matched to a target. Firm characteristics are from S&P Capital IQ: total assets, revenue, debt, cash, and capital expenditure are measured in U.S. dollars; return on assets and the EBITDA margin are measured in percent. Except for growth measures, all characteristics, including levels, ratios, emissions, and capacity measures, are averaged over fiscal years 2013–2015. Growth is the log change from 2013 to 2015. Emissions are Trucost modeled figures. Capacity is the firm's stake-weighted megawatts in the S&P asset data. *Norm. diff.* is the difference in means divided by the square root of the average of the two variances (Imbens and Rubin, 2015); p is from a weighted regression of the characteristic on a target indicator with heteroskedasticity-robust standard errors. The last column gives the number of firms with data in each group.

	Mean		Targets vs matched		Firms
	Targets	Matched	Norm. diff.	p	T / M
Size					
ln(total assets, $M)	11.27	9.85	1.64	0.00	65 / 114
ln(revenue, $M)	10.79	9.01	1.92	0.00	65 / 114
Total capacity (MW)	11,022	13,062	-0.09	0.64	65 / 113
Financial condition					
Debt / assets	0.268	0.424	-1.15	0.00	65 / 114
Cash / assets	0.061	0.053	0.19	0.23	65 / 114
Return on assets (%)	4.15	3.36	0.36	0.03	65 / 114
EBITDA margin (%)	18.8	23.5	-0.36	0.04	65 / 114
Investment					
Capex / assets	0.076	0.067	0.27	0.10	65 / 114
Growth					
Revenue growth, 2013–15 (log change)	-0.237	-0.094	-0.37	0.03	65 / 114
Asset growth, 2013–15 (log change)	-0.063	-0.042	-0.07	0.67	65 / 113
Carbon exposure					
ln(Scope 1+2, t)	17.14	17.12	0.02	0.92	65 / 114
ln(Scope 1+2+3, t)	17.71	17.32	0.35	0.05	65 / 114
Scope 3 share of total	0.356	0.146	0.98	0.00	65 / 114
Scope 1+2 per $M revenue (t)	1,681	6,416	-0.96	0.00	65 / 114
Energy portfolio					
Brown capacity (MW)	6,789	10,717	-0.25	0.23	65 / 113
Green capacity (MW)	4,233	2,345	0.18	0.31	65 / 113
Green share of capacity	0.137	0.162	-0.12	0.45	65 / 113
Green build (MW/yr)	82.3	120.4	-0.17	0.46	65 / 113
Brown build (MW/yr)	157.8	444.2	-0.41	0.06	65 / 113
Pre-trend					
Green capacity growth, 2013–15 (log change)	0.220	0.205	0.02	0.87	65 / 113
Total capacity growth, 2013–15 (log change)	0.044	0.112	-0.20	0.12	65 / 113

Table 6

Engagement and Green Investment: Matched Samples (CA100-main targets)

This table reports estimates of equation (3) for CA100-main targets using alternative matched control samples. Panel A matches targets to pure non-members on log 2015 Scope 1+2 emissions. Panel B also matches on log 2015 revenue and debt-to-assets. Panel C matches on six characteristics: log Scope 1+2, log revenue, debt-to-assets, capital expenditure over assets, green capacity share, and green-capacity growth over 2013–2015. Matching is with replacement; controls are weighted by the number of target–control pairings. Outcomes are the green share of stake-weighted capacity; green and brown capacity built through greenfield construction and expansion; the green share of new construction; and the log ratio of green to brown construction. Member × Post-2017 equals one for targets after 2017. All models include firm and year fixed effects and cover 2010–2025. Standard errors, in parentheses, are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dep. var.:	Green share (0–1) (1)	Green build (MW) (2)	Brown build (MW) (3)	Green share of new build (4)	Log ratio green/brown (5)
Panel A. Matched on log Scope 1+2 emissions					
Member × Post-2017	0.020*	131.4***	38.7	0.176***	1.040***
	(0.012)	(47.2)	(76.4)	(0.064)	(0.299)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,825	2,835	2,835	1,225	2,835
Adj. R^2	0.904	0.513	0.524	0.312	0.255
Panel B. Matched on log Scope 1+2 emissions, log revenue, and leverage					
Member × Post-2017	0.006	61.3*	−61.1	0.161**	0.906***
	(0.017)	(33.3)	(37.8)	(0.075)	(0.316)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,716	1,723	1,723	741	1,723
Adj. R^2	0.889	0.608	0.485	0.313	0.225
Panel C. Matched on all six characteristics					
Member × Post-2017	0.010	75.4**	−13.7	0.203**	0.846***
	(0.015)	(36.0)	(36.2)	(0.078)	(0.294)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,591	1,598	1,598	593	1,598
Adj. R^2	0.838	0.590	0.532	0.351	0.237

Table 7

Engagement and Green Innovation: Matched Samples (CA100-main targets)

This table reports estimates of equation (3) for green-innovation outcomes among patenting CA100-main targets and matched controls over 2010–2022. Panel A matches targets to pure non-members on log 2015 Scope 1+2 emissions. Panel B additionally matches on log 2015 revenue and debt-to-assets. Panel C matches on six characteristics: log Scope 1+2, log revenue, debt-to-assets, capital expenditure over assets, green capacity share, and green-capacity growth over 2013–2015. Matching is with replacement; controls are weighted by the number of target–control pairings. Outcomes are the inverse hyperbolic sine of annual green, non-green, and total patent filings, and the green share of filings in years with at least one filing. Member × Post-2017 equals one for targets after 2017. All models include firm and year fixed effects. Standard errors, in parentheses, are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dep. var.:	Green patents (asinh) (1)	Non-green patents (asinh) (2)	Total patents (asinh) (3)	Green share (0–1) (4)
Panel A. Matched on log Scope 1+2 emissions				
Member × Post-2017	−0.857***	−0.820***	−0.977***	−0.011
	(0.237)	(0.303)	(0.288)	(0.051)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,711	1,711	1,711	1,206
Adj. R^2	0.831	0.859	0.859	0.427
Panel B. Matched on log Scope 1+2 emissions, log revenue, and leverage				
Member × Post-2017	−0.427	−0.482*	−0.511**	0.018
	(0.285)	(0.243)	(0.246)	(0.049)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,159	1,159	1,159	945
Adj. R^2	0.899	0.930	0.931	0.447
Panel C. Matched on all six characteristics				
Member × Post-2017	−0.614**	−0.468*	−0.564**	−0.026
	(0.295)	(0.248)	(0.257)	(0.044)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,116	1,116	1,116	860
Adj. R^2	0.897	0.922	0.924	0.421

4.3.2 Evidence from the Focus-List Cutoff

The matched design compares CA100-main targets with non-members that have similar observed characteristics. I complement this approach with designs that exploit the rule used to construct the initial CA100+ focus list. Specifically, I compare firms just inside the reconstructed eligibility threshold with firms just outside it.

CA100+ ranked firms using 2015 Scope 1, Scope 2, and Scope 3 emissions reported to, or modeled by, CDP. I reconstruct this ranking from the 2015 CDP questionnaire using the 1,807 firms that report a Scope 1 or Scope 2 emissions measure, and identify rule-based CA100-main targets using ISINs. Because the coalition ranked a broader universe than the set of observed CDP respondents, its nominal top-100 criterion does not mechanically imply a cutoff at rank 100 in the reconstructed ranking. I therefore estimate the relevant threshold as the least-squares change point in a two-level step function relating CA100-main membership to reconstructed rank. This procedure identifies rank 63 as the cutoff. Appendix C reports the cutoff search procedure and results using alternative thresholds.

Figure 5 illustrates the resulting first stage. The probability of CA100-main membership is 0.76 among firms ranked 63 or higher in the emissions ordering—that is, on the high-emissions side of the cutoff—compared with 0.05 among firms below the cutoff. The resulting raw membership discontinuity is 0.71. Assignment is therefore fuzzy rather than sharp: being above the reconstructed cutoff strongly predicts focus-list membership, but does not determine it perfectly.

I use an indicator for being on the high-emissions side of the cutoff as an instrument for CA100-main membership. The running variable is log 2015 total emissions relative to the firm at the estimated threshold:

$$x_i = \ln(E_{i,2015}) - \ln(E_{63,2015}). \tag{4}$$

Of the 1,997 firms in the energy panel, 178 can be placed in the reconstructed ranking: 46 CA100-main targets, 18 CA61 firms, and 114 non-members. I exclude CA61 firms, as in the matched analysis. I use two estimators. First, I estimate a local-linear fuzzy RD model in which the outcome is each firm's change in average annual outcomes between the pre-period (2010–2017) and post-period (2018–2025). Thus, each firm contributes one observation. I use a triangular kernel and bandwidths of 1, 1.5, and 2 log points in 2015 emissions. The local first stage is strong across bandwidths: the estimated discontinuity in membership ranges from 0.78 to 0.84, with first-stage F-statistics between 11.6 and 29.0.

Second, I estimate the firm-year difference-in-differences model in equation (3) within rank windows of 25, 50, and 100 firms around the reconstructed cutoff. These local difference-in-differences specifications include firm and year fixed effects and cluster standard errors by firm. They compare targets and non-members with similar reconstructed emissions ranks, reducing reliance on comparisons between firms with markedly different emissions profiles.

Table 8 reports the results. The fuzzy-RD and local difference-in-differences estimates yield a consistent shift in the composition of new investment. The fuzzy-RD point estimates for green construction are positive but imprecise: 46 MW annually using the one-log-point bandwidth, 153 MW using the 1.5-log-point bandwidth, and 114 MW using the two-log-point bandwidth. In contrast, brown construction declines by 165–272 MW annually across the three bandwidths, with each estimate statistically significant at the 10% level. The estimated log ratio of green to brown construction rises by 1.87 at the narrowest bandwidth, and the green share of new construction increases by 0.47 in the two-log-point specification.

The local difference-in-differences estimates display the same pattern with greater precision. Within 50 ranks of the cutoff, the estimation sample contains 26 CA100-main targets and 18 non-members. Relative to non-members, targets build 151 MW more green capacity annually after 2017 and 198 MW less brown capacity. Their green share of new construction increases by 27 percentage points, and the log green-to-brown construction ratio rises by 1.74. Within 25 ranks of the cutoff, targets build 211 MW more green capacity and 162 MW less brown capacity annually, while the log green-to-brown construction ratio increases by 2.02.

Taken together, the matched, fuzzy-RD, and local difference-in-differences results consistently indicate that CA100+ engagement is associated with a reallocation of productive investment toward green generating capacity and away from brown capacity. The fuzzy-RD estimates are less precise because they rely on a limited sample near the reconstructed cutoff, but their direction and economic interpretation align with the more precisely estimated local difference-in-differences results.

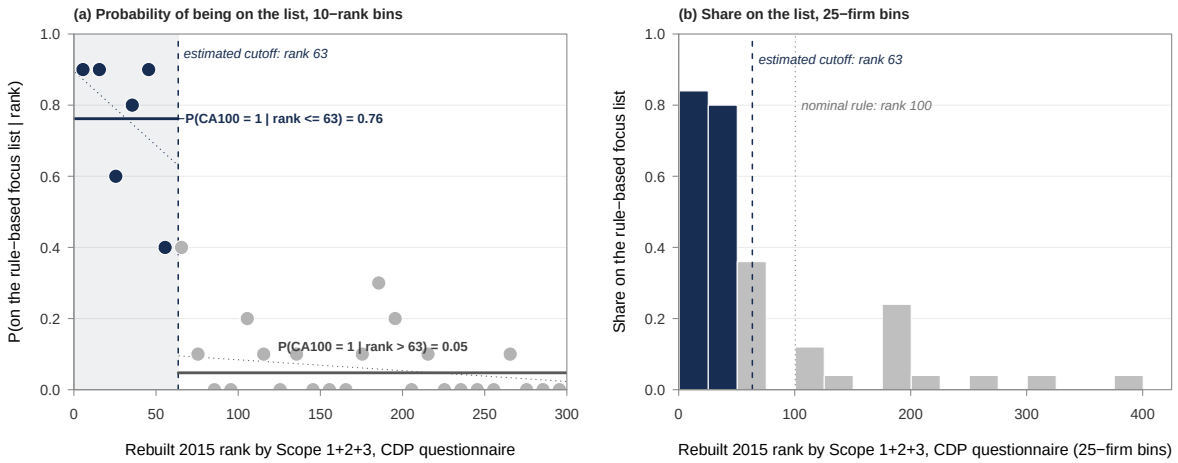


Figure 5: First-stage relationship at the focus-list cutoff. Both panels use the 1,807 respondents to the CDP 2015 questionnaire that report a Scope 1 or Scope 2 emissions figure. Firms are ranked by Scope 1+2+3 emissions, and the dashed vertical line marks the estimated cutoff at rank 63 from a least-squares change point in a two-level step function. Panel (a) reports the share of firms on the 100-company rule-based list within each 10-rank bin, $\hat{p}_b$ from $\hat{p}_b = \frac{\sum_i \mathbf{1}[R_i \in b]\, D_i}{\sum_i \mathbf{1}[R_i \in b]}$. Marker size is proportional to the number of firms in the bin. Thick lines show the conditional probability of list membership on either side of the cutoff: $P(D = 1 \mid R \leq 63) = 0.76$ and $P(D = 1 \mid 63 < R \leq 400) = 0.05$. Dotted lines are separate least-squares fits of the list indicator on rank below and above the cutoff; the shaded region denotes ranks 1–63. Panel (b) reports the share of firms on the list within each 25-firm bin of the reconstructed rank. The dotted vertical line marks the rule's nominal rank-100 threshold.

Table 8

Engagement at the Focus-List Cutoff: Main Outcomes Across Estimators

This table estimates the effect of inclusion on the rule-based focus list at the estimated cutoff, rank 63 of the reconstructed 2015 CDP emissions ranking. Each panel reports one outcome. Columns (1)–(3) are local-linear fuzzy regression-discontinuity (RD) estimates using one observation per energy-panel firm, excluding CA61 firms. The outcome is the change in the firm's annual average between 2010–2017 and 2018–2025. The running variable is log 2015 Scope 1+2+3 emissions relative to the cutoff firm, and list membership is instrumented by an indicator for ranking above the cutoff. Specifications use a triangular kernel and bandwidths of 1, 1.5, and 2 log points. Columns (4)–(6) report local difference-in-differences (DiD) estimates of equation (3) on the 2010–2025 firm-year panel, restricting the sample to firms within 25, 50, or 100 ranks of the cutoff. Local-DiD specifications include firm and year fixed effects and cluster standard errors by firm. The green share is green construction divided by total construction in years with any construction; its fuzzy-RD estimates use only firms that construct in both periods. The log ratio is $\ln(1 + \text{green built}) - \ln(1 + \text{brown built})$. Standard errors, shown in parentheses, are heteroskedasticity-robust for fuzzy-RD estimates and clustered by firm for local-DiD estimates. The bottom rows report specification details, first-stage F-statistics, adjusted R^2 values for the local-DiD models, and sample sizes. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Fuzzy RD, one observation per firm			Local DiD, firm-year panel		
Bandwidth (log points) / rank window	1.0	1.5	2.0	±25	±50	±100
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Green build (MW/yr)						
Engaged (Member) × Post	46	153	114	211*	151*	108*
	(84)	(142)	(137)	(113)	(84)	(61)
Panel B. Brown build (MW/yr)						
Engaged (Member) × Post	-272*	-209*	-165*	-162***	-198***	-147**
	(158)	(109)	(93)	(55)	(59)	(60)
Panel C. Green share of new build						
Engaged (Member) × Post	1.58	0.66	0.47*	0.38***	0.27***	0.19**
	(1.99)	(0.45)	(0.28)	(0.12)	(0.10)	(0.09)
Panel D. Log ratio, green to brown build						
Engaged (Member) × Post	1.87*	1.20	0.75	2.02**	1.74***	1.32***
	(1.02)	(1.00)	(0.94)	(0.74)	(0.53)	(0.43)
Firm fixed effects				✓	✓	✓
Year fixed effects				✓	✓	✓
Local linear, triangular kernel	✓	✓	✓			
Local DiD				✓	✓	✓
First-stage F	11.6	19.4	29.0			
Adjusted R^2, Panel A				0.74	0.71	0.65
Adjusted R^2, Panel B				0.19	0.25	0.34
Adjusted R^2, Panel C				0.45	0.39	0.38
Adjusted R^2, Panel D				0.37	0.31	0.33
Firms (above / below; targets / non-members)	21 / 24	27 / 42	35 / 57	14 / 8	26 / 18	38 / 31
Firms, Panel C (construction in both periods)	16 / 20	20 / 32	27 / 40	14 / 8	26 / 18	38 / 31

5 Net Emissions Accounting Framework

This section decomposes the net emissions effect of corporate divestitures into the channels through which a sale can affect global emissions. The central point is that the environmental consequences of a transaction depend not only on whether the divested asset continues to operate, but also on how the seller and buyer allocate capital after the transaction. A sale may alter emissions through the operating life and utilization of the transferred plant, the seller's subsequent investment, and the buyer's forgone or additional investment.

For transaction j, I decompose the net emissions effect as:

$$\text{NEE}_j = \underbrace{\Delta E^{\text{surv}}}_{\text{(1) Survival}} + \underbrace{\Delta E^{\text{op}}}_{\text{(2) Operation}} + \underbrace{\Delta E^{\text{seller}}}_{\text{(3) Seller reallocation}} + \underbrace{\Delta E^{\text{buyer,green}}}_{\text{(4) Buyer green crowd-out}} + \underbrace{\Delta E^{\text{buyer,brown}}}_{\text{(5) Buyer brown substitution}}. \tag{5}$$

Channel 1: Asset survival asks whether the seller would have retired the plant earlier than the buyer. If the buyer keeps the asset in operation longer, the sale generates additional emissions relative to the no-sale counterfactual.

Channel 2: Plant operation asks whether a plant operates more intensively, or emits more per unit of output, under its new owner, conditional on remaining open.

Channel 3: Seller reallocation captures additional green capacity constructed by the seller following divestment.

Channel 4: Buyer green crowd-out asks whether the buyer's acquisition displaces green investment that otherwise would have occurred. Such crowd-out would increase net emissions.

Channel 5: Buyer brown substitution asks whether acquiring an existing brown plant substitutes for the construction of new brown capacity. Such substitution would reduce net emissions relative to a counterfactual in which the buyer builds new fossil capacity instead.

Together, these channels distinguish genuine changes in global emissions from the simple reassignment of carbon-intensive assets across owners. Channel 3 is examined in Sections 3. The analysis below focuses on the plant-survival, plant-operation, and buyer-side channels.

5.1 Channel 1: Asset Survival

The first channel captures whether divested brown plants remain in operation longer under their buyers than they would have under their original owners. If the seller would other-

wise have retired the plant sooner, continued operation after the sale increases emissions relative to the no-transaction counterfactual.

I estimate a linear discrete-time retirement-hazard model using brown plant-years from 2010 through 2024:

$$\text{Retire}_{pt} = \beta\,\text{Sold}_p \times \text{Post}_{pt} + \delta_1 \text{Age}_{pt} + \delta_2 \text{Age}_{pt}^2 + \delta_3 \ln(\text{MW}_p) + \lambda_{\text{tech}(p),t} + \varepsilon_{pt}. \qquad (6)$$

The dependent variable equals one in the year that plant p retires its final operating unit. $\text{Sold}_p \times \text{Post}_{pt}$ equals one for plants fully divested by one of the 198 treated divesting firms in years after the sale. The specification controls for plant age, age squared, and log capacity, includes technology-by-year fixed effects, and clusters standard errors at the plant level.

Sold plants differ systematically from never-sold plants: they are, on average, larger, older, and more likely to be located in the United States. I therefore construct a matched comparison sample. Each sold plant is matched, in its sale year, to up to three never-sold plants of the same technology and country that remain at risk of retirement. Matching uses nearest neighbors on log capacity and plant age, is performed with replacement, and the regressions weight controls by their matching frequency. The baseline sample includes 945 sold plants and 1,519 matched never-sold plants.

Table 9 shows that sold plants retire sooner, rather than later. In the baseline matched specification, the annual retirement hazard rises by 1.07 percentage points following a sale. This estimate is economically large relative to the 0.60% annual retirement rate among matched controls. The estimate remains positive and statistically significant when including plant fixed effects, using equal weights rather than matching weights, and using all never-sold plants as controls. The magnitude declines when country-by-year fixed effects are included, but remains positive and statistically significant. Thus, the evidence does not support the view that divestiture systematically extends the operating lives of brown plants. If anything, sold plants are more likely to retire after changing ownership.

Table 9
Channel 1: Retirement Hazard of Sold Brown Plants

This table estimates the discrete-time retirement hazard. Observations are brown plant-years from 2010–2024 with at least one operating unit. The dependent variable equals one when a plant retires its final unit. Sold × Post equals one after a plant is fully exited by one of 198 divesting sellers during 2014–2023. All specifications control for plant age, age squared, and log capacity. Columns (1)–(4) compare sold plants with up to three matched never-sold plants of the same technology and country; columns (1)–(3) weight controls by match frequency, whereas column (4) uses equal weights. Columns (5)–(6) use all never-sold plants as controls. Technology × year, country × year, and plant fixed effects are included as indicated. *Base hazard* is the annual retirement rate among controls. Standard errors are clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dep. var.: plant retires final unit (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Sold × Post	0.0107***	0.0086***	0.0102***	0.0113***	0.0125***	0.0045**
	(0.0022)	(0.0023)	(0.0026)	(0.0022)	(0.0020)	(0.0022)
Technology × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × year FE	No	Yes	No	No	No	Yes
Plant FE	No	No	Yes	No	No	No
Control sample	Matched	Matched	Matched	Matched	All	All
Matching weights	Yes	Yes	Yes	No	–	–
Base hazard (controls)	0.60%	0.60%	0.60%	0.70%	0.67%	0.67%
Sold / control plants	945 / 1,519	945 / 1,519	945 / 1,519	947 / 1,519	947 / 12,222	947 / 12,222
Observations (plant-years)	34,150	34,135	34,149	34,165	172,132	171,892
Adj. R^2	0.011	0.003	0.040	0.012	0.008	0.011

5.2 Channel 2: Plant Operation

The second channel examines whether divested plants operate more intensively or emit more per unit of electricity generated under their new owners. I estimate a plant-level difference-in-differences specification using U.S. brown plants with observed CO_2 emissions between 2010 and 2025:

$$Y_{pt} = \beta \, \text{Sold}_p \times \text{Post}_{pt} + \alpha_p + \lambda_t + \varepsilon_{pt}, \tag{7}$$

where α_p and λ_t are plant and year fixed effects, respectively. Standard errors are clustered by plant.

The treatment group consists of 373 U.S. brown plants fully divested by the 198 firms in the divester sample. The control group consists of 905 never-sold brown plants owned by firms in the energy panel. The smaller treatment sample, relative to Channel 1, reflects the fact that measured emissions and generation data are available only for U.S. plants. The post-sale indicator equals one only in years strictly after the transaction, because the sale year largely reflects operation under the seller.

The primary outcome is log annual plant-level CO_2 emissions. Because log emissions equal log generation plus log emissions intensity, the same specification permits a decomposition into changes in electricity output and emissions per MWh. I also estimate effects on capacity factors and heat rates.

Table 10 provides no evidence that divested plants emit more after the sale. The estimated effect on plant-level emissions is 0.002 log points, with a standard error of 0.049. Although generation increases by 0.122 log points, this increase is offset by a statistically significant decline in emissions intensity of 0.120 log points. There are no meaningful changes in capacity factors or heat rates. Thus, the physical emissions profile of divested assets remains broadly unchanged after ownership changes, consistent with the evidence in Duchin et al. (2025).

Table 10
Do Sold Plants Emit Less After Sale?

This table reports plant-level difference-in-differences estimates of changes in emissions, generation, and operating performance after the sale of brown power plants. Treated plants are 373 brown plants with measured CO_2 emissions fully divested by 198 treated sellers. Controls are 905 brown plants with measured emissions ever held by one of the 1,997 energy-panel firms and not fully exited by any panel owner during 2010–2024. Outcomes are log annual CO_2 emissions, generation, emissions intensity(CO_2/MWh), capacity factor, and heat rate. Unit-level S&P Global data are aggregated to plant-years. Columns (1)–(3) use the common emissions and generation sample; columns (4)–(5) use observations with reported capacity factors and heat rates. Sold × Post equals one in years strictly after a treated plant's sale; the sale year is pre-sale. The plant-year panel covers 2010–2025, and all specifications include plant and year fixed effects. Standard errors are clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Sample:	ln(CO_2)	ln(Generation)	ln(CO_2/MWh)	ln(Capacity factor)	ln(Heat rate)
	Common emissions–generation sample			Reported sample	
	(1)	(2)	(3)	(4)	(5)
Sold × Post	0.002	0.122*	−0.120***	−0.003	0.003
	(0.049)	(0.067)	(0.034)	(0.052)	(0.007)
Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Plants	857	857	857	856	835
Observations	10,320	10,320	10,320	10,297	8,916
Adj. R^2	0.888	0.837	0.605	0.751	0.742

5.3 Channels 4 and 5: Buyer Green Crowd-Out and Brown Substitution

Channels 4 and 5 concern the buyer's alternative uses of capital. Channel 4 measures emissions reductions forgone if the acquisition crowds out green investment, such as wind or solar construction. Channel 5 measures emissions avoided if acquiring an existing brown plant substitutes for construction of new brown capacity. Green crowd-out would increase net emissions, whereas brown substitution would reduce net emissions.

I estimate both channels using a stacked difference-in-differences design:

$$\text{Built}_{b,t,g} = \beta \, \text{Buyer}_{b,g} \times \text{Post}_{t,g} + \alpha_{b,g} + \lambda_{t,g} + \varepsilon_{b,t,g}, \tag{8}$$

where $\text{Built}_{b,t,g}$ is annual green or brown capacity construction by buyer b in year t within purchase cohort g. The specification includes corporate-group-by-cohort fixed effects, $\alpha_{b,g}$, and year-by-cohort fixed effects, $\lambda_{t,g}$, with standard errors clustered by corporate group.

The treated sample consists of 106 corporate groups whose first purchase of a brown plant fully divested by one of the 198 treated sellers occurs between 2012 and 2023. Treated and control owners are required to hold at least 100 MW of capacity in the prior year. To avoid attributing seller reallocation or engagement-related investment to the buyer-side channel, I exclude buyers that are themselves treated divesters or CA100+ targets. The control group consists of 2,910 comparable owners that never acquire brown capacity from a panel firm. Each cohort stack spans event years -3 through $+5$; consequently, the most recent cohorts have shorter post-purchase windows.

Table 11 reports the baseline estimates. Buyers increase green capacity construction by 26.8 MW annually following their first acquisition, relative to never-buying owners. The estimate is precisely estimated, with a standard error of 8.4 MW. Thus, there is no evidence that acquisitions crowd out buyers' green investment. Instead, buyers construct more green capacity after the acquisition.

The estimated effect on brown construction is 18.3 MW annually, with a standard error of 17.1 MW. This estimate is positive but not statistically distinguishable from zero. Thus, the data do not provide evidence that buyers' acquisitions either systematically displace or systematically induce new brown capacity construction.

Table 12 shows that the increase in green construction is not driven by a single buyer category. Public buyers add approximately 40 MW of green capacity annually, while private-company and fund buyers add approximately 20 MW. Neither group displays a statistically significant increase in brown construction. Overall, the buyer-side evidence

does not support a leakage mechanism in which buyers offset sellers' green reallocation by reducing their own green investment or substantially expanding brown capacity.

Table 11
Channels 4–5: Construction by Buyers of Divested Plants

This table reports stacked difference-in-differences estimates of annual capacity construction by buyers of brown plants sold by treated divesters. Treated units are 69 non-divesting corporate groups whose first purchase of a fully exited brown plant occurred in 2012–2020 and that held at least 100 MW in the prior year. Controls are 2,623 non-divesting groups that held at least 100 MW, but never purchased brown capacity from a panel firm. Each cohort stack spans event years −3 to +5 and includes group × cohort and year × cohort fixed effects. Buyer × Post equals one from the purchase year onward. Outcomes are annual MW of new green and brown capacity, including greenfield construction and expansions. Standard errors are clustered by corporate group. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	New green construction (MW/year)	New brown construction (MW/year)
Dependent variable	(1) Channel 4	(2) Channel 5
Buyer × Post	**26.8*****	**18.3**
	(8.4)	(17.1)
Group × Cohort, Year × Cohort FE	Yes	Yes
Treated buyer groups	106	106
Control groups	2,910	2,910
Observations	231,469	231,469
Adj. R^2	0.322	0.306

Table 12
Channels 4–5 by Buyer Type: Public versus Private Buyers

This table reports stacked difference-in-differences estimates of annual green and brown capacity construction by buyer type. Buyer type is the S&P classification of the ultimate parent of the buyer's corporate group at its first purchase of a divested brown plant. Column (1) reports the pooled effect for all 69 non-divesting buyers. Columns (2)–(4) report estimates for public buyers, private companies or investment funds, and other buyers (governments and unclassified owners), respectively; all three buyer-type effects are estimated jointly. For each purchase-year cohort, the control group comprises 2,623 eligible non-divesting groups. Cohort stacks span event years −3 through +5 and include group × cohort and year × cohort fixed effects. Outcomes are annual MW of newly built capacity, including greenfield construction and expansions. Standard errors are clustered by corporate group. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	All non-divester buyers (1)	Public buyers (2)	Private or fund buyers (3)	Other (4)
New green construction (MW/year)	26.8*** (8.4)	40.1** (15.9)	19.9* (11.9)	23.0** (11.3)
New brown construction (MW/year)	18.3 (17.1)	15.3 (23.8)	4.3 (23.2)	80.9 (60.3)
Treated buyer groups	106	33	59	14
Control groups		2,910		
Observations		231,469		

5.4 The Five Channels and the Net Emissions Effect

Table 13 combines the five channel estimates and converts them into a five-year net emissions effect for the 198 treated divesters. Negative values denote lower global emissions. The conversion uses the capacity-factor, emissions-factor, and technology-mix assumptions described in the Appendix E.

The plant-level channels do not support the conventional leakage concern that sold fossil assets remain open longer or operate more intensively under new owners. Channel 1 indicates that sold plants retire sooner. Applying the estimated 1.07-percentage-point increase in the annual retirement hazard to the 554 plants sold between 2014 and 2020, which generate 289 Mt of CO_2 annually at their observed operating rates, implies a five-year emissions reduction of 46 Mt. Channel 2 is effectively zero: the estimated 0.002-log-point change in plant emissions corresponds to an increase of only 2 Mt over five years, with a wide confidence interval spanning substantial emissions reductions and increases. Combined, the two plant channels reduce emissions by approximately 44 Mt at the point estimates.

Channel 3 captures green capacity construction by sellers. It applies the post-divestment stacked difference-in-differences estimate of 46 MW of additional annual green construction by treated divesters, relative to never-divesting firms, to all 198 treated divesters. Using the divesters' blended green capacity factor of 0.280, a location-weighted marginal emissions factor of 0.737 tCO_2/MWh, and a five-year triangular accumulation weight, this channel implies avoided emissions of 247 Mt. This is the largest individual channel in the accounting exercise.

The buyer-side channels nearly offset one another at the point estimates. Buyers construct an additional 26.8 MW of green capacity annually, implying 67 Mt of avoided emissions over five years. Their estimated 18.3 MW annual increase in brown construction implies 62 Mt of additional emissions, although this estimate is not statistically distinguishable from zero. Thus, setting both buyer-side effects to zero would leave a net emissions effect of approximately -292 Mt, close to the headline estimate.

Summing the five channels yields a net emissions effect of -297 Mt of CO_2 over five years. The result is driven principally by additional green capacity construction by divesting sellers, which accounts for 247 Mt of avoided emissions. Green construction by buyers contributes a further 67 Mt of avoided emissions, while earlier retirement of sold plants contributes 46 Mt. The positive brown-construction channel partly offsets these reductions by 62 Mt, although that estimate is not statistically distinguishable from zero. The result does not depend materially on the buyer-side estimates because the buyer

green and brown channels nearly cancel at the point estimates. More broadly, the evidence suggests that divestiture in this setting is associated with changes in real investment and asset retirement, rather than merely the redistribution of brown assets across owners. This accounting exercise should be interpreted as a structured decomposition, not as a single reduced-form causal estimate.

Table 13
The Five Channels and Their Net Emissions Effect

Panel A summarizes the five estimated channels through which divestitures may affect emissions. Channel 1 estimates whether sold brown plants retire sooner; Channel 2 estimates changes in their emissions after sale; Channel 3 estimates green capacity construction by the divesters after the sale; and Channels 4–5 estimate green and brown capacity construction by buyers of divested plants. Panel B converts these estimates into a five-year net emissions effect for the 198 treated divesters, in million tonnes of CO_2. Negative values denote lower global emissions. Capacity effects are converted to emissions using capacity factors, 8,760 annual hours, and location- and technology-specific emissions factors. Intervals are 95% confidence intervals propagated from regression standard errors, holding conversion parameters fixed. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary of channel estimates

Channel	Dependent variable	Estimate	Std. error	Obs.
1. Survival	Plant retires in the year	0.0107***	(0.0022)	34,150
2. Operation	ln(Plant CO_2)	0.002	(0.049)	10,320
3. Seller green	Green capacity built (MW/year)	46.0**	(19.5)	118,867
4. Buyer green	Green capacity built (MW/year)	26.8***	(8.4)	231,469
5. Buyer brown	Brown capacity built (MW/year)	18.3	(17.1)	231,469

Reference quantities

Baseline retirement hazard, matched never-so (all never-sold: 0.67%)	0.60%
First-time buyers of divesters' plants, 2012 never divesters nor targets	106 of 166

Panel B. Net emissions effect over five years

	$MtCO_2$	95% interval
1. Survival: retirement brought forward	−46	[−66, −27]
2. Operation: plant run harder	+2	[−101, +95]
3. Seller's incremental green build	−247	[−452, −42]
4. Buyer green: no crowd-out found	−67	[−109, −26]
5. Buyer brown: no significant substitution found	+62	[−52, +176]
Net emissions effect	**−297**	
of which gross channels (1, 2, 5)	+17	
of which avoided channels (3, 4)	−314	

6 Conclusion

This paper examines whether firms reallocate capital toward green physical assets and green technology after divesting brown generating assets, whether investor engagement is a mechanism that induces such reallocation, and how these changes affect the net emissions consequences of divestiture.

I first document that firms' physical-capital portfolios become greener after a full exit from a brown plant. Following divestment, firms build more green capacity, while there is no statistically detectable change in new brown capacity construction. Their brown capacity stocks decline and their green capacity stocks increase, raising the green share of installed capacity. These patterns imply that divesting firms become greener both by shedding brown assets and by undertaking new green construction. In contrast, I find no corresponding increase in green technological innovation. Green, non-green, and total patent filings all decline after full-exit divestitures, while the green share of patent filings remains unchanged. Thus, divestment is associated with a shift toward green physical capital, but not toward additional green technology development. These initial post-divestment findings are descriptive and should not be interpreted as causal effects.

I next examine investor engagement as a mechanism for this reallocation. Investor engagement has been shown to affect firms' divestment decisions (Duchin et al., 2025; Berg et al., 2026). I ask whether the same pressure changes firms' subsequent allocation of productive capital. I use the rule-based selection of the initial Climate Action 100+ (CA100+) focus list to identify the effects of engagement. CA100+ is the largest investor coalition focused on corporate climate action and targets major corporate emitters (Climate Action 100+, 2021). The coalition's initial focus list was determined by a mechanical emissions-based rule, which supports comparisons between targeted firms and similar non-target firms.

Across matched difference-in-differences, fuzzy regression discontinuity, and local difference-in-differences designs, the evidence indicates that engagement shifts investment away from brown and toward green generating capacity. Engaged firms build more green capacity after the launch of CA100+, reduce or do not increase brown capacity construction, and increase the green share of new construction. However, engagement does not produce a corresponding increase in green patenting. Indeed, targeted firms generally experience a relative decline in overall patent-filing activity, with little change in the green share of their filings. One interpretation is that engagement is particularly effective at inducing visible and comparatively near-term changes in physical investment, whereas research and development is less immediately observable and may take longer to respond.

Finally, I develop an accounting framework for the net emissions effects of divestiture. The framework distinguishes five channels: (1) the survival of the transferred asset; (2) its operation after sale; (3) the seller's reallocation toward green capacity; (4) potential crowd-out of green investment by the buyer; and (5) potential substitution between acquired assets and new brown capacity by the buyer.

The results do not support the view that divestiture simply transfers carbon-intensive assets to owners who operate them longer or more intensively. First, sold brown plants retire sooner, rather than later, than comparable never-sold plants. Second, conditional on remaining in operation, I find no meaningful change in plant-level CO_2 emissions after sale, consistent with Duchin et al. (2025). Third, divesting sellers increase green capacity construction. Fourth, there is no evidence that buyers crowd out green investment after acquiring divested brown plants; instead, buyers increase green construction. Finally, there is no statistically significant evidence that buyers systematically substitute acquired brown capacity for new brown construction.

Combining the five channels produces an estimated five-year net emissions effect of approximately -297 million tonnes of CO_2. The estimate is driven principally by additional green capacity construction by divesting sellers, which accounts for 247 Mt of avoided emissions. Earlier retirement of sold plants contributes a further 46 Mt reduction, and additional green construction by buyers contributes 67 Mt. These reductions are partly offset by an estimated 62 Mt increase associated with buyers' brown construction, although that estimate is not statistically distinguishable from zero. The buyer-side green and brown construction effects nearly cancel at the point estimates.

The accounting exercise necessarily relies on assumptions that translate capacity changes into emissions, including capacity factors, emissions factors, and the attribution of sellers' post-divestment green investment to the sale. Nevertheless, the results indicate that the emissions consequences of divestiture cannot be assessed solely by tracking the ownership or subsequent operation of transferred assets.

More broadly, the paper shows that divestiture is not merely an ownership transaction. Its environmental consequences also depend on sellers' and buyers' investment decisions after the sale. Evaluations of fossil-fuel divestment should therefore account for changes in asset retirement, plant operation, and the reallocation of productive capital. The findings also suggest that coordinated investor engagement can be an effective tool for shifting firms' real investment toward green physical assets, even when its effects on longer-horizon technological innovation are less apparent.

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A Appendix Tables

A.1 Data and Descriptive

A.1.1 Analysis sample and treatment definition

Table A1
Construction of the Analysis Sample

This table reports the number of firm-year observations and distinct firms remaining at each step in constructing the 1,997-firm analysis sample from the S&P Global ownership panel. The energy-relevance filter retains firms whose own or ultimate-ultimate parent's industry group is utilities, oil and gas, mining and metals, industrials, autos, or transport. Consolidation assigns subsidiaries to energy-relevant ultimate-ultimate parents and sums capacity and flow measures. The brown-capacity screen retains entities with more than 100 MW of stake-weighted brown capacity in at least one year. *Plants* and *units* denote, respectively, power plants in which surviving firms hold a positive stake in any year and their generating units. The final sample holds stakes in 37,905 plants (15,131 brown and 22,737 green) and 85,287 units. The final column reports surviving firms as a share of the initial universe.

Step	Firm-years	Firms	Plants	Units	% firms
1. Ownership panel collapsed to ultimate parent × year	737,782	27,944	80,291	158,632	100.0
2. Energy-relevant industry filter (own or ultimate-ultimate parent)	461,432	16,408	63,942	129,796	58.7
3. Consolidation of subsidiaries into energy-relevant parents	412,280	14,434	63,942	129,796	51.7
4. Brown capacity > 100 MW in at least one year	90,548	1,997	37,905	85,287	7.1

Table A2
The Green Patent Taxonomy: CPC Classes

This table lists the classes of the Cooperative Patent Classification (CPC) Y02/Y04 climate-mitigation taxonomy that define a green patent filing in the text: a filing is green if any of its CPC codes falls in one of these classes.

CPC class	Technology area
Y02: climate change mitigation and adaptation technologies	
Y02A	Adaptation technologies
Y02B	Mitigation technologies related to buildings
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Y02D	Mitigation technologies in information and communication technologies
Y02E	Reduction of GHG emissions in energy generation, transmission or distribution
Y02P	Mitigation technologies in the production or processing of goods
Y02T	Mitigation technologies related to transportation
Y02W	Mitigation technologies related to wastewater treatment or waste management
Y04: information and communication technologies for energy	
Y04S	Smart grids and energy storage

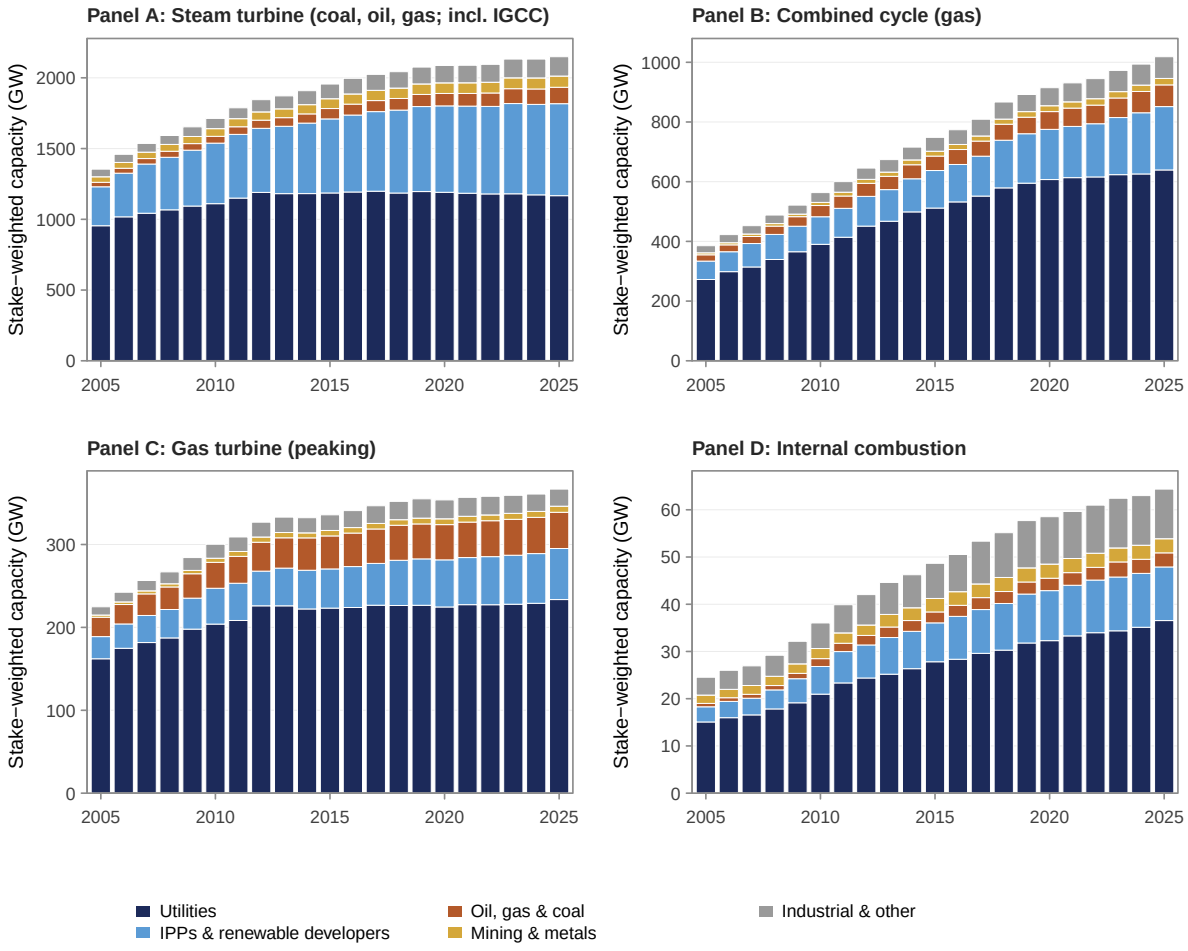


Figure A1: Brown Capacity by Technology and Owner Industry. Annual stake-weighted brown generating capacity, in gigawatts, by technology and the industry group of the owning firm in the 1,997-firm analysis sample, 2005–2025. Capacity is stacked by owner industry within each technology. Panel A combines steam-turbine capacity with the small integrated-gasification category. Vertical axes differ across panels. Financial owners are excluded by construction of the energy panel; industrial and other owners comprise conglomerate, construction, and chemical parent firms.

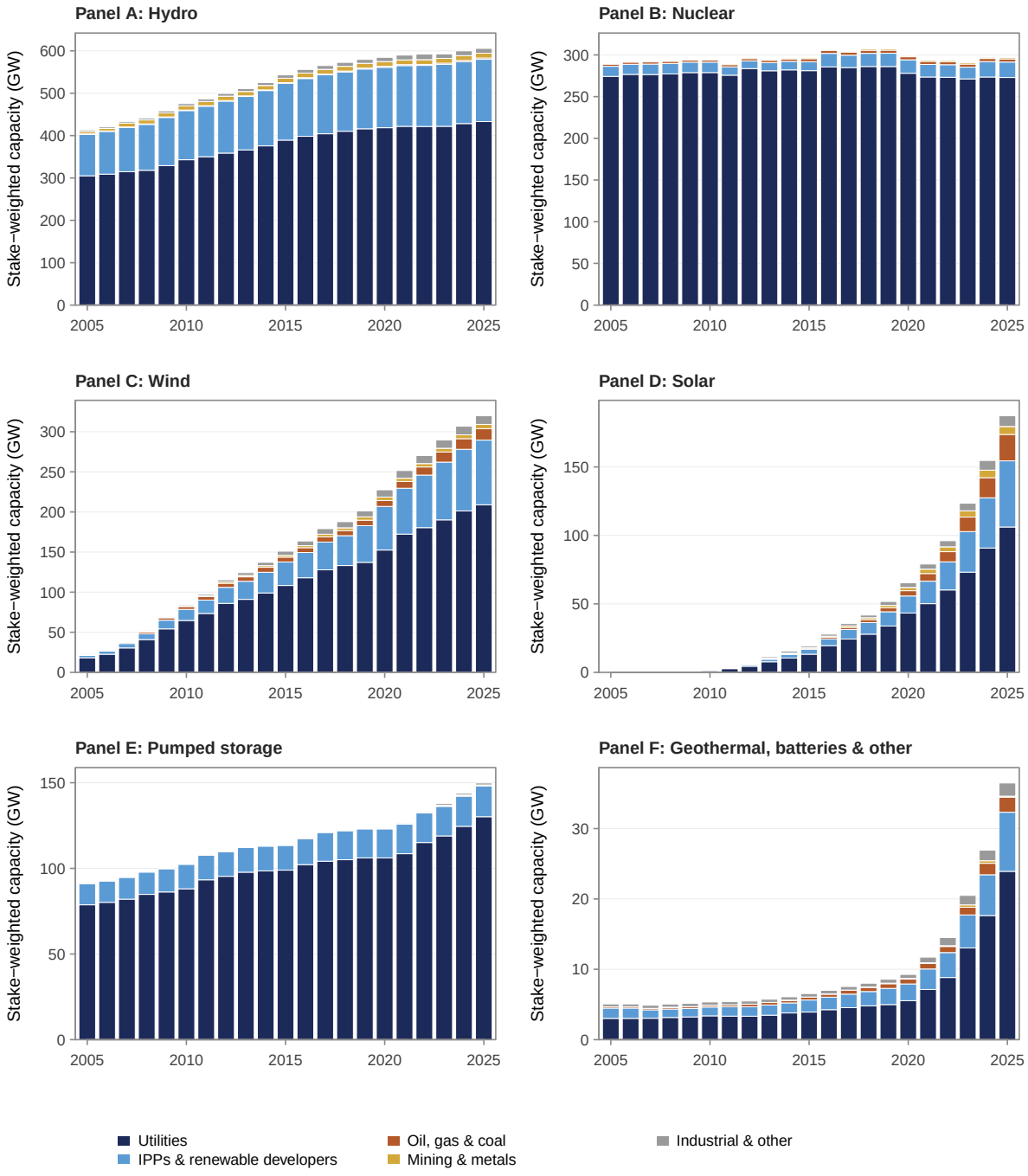


Figure A2: Green Capacity by Technology and Owner Industry. Annual stake-weighted green generating capacity, in gigawatts, by technology and the industry group of the owning firm in the 1,997-firm analysis sample, 2005–2025. Capacity is stacked by owner industry within each technology. Panel F combines geothermal, batteries, fuel cells, and other storage technologies. Vertical axes differ across panels.

B Divestment: Do Divesting Firms Invest in Green?

Table B1
Robustness of Capacity Results to Estimator and Control Sample

This table re-estimates the capacity results in Table 3 using alternative estimators and control samples. Panel A reports cumulative built capacity (greenfield construction plus expansion) and Panel B reports capacity stocks; all outcomes are stake-weighted megawatts. Columns 1–4 report green outcomes and columns 5–8 report brown outcomes. *TWFE* denotes a two-way fixed-effects regression of Divested × Post with firm and year fixed effects. *Stack* denotes the stacked cohort specification in equation (1), with firm-by-cohort and year-by-cohort fixed effects, which does not use already-treated firms as controls. *Base* uses the 1,478 clean controls in the energy panel. *Match* uses the 497 size-matched controls selected by 1:3 nearest-neighbor matching on log pre-period capacity within industry groups (Section A.1.1). All columns include the 198 divesting firms. Standard errors, in parentheses, are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A. Total built capacity								
Dep. var.:	*Total built green (MW)*				*Total built brown (MW)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × Post	75.8***	46.0**	68.9***	44.4**	−39.8**	−17.4	−23.5	−10.2
	(26.0)	(19.5)	(24.7)	(19.6)	(15.7)	(16.5)	(17.3)	(17.1)
Adj. R^2	0.555	0.478	0.553	0.486	0.446	0.439	0.463	0.461
Panel B. Capacity stocks								
Dep. var.:	*Green stock (MW)*				*Brown stock (MW)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × Post	671.3***	370.0***	545.5***	318.7**	−803.0***	−751.3***	−1,093.4***	−947.0***
	(206.7)	(123.7)	(195.8)	(125.1)	(255.0)	(179.3)	(260.0)	(187.7)
Adj. R^2	0.967	0.988	0.966	0.988	0.960	0.990	0.959	0.990
Control sample	Base	Base	Match	Match	Base	Base	Match	Match
Estimator	TWFE	Stack	TWFE	Stack	TWFE	Stack	TWFE	Stack
Observations	24,663	118,867	10,693	43,138	24,663	118,867	10,693	43,138

C Engagement

C.1 CA100 list (target)

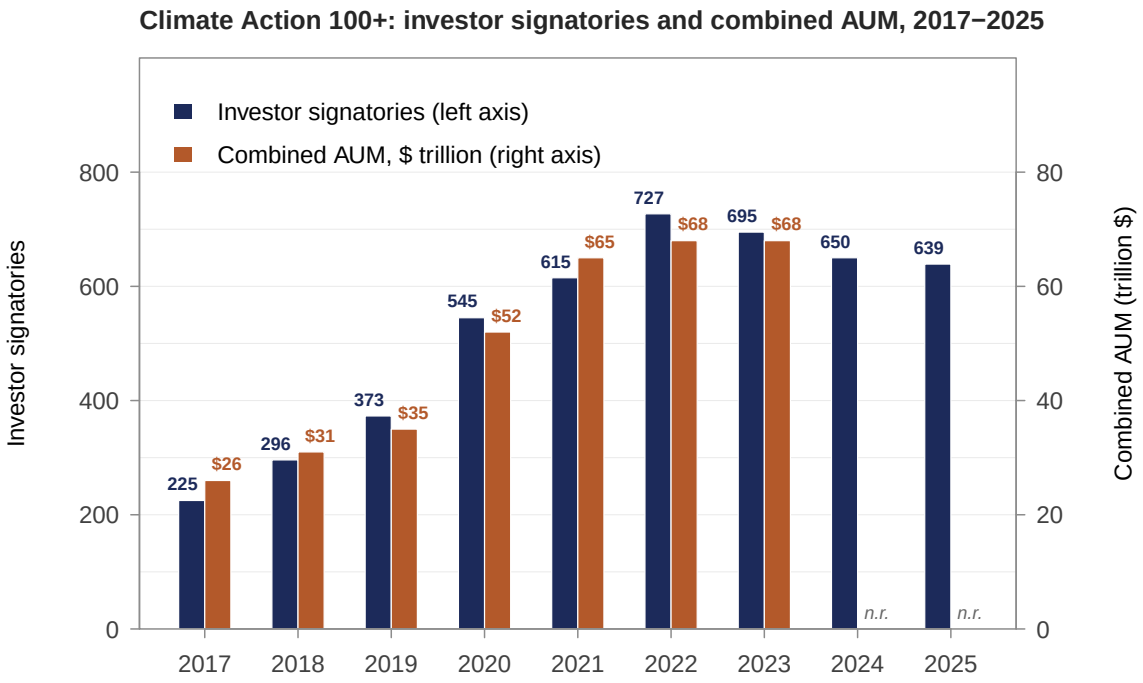


Figure C1: Climate Action 100+: growth and contraction of the investor coalition, 2017–2025. Investor signatories (navy, left axis) and their combined assets under management in trillions of dollars (brown, right axis) at each year-end. Counts for 2017–2021 are from the coalition's progress reports; the 2022–2025 counts are read from December Internet Archive snapshots of the coalition's signatory page. Combined assets were published through 2023 only; "n.r." marks years in which no figure was reported.

Table C1
Climate Action 100+ Focus List, December 2017

This table lists the 100 companies on the Climate Action 100+ Focus List released in December 2017, their country of headquarters, and whether they are included in the energy panel.

#	Company	Country	Panel
1	A.P. Moller - Maersk	Denmark	No
2	Airbus Group	Netherlands	No
3	American Electric Power Company, Inc.	United States	Yes
4	Anglo American	United Kingdom	No
5	Anhui Conch Cement	China	Yes
6	ArcelorMittal	Luxembourg	Yes
7	BASF SE	Germany	Yes
8	Bayer AG	Germany	No
9	Berkshire Hathaway	United States	Yes
10	BHP Billiton	Australia	Yes
11	Boeing Company	United States	No
12	BP	United Kingdom	Yes
13	Canadian Natural Resources Limited	Canada	Yes
14	Caterpillar Inc.	United States	Yes
15	Centrica	United Kingdom	Yes
16	Chevron Corporation	United States	Yes
17	China Petroleum & Chemical Corporation	China	Yes
18	China Shenhua Energy	China	Yes
19	CNOOC	Hong Kong	Yes
20	Coal India	India	No
21	ConocoPhillips	United States	Yes
22	Cummins Inc.	United States	Yes
23	Daikin Industries, Ltd.	Japan	No
24	Duke Energy Corporation	United States	Yes
25	E.ON SE	Germany	Yes
26	Ecopetrol Sa	Colombia	Yes
27	EDF	France	Yes
28	ENEL SpA	Italy	Yes
29	ENGIE	France	Yes
30	Eni SpA	Italy	Yes
31	Exelon Corporation	United States	Yes
32	Exxon Mobil Corporation	United States	Yes
33	Fiat Chrysler Automobiles NV	Netherlands	No
34	Ford Motor Company	United States	No
35	Formosa Petrochemical	Taiwan	Yes
36	Gas Natural SDG SA	Spain	Yes
37	General Electric Company	United States	Yes
38	General Motors Company	United States	No
39	Glencore plc	Jersey	Yes
40	Hitachi, Ltd.	Japan	Yes
41	Hon Hai Precision Industry	Taiwan	No
42	Honda Motor Company	Japan	No
43	Imperial Oil	Canada	No
44	Ingersoll-Rand Co. Ltd.	Ireland	No
45	International Paper Company	United States	Yes
46	JX Holdings, Inc	Japan	Yes
47	Koninklijke Philips NV	Netherlands	No
48	Korea Electric Power Corp	South Korea	Yes
49	LafargeHolcim Ltd	Switzerland	Yes
50	Lockheed Martin Corporation	United States	No
51	Lukoil OAO	Russia	Yes
52	LyondellBasell Industries Cl A	Netherlands	No
53	Marathon Petroleum	United States	Yes
54	Martin Marietta Materials, Inc.	United States	No
55	MMC Norilsk Nickel OSJC	Russia	No
56	Nestlé	Switzerland	No
57	Nippon Steel & Sumitomo Metal Corporation	Japan	Yes
58	Nissan Motor Co., Ltd.	Japan	No
59	NTPC Ltd	India	Yes
60	Oil & Natural Gas	India	Yes
61	OMV AG	Austria	Yes
62	PACCAR Inc	United States	No
63	Panasonic Corporation	Japan	No
64	PepsiCo, Inc.	United States	No
65	PETROCHINA Company Limited	China	Yes
66	Petróleo Brasileiro SA - Petrobras	Brazil	Yes
67	Phillips 66	United States	Yes
68	PJSC Gazprom	Russia	Yes
69	POSCO	South Korea	Yes
70	Procter & Gamble Company	United States	No
71	PTT	Thailand	Yes
72	Reliance Industries	India	Yes
73	Repsol	Spain	Yes
74	Rio Tinto	United Kingdom	Yes
75	Rolls-Royce	United Kingdom	Yes
76	Rosneft Oil Company	Russia	Yes
77	Royal Dutch Shell	United Kingdom	Yes
78	Saic Motor Corporation	China	No
79	Sasol Limited	South Africa	Yes
80	Siemens AG	Germany	Yes
81	SK Innovation Co Ltd	South Korea	Yes
82	Southern Copper Corporation	United States	No
83	Statoil ASA	Norway	Yes
84	Suncor Energy Inc.	Canada	Yes
85	Suzuki Motor Corporation	Japan	Yes
86	Teck Resources Limited	Canada	No
87	Tesoro Corporation	United States	No
88	The Dow Chemical Company	United States	Yes
89	The Southern Company	United States	Yes
90	thyssenkrupp AG	Germany	Yes
91	Toray Industries, Inc.	Japan	Yes
92	Total	France	Yes
93	Toyota Motor Corporation	Japan	Yes
94	United Technologies Corporation	United States	Yes
95	Vale	Brazil	No
96	Valero Energy Corporation	United States	Yes
97	Vedanta Ltd	India	Yes
98	Volkswagen AG	Germany	No
99	Volvo	Sweden	No
100	Wesfarmers	Australia	No

Table C2
Discretionary "+" Companies of Climate Action 100+

This table lists the 61 discretionary "+" companies of Climate Action 100+, their country of headquarters, and whether they are included in the energy panel. These firms were nominated by Climate Action 100+ signatories through a risk-perception survey and are analyzed as CA61.

#	Company	Country	Panel
1	Dangote Cement Plc	Nigeria	No
2	Eskom Holdings SOC Limited	South Africa	Yes
3	ANTAM	Indonesia	No
4	Bumi Resources	Indonesia	No
5	China Steel Corporation	Taiwan	Yes
6	Power Assets Holdings Limited	China	Yes
7	United Tractor	Indonesia	No
8	Air France-KLM	France	No
9	Bayerische Motoren Werke Aktiengesellschaft	Germany	No
10	CEZ, a.s.	Czech Republic	Yes
11	Compagnie De Saint-Gobain S.A.	France	No
12	CRH plc	Ireland	Yes
13	Daimler AG	Germany	No
14	Danone S.A.	France	No
15	Fortum Oyj	Finland	Yes
16	HeidelbergCement AG	Germany	No
17	Iberdrola, S.A.	Spain	Yes
18	Air Liquide S.A	France	Yes
19	National Grid plc	United Kingdom	Yes
20	Peugeot S.A.	France	No
21	PGE Polska Grupa Energetyczna S.A.	Poland	Yes
22	Renault S.A.	France	No
23	RWE Aktiengesellschaft	Germany	Yes
24	Severstal' Pao	Russia	No
25	SSAB AB	Sweden	No
26	SSE plc	United Kingdom	Yes
27	Unilever PLC	United Kingdom	No
28	CEMEX S.A.B. de C.V.	Mexico	No
29	Suzano Papel e Celulose	Brazil	Yes
30	The AES Corporation	United States	Yes
31	American Airlines Group Inc.	United States	No
32	Bunge Limited	United States	No
33	The Coca-Cola Company	United States	No
34	Colgate-Palmolive Company	United States	No
35	Delta Air Lines, Inc.	United States	No
36	Dominion Energy, Inc.	United States	Yes
37	Enbridge Inc.	Canada	Yes
38	FirstEnergy Corp.	United States	Yes
39	Kinder Morgan, Inc.	United States	Yes
40	NextEra Energy, Inc.	United States	Yes
41	NRG Energy, Inc.	United States	No
42	Occidental Petroleum Corporation	United States	Yes
43	PPL Corporation	United States	Yes
44	TC Energy	Canada	Yes
45	United Airlines Holdings, Inc.	United States	No
46	Vistra Energy Corp.	United States	Yes
47	Walmart, Inc.	United States	No
48	WEC Energy Group, Inc.	United States	Yes
49	Weyerhaeuser Company	United States	No
50	Xcel Energy, Inc.	United States	Yes
51	Adelaide Brighton Ltd	Australia	No
52	AGL Energy Ltd	Australia	Yes
53	Bluescope Steel Ltd	Australia	No
54	Boral Ltd	Australia	No
55	Origin Energy Ltd	Australia	Yes
56	Qantas Airways Ltd	Australia	No
57	Santos Ltd	Australia	Yes
58	South32 Ltd	Australia	Yes
59	Woodside Petroleum Ltd	Australia	No
60	Woolworths Group Ltd	Australia	No
61	Devon Energy Corporation	United States	No

Table C3
Investor Engagement and Green Investment

This table reports estimates of equation (3), comparing investment by firms targeted by the Climate Action 100+ engagement initiative with that of non-targeted firms. *CA100-main* comprises the 70 energy-panel firms on the initiative's rule-based list of the 100 largest emitters, selected mechanically using modeled 2015 Scope 1–3 emissions. *CA61* comprises the 29 energy-panel firms on the discretionary list of 61 additional targets selected by investor working groups. Member × Post-2017 equals one for targeted firms after 2017. Each target group is compared with pure non-members of the energy panel, excluding firms in the other target group. The outcomes are the green share of stake-weighted capacity; cumulative stake-weighted green and brown capacity built through greenfield construction and expansion; the green share of new construction; and the log ratio of green to brown construction. Columns (4) and (9) are estimated for firm-years with any construction and define the green share as green capacity built divided by total green and brown capacity built. Columns (5) and (10) report $\ln(1 + \text{green built}) - \ln(1 + \text{brown built})$, defined for every firm-year. All specifications include firm and year fixed effects and use energy-panel firms over 2010–2025. Standard errors, in parentheses, are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	CA100-main (rule-based, 70)					**CA61** (discretionary, 29)				
Dep. var.:	Green share	Total built green (MW)	Total built brown (MW)	Green share of new build	Log ratio green/brown	Green share	Total built green (MW)	Total built brown (MW)	Green share of new build	Log ratio green/brown
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Member × Post-2017	0.027**	77.0**	−67.4**	0.116**	0.753***	0.053***	239.3**	−82.2	0.083	0.913**
	(0.011)	(33.9)	(31.7)	(0.050)	(0.227)	(0.018)	(117.4)	(60.5)	(0.071)	(0.445)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,988	28,533	28,533	6,120	28,533	27,332	27,877	27,877	5,869	27,877
Adj. R^2	0.896	0.544	0.459	0.434	0.220	0.897	0.543	0.439	0.431	0.215

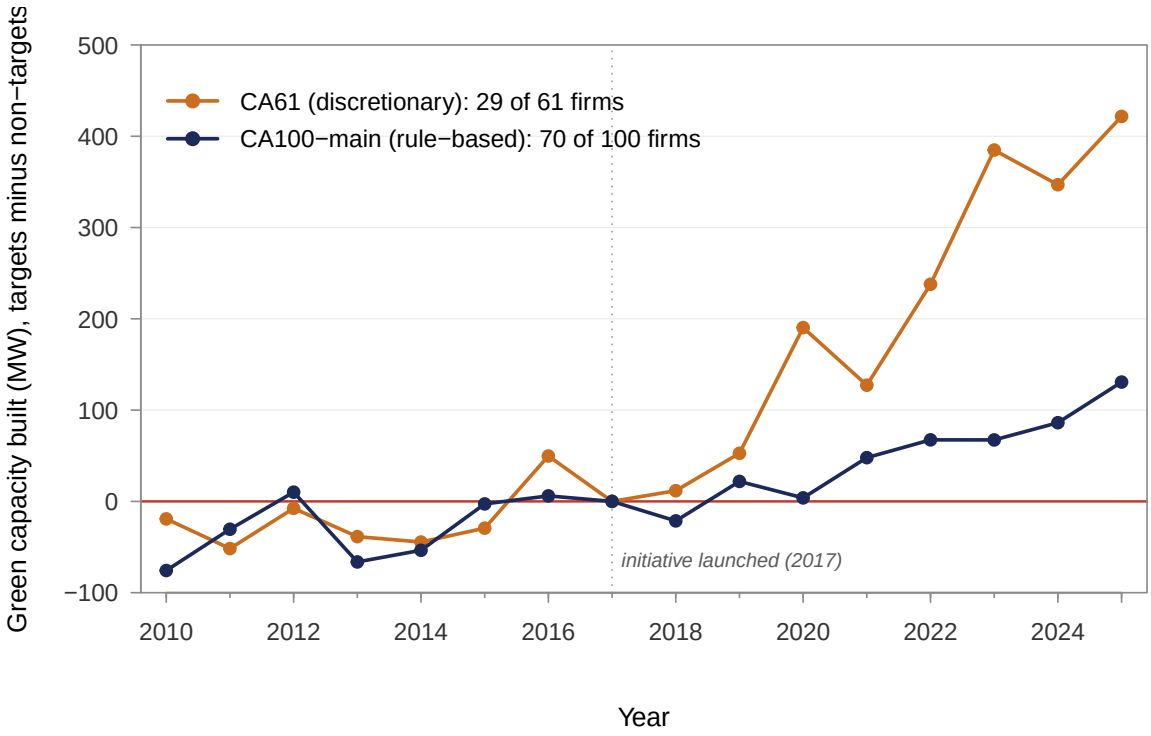


Figure C2: Green Construction by Engagement Targets, by Year. This figure reports estimates from a dynamic version of equation (3), in which the post-2017 indicator is replaced by interactions between target-group membership and calendar-year indicators. The outcome is a firm's annual stake-weighted megawatts of green capacity built through greenfield construction and expansion. Each point estimates the difference between a target group and non-targeted energy-panel firms in the indicated year, relative to 2017, the year Climate Action 100+ launched. The omitted reference year is denoted by the dotted vertical line. Each series is estimated using the relevant target group and pure non-members, excluding firms in the other target group, as in Table C3. Regressions include firm and year fixed effects, cover 2010–2025, and cluster standard errors by firm. The pooled all-members estimate, a weighted average of the two displayed series, is omitted. *CA100-main* comprises the 70 energy-panel firms on the initiative's rule-based list of the 100 largest emitters; *CA61* comprises the 29 energy-panel firms on the discretionary list of 61 additional targets.

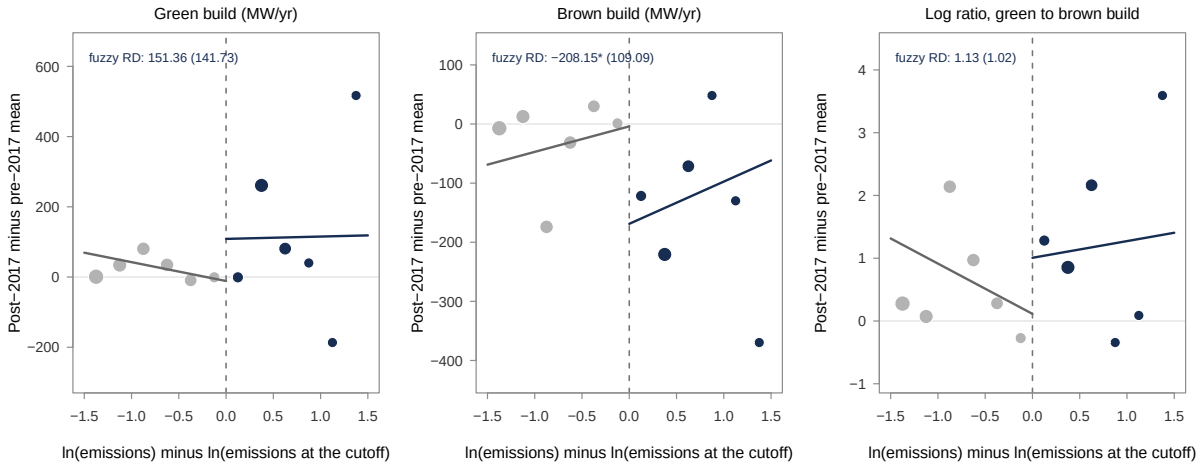


Figure C3: Main outcomes at the focus-list cutoff. The figure uses energy-panel firms, excluding CA61 firms, that are placed in the reconstructed 2015 CDP emissions ranking and lie within 1.5 log points of the cutoff. Each panel plots the change in a firm's annual average outcome between 2010–2017 and 2018–2025 by quarter-log-point bins of the running variable. Marker size is proportional to the number of firms in the bin; dark markers denote firms above the cutoff. Lines are triangular-kernel local-linear fits estimated separately on each side of the cutoff. The outcomes are annual green construction (MW), annual brown construction (MW), and the log ratio of green to brown construction, $\ln(1 + \text{green built}) - \ln(1 + \text{brown built})$. The reported number in each panel is the fuzzy RD estimate at this bandwidth from Table 8, with its heteroskedasticity-robust standard error.

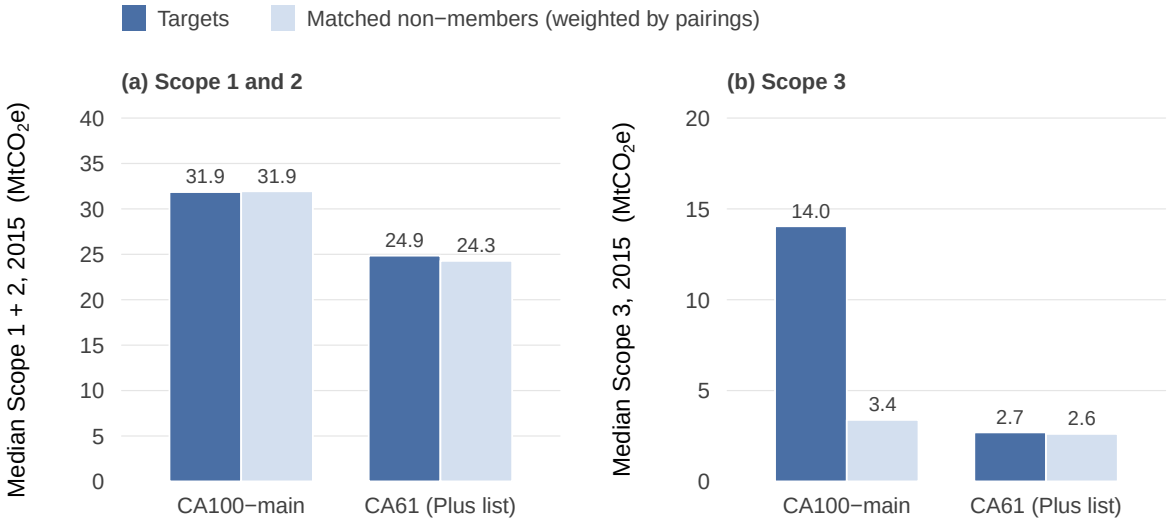


Figure C4: Median Modeled 2015 Emissions of Engagement Targets and Matched Non-Members. This figure compares median 2015 Trucost emissions for engagement targets (dark bars) and non-members matched to them with replacement on log Scope 1 plus Scope 2 emissions (light bars). Matched non-members are weighted by their number of matches, as in Panel A of Table 6. Panel (a) reports Scope 1 plus Scope 2 emissions, and Panel (b) reports Scope 3 emissions, both in million tonnes of CO_2-equivalent. The matching sample includes 65 CA100-main targets matched to 114 non-members and 26 CA61 targets matched to 63 non-members. Because matching is performed on Scope 1 plus Scope 2 emissions, targets and matched non-members have identical distributions of that measure by construction. CA100-main targets have Scope 3 emissions nearly four times those of their matched controls, whereas CA61 targets and their matched controls have similar Scope 3 emissions.

Table C4
Search for the Focus-List Cutoff

For each candidate cutoff c, this table reports the number of CDP 2015 respondents ranked at or above c in the reconstructed Scope 1–3 emissions ranking; the share of firms on the rule-based focus list among firms ranked at or above the cutoff, $\bar{D}_{\leq c}$; the corresponding share among firms ranked from $c+1$ through 400, $\bar{D}_{>c}$; the difference between these shares; and the residual sum of squares (SSE) from the associated two-level step function, $\sum_i (D_i - \hat{D}_i)^2$. $c^* = \arg\max_c \frac{n_{\leq c} n_{>c}}{n_{\leq c}+n_{>c}} \left(\bar{D}_{\leq c} - \bar{D}_{>c}\right)^2$ selects the cutoff that maximizes the between-group sum of squares, equivalently the cutoff that minimizes this SSE. The search considers every rank from 25 through 300; selected candidate cutoffs are shown below. The bolded row reports the selected cutoff.

		Share on focus list			
Cutoff c	Firms $\leq c$	Ranks $\leq c$	Ranks $> c$	Jump	SSE
50	50	0.820	0.066	0.754	28.87
55	55	0.764	0.064	0.700	30.52
60	60	0.750	0.056	0.694	29.19
63	63	0.762	0.047	0.714	**26.67**
65	65	0.738	0.048	0.691	27.79
70	70	0.700	0.045	0.655	29.02
75	75	0.667	0.043	0.624	30.06
80	80	0.625	0.044	0.581	32.14
100	100	0.500	0.047	0.453	38.35

Table C5
Fuzzy Regression-Discontinuity First Stage: Focus-List Assignment

This table reports estimates of $\hat{\pi}_1$ from $\text{CA100}_i = \pi_0 + \pi_1 \mathbf{1}[x_i \geq 0] + f(x_i) + u_i$, the discontinuity at the estimated cutoff (rank 63) in the probability that a firm is included on the rule-based Climate Action 100+ focus list. Specifications vary the functional form for $f(x)$ and the estimation window. The running variable, x, is log 2015 Scope 1–3 emissions relative to emissions of the firm at the cutoff. *Local linear* and *local quadratic* specifications fit $f(x)$ separately on either side of the cutoff within the stated bandwidth, using triangular or uniform kernel weights. Triangular weights are $1 - |x|/h$. *Difference in means* specifications omit $f(x)$. *Rank window* specifications use distance in rank from the cutoff as the running variable and apply a uniform kernel over the indicated number of ranks on each side. The left panel includes all 1,807 CDP 2015 respondents reporting Scope 1 or Scope 2 emissions. The right panel includes energy-panel firms placed in the ranking, excluding CA61 firms, which is the sample used in the fuzzy-RD analysis. F is the squared t-statistic for $\hat{\pi}_1$, and "Firms" reports the number of observations above and below the cutoff within the estimation window. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

		CDP universe (1,807 respondents)			Energy-panel firms in RD sample		
Specification and window	Bandwidth	$\hat{\pi}_1$	F	Firms (above / below)	$\hat{\pi}_1$	F	Firms (above / below)
Local linear, triangular kernel	0.50 log points	0.711*** (0.193)	13.5	22 / 33	0.838*** (0.178)	22.1	12 / 10
Local linear, triangular kernel	0.75 log points	0.503** (0.218)	5.3	31 / 56	0.780*** (0.254)	9.4	18 / 17
Local linear, triangular kernel	1.00 log points	0.553*** (0.192)	8.2	36 / 85	0.789*** (0.232)	11.6	21 / 24
Local linear, triangular kernel	1.50 log points	0.613*** (0.151)	16.5	48 / 142	0.792*** (0.180)	19.4	27 / 42
Local linear, triangular kernel	2.00 log points	0.602*** (0.128)	22.1	58 / 205	0.815*** (0.151)	29.0	35 / 57
Local linear, uniform kernel	1.00 log points	0.590*** (0.180)	10.7	36 / 85	0.761*** (0.219)	12.1	21 / 24
Local linear, uniform kernel	2.00 log points	0.585*** (0.114)	26.4	58 / 205	0.741*** (0.135)	30.2	35 / 57
Local quadratic, triangular kernel	1.00 log points	0.602*** (0.229)	6.9	36 / 85	0.851*** (0.247)	11.9	21 / 24
Local quadratic, triangular kernel	2.00 log points	0.605*** (0.197)	9.4	58 / 205	0.793*** (0.241)	10.8	35 / 57
Difference in means, no $f(x)$	1.00 log points	0.652*** (0.080)	65.8	36 / 85	0.774*** (0.097)	63.5	21 / 24
Difference in means, no $f(x)$	2.00 log points	0.673*** (0.060)	124.3	58 / 205	0.745*** (0.072)	108.5	35 / 57
Rank window, local linear, uniform kernel	±25 ranks	0.361 (0.232)	2.4	25 / 25	0.653** (0.268)	5.9	15 / 6
Rank window, local linear, uniform kernel	±50 ranks	0.551*** (0.158)	12.1	50 / 50	0.809*** (0.168)	23.1	28 / 15
Rank window, local linear, uniform kernel	±100 ranks	0.528*** (0.126)	17.6	63 / 100	0.711*** (0.144)	24.4	40 / 29
Rank window, local linear, uniform kernel	±200 ranks	0.548*** (0.119)	21.1	63 / 200	0.704*** (0.142)	24.6	40 / 55

D Buyer Side: Channels 4 and 5

Table D1
Controlling Owners of Assets Sold by Energy-Panel Firms

This table classifies buyers of plants sold by the 1,997 energy-panel firms between 2010 and 2024 according to the buyer's *controlling owner*: the ultimate parent in the S&P Global ownership hierarchy. A sale occurs when an energy-panel firm's ownership stake in a plant declines. Buyers are owners whose stakes in that plant increase within one year of the sale, excluding greenfield entrants and entities within the seller's corporate group. Sold capacity is allocated across buyers in proportion to the ownership stakes acquired. Panel A classifies controlling owners by S&P company type as reported at the data-export date. Subsidiaries of listed companies, and firms acquired by listed companies since the transaction, are classified as public. Panel B distinguishes controlling owners that are included in the energy panel from those outside it. Panel C uses the controlling owner's GICS industry, mapped to the owner-industry groups. *Brown, full exit* denotes sales in which the seller's stake in a brown plant falls to zero; *Brown, partial* denotes sales in which that stake declines but remains positive; and *Green* includes all green-plant sales. Deals count sale-year events. Shares are based on matched capacity within each asset-sale category.

	Brown, full exit			Brown, partial			Green, any sale		
	Deals	GW	Share	Deals	GW	Share	Deals	GW	Share
Panel A. Controlling-owner type									
Public company	551	150.8	47%	113	11.8	37%	1,755	79.4	68%
Private company	870	141.8	44%	131	17.0	52%	1,260	28.6	24%
Government	96	17.8	6%	37	2.9	9%	200	7.3	6%
Investment fund	41	7.5	2%	1	0.1	0%	73	1.6	1%
Other or unknown	25	2.5	1%	4	0.7	2%	61	0.8	1%
Panel B. Controlling owner inside or outside the energy panel									
Energy-panel firm (incumbent)	564	175.4	55%	97	15.4	48%	926	60.6	52%
Outside the energy panel	968	145.1	45%	185	17.0	52%	2,075	57.0	48%
Panel C. Controlling-owner industry group									
Financial owners	679	107.3	34%	97	8.5	26%	1,342	27.4	23%
Utilities	297	91.0	28%	61	9.0	28%	412	40.5	34%
IPPs & renewable developers	178	53.6	17%	30	2.8	9%	693	25.1	21%
Industrial & other	352	47.8	15%	94	10.0	31%	754	21.9	19%
Oil, gas & coal	85	16.8	5%	21	1.4	4%	84	1.7	2%
Mining & metals	25	4.0	1%	3	0.8	3%	29	0.9	1%
Matched capacity (GW)		320.5			32.5			117.6	
Distinct controlling owners		378			172			377	

Table D2
Buyer Portfolios and the Carbon Intensity of Acquired Assets

This table describes buyers of brown plants fully exited by the 1,997 energy-panel firms between 2010 and 2024. Portfolio measures are calculated in the year before each transaction and are compared with the seller's pre-sale portfolio and the acquired plants. All statistics are weighted by acquired capacity. A portfolio comprises the stake-weighted generating capacity of the buyer's corporate group. The green share is green capacity as a share of total capacity; the coal share is steam-turbine capacity as a share of total capacity. The emissions factor is the capacity-weighted average of technology-specific emissions factors, measured in tCO_2/MWh. "New to generation" is the share of acquired capacity purchased by groups with no generating capacity in the preceding year; these buyers are excluded from portfolio measures. "Browner than the buyer's book" is the share of acquired capacity whose emissions factor exceeds that of the buyer's pre-purchase portfolio. "Buyer's book with the plant added" reports the buyer's portfolio emissions factor after mechanically adding the acquired plant. Buyer type is defined by the S&P company type of the corporate group's controlling owner.

	All buyers	Public	Private	Fund	Gov't, other
Capacity acquired (GW)	320.5	150.8	141.8	7.5	20.3
New to generation (% of GW)	12.7	2.0	21.9	87.7	0.0
Buyer's portfolio, year before purchase					
Green share	0.21	0.22	0.16	0.47	0.38
Emissions factor (tCO_2/MWh)	0.57	0.58	0.57	0.30	0.48
Coal share	0.31	0.35	0.26	0.08	0.30
Portfolio size (GW)	14.9	19.4	6.4	11.1	28.4
Seller's portfolio, year before sale					
Green share	0.22	0.24	0.20	0.06	0.33
Emissions factor (tCO_2/MWh)	0.57	0.56	0.57	0.74	0.51
Portfolio size (GW)	28.3	25.0	34.1	16.1	17.5
Acquired plants					
Emissions factor (tCO_2/MWh)	0.68	0.69	0.66	0.76	0.76
Browner than buyer's book (% of GW)	58	59	56	100	61
Buyer's book with plant added (tCO_2/MWh)	0.60	0.63	0.58	0.31	0.49

Table D3
Buyer Outcomes Following a First Brown-Asset Acquisition

This table reports stacked difference-in-differences estimates from equation (1) for corporate groups that first acquire a brown plant from an energy-panel firm between 2012 and 2020. Treated groups held at least 100 MW of capacity in the year before acquisition; controls are corporate groups meeting the same capacity threshold that never acquire brown capacity from an energy-panel firm and are not treated divesters. Each cohort stack covers event years −3 through +5 and includes group-by-cohort and year-by-cohort fixed effects. Post equals one from the acquisition year onward. Column (1) reports the overall treatment effect. Columns (2) and (3) report effects for public and private-company or fund buyers, respectively, estimated jointly with an indicator for other buyers. Outcomes include portfolio composition, annual construction and acquisitions, capacity stocks, and the portfolio emissions factor. Standard errors are clustered by corporate group and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	All buyers (1)	Public buyers (2)	Private or fund buyers (3)
Green share (0–1)	−0.006	0.038*	−0.056**
	(0.015)	(0.020)	(0.025)
New green construction (MW/year)	72.8***	118.1***	36.2**
	(18.9)	(36.4)	(14.4)
New brown construction (MW/year)	−48.9	−115.6	−9.9
	(37.5)	(72.7)	(23.6)
Green share of new construction (0–1)	0.055	0.068	0.026
	(0.038)	(0.047)	(0.065)
Log ratio of green to brown construction	0.467***	0.731***	0.324*
	(0.160)	(0.280)	(0.184)
Brown acquisitions (MW/year)	55.9	119.1	−19.7
	(86.1)	(156.5)	(97.3)
Green capacity stock (MW)	697.0***	1,212.3***	271.5***
	(215.9)	(434.4)	(100.3)
Brown capacity stock (MW)	459.8**	371.6	500.6***
	(220.7)	(432.4)	(156.5)
Portfolio emissions factor (tCO_2/MWh)	−0.009	−0.025	0.014
	(0.014)	(0.016)	(0.024)
Group × Cohort FE	Yes	Yes	Yes
Year × Cohort FE	Yes	Yes	Yes
Treated groups	104	48	48
Observations	175,144	175,144	

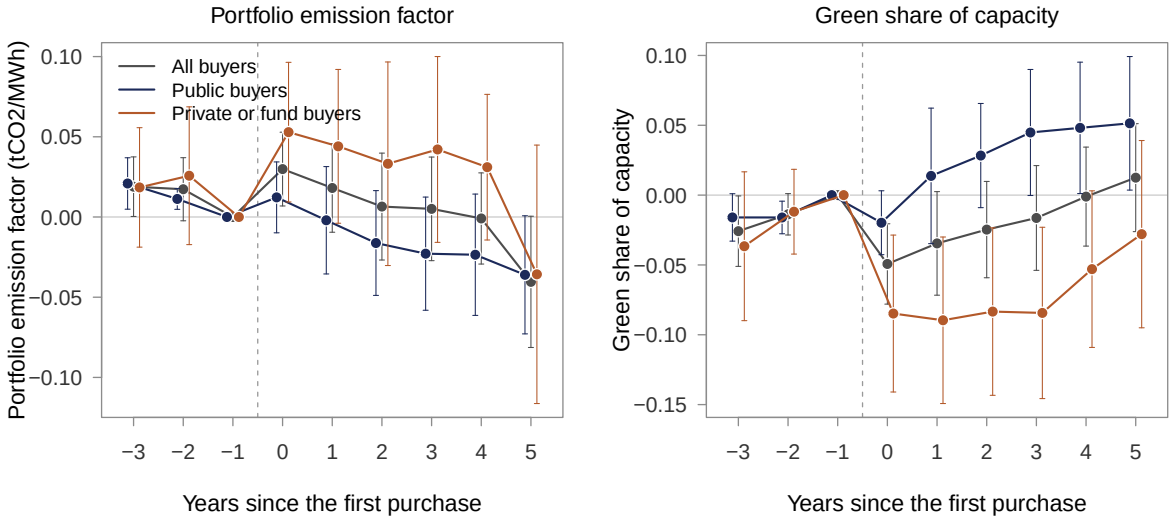


Figure D1: Does Acquiring Brown Assets Make Buyers' Portfolios Browner? This figure reports event-study estimates from the stacked difference-in-differences specification in Table D3. The single post-acquisition indicator is replaced by event-time indicators for the three years before through five years after a buyer's first acquisition of a brown plant from an energy-panel firm. Year −1 is the omitted reference period. Estimates are shown for all 104 buyer groups and separately for 48 public buyers and 48 private-company or fund buyers. The left panel reports the buyer's portfolio emissions factor, measured in tCO_2 per MWh; the right panel reports the green share of portfolio capacity. The control group consists of 2,623 corporate groups that held at least 100 MW in the year before a cohort's acquisitions, never acquired a plant from an energy-panel firm, and are not divesters. Bars denote 95% confidence intervals based on standard errors clustered by corporate group. Buyer-type series are horizontally offset for readability.

Table D4
Does Post-Sale Plant Performance Vary by Buyer Type?

This table re-estimates the plant-level difference-in-differences specification in Table 10, allowing post-sale effects to vary by buyer type. The sample comprises 373 brown plants with measured emissions that are fully exited by 198 treated divesters, and 905 brown plants owned by energy-panel firms that are never fully exited. Regressions include plant and year fixed effects, with standard errors clustered by plant. Each sold plant is assigned the type of its largest-stake external buyer at the time of sale, based on the buyer's controlling owner. Panel A distinguishes public buyers, private-company or fund buyers, and government, other, or unmatched buyers. Panel B distinguishes buyers within the 1,997-firm energy panel, buyers outside the panel, and unmatched sales. Each coefficient is the post-sale change for the indicated buyer type relative to never-sold plants. The final column reports the difference between the first two coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Buyer status				
Dependent variable	Public	Private/fund	Other/unmatched	(1)−(2)
ln(CO_2)	0.004	0.030	−0.072	−0.026
	(0.070)	(0.073)	(0.112)	(0.097)
ln(Generation)	0.139	0.139	0.035	0.000
	(0.098)	(0.092)	(0.174)	(0.129)
ln(CO_2/MWh)	−0.136***	−0.109***	−0.106	−0.026
	(0.047)	(0.040)	(0.120)	(0.059)
ln(Capacity factor)	−0.035	−0.004	0.082	−0.032
	(0.068)	(0.073)	(0.147)	(0.095)
ln(Heat rate)	−0.006	0.007	0.013	−0.013
	(0.009)	(0.012)	(0.011)	(0.014)
Panel B. Buyer location				
Dependent variable	Incumbent	Outsider	Unmatched	(1)−(2)
ln(CO_2)	0.013	0.050	−0.203	−0.037
	(0.073)	(0.067)	(0.127)	(0.095)
ln(Generation)	0.106	0.196**	−0.085	−0.090
	(0.099)	(0.087)	(0.206)	(0.126)
ln(CO_2/MWh)	−0.092**	−0.146***	−0.118	0.053
	(0.044)	(0.041)	(0.149)	(0.058)
ln(Capacity factor)	0.003	−0.007	−0.009	0.010
	(0.071)	(0.068)	(0.178)	(0.093)
ln(Heat rate)	−0.004	0.004	0.018	−0.007
	(0.011)	(0.009)	(0.013)	(0.013)
Plant and year fixed effects	Yes	Yes	Yes	
Observations: CO_2, generation, intensity		10,320		
Observations: capacity factor; heat rate		10,297; 8,916		

E Constructing the Net Emissions Effect

This appendix documents the construction of the net emissions effect (NEE) reported in Table 13. It shows how the five regression estimates in Panel A are converted into the five-year emissions effects in Panel B. All quantities are expressed in million tonnes of carbon dioxide ($MtCO_2$). A negative value denotes lower global emissions relative to the relevant no-transaction counterfactual.

Table 13 combines the paper's two accounting tables. Panel A reports the regression estimate associated with each channel, and Panel B converts each estimate into a five-year emissions effect. The conversion uses the capacity factors, emissions factors, technology mixes, sample counts, and triangular accumulation weight documented below.

E.1 Common Ingredients

Five-year horizon and triangular accumulation weight. Each channel is accumulated over a five-year horizon following the relevant event. Let $H = 5$. A megawatt brought online in year h of the event window operates for the remaining $H - h + 1$ years. Thus, a flow of one MW per year accumulates:

$$T = \sum_{h=1}^{H} (H - h + 1) = 5 + 4 + 3 + 2 + 1 = 15$$

MW-years over the five-year window. Equivalently,

$$T = \frac{H(H+1)}{2} = 15.$$

The same triangular weight is used in Channel 1. If a sale raises the annual probability that a plant retires, the effect accumulates over the remaining years of the five-year window. Under a constant annual incremental retirement hazard, $T = 15$ is therefore the expected number of plant-years avoided per unit increase in the annual hazard.

Converting capacity flows into emissions. For a capacity-flow estimate β, measured in MW per year per firm and applied to n firms, the five-year emissions conversion is:

$$\mathrm{MtCO_2} = \frac{\beta \times n \times \mathrm{CF} \times 8{,}760 \times \mathrm{EF} \times T}{10^6},$$

where CF is the capacity factor, 8,760 is the number of hours in a year, EF is the emissions factor in tCO_2/MWh, and $T = 15$ is the five-year triangular accumulation weight.

For green capacity, EF is the emissions intensity of fossil generation displaced by the incremental green generation. The resulting emissions effect enters with a negative sign. For brown capacity, EF is the technology-specific operating emissions factor, and the result enters with a positive sign.

Confidence intervals. For each channel, I compute a 95% confidence interval by replacing the estimated coefficient $\hat{\beta}$ with:

$$\hat{\beta} \pm 1.96 \times \text{s.e.}(\hat{\beta}),$$

and applying the same conversion formula. The resulting intervals reflect sampling uncertainty in the regression coefficient only. They hold fixed the capacity factors, marginal emissions factors, technology shares, plant emissions base, sample counts, and five-year horizon.

E.2 Parameters

F Conversion Parameters in Detail

Parameter	Value	Source
Operating emissions of plants sold during 2014–2020	289 Mt/year	554 plants at their own operating rates
Divesters in headline Channel 3, n_3	198	All treated divesters; Table 3 estimate
Buyers in Channels 4–5, $n_{4,5}$	106	First-time buyers that are neither divesters nor CA100+ targets
Green capacity factor, divesters, CF_3	0.280	Blended from divesters' 2014–2025 green-construction mix
Green capacity factor, buyers, CF_4	0.248	Blended from buyers' 2014–2025 green-construction mix
Marginal emissions factor, divesters, MEF_3	0.737	Location-weighted fossil-fleet emissions intensity
Marginal emissions factor, buyers, MEF_4	0.728	Location-weighted fossil-fleet emissions intensity
Brown-capacity conversion, buyers, CF × EF	0.244	Share-weighted over buyers' brown-construction mix
Triangular accumulation weight, T	15	$H(H+1)/2$, with $H = 5$

F.1 Green Capacity Factors

Green capacity is converted from MW into MWh using a capacity factor blended from each group's own mix of green technologies constructed between 2014 and 2025. The technology-specific factors are conservative roundings of fleet averages reported in the U.S. Energy Information Administration's *Electric Power Monthly*, Tables 6.07.A–B. Storage technologies receive a capacity factor of zero because they do not generate primary electricity.

The blended capacity factor is the MW-share-weighted average:

$$\mathrm{CF}_g = \sum_k s_{gk} \times \mathrm{CF}_k,$$

where s_{gk} is group g's share of constructed green MW in technology k.

	Share of green MW built		Capacity factor	
Technology	Divesters (Ch. 3)	Buyers (Ch. 4)	Conservative	EIA fleet
Wind	39%	38%	0.30	0.34
Solar	32%	33%	0.20	0.24
Batteries	7%	8%	0	0
Nuclear	8%	4%	0.90	0.92
Hydro	7%	6%	0.40	0.37
Pumped storage	7%	9%	0	0
Geothermal; fuel cells	0%	0%	0.75 / 0.55	0.70 / 0.55
Blended capacity factor (conservative)	**0.280**	**0.248**		
Blended capacity factor (EIA fleet)	0.308	0.275		

F.2 Marginal Emissions Factors

Each MWh of new green generation is valued at the emissions intensity of the fossil generation it displaces. The national benchmark is the ratio of measured CO_2 emissions to net generation for all U.S. brown plants reporting both variables, averaged over 2015–2025:

$$\mathrm{MEF}_{\mathrm{US}} = 0.731 \text{ tCO}_2/\mathrm{MWh}.$$

Regional factors are constructed using the same ratio within each NERC region. Each green plant receives its region-specific factor if it is located in the United States and has a known NERC region. Green plants outside the United States, or U.S. plants without a known region, receive the national factor. The group-specific marginal emissions factor is then the MW-weighted mean:

$$\mathrm{MEF}_g = \sum_r s_{gr} \times \mathrm{MEF}_r.$$

		Divesters (Ch. 3)		Buyers (Ch. 4–5)	
Where green MW were built	Factor	GW	Share	GW	Share
Outside the United States (national factor)	0.731	168.9	55%	38.4	59%
United States: TRE (Texas)	0.697	33.2	11%	5.1	8%
United States: WECC (West)	0.734	32.9	11%	9.3	14%
United States: SERC (Southeast)	0.686	29.9	10%	5.2	8%
United States: MRO (Upper Midwest)	0.933	27.1	9%	3.3	5%
United States: RFC (Mid-Atlantic)	0.776	10.3	3%	1.7	3%
United States: NPCC (Northeast)	0.493	6.8	2%	2.2	3%
United States: region unknown (national factor)	0.731	0.6	0%	0.1	0%
Green capacity built, 2014–2025 (GW)		309.7		65.1	
Weighted marginal emissions factor		**0.737**		**0.728**	

F.3 Channel-by-Channel Calculations

Channel 1: Asset survival, -46 MtCO$_2$. The linear discrete-time retirement-hazard regression yields:

$$\hat{\beta}_1 = 0.0107, \qquad \text{s.e.}(\hat{\beta}_1) = 0.0022.$$

Thus, after sale, a brown plant is 1.07 percentage points more likely to retire in a given year than a matched never-sold plant. The baseline annual retirement hazard among matched controls is 0.60%.

Over the five-year window, the estimated increase in the retirement hazard implies:

$$0.0107 \times 15 = 0.1605$$

expected plant-years of operation avoided per sold plant. The calculation uses the 554 plants sold between 2014 and 2020, whose stake-weighted annual operating emissions sum to 289 MtCO$_2$ per year. The resulting Channel 1 effect is:

$$\text{Ch}_1 = -\hat{\beta}_1 \times T \times 289 = -0.0107 \times 15 \times 289 = -46 \text{ MtCO}_2.$$

The 95% coefficient interval is:

$$0.0107 \pm 1.96(0.0022) = [0.0064,\ 0.0150].$$

Applying these endpoints to the same conversion gives:

$$[-66,\ -27]\ \mathrm{MtCO_2}.$$

Channel 2: Post-sale plant operation, +2 $\mathbf{MtCO_2}$. The plant-level difference-in-differences regression yields:

$$\hat{\beta}_2 = 0.002, \qquad \text{s.e.}(\hat{\beta}_2) = 0.049,$$

where the outcome is ln(Plant CO_2). The point estimate is close to zero and is not statistically distinguishable from zero.

I apply the estimated log change proportionally to the counterfactual five-year emissions base, $A = 1{,}016\ \mathrm{MtCO_2}$:

$$\mathrm{Ch}_2 = A\left(1 - e^{-\hat{\beta}_2}\right) = 1{,}016\left(1 - e^{-0.002}\right) = +2\ \mathrm{MtCO_2}.$$

The 95% coefficient interval is:

$$0.002 \pm 1.96(0.049) = [-0.094,\ 0.098].$$

Applying these endpoints gives:

$$[-101,\ +95]\ \mathrm{MtCO_2}.$$

Channel 3: Seller green reallocation, −247 $\mathbf{MtCO_2}$. The headline all-divester estimate comes from the stacked difference-in-differences regression in Table 3. It implies that treated divesters build:

$$\hat{\beta}_3 = 46.0\ \mathrm{MW}$$

more green capacity per year after divestment than never-divesting firms, with:

$$\text{s.e.}(\hat{\beta}_3) = 19.5.$$

Applying this estimate to all 198 treated divesters, using the divesters' blended capacity factor of 0.280 and location-weighted marginal emissions factor of 0.737 $\mathrm{tCO_2/MWh}$, gives:

$$\mathrm{Ch}_3 = -\frac{46.0 \times 198 \times 0.280 \times 8{,}760 \times 0.737 \times 15}{10^6} = -247\ \mathrm{MtCO_2}.$$

The 95% coefficient interval is:

$$46.0 \pm 1.96(19.5) = [7.9,\ 84.1].$$

Applying these endpoints gives:

$$[-452,\ -42]\ \mathrm{MtCO_2}.$$

Channel 4: Buyer green investment, -67 $\mathbf{MtCO_2}$. The buyer stacked difference-in-differences regression yields:

$$\hat{\beta}_4 = 26.8\ \mathrm{MW}, \qquad \text{s.e.}(\hat{\beta}_4) = 8.4.$$

Thus, the 106 eligible first-time buyers build 26.8 MW more green capacity per year after their first acquisition than comparable owners that never acquire brown plants from a panel firm.

Using the buyers' blended capacity factor of 0.248 and their location-weighted marginal emissions factor of 0.728 $\mathrm{tCO_2/MWh}$ gives:

$$\mathrm{Ch}_4 = -\frac{26.8 \times 106 \times 0.248 \times 8{,}760 \times 0.728 \times 15}{10^6} = -67\ \mathrm{MtCO_2}.$$

The 95% coefficient interval is:

$$26.8 \pm 1.96(8.4) = [10.3,\ 43.3].$$

The corresponding emissions interval is:

$$[-109,\ -26]\ \mathrm{MtCO_2}.$$

Channel 5: Buyer brown construction, $+62$ $\mathbf{MtCO_2}$. The same buyer regression yields:

$$\hat{\beta}_5 = 18.3\ \mathrm{MW}, \qquad \text{s.e.}(\hat{\beta}_5) = 17.1.$$

Thus, buyers build an estimated 18.3 MW more brown capacity annually than the control group, although this estimate is not statistically distinguishable from zero.

Using the buyers' technology-weighted brown-capacity conversion, $\mathrm{CF} \times \mathrm{EF} = 0.244$,

gives:

$$\mathrm{Ch}_5 = +\frac{18.3 \times 106 \times 0.244 \times 8{,}760 \times 15}{10^6} = +62 \text{ MtCO}_2.$$

The 95% coefficient interval is:

$$18.3 \pm 1.96(17.1) = [-15.2,\ 51.8].$$

The corresponding emissions interval is:

$$[-52,\ +176] \text{ MtCO}_2.$$