Climate strikes and corporate emissions*

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Abstract

Can geographically proximate activism induce real changes in corporate environmental performance? We exploit geocoded data on the September 2019 Global Climate Strikes and US corporate headquarters locations in a difference-in-differences design. Firms headquartered within a 5 km radius of a strike reduce Scope 1 emissions by approximately 12% and Scope 2 emissions by 7% in subsequent years, corresponding to roughly 5.3 million tons of CO_2 across treated firms. Scope 3 emissions also decline sharply, although these effects partly reflect reporting adjustments. These reductions occur under the absence of pre-trends and without measurable ex-post declines in profitability or market valuation, suggesting that firms adjust along efficiency-enhancing margins. Effects are concentrated in low-emission industries and firms with more gender-diverse boards, increase with crowd size and favorable protest settings (dry weather, walkability, and large metropolitan cities), and attenuate with increasing treatment radius size, consistent with a localized stakeholder pressure mechanism. Our findings provide causal evidence that, despite lacking formal governance rights, spatially proximate social movements can function as an informal external governance mechanism that shapes real corporate environmental outcomes.

Keywords: Corporate environmental responsibility, Climate activism, Carbon emissions, Social movements, Firm environmental behavior.

JEL classification: D22, G30, M14, Q56.

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1 Introduction

Can actors with no ownership stake, voting rights, or formal governance access discipline firms' real environmental behavior? Standard models of corporate governance emphasize monitoring and intervention by capital providers, regulators, and boards. Yet, firms are also exposed to geographically concentrated stakeholders who can impose reputational costs without formal authority. We examine whether localized, non-investor stakeholder activism can induce economically meaningful reductions in corporate carbon emissions.

To address this question, we draw on the 2019 Global Climate Strike, the largest coordinated protest movement in history (Martiskainen et al., 2020). Over two consecutive Fridays (September 20 and 27), more than seven million people worldwide, many of whom high school students and adolescents, took to the streets demanding climate action. While the strikes received widespread media coverage, they also directly exposed firms headquartered near protest sites to salient, visible stakeholder pressure.[1] Because headquarters locations are predetermined and the strikes occurred on fixed dates, proximity captures differential exposure to a sudden, localized increase in stakeholder scrutiny. Our identification exploits fine-grained cross-sectional variation in the geographic distance between corporate headquarters and protest sites. We compare firms within the same metropolitan areas and examine how emission outcomes vary with proximity to protest locations.

We conceptualize climate strikes as an informal external governance shock that increases the expected reputational cost of environmental underperformance. Firms are accountable not only to capital providers but also to stakeholders, whose pressure can impose economic costs when environmental practices fall short of expectations. Prior research shows that institutional investors influence corporate environmental outcomes through formal governance mechanisms (Dyck et al., 2019; Flammer et al., 2021). In contrast, climate activism lacks formal authority but may nonetheless affect managerial incentives by increasing public visibility and scrutiny. Geographic proximity further amplifies this channel, as local audiences are more exposed to protest activity and better positioned to monitor and respond, thereby shifting managerial trade-offs between abatement costs and the expected costs of environmental backlash.[2]

[1]There is an abundance of anecdotal accounts of large firms publicly acknowledging the protests, and in some cases temporarily closing offices or allowing participation, underscoring the salience of the events for nearby corporations (Ivanova, 2019; Garcia, 2019; Wired, 2019).

[2]This is consistent with evidence that individuals living near protest sites align their attitudes with those of the protesters (Andrews et al., 2016; Xu and Guo, 2023).

To analyze whether such pressure affects corporate environmental performance, we use geolocated US headquarters and protest data matched to firm-specific emissions. Because emission disclosure was voluntary during our sample period, our analysis is limited to reporting firms, which we address by using a two-step estimation procedure that accounts for the propensity to disclose emissions. We find that firms headquartered within 5 km of protest sites experience significant post-strike declines in emission intensity, with these effects diminishing with treatment distance, consistent with localized exposure driving strategic adjustments. These reductions are economically meaningful. Scope 1 and Scope 2 intensities fall by roughly 12% and 7%, respectively, corresponding to a cumulative reduction of about 5.3 million tons across treated firms in the post-strike period. These reductions occur without detectable impacts on next-year profitability (ROA or Tobin's Q), suggesting efficiency-oriented rather than costly compliance responses. Scope 3 emissions decline sharply as well but should be interpreted with caution, as they are more likely than the other scopes to result from changes in accounting practices. The highly localized pattern and absence of pre-trends support a causal interpretation of nearby activist exposure, distinct from broader ESG or macro shocks.

Cross-sectional analyses further reveal that these effects are concentrated among firms in low-emission industries (Ilhan et al., 2021; Martinsson et al., 2024), and those with above-median board gender diversity (Bear et al., 2010; Byron and Post, 2016; Liu, 2018; Post et al., 2011), consistent with emission abatement costs and internal governance amplifying sensitivity to external legitimacy pressures. We further document that emission reductions increase linearly with attendance size. Effects are also stronger when strikes are held in non-rainy locations, highly walkable areas, and large metropolitan centers, conditions typically favoring higher protest turnout and visibility. In sum, the results of these analyses highlight that both firm characteristics and protest salience are key transmission channels through which collective action influences corporate environmental behavior.

Altogether, we provide causal evidence that localized social movements can shape firm behavior, advancing several strands of literature. First, we contribute to research on corporate responses to collective social action. While prior work on movements like Black Lives Matter, Occupy Wall Street, and #MeToo focuses on market reactions (e.g., Billings et al., 2022; Neu et al., 2022; Brownen-Trinh and Orujov, 2023; Barrett et al., 2024; Pajuste et al., 2024), we show that the Global Climate Strike prompted real operational adjustments in corporate environmental performance, beyond capital movements and investor reallocations (Fang and Parida, 2025; Ramelli et al., 2021; Schuster et al., 2023).

Second, we contribute to the literature on geographic proximity in finance (e.g., Alam et al., 2014; Kuchler et al., 2022; Mengoli et al., 2025; Petersen and Rajan, 2002) by identifying localized grassroots collective action as a distinct pressure mechanism. Using geolocation data, we document a sharp spatial gradient in treatment effects, with emission reductions concentrated among firms headquartered within a narrow radius of protest sites and attenuating rapidly with distance. The effects are strongest under high-visibility protest conditions and in settings where abatement costs are lower, consistent with a salience-driven pressure channel rather than aggregate shocks.

Third, we extend research on local social environments and stakeholder pressures. One line of work identifies local factors such as county religiosity, political affiliation, media partisanship, and regional culture in shaping firm policies and decision-making (e.g., Callen and Fang, 2015; Di Giuli and Kostovetsky, 2014; Guiso et al., 2006; Hilary and Hui, 2009; Knill et al., 2022; Kumar et al., 2011), while another stream studies the environmental outcomes of more formal governance channels, such as governments, shareholder activists, and institutional investors (Barko et al., 2022; Dimson et al., 2015; Dyck et al., 2019; Flammer et al., 2021; Jouvenot and Krueger, 2019). We extend these fields by showing that firms adjust real emissions in response to discreet, highly visible activism organized by actors without formal governance rights. This evidence suggests that corporate environmental behavior is shaped not only by capital market and governmental discipline but also by geographically proximate social movements.

Finally, our results carry implications for policymakers, activists, and regulators. Highly localized collective action may effectively influence corporate environmental responsibility by inducing efficient voluntary reductions—effects, strongest where proximity meets visibility and abatement costs are low. For regulators, the evidence suggests that high-emitting firms or those with weaker sensitivity to stakeholder pressures may require more direct oversight to achieve emissions reductions. Overall, our results demonstrate that where and how social pressure is applied matters, and that geographically localized activism can produce meaningful corporate climate action.

2 Data and model

2.1 Sample and emission data

Our sample collection starts from the Compustat universe, where we obtain information on all US-headquartered companies. We further augment this data using CRSP, and

LSEG ESG over the period 2016-2023. We exclude observations with missing control variables as described in Section 2.3. To enable robust pre-post comparisons, we require firms to have all data available for at least two years before and two years after the September 2019 climate strikes, that is, from 2017 to 2021. Applying these criteria results in a sample of 1,512 firms and 11,970 observations.

Next, we add firm-level CO_2-equivalent emissions to the sample. Consistent with prior literature, we rely on Scope 1, Scope 2, and Scope 3 emissions from LSEG ESG, which are directly reported by firms or via direct filings to the CDP (Ardia et al., 2023; Seltzer et al., 2022). Scope 1 captures direct emissions from sources owned or controlled by the firm, Scope 2 captures indirect emissions from purchased energy, and Scope 3 encompasses all other indirect emissions across the firm's value chain. We winsorize all emissions at the 1% level and analyze both revenue-scaled and unscaled values. Restricting the sample to reporting firms yields 579 firms and 4,430 observations. Specifically, 570 firms report Scope 1 emissions, 567 report Scope 2, and 414 report Scope 3 emissions.

We acknowledge that reported emissions are subject to measurement concerns. During our sample period, disclosure was largely voluntary[3], and firms may have revised historical data (Cohen et al., 2025), which may introduce noise in absolute levels. Nevertheless, reported emissions are the economically relevant measure in our setting. Because we examine the impact of local climate strike exposure, our identification relies on firm-specific responses, which are reflected in reported disclosures but not captured by third-party estimates. Vendor-based estimates often mechanically reflect firm size and industry averages (Aswani et al., 2024), potentially obscuring variation central to our identification. Moreover, our design exploits within-firm changes around a discrete event. Even if absolute levels contain noise, differential year-to-year changes remain informative, whereas model-based estimates may fluctuate due to methodological updates unrelated to firm behavior, adding noise to our event-based approach.

2.2 Strike and headquarters locations

2.2.1 Climate strikes

Our primary source of strike location data comes from Fridays For Future (FFF), which granted us access to its historical event database.[4] Events are based on standardized

[3]The SEC has since adopted new rules to enhance and standardize climate-related disclosures for investors. See https://www.sec.gov/newsroom/press-releases/2024-31.

[4]We thank Fridays For Future for access and clarification of their data procedures.

strike reports including date, city, and estimated attendance. We focus on September 20 and 27, 2019, the two major Global Climate Strike dates, and identify 997 U.S.-based events.[5] Because FFF data rely on voluntary reporting, some events may be unobserved. To mitigate potential undercoverage, such as events organized by other groups (e.g., Future Coalition, Earth Strike, 350.org), we augment the data using the Crowd Counting Consortium (CCC).[6] The CCC compiles structured data on U.S. political protests from media and open sources. We identify climate-related events and incorporate locations not already covered by FFF, yielding 114 additional events and a total of 1,111 strike locations.

Location information typically includes city and state or a focal point. For suburbs or urban villages, we assign the geographic center as the strike point, while for major cities, we use city hall as the reference point. This assumption is consistent with evidence that climate strikes predominantly occurred in central-city or downtown areas, where visibility, institutional proximity, and public accessibility are highest (Ferstl, 2025; Heaney and Rojas, 2006).[7] Because these events were generally mobile, we define treatment using a radius around each geocoded location (see Section 2.2.3).

In practice, we use the Google Maps API to identify strike sites by querying "city hall" in combination with the respective city and state, or the name of the urban village or suburb in combination with the the primary city of the metropolitan area and the state. We extract the corresponding longitude and latitude coordinates and use these as the strike location points and plot these in Figure 1a. Strike locations are geographically dispersed across all major census regions, including the Northeast, Midwest, South, and West, as well as Alaska and Hawaii. Events cluster in densely populated metropolitan areas, particularly along the Northeast megalopolis (Boston–New York–Washington, D.C.), the West Coast, South Florida, and major urban centers in the Midwest, Texas, and Colorado.

$<$ Insert Figure 1 about here. $>$

[5] Attendance figures are noisy, but in Table 10 we show that emission reductions scale with crowd size. Event-study estimates reveal no differential pre-trends.

[6] See https://ash.harvard.edu/programs/crowd-counting-consortium/.

[7] For illustration purposes, in New York City, protesters assembled at Foley Square in Lower Manhattan and marched toward Battery Park, traversing the city's financial and governmental districts (Lee, 2019). In New Haven, participants gathered at New Haven Green, a large park right at the center of the downtown area and across from the city hall (Martiskainen et al., 2020). In Chicago, students gathered at Grant Park, a stone's throw away from the Chicago city hall (Rodriguez, 2019), while in Los Angeles, students gathered downtown at Pershing Square to directly march towards city hall (Aldridge, 2019). Similar patterns were observed in cities such as Washington, D.C., and Seattle, where rallies and marches took place in downtown near city halls, and central business districts.

2.2.2 Corporate headquarters location

We identify strike exposure through proximity to firm headquarters, as they are at the center of strategic decision-making that shapes firms' carbon footprints (Birkinshaw et al., 2006; Mintzberg, 1979). Corporate headquarters locations are drawn from firms' annual report filings with the SEC. While several commercial databases provide headquarters addresses, there is a risk that they overwrite historical address information following relocations (see Gao et al., 2021). This is particularly problematic given the recent uptick in headquarters relocations among publicly traded US firms.[8] To avoid that incorrect addresses would result in a misclassification of firms' treatment status, we ensure historical accuracy by extracting the 2019 headquarters addresses from firms' 10-K filings for fiscal year 2020, which report the address of the principal executive offices on the cover page. We then geocode these addresses using the Google Maps API to obtain precise longitude and latitude coordinates. These coordinates are used to calculate distances between firms and strike locations in our empirical analysis.

We report the locations of the corporate headquarters of our sample firms in Figure 1b. Headquarters are heavily concentrated in major metropolitan areas, particularly in the coastal regions and important inland cities, while rural regions and the Mountain West exhibit less coverage.

2.2.3 Identifying treatment status

This paper aims to examine how exposure to climate strike events has altered corporate emissions in subsequent years. Exposure to these strikes should subject firms to the dynamics of collective action, making external stakeholder pressures more tangible. Given the absence of exact protest route data, we consider a firm as treated if its headquarters lies within a 5 km radius of any of our identified strike locations. Given the mobilie nature of the strikes, we believe the 5 km buffer strikes a reasonable balance between capturing meaningful exposure and limiting misclassification of firms with minimal likelihood of contact. Any remaining measurement error in exposure should bias our estimates toward zero.[9]

[8] According to recent estimates, 8.9% of US publicly traded corporations in the US moved their headquarters during the 2022 fiscal year, see https://www.worldpropertyjournal.com/real-estate-news/united-states/miami-real-estate-news/commercial-real-estate-news-2023-corporate-headquarters-relocation-report-corporate-relocations-data-top-cities-companies-are-moving-to-in-2023-13731.php.

[9] In Table 14, we will increase this radius to 10 km and 25 km and document such an attenuating effect.

In Figure 2, we plot the distribution of our firms alongside the strike locations. Overall, of the 579 firms in our sample, we consider 192 as treated, as they are located within a 5 km radius of a strike event, while 387 are considered untreated. Out of these 192 firms, 187 report Scope 1 emissions, 186 report Scope 2 emissions and 149 report Scope 3 emissions. For illustration purposes, we further present examples of this treatment identification procedure for both the Phoenix city area and Seattle city area in Figure 3.

< Insert Figures 2 and 3 about here. >

2.3 Control variables

We control for a broad set of firm-level characteristics drawn from Compustat and CRSP. Detailed variable definitions are provided in Appendix A.

From Compustat, we construct the following accounting-based controls. Firm size is measured as the natural logarithm of market capitalization, computed as the product of share price and shares outstanding. The book-to-market ratio is the natural logarithm of the ratio of book equity to market capitalization. Profitability is proxied by return on assets, computed as net income scaled by total assets. Leverage is defined as the total debt scaled by book equity. Asset growth is computed as the year-over-year percentage change in total assets, sales growth as the year-over-year percentage change in revenues, and earnings per share growth as the year-over-year percentage change in diluted earnings per share. The natural logarithm of property, plant, and equipment enters the regressions to control for capital intensity. Industry competition is captured by the Herfindahl–Hirschman Index (HHI), constructed at the two-digit SIC level for each year as the sum of squared market shares, where each firm's market share is computed as its revenues relative to total industry revenues.

From CRSP, we construct two risk measures. Market beta is estimated using a 60-month rolling regression of firm excess returns on market excess returns following the Capital Asset Pricing Model (CAPM). Idiosyncratic volatility is estimated as the standard deviation of residuals from a 21-day rolling regression of firm returns on the Fama-French three-factor model. Factor returns for both estimations are obtained from the Kenneth French Data Library.[10]

Furthermore, we control for county- and state-level variables. Following Zhang et al. (2024), we construct a county-level measure of climate change social norms (CCSN) using

[10] See, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

principal component analysis applied to survey responses from the Yale Climate Opinion Maps. Specifically, for each county and year, the CCSN measure is derived from three survey items: the estimated percentage of residents who are somewhat or very worried about global warming, the estimated percentage who believe global warming is happening, and the estimated percentage who think global warming will harm people in the United States a moderate amount or a great deal. The first principal component of the sum of these three items is extracted separately for each year over the sample period, yielding a time-varying, county-level index that captures the local prevalence of climate change concerns. Firms are matched to their county of headquarters to obtain the corresponding CCSN value.

At the state level, we control for two policy-related variables. First, we include an indicator for whether the state participates in the Regional Greenhouse Gas Initiative (RGGI), a mandatory cap-and-trade program covering CO_2 emissions from the power sector. Second, we control for the stringency of state-level greenhouse gas emissions targets, distinguishing between targets that are statutory, executive, recommended, or combinations thereof, to account for the heterogeneity in the regulatory environment faced by firms across states.

All continuous variables are winsorized at the 1% level to mitigate the influence of outliers.

2.4 Empirical strategy

We use a difference-in-differences specification to assess the effect of the proximity to the 2019 Global Climate Strikes on corporate emissions reductions. Our baseline specification takes the following form:

$$\ln(Emissions_{it}) = \beta_0 + \beta_1 Strike_i + \beta_2 Strike_i \times Post_t + \mathbf{X}'_{it}\gamma + \alpha_t + \delta_j + \epsilon_{it}, \qquad (1)$$

where $\ln(Emissions_{it})$ is the natural logarithm of reported Scope 1, Scope 2, or Scope 3 emissions for firm i in year t, measured either scaled by revenues or unscaled. $Strike_i$ is an indicator variable equal to one if firm i's headquarters is within 5 km of a climate strike location, and zero otherwise. $Post_t$ is an indicator equal to one for years 2020 onward (i.e., after the September 2019 strikes). $\mathbf{X}_{it}$ is the vector of time-varying firm-level controls, county-level controls, and state-level policy controls defined in Section 2.3. α_t and δ_j denote year and industry (two-digit SIC) fixed effects, respectively. Standard errors are two-way clustered at the firm and year levels to account for serial correlation within firms and common shocks across firms and within years.

Corporate emissions disclosure was voluntary during our sample period, which may introduce self-selection bias if the decision to disclose is correlated with unobserved firm characteristics that also affect emission levels. To address this concern, we estimate a first-stage probit model using the full sample of 11,970 observations, predicting the probability of disclosing Scope 1, Scope 2, and Scope 3 emissions separately. The selection equation includes the full set of control variables, the treatment status, and the average disclosure rate of emissions within the firm's two-digit SIC industry. The industry-level disclosure captures industry-specific norms and peer effects that influence the disclosure decision but are unlikely to directly affect a firm's emission levels, conditional on the included controls. From each first-stage probit regression, we compute the inverse Mills ratio (IMR), which captures the expected value of the error term conditional on selection into disclosure. The IMR is then included as a control variable in all second-stage regressions to correct for potential self-selection bias.[11]

The coefficient of interest in Eq. (1) is β_2, which captures the differential change in emissions for firms in the post strike period relative to control firms. Under the parallel trends assumption, β_2 identifies the causal effect of localized exposure to climate strikes on corporate emissions.

To assess the validity of the parallel trends assumption and examine the timing of treatment effects, we estimate a dynamic specification that replaces the single post-treatment interaction with separate interactions for each year relative to the strike event:

$$\begin{aligned}\ln(Emissions_{it}) = \beta_0 + \beta_1 Strike_i + \sum_{k=1}^{3} \mu_k Strike_i \times Before_k \\ + \sum_{k=1}^{4} \eta_k Strike_i \times Post_k + \mathbf{X}'_{it}\gamma + \alpha_t + \delta_j + \epsilon_{it},\end{aligned} \tag{2}$$

where $Before_k$ is an indicator variable equal to one for year $2019 - k$ (e.g., $Before_1$ corresponds to 2018), and $Post_k$ is an indicator variable equal to one for year $2019 + k$ (e.g., $Post_1$ corresponds to 2020). The reference year is 2019, the year in which the climate strikes occurred. The coefficients μ_1, μ_2, and μ_3 test for pre-treatment differences in trends between treated and control firms, while η_1, η_2, η_3, and η_4 capture the dynamic evolution of treatment effects in the four years following the strikes. Insignificant pre-treatment coefficients support the parallel trend assumptions, while the post-treatment

[11] We report the results of the first-stage Probit regressions for our main results in Appendix B.

coefficients reveal whether emission reductions are immediate, gradual, or delayed.

To ensure covariate balance and improve the comparability of treated and control groups, we implement entropy balancing on firm-level controls (Hainmueller, 2012). Entropy balancing is a preprocessing method that reweights control observations to match the first, second, and third moments (mean, variance, and skewness) of treated firms' covariate distributions in the pre-treatment period.

3 Results

3.1 Descriptive statistics

We display the summary statistics of our treated firms and our control sample in Table 1 alongside a direct comparison in Table 2. The two groups are broadly comparable with respect to raw emission levels, profitability, growth, and industry concentration. Although treated firms are modestly larger on average, it appears that these firms are not mechanically more polluting ex-ante as their Scope 1 emission intensity is somewhat lower. On the other hand, their raw Scope 3 emissions are more sizeable. The most important differences across the two groups reside in their systematic risk and idiosyncratic volatility, where treated firms exhibit significantly lower levels. Furthermore, treated firms tend to be located in counties with higher CCSN and in states that are more likely to participate in the RGGI. The correlation matrix is presented in Appendix C.

$<$ Insert Tables 1 and 2 about here. $>$

3.2 Carbon strikes and corporate carbon emission

In Table 3 we report difference-in-differences estimates of the effect of the 2019 climate strikes on corporate greenhouse gas emissions. Columns (1) through (6) present results for Scope 1, Scope 2, and Scope 3 emissions, reported both as emission intensity (Panel A) and in levels (Panel B). Firms headquartered within 5 km of a strike location experience statistically significant post-2019 reductions across specifications. We find no evidence of differential pre-trends in the three years prior to the strikes, and the estimated effects are concentrated among nearby firms, supporting a localized exposure mechanism rather than aggregate shocks or nationwide information diffusion. Figure 4 illustrates the corresponding dynamic treatment effects for all three emission scopes.

$<$ Insert Table 3 and Figure 4 about here. $>$

Our results are economically meaningful. The main post-strike interaction effects indicate that treated firms substantially reduced their carbon emissions. In the baseline specification, Scope 1 emission intensity declines by approximately 12%, Scope 2 by 7%. Using unscaled emissions, Scope 1 emissions fell by approximately 12,051 tons per treated firm relative to pre-treatment levels, while Scope 2 emissions declined by roughly 15,744 tons per firm. With 192 treated firms in our sample, this corresponds to a back-of-the-envelope cumulative reduction of about 5.3 million tons of CO_2 across Scope 1 and Scope 2 in the years following the strikes, relative to 2019 levels.

Scope 3 emissions also experience a large decline, approximately 68.8% with regards to emission intensity, or 240,099 tons of raw emissions per treated firm. However, while these numbers appear large at first glance, they need to be interpreted with particular caution. By default treated firms also emit about 275,600 tons of Scope 3 CO_2 emissions more compared to the control sample in the pre-treatment period (See Table 2), with Scope 1 and Scope 2 emissions being qualitatively similar across groups. As such, this reduction primarily reflects a correction toward levels observed in non-treated control firms. Unlike Scope 1 and Scope 2, which are closely tied to observable operational inputs such as fuel and electricity use, Scope 3 emissions encompass upstream and downstream value-chain activities beyond the firm's direct control. Prior research documents substantial heterogeneity in Scope 3 reporting, higher rates of missing disclosure, and greater managerial discretion in estimation (Comello et al., 2022; Bolton et al., 2021). Consequently, observed changes may largely reflect reporting adjustments and methodological changes rather than operational reductions.[12] Yet, even if part of the estimated Scope 3 emission reductions reflect ex-post convergence of methodologies towards industry common practices rather than physical abatement, the documented post-2019 shift remains economically and conceptually remarkable as it is consistent with an increased managerial attention to emission measurement induced by exposure to local climate strikes.

Altogether, across all emission scopes we find evidence corporate environmental changes for firms exposed to local climate strikes. The dynamic coefficients further show that these effects persist and, in some cases, strengthen over the four years following the strikes, consistent with this phenomenon not being a temporary artifact, but a rather permanent adjustment to the corporate strategy.

[12] For example, Target's 2021 ESG report revised its 2019 (2020) Scope 3 emissions from 55,789,000 (64,789,000) tons to 49,754,000 (56,645,000) tons, while General Mills revised its 2020 Scope 3 emissions from 16,700,000 to 13,546,000 tons.

3.3 Additional analyses

3.3.1 Resource efficiency

If localized stakeholder pressure induces substantive changes in production processes, we would expect to observe improvements not only in direct emissions but also in related dimensions of environmental performance. We therefore examine whether exposure to climate strikes affects firms' resource efficiency, including waste generation, water withdrawal, and energy use relative to revenue. We draw this data from LSEG ESG.

The estimates in Table 4 indicate that firms headquartered near climate strike locations adjusted their broader resource usage following the strikes. The post-strike interaction terms show that treated firms reduced waste intensity by roughly 37%, energy intensity by about 24%, with no statistically significant change in water intensity. These effects are again concentrated in the years immediately after the strikes, while the absence of differential pre-trends in the three years prior to the strikes supports the interpretation that these changes are linked to local exposure to collective climate action rather than broader time-varying shocks. This reinforces the narrative from Table 3 local stakeholder pressure prompted coordinated improvements not only in direct emissions but also in overall resource efficiency.

< Insert Table 4 about here. >

3.3.2 Performance implications of post-strike emission reductions

Our main findings raise the natural concern as to whether rapid responses to local climate strikes induce firms to reduce emissions in ways that compromise shareholder wealth. It is possible that firms over-adjust to visible social pressure, such that the realized emission reductions could come at the expense of operational efficiency, profitability, or market valuation. Alternatively, firms may identify efficiency-enhancing margins that allow them to reduce emissions without harming, or even positively influencing performance.

To examine this, we estimate difference-in-differences specifications in which next-year ROA and Tobin's Q are regressed on the triple interaction $Strike \times Post \times Scope\ Growth$. This coefficient captures whether strike-induced emission changes translate into differential financial performance relative to control firms. We report these results in Table 5. We find that, across all specifications, the triple interaction terms are generally small, largely statistically insignificant, and economically negligible. Firms that reduced Scope

1, 2, or 3 emissions following local climate strikes did not experience measurable declines in accounting profitability or market valuation.

Taken together, these results suggest that the emission reductions and broader resource efficiency improvements observed in the wake of climate strikes were achieved without sacrificing shareholder value. Firms appear to have adjusted along efficiency-enhancing margins, reducing emissions while maintaining performance.

< Insert Table 5 about here. >

3.4 Cross-sectional tests

To better understand the mechanisms driving the documented emissions reductions, we conduct a series of split-sample analyses based on the firms' environmental and prosocial profile, as well as local strike conditions that may affect the treatment response.

3.4.1 Firm environmental and prosocial profile

We present the difference-in-differences estimates in Table 6, where we classify firms according to their two-digit SIC codes into high-emission (top-polluting) and low-emission industries, as per Ilhan et al. (2021) and Seltzer et al. (2022).[13] This distinction allows us to examine whether local climate strikes elicit heterogeneous responses across firms' environmental profiles. We find economically meaningful reductions following strikes for firms in low-emission industries. Scope 1 emissions decline by roughly 20%, Scope 2 by 13–14%, and Scope 3 by over 80%, indicating that these firms can adjust operations efficiently in response to localized social pressure. In contrast, top-polluting industries show little evidence of emission reductions; in some cases, Scope 1 and Scope 2 emissions slightly increase.

This divergence across industry profiles can be explained by differences in technological constraints, as well as by plausibly higher marginal abatement costs, such that immediate downward carbon adjustments are less feasible for firms in top-polluting industries. However, this response may also reflect a lower perceived salience of local strikes. Given that these industries contribute disproportionately to overall emissions,

[13] The top polluting industries are electricity, gas and sanitary, oil and gas extraction, transportation by air, petroleum and coal, chemical and allied products, primary metal, railroad transport, food and kindred products, paper and allied products, motor freight transportation, metal mining, general merchandise stores, stone, clay and glass, non-classifiable establishments, and transportation equipment.

any changes here would have been highly consequential. The absence of measurable reductions for these firms highlights the limits of localized social pressure as a driver of corporate environmental action.

$<$ Insert Table 6 about here. $>$

Next, an open question is whether climate strikes primarily affect firms that have already previously committed to emission reductions, or whether their influence also affects firms without established environmental strategies. That is, firms with emission targets may simple be more ready to make emission adjustments. Table 7 addresses this issue by partitioning the sample based on whether firms had established emission reduction targets prior to 2019. The results indicate that the response to climate strikes is not confined to firms with prior commitments. Both groups exhibit economically comparable reductions in Scope 1 emissions. Scope 2 reductions are somewhat larger among firms without pre-existing targets, suggesting that these firms may have had greater adjustment margins. In contrast, significant Scope 3 reductions are observed primarily among firms with established targets. Overall, the evidence does not support the view that climate strikes only mobilize pre-strike committed firms, and is consistent with local stakeholder pressure reinforcing existing environmental commitments while also prompting new adjustments among firms that had not previously formalized such objectives.

$<$ Insert Table 7 about here. $>$

Table 8 examines whether internal governance structures shape firms' responsiveness to local climate strikes. We operationalize this by partitioning firms based on whether board gender diversity is above or below the 2019 sample median. Gender socialization theory would dictate that women, on average, place greater weight on social welfare considerations, long-term stakeholder outcomes, and ethical risk mitigation (Girardone et al., 2021; Liu, 2018). Within a corporate governance setting, greater female representation may therefore increase board sensitivity to local stakeholder pressure arising from direct climate strike exposure. Across both scaled (Panel A) and unscaled (Panel B) specifications, emission reductions are concentrated among firms with high board gender diversity. For these firms, the $Strike \times Post$ coefficients imply economically meaningful declines in Scope 1, 2, and 3 emissions. In contrast, firms with below-median female board representation exhibit small and statistically insignificant changes across all emission scopes. Board composition thus constitutes an important channel through which external stakeholder pressure operates, with governance structures that incorporate greater female representation appearing more responsive to social and environmental concerns.

< Insert Table 8 about here. >

3.4.2 Local salience of strike conditions

Political environment. The local political environment may condition the effectiveness of climate strikes in inducing corporate responses and be less impactful in Republican-leaning states, where skepticism toward climate change is more prevalent (Smith et al., 2024).[14] If corporate stakeholders are less likely to perceive climate change as an urgent risk, protest-induced pressure may be weaker in Republican states as opposed to Democratic-leaning states, where climate change is more politically salient.

We partition our sample on whether there was a Democratic or Republican governor at the time of the climate strikes, as a proxy for the prevailing local beliefs about climate risk. The results of this partitioning is reported in Table 9. The results do not reveal a systematic pattern across political regimes. While some coefficients differ in magnitude, the overall response of treated firms is qualitatively similar across Red and Blue states. The absence of a differential response suggests that the emission reductions documented in the main analysis are not solely driven by pre-existing political ideology or regulatory environments.

< Insert Table 9 about here. >

Attendance. Table 10 examines whether the intensity of local climate activism amplifies firms' emission responses. Crowd size is theoretically central because larger protests are more visible, attract greater media coverage, and signal broader community support, thereby providing firms with a salient signal of reputational and stakeholder pressure. We find that protest attendance near a firm's headquarters is associated with significantly larger post-2019 reductions in scaled and unscaled emissions. The event-study specification further shows no consistent evidence of differential negative pre-trends and exhibits persistence following the strikes. Panel B reports nearly identical results for unscaled emissions, reinforcing the interpretation that larger and more visible climate strikes increase the salience of stakeholder pressure and induce stronger and sustained real reductions in corporate greenhouse gas emissions.

< Insert Table 10 about here. >

[14] Survey evidence consistently documents a strong link between climate attitudes and partisanship. For example, a recent PEW survey reports that 22% of Republicans, compared to 70% of Democrats, believe human activity contributes substantially to climate change (Pew Research Center, 2024).

Weather conditions. Table 11 examines whether precipitation on strike days attenuates the treatment effect. If climate strikes operate through local visibility and stakeholder exposure, adverse weather should weaken the response by reducing attendance and observability. We do so by merging firm headquarters with station-level data from the National Centers for Environmental Information (NCEI) and assign to each firm the precipitation recorded at the nearest weather station on September 20 and 27. We then split the sample based on whether any precipitation occurred on the protest day.[15]

Emission reductions are concentrated among treated firms in locations without precipitation, while estimates for rainy events are generally small and statistically insignificant. This differential pattern is consistent with a visibility-based mechanism and difficult to reconcile with explanations based on contemporaneous aggregate shocks or regulatory changes.

< Insert Table 11 about here. >

Protest infrastructure. Next, we exploit cross-sectional variation in protest infrastructure using the Environmental Protection Agency's National Walkability Index. Walkability proxies for the ease with which individuals can access and congregate in public spaces and may therefore affect protest participation and visibility. We compute the average walkability within the 5 km strike radius and partition treated firms based on whether the strike occurred in an above-median walkability area, alongside all control firms.

Table 12 shows that emission reductions are concentrated in more walkable locations. Treated firms in high-walkability areas exhibit economically meaningful declines in Scope 1 and Scope 3 emissions, while effects in less walkable areas are small and statistically insignificant. Scope 2 effects are weaker but remain detectable for unscaled emissions.

< Insert Table 12 about here. >

City size. Finally, we examine whether treatment effects vary with city size (Table 13). Urban scale may affect both the visibility and amplification of collective action, as strikes in larger metropolitan areas are more likely to attract greater attendance and media attention. Partitioning cities by a population threshold of 250,000, we find that emission reductions are concentrated in larger metropolitan areas. Treated firms headquartered

[15] Results are similar using a 1 mm precipitation threshold.

in large cities exhibit statistically significant declines in Scope 1 and Scope 3 emissions, whereas estimates for smaller cities are economically small and statistically insignificant.

< Insert Table 13 about here. >

Taken together, results are consistent with the interpretation that local protest conditions influence the strength of the treatment effect. When environments are more conducive to participation and visibility, firms appear more responsive. Yet, when participation frictions are higher, the estimated effects attenuate.

3.5 Robustness tests

3.5.1 Altering treatment radius

Our identification strategy relies on local exposure, defined by a 5 km radius around strike locations. In Table 14, we assess the sensitivity of our results to alternative distance thresholds of 10 km and 25 km.

For Scope 1 emissions (Panel A), firms within 5 km exhibit statistically significant reductions of approximately 12%, both in intensity and levels. Similar effects are observed at 10 km, but estimates become small and insignificant at 25 km. Scope 2 emissions (Panel B) show a comparable pattern, with significant reductions at 5 km that dissipate at larger radii. Scope 3 emissions (Panel C) display the same spatial gradient, with effects weakening at 10 km and disappearing entirely at 25 km.

Overall, the magnitude and significance of the treatment effect decline with distance, consistent with a localized mechanism. The spatial decay supports the interpretation that climate strikes influence corporate emissions through proximate stakeholder pressure rather than broader aggregate trends or nationwide information diffusion.

< Insert Table 14 about here. >

3.5.2 Coefficient stability under unobservables

We assess robustness to omitted variable bias using the coefficient stability approach of Oster (2019). Following common practice, we set the maximum R^2 to 1.3 times the baseline R^2, allowing unobservables to increase explanatory power by 30% beyond the fully controlled specification. Given the high baseline fit, this constitutes a conservative bound. Results reported in Appendix D show that, across emission measures, the implied δ statistics suggest selection on unobservables would need to be at least as strong than the selection on observables to eliminate the estimated effects. In some cases, δ is negative, implying that unobserved selection would have to operate in the opposite direction to overturn the results. The bias-adjusted coefficients (β^*) remain economically meaningful and negative throughout. Overall, the findings indicate that omitted variable bias is unlikely to explain our results under proportional selection.

3.5.3 Addressing firm location sorting

A natural concern is that firms self-select their headquarters into areas reflecting their long-run environmental preferences or susceptibility to stakeholder pressure. Our prior results largely mitigate this concern, (i) given the absence of pre-strike pre-trends, (ii) since emission reductions are concentrated among firms exposed to nearby strikes, and (iii) treatment effects decay with treatment distance. Moreover, emission reductions occur for firms both with and without prior emission targets (Table 7). Such patterns are unlikely if environmental behavior were predetermined by location.

We nonetheless conduct additional tests to rule out sorting. First, in Appendix E, we exploit the heterogeneity in 2019 county-level climate change social norms (CCSN).[16] If strikes merely occurred in environmentally progressive counties, treated and untreated firms in high-norm areas should not differ. Instead, reductions arise only among strike-exposed firms in both low- and high-norm counties. While effects are sometimes stronger in high-norm areas, exposure remains necessary, consistent with protest salience rather than ideological sorting.

Second, firms in denser areas are plausibly more embedded in their local communities and more exposed to reputational pressure. We link firm coordinates to OpenStreetMap land-use data and classify headquarters by zoning (residential, commercial, retail, industrial, mixed-use, or unknown), and also measure the number of households within a 1 km radius using NCEI data, defining high embeddedness as above the 75th percentile of local household density. Including zoning fixed effects and partitioning by household density, our main results remain robust. Both sets of untabulated results are available upon request, and are consistent with localized strike exposure, rather than pre-existing location choices, driving the observed emission changes.

Taken together, these additional analyses are inconsistent with sorting as the primary explanation and favor a localized stakeholder-pressure mechanism.

[16] Results are similar using 2018 data and when including county fixed effects.

4 Conclusion

Our results show that localized climate activism significantly reduces corporate carbon emissions. Firms headquartered within 5 km of the 2019 Global Climate Strikes cut Scope 1 emissions by 12% and Scope 2 emissions by 7% in subsequent years, amounting to an aggregate reduction of 5.3 million tons of CO_2 across treated firms. Scope 3 emission show a similar pattern, but are more sensitive to changes in reporting practices. The observed effects persist throughout our sample period and occur without detectable declines in profitability or market valuation.

The evidence is consistent with a localized legitimacy channel. Highly visible protests increase stakeholder salience and raise the reputational costs of inaction, inducing firms to implement operational and efficiency improvements rather than value-destroying contraction. Effects are strongest when protest visibility is plausibly greater (such as in large metropolitan areas, under favorable weather conditions, and in walkable locations) and increase with attendance. Emission reductions are concentrated among firms with lower abatement costs and more responsive governance structures, consistent with heterogeneous adjustment capacity.

Our findings establish geographically proximate social movements as an informal external governance mechanism. Even without ownership, regulation, or formal authority, localized activism induces persistent real changes in corporate behavior through reputational and spatial channels.

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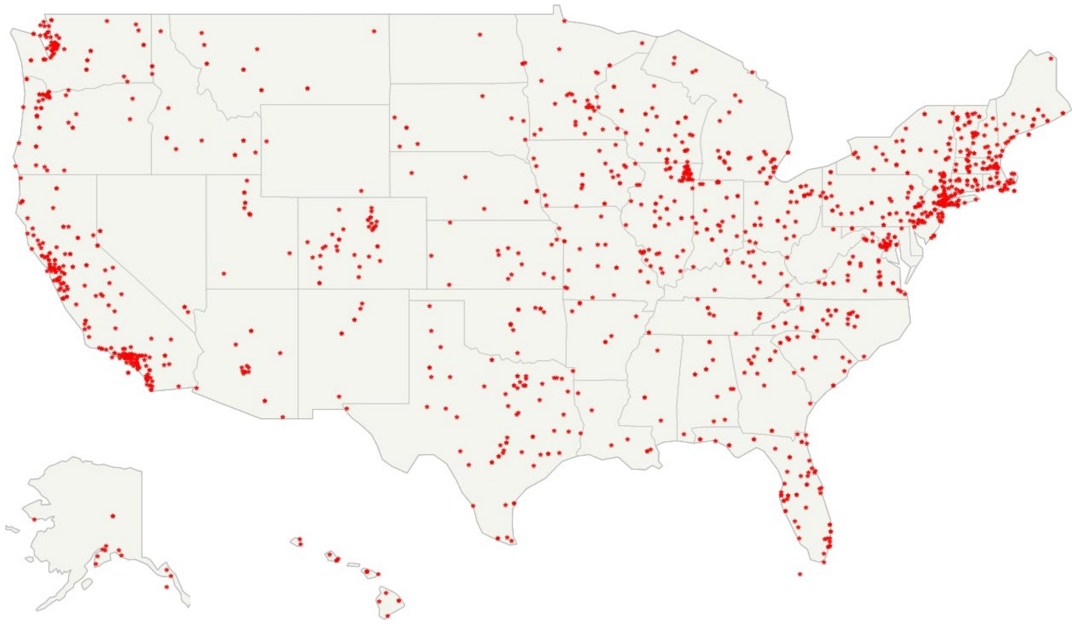
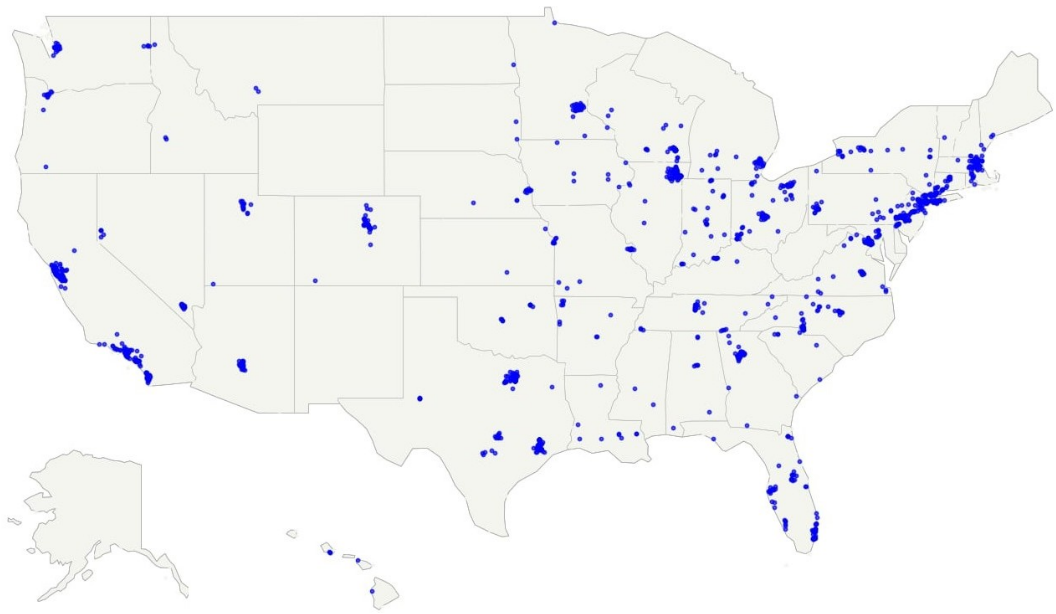


(a) Strike locations



(b) Firms HQ locations

Figure 1: **US climate strike locations and firm headquarters**

Figures (a) and (b) respectively plot the 1,111 climate strike locations, and the 579 firm headquarters locations across the US.

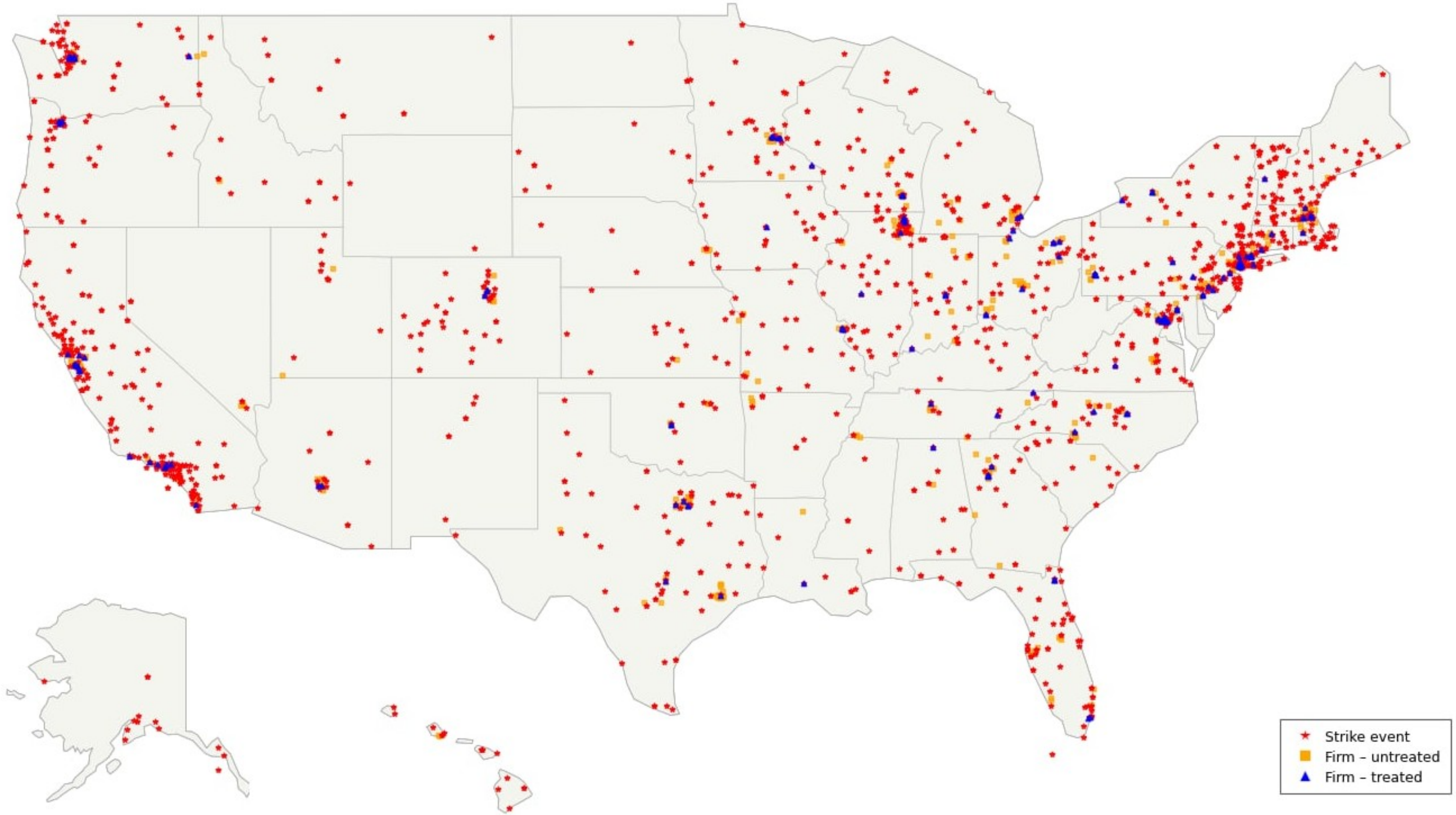
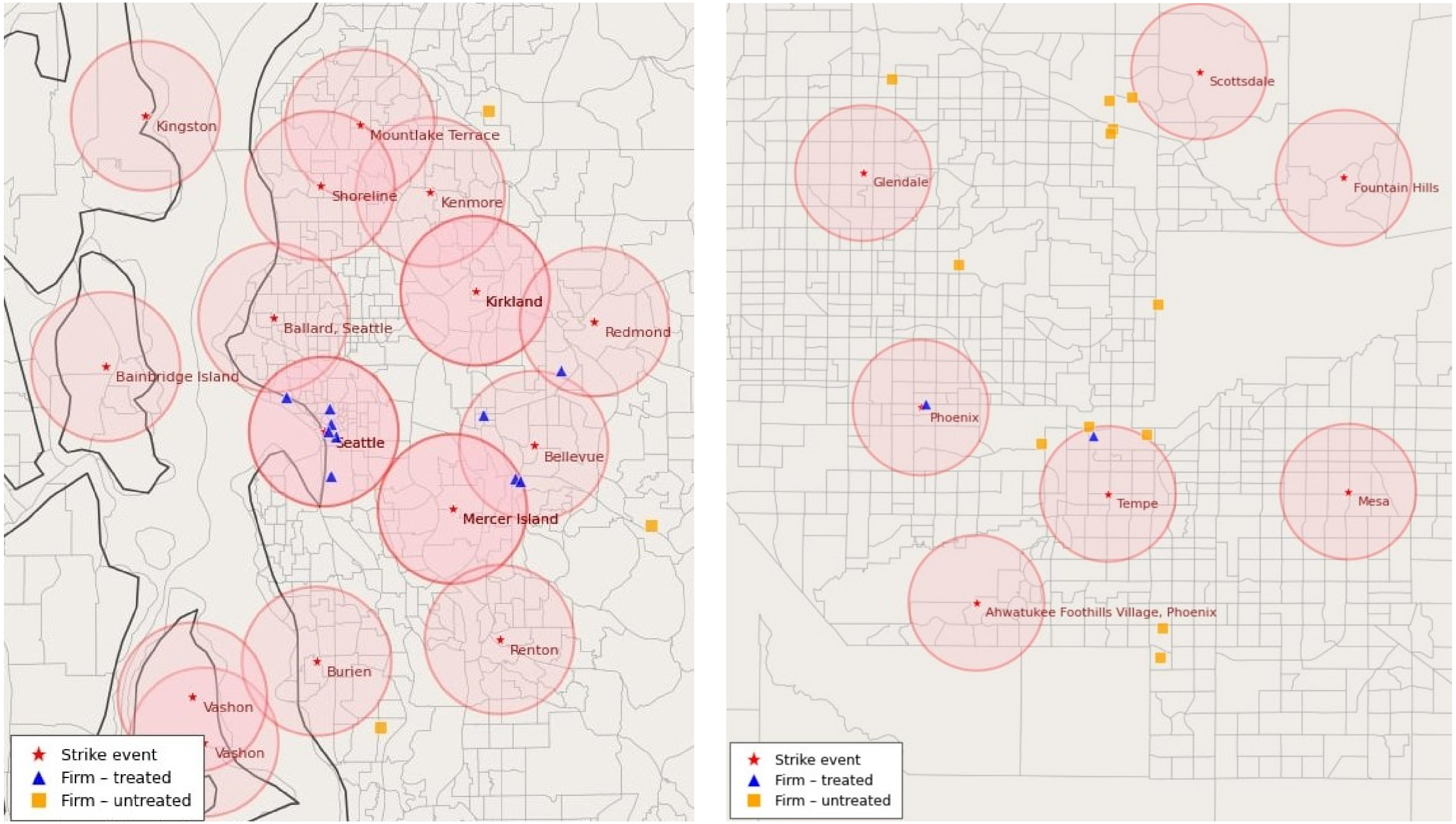


Figure 2: **US climate strike locations, and firm headquarter treatment**

This Figure reports the geographical distribution of climate strikes across the US alongside firm headquarter location alongside treatment. Strikes are presented as (red) stars, treated firms are represented as (blue) triangles, and are located within a 5 km radius of strike events, while untreated firms are outside of this 5 km bound and represented as (yellow) squares.

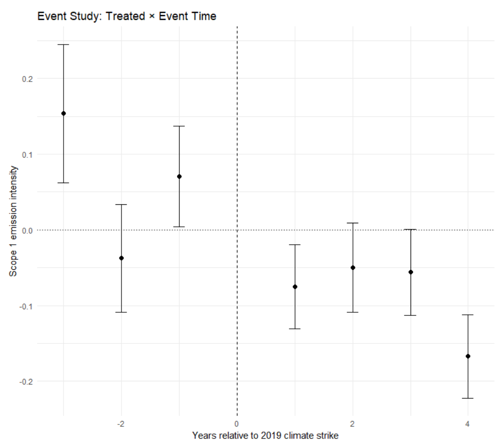


(a) Seattle, WA

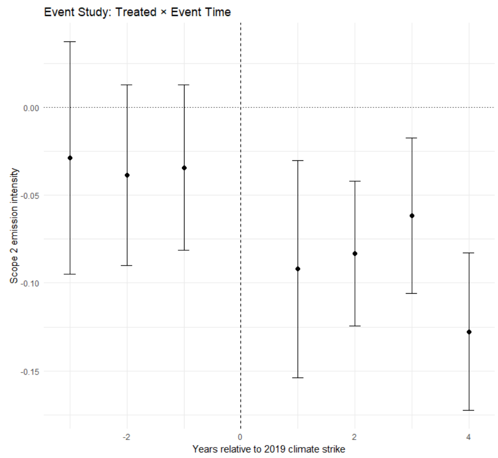
(b) Phoenix, AZ

Figure 3: **Examples of treatment identification**

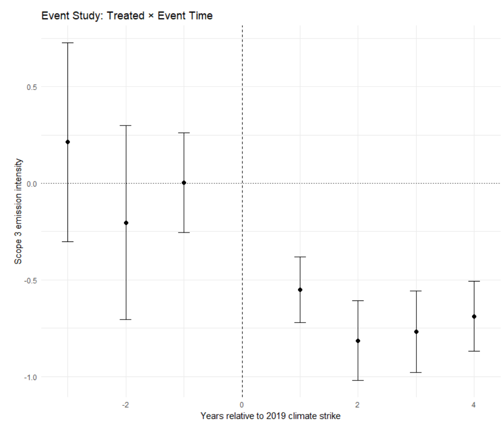
Figures (a) and (b) demonstrate the presence of climate strikes (presented as stars) in Seattle, WA (Fig (a) and Phoenix, AZ (Fig (b), alongside firm headquarter locations. Treated firms (represented as triangles) are located within a 5 km radius of strike events, while untreated firms are outside of this 5 km bound and represented as squares.



(a) Scope 1



(b) Scope 2



(c) Scope 3

Figure 4: **Dynamic effects of local treatment on Scope 1, Scope 2, and Scope 3 emissions**

Figures (a) through (c) demonstrate the dynamic effects of the corporate carbon emissions before and after the 2019 climate strikes, for treated firms as presented in Table 3. Figure (a) presents the results for Scope 1 emissions, Figure (b) presents the results for Scope 2 emissions and Figure (c) Scope 3 emissions.

Table 1: **Summary Statistics**

	P25	Median	P75	Mean	St.Dev	Obs	Firms
Panel A: Treated firms							
Scope1	9.041	11.112	12.965	10.976	2.874	1,172	187
Scope2	10.284	11.590	13.073	11.644	1.886	1,169	186
Scope3	11.452	13.975	16.044	13.645	2.905	828	149
Scope1Int	0.017	1.986	3.560	1.906	2.586	1,172	187
Scope2Int	1.585	2.611	3.518	2.575	1.467	1,169	186
Scope3Int	2.549	4.376	6.197	4.265	2.460	828	149
Ln(Size)	8.076	9.305	10.614	9.353	1.695	1,470	192
Ln(BTM)	-1.766	-1.206	-0.720	-1.310	0.971	1,470	192
ROA	0.028	0.056	0.090	0.061	0.071	1,470	192
Asset Growth	-0.800	4.603	11.971	9.851	26.322	1,470	192
Leverage	0.411	0.794	1.591	1.564	2.467	1,470	192
Ln(PPE)	6.954	8.021	9.152	8.072	1.645	1,470	192
Sales Growth	-0.152	6.329	13.731	8.239	20.758	1,470	192
EPS Growth	-36.137	3.506	34.751	4.318	291.151	1,470	192
Beta	0.810	1.083	1.423	1.138	0.507	1,470	192
IVol	0.777	1.020	1.393	1.206	0.754	1,470	192
HHI	467.079	685.559	1,254.609	1,107.660	1,041.201	1,470	192
CCSN	27.030	40.524	52.535	38.477	17.912	1,462	192
RGGI	0.000	0.000	1.000	0.361	0.480	1,470	192
Panel B: Control firms							
Scope1	9.335	11.149	13.313	11.289	2.880	2,313	383
Scope2	10.231	11.539	12.936	11.528	2.065	2,272	381
Scope3	11.391	13.850	15.650	13.510	2.898	1,294	265
Scope1Int	0.643	2.292	4.486	2.463	2.541	2,313	383
Scope2Int	1.761	2.801	3.720	2.681	1.591	2,272	381
Scope3Int	2.639	4.696	6.152	4.364	2.515	1,294	265
Ln(Size)	7.930	9.026	10.104	9.060	1.567	2,960	387
Ln(BTM)	-1.691	-1.079	-0.568	-1.190	0.923	2,960	387
ROA	0.022	0.055	0.095	0.057	0.084	2,960	387
Asset Growth	-1.129	4.833	12.199	9.011	23.015	2,960	387
Leverage	0.378	0.704	1.283	1.316	2.225	2,960	387
Ln(PPE)	6.840	7.827	9.008	7.939	1.669	2,960	387
Sales Growth	-1.693	5.689	14.745	8.321	23.408	2,960	387
EPS Growth	-50.093	1.223	38.616	-1.312	301.455	2,960	387
Beta	0.890	1.170	1.478	1.223	0.550	2,960	387
IVol	0.815	1.094	1.513	1.279	0.718	2,960	387
HHI	472.910	693.787	1,413.129	1,050.835	847.121	2,960	387
CCSN	16.416	28.993	44.067	28.185	18.197	2,951	387
RGGI	0.000	0.000	0.000	0.147	0.354	2,960	387

This Table reports summary statistics for treated and control firms separately. Panel A covers treated firms, defined as those headquartered within 5 km of a climate strike location, and Panel B covers all remaining firms in the sample. Scope 1, Scope 2, and Scope 3 are the natural logarithms of CO_2 equivalent emissions. Scope1Int, Scope2Int, and Scope3Int are the corresponding emission measures scaled by revenues, also in natural logarithm form. Ln(Size) is the natural logarithm of market capitalization. Ln(BTM) is the natural logarithm of the book-to-market ratio. ROA is return on assets. Asset Growth, Sales Growth, and EPS Growth are year-over-year percentage changes in total assets, revenues, and diluted earnings per share, respectively. Leverage is total debt scaled by book equity. Ln(PPE) is the natural logarithm of property, plant and equipment. Beta is market beta estimated from a 60-month rolling CAPM regression. IVol is idiosyncratic volatility estimated from a 21-day rolling Fama-French three-factor model regression. HHI is the Herfindahl–Hirschman Index computed at the two-digit SIC level. CCSN is a county-level climate change social norms index constructed following Zhang et al. (2024) using principal component analysis applied to survey responses from the Yale Climate Opinion Maps. RGGI is an indicator variable equal to one if the firm's headquarters state participates in the Regional Greenhouse Gas Initiative. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1% level.

Table 2: **Difference-in-means - Pre-treatment period**

	Mean Treated	Mean Control	Diff	tstat
Scope1	11.540	11.720	-0.180	-0.930
Scope2	12.167	12.029	0.138	1.098
Scope3	13.010	12.550	0.460	1.787*
Scope1Int	2.305	2.722	-0.417	-2.347**
Scope2Int	2.941	3.000	-0.059	-0.594
Scope3Int	3.510	3.229	0.281	1.216
Ln(Size)	9.165	8.897	0.268	3.240***
Ln(BTM)	-1.289	-1.149	-0.139	-2.981***
ROA	0.063	0.057	0.006	1.631
Asset Growth	9.518	9.502	0.016	0.012
Leverage	1.454	1.140	0.314	2.626***
Ln(PPE)	7.809	7.749	0.061	0.689
Sales Growth	7.976	8.678	-0.702	-0.763
EPS Growth	31.842	2.430	29.412	2.032**
Beta	1.104	1.211	-0.107	-4.141***
Ivol	1.173	1.264	-0.091	-2.551**
HHI	1,058.395	1,013.705	44.690	0.909
CCSN	34.913	24.557	10.356	11.539***
RGGI	0.300	0.117	0.182	8.388***

This Table reports difference-in-means tests comparing treated and control firms during the pre-treatment period. Treated firms are defined as those headquartered within 5 km of a climate strike location, while control firms are all remaining firms in the sample. Scope 1, Scope 2, and Scope 3 are the natural logarithms of winsorized CO_2 equivalent emissions. Scope1Int, Scope2Int, and Scope3Int are the corresponding emission measures scaled by revenues, also in natural logarithm form. Ln(Size) is the natural logarithm of market capitalization. Ln(BTM) is the natural logarithm of the book-to-market ratio. ROA is return on assets. Asset Growth, Sales Growth, and EPS Growth are year-over-year percentage changes in total assets, revenues, and diluted earnings per share, respectively. Leverage is total debt scaled by book equity. Ln(PPE) is the natural logarithm of property, plant and equipment. Beta is market beta estimated from a 60-month rolling CAPM regression. IVol is idiosyncratic volatility estimated from a 21-day rolling Fama-French three-factor model regression. HHI is the Herfindahl–Hirschman Index computed at the two-digit SIC level. CCSN is climate change social norms, and RGGI is an indicator for participation in the Regional Greenhouse Gas Initiative. The column Diff reports the difference in means between treated and control firms, and tstat reports the corresponding t-statistic. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: **Effect of climate strikes on emissions**

Dependent Variables:	Scope 1		Scope 2		Scope 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Emissions scaled by revenue						
Strike × Post	-0.121***		-0.069**		-0.688***	
	(0.034)		(0.021)		(0.183)	
Strike × $Before_3$		0.153***		-0.028		0.220
		(0.039)		(0.028)		(0.218)
Strike × $Before_2$		-0.038		-0.038		-0.215
		(0.030)		(0.021)		(0.214)
Strike × $Before_1$		0.070**		-0.034		-0.004
		(0.029)		(0.020)		(0.112)
Strike × $Post_1$		-0.075**		-0.092***		-0.542***
		(0.024)		(0.026)		(0.071)
Strike × $Post_2$		-0.050*		-0.083***		-0.804***
		(0.025)		(0.017)		(0.089)
Strike × $Post_3$		-0.056*		-0.061**		-0.759***
		(0.024)		(0.019)		(0.090)
Strike × $Post_4$		-0.168***		-0.127***		-0.678***
		(0.023)		(0.019)		(0.078)
Strike	0.089	0.053	0.150*	0.172*	0.782***	0.792***
	(0.115)	(0.108)	(0.078)	(0.074)	(0.223)	(0.168)
Observations	3,446	3,446	3,402	3,402	2,104	2,104
Adjusted R^2	0.764	0.764	0.668	0.667	0.456	0.455
Panel B: Unscaled emissions						
Strike × Post	-0.124**		-0.085**		-0.690***	
	(0.040)		(0.028)		(0.185)	
Strike × $Before_3$		0.151**		-0.029		0.191
		(0.043)		(0.035)		(0.214)
Strike × $Before_2$		-0.057		-0.030		-0.242
		(0.032)		(0.027)		(0.212)
Strike × $Before_1$		0.075*		-0.010		0.013
		(0.037)		(0.025)		(0.104)
Strike × $Post_1$		-0.024		-0.040		-0.526***
		(0.022)		(0.024)		(0.070)
Strike × $Post_2$		-0.069**		-0.114***		-0.827***
		(0.025)		(0.021)		(0.092)
Strike × $Post_3$		-0.108***		-0.098***		-0.772***
		(0.025)		(0.025)		(0.095)
Strike × $Post_4$		-0.174***		-0.148***		-0.691***
		(0.021)		(0.030)		(0.085)
Strike	0.032	-0.0004	0.117	0.131*	0.704**	0.721***
	(0.111)	(0.103)	(0.071)	(0.067)	(0.225)	(0.172)
Observations	3,446	3,446	3,402	3,402	2,104	2,104
Adjusted R^2	0.825	0.825	0.815	0.814	0.578	0.577
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. $Before_3$, $Before_2$, and $Before_1$ denote the three years preceding the strikes and $Post_1$ through $Post_4$ denote the four years following them. Covariate balance between treated and control firms is achieved via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, HHI, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: **Effect of climate strikes on resource efficiency actions**

Dependent Variables:	Waste		Water		Energy	
	(1)	(2)	(3)	(4)	(5)	(6)
Strike × Post	-0.368***		-0.090		-0.244**	
	(0.083)		(0.049)		(0.081)	
Strike × $Before_3$		0.172**		0.231***		0.124*
		(0.051)		(0.040)		(0.059)
Strike × $Before_2$		0.126*		0.044		0.140**
		(0.055)		(0.037)		(0.055)
Strike × $Before_1$		0.267***		0.180***		0.096*
		(0.057)		(0.035)		(0.047)
Strike × $Post_1$		-0.297***		-0.030		-0.224***
		(0.045)		(0.027)		(0.040)
Strike × $Post_2$		-0.277***		0.032		-0.203***
		(0.044)		(0.024)		(0.040)
Strike × $Post_3$		-0.233***		-0.003		-0.086*
		(0.063)		(0.024)		(0.044)
Strike × $Post_4$		-0.139		0.045		-0.147**
		(0.080)		(0.025)		(0.045)
Strike	0.261	0.127	0.296	0.195	0.124	0.044
	(0.181)	(0.158)	(0.159)	(0.132)	(0.123)	(0.091)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,072	2,072	2,608	2,608	3,034	3,034
Adjusted R^2	0.699	0.698	0.695	0.694	0.747	0.747

This Table reports difference-in-differences estimates of the effect of climate strikes on the natural logarithm of total waste to revenues (columns 1 and 2), total water withdrawal to revenue (columns 3 and 4), and total energy use to revenues (columns 5 and 6). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. $Before_3$, $Before_2$, and $Before_1$ denote the three years preceding the strikes and $Post_1$ through $Post_4$ denote the four years following them. Covariate balance between treated and control firms is achieved via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: **Effect of climate strikes and emission reduction on financial outcomes**

Dependent Variables:		ROA			Tobin Q	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Emissions scaled by revenue						
Scope1 Growth	0.013			-0.020		
	(0.015)			(0.126)		
Strike × Scope1 Growth	-0.033			-0.048		
	(0.017)			(0.175)		
Scope1 Growth × Post	-0.040			0.194		
	(0.024)			(0.201)		
Strike × Scope1 Growth × Post	0.058*			-0.154		
	(0.027)			(0.246)		
Scope2 Growth		0.030			-0.034	
		(0.018)			(0.160)	
Strike × Scope2 Growth		-0.060**			0.029	
		(0.022)			(0.217)	
Scope2 Growth × Post		-0.040			0.203	
		(0.031)			(0.192)	
Strike × Scope2 Growth × Post		0.107**			0.287	
		(0.037)			(0.325)	
Scope3 Growth			-0.002			0.020
			(0.003)			(0.014)
Strike × Scope3 Growth			0.005			-0.028
			(0.004)			(0.022)
Scope3 Growth × Post			0.003			-0.017
			(0.003)			(0.051)
Strike × Scope3 Growth × Post			-0.008*			0.095
			(0.004)			(0.069)
Strike	0.002	-0.003	0.0009	-0.048	-0.044	0.038
	(0.003)	(0.003)	(0.003)	(0.061)	(0.064)	(0.101)
Strike × Post	0.005	0.015*	0.005	0.094	0.154**	0.090
	(0.006)	(0.007)	(0.005)	(0.065)	(0.053)	(0.103)
Observations	2,360	2,321	1,329	2,360	2,321	1,329
Adjusted R^2	0.413	0.425	0.481	0.844	0.845	0.847
Panel B: Unscaled emissions						
Scope1 Growth	-0.022			0.094		
	(0.021)			(0.069)		
Strike treated × Scope1 Growth	0.020			-0.084		
	(0.026)			(0.127)		
Scope1 Growth × Post	0.027			-0.028		
	(0.031)			(0.174)		
Strike × Scope1 Growth × Post	-0.030			-0.103		
	(0.037)			(0.233)		
Scope2 Growth		0.0001			0.081	
		(0.006)			(0.159)	
Strike × Scope2 Growth		-0.010			0.030	
		(0.008)			(0.197)	
Scope2 Growth × Post		0.025			-0.043	
		(0.021)			(0.195)	
Strike × Scope2 Growth × Post		0.019			0.346	
		(0.017)			(0.251)	
Scope3 Growth			-0.002			0.023
			(0.002)			(0.016)
Strike × Scope3 Growth			0.005			-0.026
			(0.003)			(0.023)
Scope3 Growth × ¨Post			0.003			-0.018
			(0.003)			(0.054)
Strike × Scope3 Growth× Post			-0.008*			0.084

Continued on next page

Table 5: (continued)

Dependent Variables:		ROA			Tobin Q	
	(1)	(2)	(3)	(4)	(5)	(6)
			(0.004)			(0.072)
Strike	0.002	0.002	0.0006	-0.043	-0.048	0.040
	(0.003)	(0.005)	(0.003)	(0.056)	(0.066)	(0.102)
Strike × Post	0.003	0.006	0.006	0.102	0.134*	0.086
	(0.005)	(0.006)	(0.005)	(0.053)	(0.062)	(0.107)
Observations	2,360	2,321	1,329	2,360	2,321	1,329
Adjusted R^2	0.410	0.421	0.481	0.843	0.844	0.847
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes and emission reductions on financial outcomes. The dependent variables are next-year return on assets (ROA) and next-year Tobin's Q. *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Scope1 Growth, Scope2 Growth, and Scope3 Growth denote the year-over-year logarithmic growth in Scope 1, Scope 2, and Scope 3 emissions, respectively, either scaled by revenue (Panel A) or unscaled (Panel B). The key variable of interest is the triple interaction *Strike* × *Post* × *ScopeGrowth*, which captures whether emission reductions induced by climate strikes translate into differential financial performance. Covariate balance between treated and control firms is achieved via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, current-period ROA (in columns with ROA as the dependent variable) or current-period Tobin's Q (in columns with Tobin's Q as the dependent variable), asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: **Environmental profile, climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
	Top Polluters (1)	Non- Top Polluters (2)	Top Polluters (3)	Non- Top Polluters (4)	Top Polluters (5)	Non- Top Polluters (6)
Panel A: Emissions scaled by revenue						
Strike × Post	0.153**	-0.209***	0.154**	-0.132**	-0.090	-0.898***
	(0.062)	(0.046)	(0.056)	(0.038)	(0.317)	(0.230)
Strike	0.078	0.067	0.126	0.186	0.286	1.050***
	(0.158)	(0.155)	(0.121)	(0.102)	(0.309)	(0.271)
Observations	1,270	2,176	1,234	2,168	702	1,402
Adjusted R^2	0.758	0.646	0.692	0.662	0.397	0.432
Panel B: Unscaled emissions						
Strike × Post	0.126*	-0.197***	0.132**	-0.143**	-0.168	-0.846***
	(0.059)	(0.042)	(0.054)	(0.042)	(0.328)	(0.231)
Strike	0.048	0.034	0.091	0.192*	0.159	1.020***
	(0.151)	(0.151)	(0.125)	(0.086)	(0.296)	(0.270)
Observations	1,270	2,176	1,234	2,168	702	1,402
Adjusted R^2	0.811	0.751	0.780	0.823	0.573	0.545
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions, estimated separately for top polluting and non-top polluting firms based on their industry classification. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: **Commitment to climate change, climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
ERT before 2019	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Emissions scaled by revenue						
Strike × Post	-0.172**	-0.171**	-0.178***	-0.051*	-0.596	-0.715**
	(0.057)	(0.052)	(0.045)	(0.026)	(0.345)	(0.230)
Strike	0.141	0.001	0.260*	0.085	0.279	0.731**
	(0.186)	(0.148)	(0.126)	(0.112)	(0.432)	(0.257)
Observations	1,654	1,792	1,610	1,792	756	1,348
Adjusted R^2	0.772	0.803	0.670	0.713	0.429	0.520
Panel B: Unscaled emissions						
Strike × Post	-0.219***	-0.142**	-0.225**	-0.058	-0.663	-0.693**
	(0.061)	(0.056)	(0.090)	(0.041)	(0.388)	(0.228)
Strike	0.049	-0.050	0.200	0.056	0.222	0.668**
	(0.178)	(0.141)	(0.127)	(0.107)	(0.468)	(0.263)
Observations	1,654	1,792	1,610	1,792	756	1,348
Adjusted R^2	0.819	0.839	0.773	0.820	0.555	0.586
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions, estimated separately for firms without and with an emission reduction target (ERT) set before 2019. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: **Board gender diversity, climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
Board Gender Diversity	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Panel A: Emissions scaled by revenue						
Strike × Post	-0.052	-0.246***	0.030	-0.110**	-0.742	-0.642**
	(0.079)	(0.054)	(0.080)	(0.041)	(0.474)	(0.214)
Strike	-0.056	0.278	-0.070	0.238*	-0.037	0.834**
	(0.232)	(0.149)	(0.131)	(0.105)	(0.554)	(0.253)
Observations	1,102	2,301	1,078	2,281	554	1,522
Adjusted R^2	0.794	0.770	0.731	0.659	0.622	0.442
Panel B: Unscaled emissions						
Strike × Post	-0.120	-0.228***	-0.038	-0.108*	-0.838	-0.650**
	(0.081)	(0.047)	(0.072)	(0.047)	(0.488)	(0.216)
Strike	-0.100	0.217	-0.133	0.197*	-0.030	0.771**
	(0.229)	(0.143)	(0.158)	(0.096)	(0.526)	(0.245)
Observations	1,102	2,301	1,078	2,281	554	1,522
Adjusted R^2	0.848	0.830	0.806	0.831	0.707	0.571
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions, estimated separately for firms with low (below-median) and high (above-median) board gender diversity as of 2019. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof).We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: **State governor's political party, climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
States	Red (1)	Blue (2)	Red (3)	Blue (4)	Red (5)	Blue (6)
Panel A: Emissions scaled by revenue						
Strike × Post	-0.065	-0.110*	-0.093**	-0.041	-0.491	-0.597**
	(0.050)	(0.053)	(0.030)	(0.044)	(0.349)	(0.210)
Strike	-0.303	0.267*	0.014	0.173	0.527	0.650**
	(0.267)	(0.137)	(0.159)	(0.110)	(0.322)	(0.247)
Observations	1,370	2,056	1,337	2,045	726	1,364
Adjusted R^2	0.783	0.759	0.735	0.677	0.604	0.493
Panel B: Unscaled emissions						
Strike × Post	-0.018	-0.120*	-0.082	-0.064	-0.442	-0.629**
	(0.066)	(0.056)	(0.046)	(0.049)	(0.342)	(0.210)
Strike	-0.358	0.162	0.005	0.081	0.530	0.505*
	(0.252)	(0.134)	(0.139)	(0.095)	(0.323)	(0.256)
Observations	1,370	2,056	1,337	2,045	726	1,364
Adjusted R^2	0.845	0.829	0.869	0.819	0.694	0.627
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions, estimated separately for firms headquartered in Republican-governed and Democratic-governed states, based on the governor's party affiliation in 2019. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: **Effect of attendance at climate strikes on emissions**

Dependent Variables:	Scope 1		Scope 2		Scope 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Emissions scaled by revenue						
Attendance × Post	-0.030***		-0.014**		-0.084**	
	(0.007)		(0.004)		(0.031)	
Attendance × Before_3		0.043***		-0.002		-0.036
		(0.011)		(0.007)		(0.043)
Attendance × Before_2		0.016		0.000		-0.056
		(0.010)		(0.007)		(0.043)
Attendance × Before_1		0.023***		0.000		-0.040
		(0.006)		(0.006)		(0.027)
Attendance × Post_1		-0.013***		-0.014**		-0.098***
		(0.003)		(0.005)		(0.012)
Attendance × Post_2		-0.014***		-0.017***		-0.135***
		(0.003)		(0.003)		(0.019)
Attendance × Post_3		-0.008		-0.009		-0.108***
		(0.005)		(0.005)		(0.018)
Attendance × Post_4		-0.023***		-0.016**		-0.107***
		(0.004)		(0.005)		(0.015)
Attendance	0.005	-0.011	0.010	0.010	0.083**	0.111***
	(0.021)	(0.018)	(0.013)	(0.013)	(0.034)	(0.028)
Observations	3,446	3,446	3,402	3,402	2,104	2,104
Adjusted R^2	0.765	0.764	0.667	0.666	0.452	0.451
Panel B: Unscaled emissions						
Attendance × Post	-0.028***		-0.012**		-0.084**	
	(0.008)		(0.005)		(0.033)	
Attendance × Before_3		0.036**		-0.011		-0.051
		(0.012)		(0.007)		(0.043)
Attendance × Before_2		0.006		-0.008		-0.068
		(0.011)		(0.007)		(0.043)
Attendance × Before_1		0.021**		-0.002		-0.039
		(0.007)		(0.006)		(0.026)
Attendance × Post_1		-0.007**		-0.008		-0.096***
		(0.003)		(0.005)		(0.013)
Attendance × Post_2		-0.015***		-0.020***		-0.146***
		(0.004)		(0.004)		(0.020)
Attendance × Post_3		-0.016**		-0.015**		-0.114***
		(0.006)		(0.005)		(0.018)
Attendance × Post_4		-0.026***		-0.020**		-0.110***
		(0.005)		(0.006)		(0.016)
Attendance	-0.004	-0.017	0.003	0.007	0.065	0.098**
	(0.020)	(0.018)	(0.012)	(0.011)	(0.035)	(0.028)
Observations	3,446	3,446	3,402	3,402	2,104	2,104
Adjusted R^2	0.825	0.825	0.815	0.814	0.575	0.574
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of attendance at climate strikes on corporate greenhouse gas emissions. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Attendance* is the logarithm of one plus the total attendance at the climate strikes located within 5 km of the firm's headquarters. *Post* is an indicator variable equal to one for years after 2019. $Before_3$, $Before_2$, and $Before_1$ denote the three years preceding the strikes and $Post_1$ through $Post_4$ denote the four years following them. Covariate balance between treated and control firms is achieved via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, HHI, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: **Precipitation, climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
Rainy day	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Emissions scaled by revenue						
Strike × Post	-0.129**	-0.077	-0.074**	-0.098	-0.892**	-0.061
	(0.053)	(0.070)	(0.027)	(0.055)	(0.269)	(0.311)
Strike	0.262	-0.322	0.105	-0.022	0.978**	-0.330
	(0.150)	(0.179)	(0.095)	(0.151)	(0.301)	(0.331)
Observations	1,837	1,550	1,812	1,535	1,206	864
Adjusted R^2	0.771	0.827	0.743	0.686	0.500	0.542
Panel B: Unscaled emissions						
Strike × Post	-0.140**	-0.086	-0.117**	-0.109	-0.935**	-0.109
	(0.051)	(0.061)	(0.038)	(0.065)	(0.283)	(0.308)
Strike	0.148	-0.236	0.015	0.087	0.882**	-0.219
	(0.140)	(0.193)	(0.095)	(0.129)	(0.311)	(0.326)
Observations	1,837	1,550	1,812	1,535	1,206	864
Adjusted R^2	0.831	0.851	0.854	0.823	0.609	0.638
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions, estimated separately for firm locations that experienced rain and those that did not. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: **Walkable climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
Walkable	No	Yes	No	Yes	No	Yes
Strike	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Emissions scaled by revenue						
Strike × Post	-0.110	-0.141***	-0.095	-0.052	-0.486	-0.744***
	(0.060)	(0.036)	(0.075)	(0.028)	(0.441)	(0.200)
Strike	0.012	0.043	0.152	0.128	0.135	0.820***
	(0.204)	(0.118)	(0.161)	(0.091)	(0.415)	(0.225)
Observations	2,467	3,262	2,426	3,218	1,384	1,999
Adjusted R^2	0.761	0.778	0.657	0.673	0.610	0.477
Panel B: Unscaled emissions						
Strike × Post	-0.098	-0.147**	-0.093	-0.072*	-0.455	-0.766***
	(0.053)	(0.043)	(0.065)	(0.037)	(0.450)	(0.206)
Strike	-0.054	0.010	0.087	0.120	0.022	0.779**
	(0.205)	(0.117)	(0.132)	(0.080)	(0.404)	(0.227)
Observations	2,467	3,262	2,426	3,218	1,384	1,999
Adjusted R^2	0.854	0.829	0.841	0.81462	0.700	0.593
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of walkable and non-walkable climate strikes on corporate greenhouse gas emissions. We use the National Walkability Index developed by the EPA to determine whether a climate strike was in a location with a walkability above average. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: **City size, climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
City	Small (1)	Large (2)	Small (3)	Large (4)	Small (5)	Large (6)
Panel A: Emissions scaled by revenue						
Strike × Post	0.022	-0.187**	-0.056	-0.0004	-0.472	-0.742*
	(0.045)	(0.073)	(0.035)	(0.053)	(0.266)	(0.329)
Strike	-0.009	0.078	0.181	-0.105	0.443	0.614
	(0.176)	(0.204)	(0.097)	(0.146)	(0.319)	(0.329)
Observations	1,741	1,601	1,731	1,567	1,024	1,027
Adjusted R^2	0.709	0.825	0.669	0.713	0.474	0.495
Panel B: Unscaled emissions						
Strike × Post	-0.002	-0.202**	-0.091	-0.015	-0.457	-0.821**
	(0.050)	(0.071)	(0.056)	(0.053)	(0.272)	(0.324)
Strike	-0.104	0.174	0.086	0.009	0.315	0.719*
	(0.167)	(0.203)	(0.099)	(0.124)	(0.307)	(0.330)
Observations	1,741	1,601	1,731	1,567	1,024	1,027
Adjusted R^2	0.794	0.876	0.804	0.870	0.626	0.607
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions, estimated separately for climate strike locations in small cities (population less than 250,000 in 2019) and large cities. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14: **Altering the treatment identification radius**

Distance from HQ:	5 Km		10 Km		25 Km	
Emissions	Scaled (1)	Unscaled (2)	Scaled (3)	Unscaled (4)	Scaled (5)	Unscaled (6)
Panel A: Scope 1						
Strike × Post	-0.121***	-0.124**	-0.122**	-0.123**	0.149	0.217
	(0.034)	(0.039)	(0.035)	(0.045)	(0.168)	(0.179)
Strike	0.088	0.031	0.311**	0.227*	0.093	0.039
	(0.115)	(0.111)	(0.128)	(0.118)	(0.222)	(0.198)
Observations	3,446	3,446	3,446	3,446	3,446	3,446
Adjusted R^2	0.764	0.825	0.753	0.832	0.812	0.842
Panel B: Scope 2						
Strike × Post	-0.068**	-0.085**	-0.038	-0.048	0.045	0.085
	(0.021)	(0.028)	(0.032)	(0.035)	(0.057)	(0.054)
Strike	0.151*	0.116	0.210*	0.136	-0.177	-0.218
	(0.078)	(0.071)	(0.098)	(0.088)	(0.154)	(0.130)
Observations	3,402	3,402	3,402	3,402	3,402	3,402
Adjusted R^2	0.668	0.815	0.635	0.797	0.769	0.836
Panel C: Scope 3						
Strike × Post	-0.700***	-0.699***	-0.531*	-0.477*	0.176	0.261
	(0.178)	(0.181)	(0.231)	(0.210)	(0.410)	(0.426)
Strike	0.783***	0.705**	0.534*	0.334	-0.342	-0.378
	(0.223)	(0.224)	(0.269)	(0.247)	(0.374)	(0.403)
Observations	2,104	2,104	2,104	2,104	2,104	2,104
Adjusted R^2	0.456	0.578	0.436	0.560	0.535	0.595
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions using alternative definitions of treatment based on the distance between the firm's headquarters and the nearest climate strike location. Columns (1)–(2) define treated firms as those headquartered within 5 km of a climate strike, columns (3)–(4) within 10 km, and columns (5)–(6) within 25 km. The dependent variables are the natural logarithm of Scope 1 (Panel A), Scope 2 (Panel B), and Scope 3 (Panel C) emissions, either scaled by revenue or unscaled. *Strike* is an indicator variable equal to one if the firm's headquarters falls within the relevant distance threshold of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Appendix A: **Variable definitions**

Variable	Description
Strike	Dummy variable equal to 1 if the firm headquarters is within 5 km of a climate strike.
Post	Dummy variable equal to 1 for the years after 2019.
Scope1	Natural logarithm of direct CO_2 equivalent emissions in tonnes from sources owned or controlled by the firm.
Scope2	Natural logarithm of indirect CO_2 equivalent emissions in tonnes from the generation of purchased energy.
Scope3	Natural logarithm of other indirect CO_2 equivalent emissions in tonnes occurring across the firm's value chain, including both upstream and downstream activities.
Scope1Int	Natural logarithm of Scope 1 CO_2 equivalent emissions in tonnes divided by net sales or revenue in US dollars in millions.
Scope2Int	Natural logarithm of Scope 2 CO_2 equivalent emissions in tonnes divided by net sales or revenue in US dollars in millions.
Scope3Int	Natural logarithm of Scope 3 CO_2 equivalent emissions in tonnes divided by net sales or revenue in US dollars in millions.
Scope1 Growth	Logarithmic growth of scaled or unscaled Scope 1 CO_2 equivalent emissions.
Scope2 Growth	Logarithmic growth of scaled or unscaled Scope 2 CO_2 equivalent emissions.
Scope3 Growth	Logarithmic growth of scaled or unscaled Scope 3 CO_2 equivalent emissions.
Ln(Size)	Natural logarithm of market capitalization, computed as the product of share price and shares outstanding.
Ln(BTM)	Natural logarithm of the ratio of book equity to market capitalization.
ROA	Net income scaled by total assets.
Asset Growth	Year-over-year percentage change in total assets.
Leverage	Total debt scaled by book equity.
Ln(PPE)	Natural logarithm of property, plant, and equipment.
Sales Growth	Year-over-year percentage change in revenue.
EPS Growth	Year-over-year percentage change in earnings per share.
Beta	Market beta estimated using a 60-month rolling regression of firm excess returns on market excess returns following CAPM.
IVol	Idiosyncratic volatility estimated as the standard deviation of residuals from a 21-day rolling regression of firm returns on the Fama-French three-factor model.
HHI	Herfindahl–Hirschman index, calculated as the sum of the squared market shares of all firms within the same two-digit SIC industry, and where market share is calculated as the firm's revenue relative to the cumualtive industry revenue.

Continued on next page

Variable	Description
CCSN	Climate change social norm computed using principal component analysis applied to survey responses from the Yale Climate Opinion Maps (Zhang et al., 2024).
RGGI	Dummy variable equal to 1 if firm's headquarter state participates in the Regional Greenhouse Gas Initiative (https://www.rggi.org/).
State target	Categorical variable for state-level greenhouse gas emissions targets, distinguishing between statutory targets, executive, recommended, or combinations thereof (https://www.c2es.org/).
Waste	Total amount of waste produced in tonnes divided by net sales or revenue in US dollars in millions.
Water	Total water withdrawal in cubic meters divided by net sales or revenue in US dollars in millions.
Energy	Total direct and indirect energy consumption in gigajoules divided by net sales or revenue in US dollars in millions.
ERT	Dummy variable equal to 1 if the firm set an emission reduction target before 2019.
Board gender diversity	Percentage of females on the board.
Top Polluters	Firms in top polluting industries based on Ilhan et al. (2021) and Seltzer et al. (2022).
Red (Blue) State	Dummy variable equal to 1 if the state in which the firm is headquartered had a Republican (Democrat) governor elected at the time of the climate strike.
Attendance	Logarithm of one plus the total attendance at the climate strikes located within 5 km of the firm's headquarters.
Precipitation	Dummy variable equal to 1 if the cumulative precipitation on September 20 and 29 for the closest weather station accounts to zero.
Walkability	Dummy variable equal to 1 if firms are treated by a strike with higher-than-average walkability.

Appendix B: **First-stage probit regression**

	Scope 1	Scope 2	Scope 3
	(1)	(2)	(3)
Strike	0.072*	0.076**	0.118***
	(0.037)	(0.037)	(0.039)
Industry Disclosure	3.048***	3.053***	3.197***
	(0.128)	(0.129)	(0.169)
Ln(Size)	0.349***	0.344***	0.357***
	(0.021)	(0.021)	(0.022)
Ln(BTM)	0.081***	0.069**	0.097***
	(0.028)	(0.028)	(0.030)
ROA	0.500**	0.484**	0.357
	(0.206)	(0.206)	(0.226)
Asset Growth	−0.002***	−0.002***	−0.002**
	(0.001)	(0.001)	(0.001)
Leverage	0.038***	0.040***	0.048***
	(0.010)	(0.010)	(0.010)
Ln(PPE)	0.279***	0.271***	0.178***
	(0.018)	(0.018)	(0.018)
Sales Growth	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)
EPS Growth	−0.0001**	−0.0001**	−0.0001
	(0.0001)	(0.0001)	(0.0001)
Beta	0.087***	0.075**	0.019
	(0.032)	(0.032)	(0.035)
Ivol	−0.097***	−0.101***	−0.008
	(0.023)	(0.023)	(0.025)
HHI	−0.0001***	−0.0001***	−0.0001***
	(0.00002)	(0.00002)	(0.00002)
CCSN	−0.001	0.0002	0.005***
	(0.001)	(0.001)	(0.001)
RGGI	0.155***	0.147***	0.021
	(0.046)	(0.046)	(0.048)
State target: Recommended	−0.560***	−0.552***	−0.141
	(0.201)	(0.200)	(0.219)
State target: Executive	−0.069	−0.084	0.034
	(0.053)	(0.053)	(0.058)
State target: Statutory	0.047	0.031	0.163***
	(0.053)	(0.053)	(0.055)
State target: Statutory and executive	0.061	0.035	0.209***
	(0.051)	(0.051)	(0.054)
State target: Executive and recommended	0.704***	0.722***	0.804***
	(0.224)	(0.223)	(0.215)
State target: Statutory, executive, and recommended	0.050	0.023	0.250**
	(0.099)	(0.099)	(0.099)
Constant	−5.994***	−5.925***	−5.972***
Observations	11,357	11,357	11,374
Pseudo R^2	0.455	0.449	0.398

This Table reports the first-stage Probit regression estimates of the probability of disclosing Scope 1, Scope 2, and Scope 3 emissions. *Strike* is an indicator variable equal to one if the firm's headquarters falls within the relevant distance threshold of a climate strike location. *Industry Disclosure* is the average disclosure rate for Scope 1, 2, or 3 emissions, respectively, calculated across all firms within the same two-digit SIC industry. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof). Standard errors are reported in parentheses. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix C: **Correlation matrix**

Panel A: Emissions Variables	Scope1	Scope2	Scope3	Scope1Int	Scope2Int	Scope3Int
Scope1	1.000					
Scope2	0.724	1.000				
Scope3	0.594	0.603	1.000			
Scope1Int	0.869	0.464	0.408	1.000		
Scope2Int	0.505	0.707	0.346	0.627	1.000	
Scope3Int	0.423	0.336	0.877	0.474	0.426	1.000

Panel B: Control Variables	Ln(Size)	Ln(BTM)	ROA	Asset Growth	Leverage	Ln(PPE)	Sales Growth	EPS Growth	Beta	Ivol	HHI	CCSN	RGGI	Strike
Ln(Size)	1.000													
Ln(BTM)	-0.472	1.000												
ROA	0.314	-0.373	1.000											
Asset Growth	0.041	-0.025	0.128	1.000										
Leverage	0.032	-0.458	-0.076	-0.044	1.000									
Ln(PPE)	0.655	-0.045	0.035	-0.074	0.173	1.000								
Sales Growth	0.063	-0.014	0.216	0.409	-0.064	-0.003	1.000							
EPS Growth	0.050	-0.085	0.129	0.020	-0.015	-0.031	0.032	1.000						
Beta	-0.301	0.259	-0.219	-0.036	0.089	-0.001	0.012	-0.035	1.000					
Ivol	-0.398	0.251	-0.273	-0.001	0.061	-0.115	0.036	-0.071	0.280	1.000				
HHI	0.042	0.001	0.037	-0.024	0.064	0.178	-0.028	-0.016	-0.007	0.042	1.000			
CCSN	0.209	-0.192	0.061	0.013	0.025	0.000	0.015	0.035	-0.095	-0.066	-0.114	1.000		
RGGI	0.054	-0.076	0.032	0.022	0.009	-0.101	0.012	0.020	-0.096	-0.037	-0.109	0.357	1.000	
Strike	0.085	-0.060	0.022	0.016	0.051	0.037	-0.002	0.009	-0.075	-0.047	0.029	0.259	0.244	1.000

This Table reports the correlation matrix of the variables used in the difference-in-differences regressions. *Strike* is an indicator variable equal to one if the firm's headquarters falls within the relevant distance threshold of a climate strike location. Variable definitions are provided in Appendix A.

Appendix D: **Coefficient stability analysis**

	Scope1Int	Scope2Int	Scope3Int	Scope1	Scope2	Scope3
δ*	-0.896	1.629	0.977	-2.283	-4.826	5.346
β*	-0.275	-0.040	-0.440	-0.201	-0.117	-0.668

This Table reports coefficient stability statistics following Oster (2019). δ^* denotes the proportional degree of selection on unobservables relative to selection on observables required to attenuate the baseline treatment effect to zero, assuming a maximum R^2 of $R_{\max} = 1.3 \times R^2_{\text{full}}$. Values of δ^* greater than one in magnitude indicate that unobserved selection would need to be at least as strong as selection on observables to eliminate the estimated effect. Negative values of δ^* imply that selection on unobservables would have to operate in the opposite direction of selection on observables to overturn the results. β^* reports the bias-adjusted treatment effect under the assumed proportional selection and $R_{\max}$. Variable definitions are provided in Appendix A.

Appendix E: **Climate change social norms, climate strikes and emissions**

Dependent Variables	Scope 1		Scope 2		Scope 3	
CCSN	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Panel A: Emissions scaled by revenue						
Strike × Post	-0.161**	-0.110*	-0.067	-0.070**	-0.221	-0.714**
	(0.060)	(0.054)	(0.048)	(0.025)	(0.351)	(0.265)
Strike	0.152	0.034	0.189	0.081	0.497	0.591*
	(0.183)	(0.162)	(0.116)	(0.118)	(0.302)	(0.255)
Observations	1,671	1,732	1,629	1,730	852	1,224
Adjusted R^2	0.818	0.741	0.725	0.667	0.554	0.501
Panel B: Unscaled emissions						
Strike × Post	-0.154**	-0.138**	-0.051	-0.122**	-0.191	-0.752**
	(0.057)	(0.053)	(0.047)	(0.040)	(0.371)	(0.272)
Strike	0.043	-0.014	0.064	0.070	0.416	0.550*
	(0.179)	(0.151)	(0.100)	(0.114)	(0.303)	(0.268)
Observations	1,671	1,732	1,629	1,730	852	1,224
Adjusted R^2	0.876	0.817	0.831	0.835	0.637	0.625
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This Table reports difference-in-differences estimates of the effect of climate strikes on corporate greenhouse gas emissions, estimated separately for firms located in counties with low (below-median) and high (above-median) climate change social norms (CCSN) as of 2019. The dependent variables are the natural logarithm of Scope 1, Scope 2, and Scope 3 emissions, either scaled by revenue (Panel A) or unscaled (Panel B). *Strike* is an indicator variable equal to one if the firm's headquarters is located within 5 km of a climate strike location. *Post* is an indicator variable equal to one for years after 2019. Covariate balance between treated and control firms is achieved in each subsample via entropy balancing, with the resulting weights applied in the regression. All specifications include year and industry fixed effects. Control variables include the natural logarithm of firm size, the natural logarithm of the book-to-market ratio, return on assets, asset growth, leverage, the natural logarithm of property, plant and equipment, sales growth, earnings per share growth, market beta, idiosyncratic volatility, the Herfindahl–Hirschman Index, a county-level measure of climate change social norms, an indicator for participation in the Regional Greenhouse Gas Initiative, and state-level emissions targets (classified as statutory, executive, recommended, or combinations thereof).We control for self-selection bias in emissions disclosure using the inverse Mills ratio from a first-stage probit model. Standard errors, reported in parentheses, are two-way clustered at the firm and year levels. Variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.