The Unseen Cost of Green Policies: The Impact of Environmental Regulation on Workplace Safety*

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September 2025

Abstract

Leveraging three environmental regulatory changes as quasi-natural experiments, and employing difference-in-differences models, we find robust evidence that stringent environmental regulations increase workplace safety violations across all experimental settings. This effect is primarily due to financial constraints and operational adjustments required for compliance, with their interaction further intensifying the effect. The adverse impact is more pronounced when stakeholders heighten their focus on environmental issues and when product market competitiveness is intense. Our findings reveal a significant unintended consequence of climate policies, underscoring a critical trade-off between environmental and social dimensions of ESG.

Keywords: climate policy, workplace safety, financial constraints, operational adjustment, ESG.
JEL code: G38; K32

*We thank Kewei Hou, Pei-Fang Hsieh, Zhongchen Hu, Amir Kermani, Lilian Ng, Chen Shen, Elena Simintzi, Renxuan Wang, and the participants of the Asian Finance Association Annual Conference 2024, Western Economic Association International Annual Conference 2024, Financial Management Association (FMA) Annual Meeting 2024, FMA Doctoral Student Consortium 2024, New Zealand Finance Meeting 2024, Australasian Finance and Banking Conference 2024, and China International Conference in Finance 2025 for their valuable comments and suggestions. All remaining errors are our own.

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1. Introduction

Governments worldwide are enacting various regulations to address the escalating challenges of climate change. However, environmental issues are complex and intertwined with other societal challenges, complicating the assessment of policy effectiveness and the potential for unintended consequences. One critical but under-researched aspect is how the transition toward a green economy affects workplace safety. For instance, the International Labor Organization (ILO, 2024) has highlighted the need to examine the impact of climate change on worker safety and health, urging stakeholders to integrate occupational health and safety measures into their frameworks.[1] Despite the importance and urgency of this issue, empirical evidence remains scarce.

Existing literature has extensively studied the economic and operational impacts of environmental regulations, such as their impact on industrial activities, employment, wage, and corporate actions (e.g., Becker and Henderson, 2000; Greenstone, 2002; Walker, 2011, 2013; Bartram et al., 2022; Brown et al., 2022; Dang et al., 2023). However, the non-pecuniary consequences of these policies, particularly for employee welfare and workplace safety, are less understood. This study addresses this gap by investigating how environmental regulations influence workplace safety.

Workplace safety is a crucial element of employee welfare, with work-related injuries and diseases claiming approximately 2.3 million lives annually (ILO, 2003). Furthermore, workplace safety is an integral part of the "social" dimension of corporate Environmental, Social, and Governance (ESG) performance. Yet, the interplay between environmental and social dimensions of ESG remains ambiguous. On one hand, environmental initiatives may compete with workplace safety for financial resources, as firms prioritize compliance with environmental regulations. Faced with the challenge of balancing

[1]See recent reports and articles by the International Labor Organization (https://www.ilo.org/publications/ensuring-safety-and-health-work-changing-climate), the European Agency for Safety and Health at Work (https://oshwiki.osha.europa.eu/en/themes/climate-change-impact-occupational-safety-and-health-osh#_edn42), and the Institution of Safety and Health (https://iosh.com/news-and-opinion/the-impacts-of-climate-change-on-osh).

competing tasks with limited resources, managers must weigh the relative incentives and measurability of competing objectives. Since safety outcomes are inherently probabilistic, reduced safety investments may not immediately lead to incidents. Thus, the drive for environmental compliance can inadvertently compromise workplace safety. On the other hand, regulatory pressure for environmental performance can also enhance stakeholder attention to ESG practice, potentially improving workplace safety. From this perspective, environmental initiatives may boost the focus on social welfare, suggesting potential complementarity between environmental and social objectives. Taken together, the overall impact of environmental regulation on workplace safety remains theoretically ambiguous and warrants thorough empirical investigation.

Our empirical strategy employs three major environmental regulations in the United States: the 1990 Clean Air Act Amendments (hereafter *CAAA*), the revisions of the National Ambient Air Quality Standards from 1990 to 2018 (hereafter *NAAQS Revisions*), and the California Cap-and-Trade Program in 2012 (hereafter *California ETS*). These regulations impose a sudden environmental compliance burden on a subset of firms, designated as the treatment group, while other firms that are not affected serve as the control group. Using difference-in-differences (DiD) models and establishment-level safety violations data from the Occupational Safety and Health Administration (OSHA), we find consistent evidence across all three regulatory settings that stricter environmental regulations are associated with an increase in safety violations among affected firms compared to their unaffected counterparts. The economic impact is also substantial, with plants affected by the regulations experiencing an increase in safety violations ranging from 28% to 400%, depending on the model specifications.

We then investigate the underlying mechanisms behind the observed detrimental impact of environmental regulation on workplace safety. First, we consider financial constraint, as abundant evidence in the finance literature suggests that financial constraints are linked to increased pollution and safety incidents (e.g., Cohn and Wardlaw, 2016; Cohn et al., 2021; Dang et al., 2022; Xu and Kim, 2022). Using multiple proxies of financial constraints, we observe that financial constraints intensify the negative impact of environmental regulations on safety.

We further examine whether firms divert resources away from safety in response to tightened environmental regulations. Drawing on recent literature that utilizes labor inputs to measure firm investment in environment and AI initiatives (Darendeli et al., 2022; Babina et al., 2024), we examine how firms reallocate resources between safety and environmental roles by analyzing the ratio of safety job postings relative to environmental postings, as well as the number of safety personnel. Our findings reveal that affected firms prioritize hiring for environmental positions over safety roles, resulting in a decline in safety personnel. These results align with the notion that environmental regulatory pressures intensify resource competition, leading to reduced safety investments and, consequently, adverse safety performance.

The second mechanism that we explore is operational adjustment. Environmental policy directives often compel firms to integrate new technologies or equipment to achieve compliance with environmental standards.[2] Specifically, firms must adopt green technologies or modify their production processes. These operational changes introduce novel tasks for workers, often carrying new safety risks. Given that workplace accidents are more likely to occur when workers are assigned novel tasks rather than routine tasks (Grote, 2012), we hypothesize that firms subject to stringent environmental mandates are more likely to undertake significant operational adjustments, subsequently leading to a higher incidence of safety violations.

Quantifying the extent of operational adjustments in response to the green transition is challenging. We address this issue using two approaches. First, drawing on prior research that distinguishes production and process innovation (Bena and Simintzi, 2024)

[2]The Environmental Protection Agency (EPA) offers guidance to encourage companies to embrace innovative technologies for environmental protection. For illustrative information, please refer to the Clean Air Technology Center Products page: https://www.epa.gov/catc/clean-air-technology-center-products#factsheets.

and leveraging the green-patent classifications (e.g., Sautner et al., 2023), we construct a measure of green-process patent. This measure reflects firms' investment in environmentally friendly process innovations, which often require significant changes to their production workflows. Second, we utilize the EPA's Pollution Prevention (P2) database, which provides plant-year-level abatement activities such as source reduction measures. This measure, as employed by Duchin et al. (2025), captures the abatement efforts that often lead to operational process changes. Our analysis reveals that firms subjected to stringent environmental mandates undertake more operational adjustments than their unaffected counterparts. Furthermore, firms that make substantial changes in their production processes experience a higher incidence of safety violations. These findings are consistent with the notion that environmental regulatory pressures drive operational adjustments, including the adoption of green technologies and abatement processes, which inadvertently increase safety risks.

We further explore the interplay between operational adjustments and financial constraints. If resource limitations drive the link between environmental regulations and safety violations, this effect should be stronger in financially constrained firms that undertake substantial operational changes. Conversely, financially robust firms can mitigate operational risks through careful planning and worker training. Our findings support this hypothesis: financially robust firms, despite engaging in significant operational adjustments, do not exhibit significantly increased safety violations. In contrast, financially constrained firms, especially privately held firms, that undergo operational adjustments report significantly more safety violations compared to those making minor operational changes. This finding extends prior literature on the role of financial constraints in workplace safety (e.g., Cohn and Wardlaw, 2016) by highlighting an underlying mechanism in the context of climate finance: the operational changes required for green transition demand additional resource support to buffer against safety risks, and financial constraints intensify resource limitations, leading to compromised safety performance

Finally, we explore how external factors moderate the effect of environmental regulations on workplace safety. Considering stakeholder attention to climate change, we find a stronger impact of environmental regulations on safety violations when stakeholder interest in climate change is elevated. This evidence contradicts the hypothesis that heightened stakeholder attention to climate issues prompts firms to improve overall ESG practices, leading to better safety performance.

One additional notable finding is the differing impact of various environmental regulations on workplace safety. Specifically, we find that regulations controlling toxic pollutants (*CAAA* and *NAAQS Revisions*) have a transient negative effect on workplace safety, while the *California ETS*, which targets carbon emission, shows a more sustained adverse effect.[3] Through a detailed comparison of the regulatory frameworks and supplementary tests, we provide two suggestive explanations for this divergence. First, *CAAA/NAAQS Revisions* mandate immediate operational changes to fulfill environmental compliance, while *California ETS* allows firms to either purchase carbon allowances or reduce emissions. Second, *CAAA/NAAQS Revisions* provide clear abatement technology guidance, whereas *California ETS* lacks specific decarbonization protocols. As a result, the absence of cost-efficient decarbonization technologies and the flexible compliance options under *California ETS* incentives firms to opt for purchasing carbon allowances rather than making operational changes. Conversely, firms regulated by *CAAA/NAAQS Revisions* undertake operational adjustments, which introduce temporary unfamiliar tasks and operational challenges for workers, resulting in transitory safety concerns. Through this analysis, we hope to shed light on how the availability of green technology and the design of environmental regulations influence the balance between environmental compliance and workplace safety.

[3] We recognize the limitations of straightforward comparisons between different regulations due to variations in sample periods and firm coverage. However, these regulations represent two distinct regulatory approaches to achieving environmental goals. Given the importance of regulation design to policymakers and stakeholders in addressing climate change, we offer some suggestive explanations. We detail this discussion in Section 5.

Our paper contributes to three important strands of literature. First, we expand upon the research exploring the economic consequences of environmental regulations and climate transition risks (e.g., Becker and Henderson, 2000; Greenstone, 2002; Walker, 2011, 2013; Bartram et al., 2022; Dang et al., 2023; Ivanov et al., 2024). While prior research primarily focuses on the impact of environmental policy risks on economic and financing outcomes, we investigate the non-pecuniary aspects of employee welfare. This issue is particularly urgent amid the growing emphasis on mitigating climate change through regulatory interventions. Our study contributes to this debate by revealing the intricate interplay between environmental compliance and labor protection, offering a deep analysis of the underlying mechanisms. Specifically, we show that operational adjustments—often an inevitable component of decarbonization—can introduce new safety risks, particularly in financially constrained firms. These results highlight that providing additional financial resources for such firms could facilitate the green transition while mitigating negative social impacts.

Second, we contribute to the workplace safety literature (e.g., Cohn and Wardlaw, 2016; Caskey and Ozel, 2017; Cohn et al., 2021; Bradley et al., 2022; Liang et al., 2023) by identifying new channels through which external factors influence safety outcomes. While existing research often examines workplace safety through a shareholder or market-driven lens, we identify shifts in resource allocation and operational adjustments as critical drivers of increased safety risks under environmental regulatory pressures. To the best of our knowledge, our paper is the first to link operational process changes directly to workplace safety. By uncovering these mechanisms, our study opens new avenues for workplace safety research to explore how external factors, such as regulatory requirements and financial constraints, impact safety outcomes through resource allocation and process changes.

Finally, we contribute to the ongoing ESG debate by illuminating the tensions between the environmental ("E") and social ("S") dimensions of ESG. Prior research has largely focus on ESG's financial outcomes (e.g., Krueger, 2015; Albuquerque et al., 2019; Edmans, 2023; Starks, 2023), ESG measurement challenges (Berg et al., 2022), and the interplay between the environmental (E) and governance (G) aspects of ESG (Deng et al., 2013; Krueger, 2015; Ferrell et al., 2016). We enrich this dialogue by examining how environmental regulations impact workplace safety, providing direct evidence of climate transition risks. Several concurrent papers address similar questions.[4] Farzamfar et al. (2022) use Violation Tracker data[5] to document a negative relationship between environmental and social violation penalties, suggesting conflict between environmental and social objectives. Conversely, Li et al. (2024) find a positive relationship between workplace safety and environmental performance, measured by toxic release and ESG ratings, indicating complementarity between environmental and social outcomes. Our study differs from these papers by directly investigating the causal effects of environmental regulations on workplace safety across multiple regulatory settings, rather than exploring general environmental-social performance relationships. This focus allows us to offer robust evidence on the safety risks associated with climate transition policies, bridging an important gap in ESG literature.

The remainder of the paper is structured as follows. Section 2 discusses the institutional background and empirical strategy. Section 3 describes the data and sample construction. Section 4 presents our empirical results. In Section 5, we discuss the differences between the results documented under the various regulatory settings. Section 6 concludes the paper.

[4]Using China environmental regulation and China-listed firms' data, Huang et al. (2024) also study the tension between E and S. They find that Chinese firms under greater climate pressure experience low employee-related social performance.

[5]Safety violations constitute the dominant component of social violations in the Violation Tracker database. However, since Violation Tracker only includes violations with penalties above $5,000, its coverage of safety violations is substantially smaller than the OSHA violations data used in our analysis. We further discuss the differences between Violation Tracker and OSHA violations data in Section 3.

2. Institutional Background and Identification

In this section, we discuss the environmental regulations that form the foundation of the difference-in-differences analyses employed in this study. We detail the identification strategy, explaining how we implement these regulations as our empirical design. Our first two analyses hinge on the U.S. Clean Air Act, including the Clean Air Act Amendments in 1990 and the revisions of the National Ambient Air Quality Standards. The third analysis utilizes the California Cap-and-Trade Program.

2.1. The Clean Air Act and the NAAQS

The Clean Air Act (CAA) is the United States' fundamental federal law designed to regulate all sources of air emissions. Originally enacted in 1963, the Act has undergone significant revisions in 1970, 1977, and 1990, with the 1970 amendments empowering the Environmental Protection Agency (EPA) to establish the National Ambient Air Quality Standards (NAAQS). The NAAQS is a mechanism to protect public health and the environment by specifying strict limits on pollution levels for six key air pollutants.[6] The 1977 amendments further strengthened the Act by mandating an annual review of each U.S. county's air quality status, categorizing them as either in attainment or out of attainment (nonattainment) with NAAQS standards.

Compliance with the CAA and the NAAQS is compulsory. When a county falls out of compliance for a regulated pollutant, the EPA requires state authorities to develop regulatory plans—known as State Implementation Plans (SIPs)—to bring the county into compliance. Noncompliance with these requirements results in severe sanctions from the EPA.[7] SIPs are comprehensive documents that lay out plant-specific regulations, including strict emissions limits and guidelines for necessary changes in production processes, such

[6] The NAAQS cover six criteria air pollutants, including ozone, nitrogen dioxide, particulate matter, sulfur dioxide, carbon monoxide, and lead.

[7] Sanctions could be in the form of withholding federal grant monies (e.g., highway construction funds), direct EPA enforcement and control, penalty fees, and bans on the construction of new establishments with the potential to pollute.

as mandating the installation of state-of-the-art pollution control technologies.

The 1990 Clean Air Act Amendments as a Research Design. The 1990 Clean Air Act Amendments (*CAAA*) is the latest major amendment of the CAA, introducing a new particulate matter standard (PM10). Additionally, the EPA formally evaluated existing nonattainment designations so that 137 counties found themselves in nonattainment for at least one new pollutant. This represents a 34% increase, by far the largest documented increase in nonattainment designations since 1978.[8] Walker (2013) employs *CAAA* to examine labor reallocation and documents that the costs associated with environmental policy-induced reallocations of labor are significant. In line with Walker's (2013) empirical design, we investigate safety violations three years before and after the implementation of *CAAA* using the following DiD regression model.

$$Violations_{it} = \alpha_0 + \beta_1 CAAA_i \times Post\_1990_t + \beta_2 X_{it} + \beta_3 \theta_i + \beta_4 \delta_t + \epsilon_{it} \tag{1}$$

where i indexes plant, and t indexes year. *Violations* is the number of safety violations. Given that *Violations* is a count variable, we estimate fixed effects Poisson models (Cohn et al., 2022).[9] *CAAA* is equal to one for plants located in counties that were designated as nonattainment due to *CAAA* and zero for plants located in counties that maintained attainment status throughout the study window. *Post_1990* is an indicator variable equal to one if the year is after 1990 and zero otherwise. X represents a set of plant-level characteristics, including the natural logarithm of the number of employees (*Log Emp*) and workers' union status (*Union*). We do not include firm-level characteristics because the source of our firm variables, Capital IQ, begins in 1994. We include plant-fixed effects, θ, and either year- or industry-year-fixed effects, δ, to control for unobserved plant-, time-, and industry-time-invariant characteristics that may influence our findings.

The NAAQS Revisions as a Research Design. As noted above, the last major

[8] The data on U.S. counties classifications into attainment and nonattainment provided on the EPA's website begins in 1992. We obtain earlier years' classifications from Walker (2013).

[9] Our findings are robust to using OLS regressions with a log-transformed dependent variable.

amendments of the CAA occurred in 1990. However, the NAAQS thresholds have undergone discrete revisions by the EPA (*NAAQS Revisions*).[10] These revisions are triggered by new scientific findings about air pollution, making them largely exogenous to firm characteristics. For example, in 2015, the EPA updated the Ozone standard following a comprehensive evaluation of a wide range of new scientific evidence. This revision significantly expanded and reinforced the understanding of ozone-related health effects compared to the prior review in 2008.[11]

NAAQS Revisions have a few notable beneficial features as an identification setting. First, all counties are classified based on the same NAAQS thresholds, reducing concerns that designations are driven by county-specific characteristics. Second, the federal enforcement of NAAQS reduces the tendency for *NAAQS Revisions* to be significantly influenced by other county- or state-level regulations. Third, only a subset of counties is designated as nonattainment following a change in the NAAQS thresholds. This makes it possible to generate our treated and control groups based on the geographical differences in environmental regulatory stringency.

Using Ozone *NAAQS Revisions* as identification, Choi et al. (2022) find that the stock market internalizes the perceived benefits and costs of local environmental regulation. Our second empirical strategy expands upon Choi et al., relying on the nonattainment designations induced by revisions to the NAAQS thresholds of all the regulated pollutants occurring between 1990 and 2018. Specifically, we investigate safety violations for plants in counties that were designated as nonattainment due to *NAAQS Revisions* during the sample period (the treated group) relative to plants in counties that were not labeled as nonattainment (the control group) using a staggered DiD approach. As Baker et al. (2022) point out, the comparisons of treatment effects between earlier and later treated samples in staggered DiD designs are inappropriate when treatment effects are dynamic. We mitigate

[10] See the Online Appendix, Table OA1, for a list of the NAAQS Revisions used in our analysis.

[11] https://www.federalregister.gov/documents/2015/10/26/2015-26594/national-ambient-air-quality-standards-for-ozone

this concern by ensuring that our control group only includes counties that were never designated as nonattainment during the sample period.[12] We estimate the following DiD model for the sample period 1987 – 2021.[13]

$$Violations_{it} = \alpha_0 + \beta_1 NA_i \times Post\_NA_t + \beta_2 X_{it} + \beta_3 \theta_i + \beta_4 \delta_t + \epsilon_{it} \tag{2}$$

where *NA* is an indicator variable that equals one if a county entered nonattainment status due to *NAAQS Revisions* during the sample period and zero otherwise. *Post_NA* is one after the county is classified as nonattainment and zero otherwise. *X* represents a set of plant- and firm-level characteristics. The plant-level control variables are the same as those included in Equation (1). Following the literature on workplace safety (e.g., Cohn and Wardlaw, 2016; Cohn et al., 2021; Bradley et al., 2022), we control for firm-level characteristics, including *Firm Size* (natural logarithm of total assets), *Leverage* (total debt/total assets), *Tangible Assets* (net property, plant, and equipment/total assets), *Cash Holding* (cash and short-term investments/total assets), and *Profitability* (earnings before extraordinary items/total assets). All other variables as the same as previously defined.

2.2. The California Cap-and-Trade Program

The California Cap-and-Trade Program (*California ETS*) is a landmark initiative that establishes a comprehensive cap-and-trade system spanning multiple sectors.[14] It is North America's maiden extensive cap-and-trade system and the only mandatory cap-and-trade program introduced in any state within the United States that covers the majority of firms with high greenhouse gas (GHG) emissions across industries. Covering nearly 85% of the state's GHG emissions, the program is designed to incorporate a wide array of facilities,

[12] We also show in the Online Appendix, Table OA4, that our conclusion remains qualitatively unchanged when we use a stacked DiD regression around the Ozone *NAAQS Revisions*.

[13] We begin from 1987 because the EPA's database on toxic release inventories starts from 1987. This gives us three years prior to the first major NAAQS revision in 1990. Also, given that the Capital IQ data begins in 1994, we supplement our firm variables with Compustat data for the years before 1994.

[14] Cap-and-trade is a market-based emissions trading system that establishes a declining cap on emissions over time and distributes tradeable credits under the cap.

specifically targeting power generation and industrial plants that emit 25,000 or more metric tons of carbon dioxide equivalent (MT CO_2e) annually.

The California Cap-and-Trade Program operates on a market-driven approach, allowing entities to trade compliance instruments through auctions and allocations. Participants must adhere to a vintage-specific schedule for emissions reductions, managing their compliance obligations through the acquisition of allowances and credits on the open market. As a cap-and-trade mechanism, the program offers regulated entities two primary compliance strategies. GHG emitters can implement emission reduction strategies. Alternatively, polluters unable to achieve their emissions targets through reductions must purchase allowances in quarterly auctions or acquire offsets by trading with other covered entities that possess surplus credits. This program is the foundation of California's climate policy, which is anchored in three key GHG emission reduction targets: returning emissions to 1990 levels by 2020, achieving a 40% reduction below 1990 levels by 2030, and reaching an 80% reduction by 2050. In pursuit of these critical goals, the California Air Resources Board (CARB) launched the cap-and-trade program in 2012, introducing compliance obligations that began in January 2013.

The California Cap-and-Trade Program as a Research Design. Using a difference-in-differences framework around *California ETS*, Bartram et al. (2022) show that financially constrained firms shift emissions and output from California to other states where they have similar plants that are underutilized. In a similar vein, Ivanov et al. (2024) find that high emission firms affected by *California ETS* face shorter loan maturities, lower access to bank financing, higher interest rates, and higher participation of shadow banks in their lending syndicates. Inspired by these papers, we exploit variation in the treatment of *California ETS* in the cross-section (i.e., California GHG emitters compared to other GHG emitters) and time series (i.e., before compared to after the introduction of the rule in 2012) to implement a DiD analysis.[15] Particularly, we examine the impact of *California ETS* on

[15]California is among the largest pro-climate states in the United States. Hence, it is worth acknowledging that California may generally be different from other states in terms of climate policy changes.

workplace safety from 2009 to 2015 by estimating the following DiD regression model.

$$Violations_{it} = \alpha_0 + \beta_1 Cal_i \times Post\_2012_t + \beta_2 X_{it} + \beta_3 \theta_i + \beta_4 \delta_t + \epsilon_{it} \tag{3}$$

where *Cal* is an indicator variable equal to one if a plant is in California and zero otherwise. *Post_2012* is an indicator variable equal to one if the year is after 2012 and zero otherwise. Like in Equation (2), we include plant- and firm-level control variables, X, including *Log Emp*, *Union*, *Firm Size*, *Leverage*, *Tangible Assets*, *Cash Holding*, and *Profitability*. Similarly, we incorporate plant-fixed effects, θ, and industry-year-fixed effects, δ. The definitions of the variables in the regression model are the same as previously defined.

3. Data

3.1. Data Sources

Our measure of workplace safety is the number of safety violations committed by a plant in a year. We obtain comprehensive plant-level data on health and safety violations from the U.S. Occupational Safety and Health Administration (OSHA). The literature also employs two alternative datasets to assess workplace safety: OSHA injuries and Violation Tracker violations (e.g., Cohn and Wardlaw, 2016; Heese and Pérez-Cavazos, 2020; Cohn et al., 2021; Li and Raghunandan, 2021; Heese et al., 2022). However, OSHA violations data surpasses these alternative sources and better aligns with our study for the following reasons.

First, unlike OSHA's injury data, which is only available from 1996 to 2011, with a major structural change of definitions in 2001, the violations data is available from the 1970s until the present date with no major structural change. The long period of coverage allows us to implement an extensive and more complete DiD analysis around the three regulatory settings studied in this research. Second, OSHA's safety violation is more comprehensive than the Violation Tracker database. This is because Violation Tracker includes only safety violations with a penalty above $5,000, whereas OSHA violations cover all safety violations irrespective of the penalty amount. Given that many safety violations result in small penalties, Violation Tracker covers a small fraction of the OSHA violations database. During the period 2000 – 2021, for instance, the number of safety-related violations recorded in Violation Tracker (177,148) is only about 14 percent of that contained in the OSHA violations data (1,272,134).[16] A growing body of literature also uses safety violations to measure safety performance (e.g., Wiengarten et al., 2017; Johnson, 2020).

We draw on multiple resources to construct plant-level pollution-related characteristics. Our first source is EPA's Toxic Release Inventories (TRI). TRI monitors the waste management practices of over 800 toxic chemicals that threaten human health and the environment. Facilities in various U.S. industry sectors are required to report annually on the amounts of each chemical they release into the environment. For the *NAAQS Revisions* setting, TRI allows us to identify regulated plants within nonattainment counties, and for *California ETS*, we are able to identify GHG emitters as described in the later sections. Our second source of plant-level emission-related data is the Air Facility Subsystem (AFS), also maintained by the EPA. AFS database provides facility-level data detailing the regulatory programs for which the establishment is permitted (and regulated) as well as the pollutants for which the permit is issued.[17] Following Walker (2013), the *CAAA* setting relies on AFS to identify regulated firms in nonattainment counties.

We supplement our analysis with additional data sources. Firm-level variables are gathered from the Capital IQ database. To assess green patents, we utilize patent data from PatentsView and Bena and Simintzi (2024).[18] In our mechanism tests, we use data on abatement adjustment from EPA's Pollution Prevention (P2) database. Proxies of stakeholder attention to climate change are from the World Values Survey (WVS) and the Yale

[16]Online Appendix, Table OA2, compares the coverage of OSHA violations and Violation Tracker.

[17]A major drawback of the dataset is that there is no date information regarding when the operating permits were issued. We gauge the date based on the year of nonattainment designations (Walker, 2013).

[18]Support for the PatentsView database and the team that works on it comes from the Office of the Chief Economist at the United States Patent and Trademark Office (USPTO).

Climate Opinion Maps. To evaluate safety investments, we use data on safety employees and environment- and safety-related job postings from Lightcast (formerly Emsi and Burning Glass Technologies).

3.2. Sample Construction

To generate the sample for the *CAAA* setting, we begin with the universe of plants covered in both the OSHA violations and EPA's AFS databases. Specifically, we map facilities in the OSHA violations data with those in the AFS data using a fuzzy matching procedure based on names and ZIP codes. This step generates 79,515 plant-year observations. Next, we eliminate all observations that are outside the sample period of three years before and after 1990. Since only polluting plants are regulated, we delete establishments that do not emit the six toxic chemicals regulated by the Clean Air Act. Finally, we delete apparently abnormal observations, such as negative violations and employees. The resulting sample includes 3,531 plant-year observations. Panel A of Appendix B summarizes these steps.

We create the *NAAQS Revisions* sample by first fuzzy-matching OSHA and TRI plants based on names and ZIP codes. This procedure results in 85,594 plant-year observations. Afterward, we keep observations that are within the sample period for our *NAAQS Revisions* setting, i.e., 1987 – 2021. Then, we delete non-polluting plants as they are not regulated by the Clean Air Act. We also eliminate nonattainment designations before 1987 and abnormal observations. The final sample for the *NAAQS Revisions* includes 13,945 plant-year observations. These steps are summarized in Panel B of Appendix B.

The generation of our *California ETS* sample is in line with that of the *NAAQS Revisions* sample. First, we fuzzy-match OSHA and TRI plants based on names and ZIP codes, which results in 85,594 plant-year observations. Next, we keep observations that are within the sample period 2009 – 2015. Then, we delete establishments that do not emit greenhouse gases above 25,000 metric tons of carbon dioxide equivalents (MT CO_2e) per year.

Finally, we eliminate abnormal observations to arrive at our final sample of 1,052 plant-year observations.[19] An alternative dataset used in the literature is EPA's Greenhouse Gas Reporting Program (GHGRP) data, which provides GHG data from large GHG emission sources in the U.S. (Bartram et al., 2022; Ivanov et al., 2024). We use TRI because GHGRP starts in 2010, while our analyses begin in 2009, three years before the launch of the California Cap-and-Trade Program. Nonetheless, our findings hold when we focus on plants covered in the GHGRP database, as shown in the Online Appendix, Table OA5.

Finally, to accommodate firm-level characteristics in our empirical analyses, we use the following steps to merge the plant-level data with the firm variables supplied by Capital IQ. We link the name and address of OSHA establishments with Capital IQ. In the case of unlinked plants, we use Capital IQ's name-matching template to map the establishment names with Capital IQ firms. We manually verify all the fuzzy matching techniques employed in this study using Google searches, company websites, and firm information from Capital IQ. We drop discernibly abnormal values, such as negative assets. The final samples with firm-level variables include 4,635 and 452 for the *NAAQS Revisions* and *California ETS* settings, respectively.

3.3. Summary Statistics

Table 1 presents the summary statistics of the plants and firms we employ in our study. Generally, the industry coverage of our samples is comparable across the three settings. Panel A shows that plants in the *CAAA* sample commit about 8 safety violations on average, which is the highest among the three samples. Aside from Violations, the other plant-level characteristics are comparable across the settings. Similarly, the firm-level variables are not considerably dissimilar between the *NAAQS Revisions* (Panel B) and *California ETS* (Panel C) samples. With the mean Log Plant value of around 0.8, for instance, the sample firms have an average of 2 plants during the sample periods. Overall, the statistics align

[19] In the Online Appendix OA3, we describe how we identified establishments that emit greenhouse gases above 25,000 metric tons of carbon dioxide equivalent per year from the TRI data.

with existing studies. For example, the average number of safety violations is higher in the early 1990s (Panel A) than in the 2010s (Panel C), consistent with Cohn et al.'s (2021) observation that there have been improvements in workplace safety over the past few decades.

[Insert Table 1 about here]

4. Empirical Results

In this section, we present and discuss three sets of findings. First, we provide the baseline and dynamic results of testing the effect of environmental regulation on safety violations using the three regulatory settings discussed above. Second, we explore the underlying mechanism behind the relationship between environmental regulation and safety. Finally, we present further heterogeneity tests that sharpen our conclusions.

4.1. Baseline Results

4.1.1. The 1990 Clean Air Act Amendments and Workplace Safety

We test the effect of *CAAA* on safety violations by estimating Equation (1) and presenting the results in Table 2. Columns (1) and (2) report the baseline effect of *CAAA* on safety violations, whereas Columns (3) and (4) report the dynamic trend in the relation. We include plant-level control variables and plant-fixed effects in all columns. The first and third columns include year-fixed effects. The second and fourth columns include industry-year-fixed effects. The first two columns show that the coefficient on the variable of interest, *CAAA* × *Post_1990*, is consistently positive and significant. For instance, in Column (1), the coefficient is 0.652 and significant at the five percent level. Economically, the result indicates that plants in counties that were designated as nonattainment due to *CAAA* (i.e., those exposed to strict environmental regulation) increased safety violations by about 91.9 percent (= exp(0.652) – 1) compared to their counterpart plants in attainment counties (i.e., those exposed to less stringent environmental regulation). This huge economic magnitude is driven by the extensive margin as environmental regulations not only increase the incidence of violations but also cause plants that had no violations in the pre-event period to experience violations in the post-event period.[20]

To investigate the dynamic trend in the relation between *CAAA* and safety violations, we interact *CAAA* and $Post\_1990_n$, defined as one if the year is n years relative to 1990 and zero otherwise. Then, we regress safety violations on the interaction terms and the control variables included in Columns (1) and (2). We observe that our coefficients of interest are insignificant until after 1990. Specifically, the relationship becomes significant two years after the amendments. The delayed effect can be attributed to firms needing some time to fully incorporate the new standards into their operations.

[Insert Table 2 about here]

Figure 1 graphs the dynamic trend of the impact of *CAAA* on *Violations*. Panel A depicts a plot of the coefficients from the regression of *Violations* on the interaction of *CAAA* and $Post\_1990_n$. We also display the 90% confidence interval. The coefficients noticeably increase in magnitude after 1990. Moreover, the difference in *Violations* between the treated and control plants is significantly distinguishable only after 1990. The trend flow is much clearer in Panel B, where the separate evolution of the average *Violations* for the treated and control samples are closely aligned before the nonattainment designations induced by *CAAA*. The treated plants' average *Violations* diverges upwards after the shock in 1990, indicating that safety violations in the treated plants increased after the implementation of *CAAA* relative to the control plants.

[Insert Figure 1 about here]

[20] The effect of extensive margin is less pronounced in the *NAAQS Revisions* setting, which has a relatively larger sample size with a smaller number of zero *Violations*.

4.1.2. The NAAQS Revisions and Workplace Safety

In Table 3, we test the effect of *NAAQS Revisions* on safety violations by regressing safety violations on *NA* × *Post_NA* and other control variables. Across all columns, we include plant-level control variables, plant-fixed effects, and industry-year-fixed effects. In addition, Columns (2) and (4) control for firm-level characteristics, including firm size, cash holding, profitability, tangibility, book leverage, and the natural logarithm of the number of plants owned by firms.

The coefficient of interest for the baseline specification is on the interaction term *NA* × *Post_NA* because it captures the DiD effect of *NAAQS Revisions* on workplace safety. Like *CAAA*, the sign on *NA* × *Post_NA* is consistently positive in the first two columns. The coefficients are 0.245 and 0.416 with and without firm-level controls, respectively. They are also statistically significant at the one percent level. In terms of economic magnitude, Column (1) suggests that nonattainment designations induced by *NAAQS Revisions* increase safety violations of the treated plants by 28 percent (= exp(0.245) − 1) compared to the treated plants.

In the last two columns, we explore the dynamic trend in the relationship between *NAAQS Revisions* and safety violations. In particular, we regress safety violations on the interaction terms between NA and $Post\_NA_n$, where $Post\_NA_n$ is one if the year is n years relative to the event year and zero otherwise. The interaction terms' coefficient is insignificant in all columns before the event years, after which the estimates become statistically and economically significant.[21] The results suggest that there is no significant difference in safety violations between the treated and control groups before the event years.

[Insert Table 3 about here]

To better compare the dynamic of the effect, we plot the coefficients of the dynamic regressions with their 90% confidence interval in Panel A of Figure 2. The magnitudes

[21] $Post\_NA_0$ is omitted so that the effects are estimated relative to this year.

significantly increase after *NAAQS Revisions*. Panel B separately graphs the time trend of the average *Violations* for the treated and control samples. The average *Violations* for the treated and control plants are closely aligned before nonattainment designations induced by *NAAQS Revisions*. Following nonattainment designations, however, the trends diverge, with treated plants' average *Violations* increasing relative to that of the control plants. This is consistent with the parallel trend assumption.

[Insert Figure 2 about here]

4.1.3. The California Cap-and-Trade Program and Workplace Safety

In this subsection, we examine whether and to what extent workplace safety responds to the increase in environmental regulatory stringency that comes with the introduction of the California Cap-and-Trade Program. We estimate Equation (3) and present the results in Table 4. The baseline estimates and the dynamic DiD results are reported in the first two and last two columns, respectively. All columns include plant-level control variables as well as plant- and industry-year-fixed effects. Additionally, Columns (2) and (4) include firm-level control variables. In the first two columns, the results suggest that firms' violations of safety standards increase in the presence of emission trading schemes. The estimates are statistically significant and economically huge. The coefficient of interest in Column (1), for instance, is 1.612, indicating that California GHG-emitting plants increased safety violations by about 4 times (= exp(1.612) – 1) compared to non-California GHG-emitting plants. Like *CAAA*, the effect is huge on the extensive rather than intensive margin, suggesting that *California ETS* caused plants that had no violations in the pre-event period to experience violations in the post-event period. For our dynamic DiD tests, the coefficient of the interaction terms between *Cal* and $Post\_2012_n$ becomes significant only after 2012, supporting the parallel trend assumption and substantiating the evidence that the increase in safety violations is indeed caused by *California ETS*.

One concern is that the documented effect may not stem from the ETS regulation but from differences between plants located in California and those outside California. To address this concern, we perform a placebo test using plants in California with GHG emissions below the 25,000 MT CO_2e threshold as the treatment group. These plants are not subject to regulation under *California ETS* but are located in California. We find no significant change in safety performance between the treatment and control groups in this test. The results are presented in Table OA6 in the Online Appendix.

[Insert Table 4 about here]

We again graphically depict the dynamic regressions in the parallel trend graph as shown in Figure 3. In Panel A, we observe an increased and significant trend after *California ETS*. In Panel B, the average *Violations* for California GHG polluters are aligned with that of non-California GHG polluters until 2012. Upon the implementation of the cap-and-trade program, average *Violations* of the California plants rise sharply above those of the non-California plants, supporting the causality of the documented relationship.[22]

[Insert Figure 3 about here]

4.1.4. Robustness Checks

The exploitation of multiple quasi-natural experiments reduces endogeneity concerns in our documented findings. Nevertheless, we conduct further robustness tests in this section. A concern of staggered DiD designs is that comparisons of treatment effects between earlier and later treated samples may be inappropriate when treatment effects are dynamic (Baker et al., 2022). This can bias the average treatment effect of an unknown sign. Even though the use of clean treated and control groups in our regressions mitigates this problem, we show in the Online Appendix, Table OA4, that our baseline results still

[22] As presented in the Online Appendix, Table OA5, our conclusions are not significantly impacted if we restrict our sample to plants covered in the GHGRP database.

hold if we use stacked instead of staggered regressions. This test utilizes the four Ozone *NAAQS Revisions* in 1992, 2004, 2012, and 2018.

In untabulated results, we also confirm that, first, using the natural logarithm of *Violations* as an alternative measure of workplace safety does not significantly impact our findings. Second, our results are robust to using OLS instead of Poisson models. Third, our baseline results are not driven by the level at which we cluster standard errors in the regressions. These consistent findings across various sensitivity tests reinforce the robustness of the evidence presented in this study.

4.2. Mechanisms

We explore the economic reasons underlying the positive relationship between environmental regulation and safety violations.[23] Our study argues that the potential conflict between climate policies and workplace safety can arise from two main sources, the first of which is competing demands for limited financial resources. Specifically, financial resources are vital for both safety and environmental performance (Cohn and Wardlaw, 2016; Xu and Kim, 2022). As firms strive to comply with stringent environmental regulations, they could find themselves reallocating financial resources that could otherwise be used for workplace safety initiatives. Our second channel relies on the production process adjustments demanded by environmental regulations (Walker, 2013). Change in production methods entails deviations from previous routines, introducing potential new job hazards that can increase safety fractures (Grote, 2012).

4.2.1. Financial Constraints

First, we test the hypothesis that the financial constraint is a channel through which environmental regulation increases safety violations. We employ three measures of financial constraints including firm size, *WW Index* (Whited and Wu, 2006), and dividend pay-

[23] Due to the limited *CAAA* and *California ETS* samples, our further analyses focus on the *NAAQS Revisions* sample.

out. Firms are categorized as financially constrained if they are above the median for *WW Index*, if they are below the median for firm size, and if they have dividend payout. Table 5 reports the results of the analysis, which compares the effect of environmental regulation on safety violations between subsamples partitioned based on the financial constraint measures.

We find a stronger effect for financially constrained firms. For instance, Columns (3) and (4), which proxy financial constraints by *WW Index*, show that *NAAQS Revisions* significantly increase the treated plants' *Violations* by 0.56 compared to the control plants for the high *WW Index*, whereas the effect is an insignificant 0.03 for the low *WW Index* subsample. The p-values of the differences across the subgroups' estimates are also significant at the 1% level. Furthermore, the results from using firm size and dividend payout corroborate those from using *WW Index*. Taken together, the findings align with our prediction that the effect of environmental regulation on safety violations is concentrated in financially constrained firms.

[Insert Table 5 about here]

If financial constraint explains the adverse impact of environmental regulation on workplace safety, then we expect affected firms to reduce their resources allocated to safety issues. We test this conjecture by investigating the impact of environmental regulation on firms' resource allocation and safety investments. We test resource allocation by looking at hiring priorities as measured by safety relative to environmental jobs in online job postings. Table 6, Columns (1) and (2), present the results. *Safety/Env. Jobs* is the ratio of safety- to environment-related online job postings. We find a significant decrease in this ratio. Meanwhile, Columns (3) and (4) show that the number of safety personnel (*Safety Employees*) decreases. Linked to the financial constraints evidence documented in this section, the results suggest firms adjust their financial resources in favor of environmental policy compliance at the expense of workplace safety upon the enactment of environmental policies.

[Insert Table 6 about here]

4.2.2. Operational Changes

We then test our conjecture that the operational changes induced by environmental regulation explain the documented effect on workplace safety. We use two measures of environmental policy-induced operational changes, including the number of granted green patents with process-related claims (*Green Process Patents*) and whether plants adjust their pollution sources (*Abatement Tech Changes*). To compute *Green Process Patents*, we first identify "green" patents from the universe of patents in the PatentsView database by applying the OECD green patent classification approach (e.g., Sautner et al., 2023).[24] Second, we merge the green patents with the process-related patent claims provided by Bena and Simintzi (2024). We classify green patents with process claim data as process-related green patents. Panel A of Table 7 shows that *NAAQS Revisions* increase *Green Process Patents* and *Abatement Tech Changes*.

We next study whether the change of operation is related to the increase in safety violations. In Panel B, we partition the sample into two subgroups based on *Green Process Patents* and *Abatement Tech Changes* after *NAAQS Revisions*. Particularly, firms with *Green Process Patents* above the sample median are classified as high and otherwise as low. Similarly, plants that make *Abatement Tech Changes* are classified as high and otherwise as low. We document consistent evidence that the relationship between *NAAQS Revisions* and workplace safety is more than two times larger for firms that make substantial production process changes than those that make no or fewer changes.

[Insert Table 7 about here]

4.2.3. Financial Constraints and Operational Changes

Firms' financial resources are vital in making operational changes following the introduction of strict environmental policies. That is, how operational changes influence

[24] An explanation of how the OECD classifies patents as green is provided by Haščič and Migotto (2015).

the relationship between environmental regulation and workplace safety could rely on the role of financial constraint. More specifically, we expect the limited financial resources for financially constrained firms to aggravate the role of operational changes in increasing safety violations following the enactment of environmental regulation compared to financially sound firms. We test this hypothesis by first partitioning the *NAAQS Revisions* sample into financially constrained and unconstrained subsamples. Within the financially constrained firms, we perform cross-sectional tests based on production process changes like Panel B of Table 7, where process change is proxied by Green Process Patents. We repeat the tests for the financially unconstrained subsample. The results are presented in Table 8.[25] We demonstrate that the role of operational changes in the environmental regulation–workplace safety relationship is concentrated among financially constrained firms.

[Insert Table 8 about here]

4.3. Heterogeneity tests

In this section, we explore whether the effect of environmental policies on workplace safety varies predictably with stakeholder attention, industry pressure, firms' geographic dispersion, and stock ownership type. These tests shed additional light on the economic mechanisms, painting a more complete picture of the relationship documented in this study.

4.3.1. Stakeholder Attention

Our results so far suggest that E clashes with S although, theoretically, E can promote S. We throw more light on this using stakeholder attention to firms' environmental endeavors. We investigate whether the attention of relevant stakeholders on climate

[25]For brevity of presentation, we report results for firm size and *WW Index* as proxies of financial constraints. Using the other financial constraint measures does not significantly impact our conclusion.

change explains why environmental policies increase firms' safety violations. We use two measures of stakeholder attention on climate change. The first proxy, *WVS Env. Attention*, is an index based on the responses to World Values Survey questions on the environmental priorities of respondents in the U.S. (Krueger et al., 2024). The index, which ranges from 0 to 1, captures the extent to which people in the U.S. are concerned about the environment. For our second proxy, we measure stakeholder attention on climate change using the Yale Climate Opinion Maps on climate regulations, *Env. Regulation Opinion*.

We partition the sample into high and low based on the median. In the first two columns of Table 9, *NAAQS Revisions* significantly increase safety violations when WVS Env. Attention is high, whereas the corresponding estimate for the low *WVS Env. Attention* group is not significant. Although the relationship between *NAAQS Revisions* and *Violations* is statistically significant for both high and low *Env. Regulation Opinion* groups, the effect is considerably larger when *Env. Regulation Opinion* is high. The findings suggest that corporate stakeholder attention to climate change plays a key role in the effect of climate regulation on workplace safety.

[Insert Table 9 about here]

4.3.2. Product Market Competitiveness

We also study the role of industry pressure, particularly product market competition, in the relationship between environmental policies and workplace safety. The objective of this test is to understand whether and how the "pressure to survive" in the industry intensifies the shift in focus from workplace safety compliance to environmental policy compliance following the passage of environmental regulation. Noncompliance with environmental regulations can lead to the forfeiting of operating permits and plant shutdowns. By contrast, penalties for safety violations tend to be minuscule, as is well-recognized in the literature (Pagell et al., 2020). Further, our discussion with practitioners indicates that some firms would rather pay for safety penalties than miss an important delivery deadline for their customers.

Moreover, Pagell et al. (2020) find that firms providing safer workplaces are associated with significantly lower odds of survival, attributing this outcome to inherent trade-offs between safety and productivity. Product market competition amplifies these pressures, as evidenced by prior research showing that increased competition adversely affects firm safety performance (McManus and Schaur, 2016). When environmental regulations demand substantial resource allocation for compliance, firms operating under competitive pressures may be compelled to deprioritize safety initiatives to maintain their competitive edge. Consequently, we expect that the relationship between environmental regulation and safety violations will be more pronounced for firms operating in highly competitive product markets.

Our measures of product market competition are *Sales HHI*, defined as the Herfindahl-Hirschman Index based on firms' sales at the industry level, and *Oligopoly*, calculated as the proportion of sales in a firm's industry that is accounted for by the two largest firms. We partition the samples into high and low based on the respective measures' median values. In Table 10, the effect is consistently larger when competition is higher, which is when *Sales HHI* and *Oligopoly* are lower. The evidence suggests that external pressure from the industry is influential in the effect of green policies on workplace safety.

[Insert Table 10 about here]

4.3.3. Geographic Arbitrage

Extant research suggests that the spread of plants across multiple locations is crucial in the impact of environmental policies on the firm. The effect of environmental regulation on firms that operate plants in both regulated and unregulated areas is less significant than on firms that operate plants in single locations (Walker, 2013; Bartram et al., 2022). This is because such firms can shift operations from highly regulated areas to less regulated areas where they have underutilized similar plants. Therefore, we test whether firms with plants spread across regulated and unregulated counties (*Dispersed Firms*) experience a weaker environmental regulation effect on workplace safety than firms that operate plants in one area (*Concentrated Firms*).

In Table 11, we estimate the response of workplace safety to environmental regulation in a subsample format for *Concentrated* and *Dispersed* firms. Location is defined in terms of county. We find that the magnitude and significance of the effect of environmental regulation on safety violations is indeed more pronounced for *Concentrated Firms* than for *Dispersed Firms*. For instance, in the Columns (3) – (4) specification, the coefficient on $NA \times Post\_NA$ is 0.970 and statistically significant at the 1% level. The corresponding estimate for *Dispersed Firms* is 0.267, which is about four times less and only marginally significant.

[Insert Table 11 about here]

4.3.4. Private and Public Firms

In our last test, we examine whether private firms are differentially affected compared to public firms. We argue that the substantial fundamental dissimilarities between the two firm types regarding financial constraints and stakeholder attention could have implications for the relationship between environmental regulation and workplace safety. Private firms tend to be more financially constrained than public firms (e.g., Saunders and Steffen, 2011; Erel et al., 2015). In support of this evidence, Ivanov et al. (2024) also observe that public firms are usually larger in size compared to private firms. Therefore, consistent with our financial constraints channel, our results would be more pronounced for private firms than for public firms.

However, an opposing direction of effect could be expected from the stakeholder attention perspective. This is because public ownership comes with more external public scrutiny than private ownership (Liang et al., 2023). Consequently, with the introduction of new environmental regulations, public firms are likely to be under more environmental policy compliance oversight and pressure. This argument is in line with the increasing shareholder demand for more disclosures on public firms' ESG endeavors (Krueger et al., 2024). In Table 12, we find that the effect of environmental regulation on safety violations is considerably larger for private firms than their public counterparts under all specifications. The evidence suggests that, regarding stock ownership type, the financial constraints channel dominates.

[Insert Table 12 about here]

5. Do Institutional Differences in Environmental Regulations Matter?

5.1. The Difference in Dynamic Impact Between CAAA/NAAQS Revisions vs California ETS

Our analysis confirms that stricter environmental regulations lead to an increase in safety violations. However, regarding the dynamic effect, we find that the Clean Air Act, aimed at controlling toxic pollutants (including *CAAA* and *NAAQS Revisions*), and the California Cap-and-Trade System (*California ETS*), designed to curb carbon emission, have distinct temporal impacts on workplace safety.

Specifically, the *CAAA*/*NAAQS Revisions* demonstrate a transient effect on safety violations. Table 2 and Figure 1 illustrate that the impact of *CAAA* is significant in the second year following policy implementation but diminishes by the third year. Similarly, tests based on *NAAQS Revisions* presented in Table 3 and Figure 2 indicate that firms experience a higher rate of violations from the first year of post-implementation, but the effect declines over time, with differences becoming non-significant after three years. On the other hand, the *California ETS* shows a more enduring effect on workplace safety. As depicted in Table 4 and Figure 3, the impact on firms subjected to *California ETS*, compared to those not affected, remains significant from the first to the third year of post-implementation, suggesting a lasting influence of *California ETS* on safety outcomes.

Recognizing the limitations of a straightforward comparison due to variations in sample periods and firm coverage, we conduct more analysis to ensure this differential finding is robust. First, we extend the post-event window to six years of post-implementation for both the 1990 *CAAA* and 2012 *California ETS*. We observe that the impacts are indeed enduring. According to our findings documented in the online appendix, the significant post-event differences for *California ETS* span all post-event years from 2013 to 2018, whereas, for *CAAA*, significance was only noted in 1992 (two-year post-implementation) and returned to baseline from 1993 to 1996.

Another possibility is that the *California ETS* sample contains certain industries that are more likely to endure long-lasting effects due to environmental regulations. To determine if industry-specific factors might drive these differences, we analyzed the top 10 industries across the three samples. Our analysis, as detailed in the online appendix, shows substantial overlap in industry coverage between the *California ETS* and *CAAA* samples, and similarly for *NAAQS Revisions*, suggesting that industry composition is unlikely to account for the observed differences.

5.2. Possible Explanation

To enhance our understanding of the differential impacts between the Clean Air Act and the California Cap-and-Trade System, we provide some potential explanations rooted in the regulatory design and technology availability.

First, we consider the regulatory design. The regulatory focus of the Clean Air Act, including *CAAA* and *NAAQS Revisions*, is primarily on reducing toxic chemicals harmful to human health and the environment. In contrast, the *California ETS* focuses on reducing greenhouse gases (GHG), a process that is inherently more complex than controlling specific toxic chemicals. Achieving GHG reductions often necessitates significant modifications to energy sources and production processes, whereas reducing specific types of toxic chemicals can typically be accomplished through simpler measures such as altering input materials, adding filters, or adopting standard abatement technologies. Therefore, from the firms' perspective, compliance with the *California ETS* by reducing carbon emissions is much more challenging than compliance with the *CAAA/ NAAQS Revisions*.

Moreover, the regulatory approaches differ significantly. The *CAAA/NAAQS Revisions* mandate specific operational adjustments to reduce targeted pollutants without allowing firms to opt out via financial payments. In contrast, *California ETS* operates as a cap-and-trade system, offering polluters two compliance options: they can either modify operations to cut emissions (the "operational approach") or purchase allowances (the "financial approach").

Second, the technology guidelines are well specified under *CAAA/ NAAQS Revisions* but absent in *California ETS*. The Clean Air Act requires states to develop detailed State Implementation Plans (SIPs). These SIPs contain plant-specific guidelines in the form of pollution limits and obligatory redesigns in production technologies. For instance, facilities in nonattainment areas, particularly new plants or those undergoing significant expansions, are compelled to employ "Lowest Achievable Emission Rates" (LAER) technologies, prioritizing emissions reductions without regard to cost. Existing facilities not undergoing major expansions in nonattainment areas must meet "Reasonably Available Control Technology" (RACT) standards, which are based on technological and economic feasibility. Conversely, polluters in attainment counties must meet the "Best Available Control Technology" (BACT) standards, which consider the economic implications of pollution control measures. In contrast, the California Air Resources Board (CARB) does not provide detailed technological guidance for achieving emission reductions.

Overall, the difference in the regulatory approach, combined with the varying technical challenges associated with reducing toxic chemicals versus carbon emissions, may explain the observed difference in temporal patterns of safety violations. The compliance pressure from *CAAA/NAAQS Revisions* is mainly on the operational side. Facing nonattainment, firms must make operational adjustments to comply, resulting in unfamiliar tasks for workers and a temporary spike in safety violations that tend to decrease after the transition period. In contrast, the lack of cost-efficient decarbonization technology, coupled with the option to comply by purchasing carbon allowances, may lead firms governed by the *California ETS* to favor a "financial approach"—purchasing allowances—over an "operational approach." According to Bartram et al. (2022), the estimated cost of an emission allowance under the California Cap-and-Trade program is approximately $12 per ton of carbon. However, the cost of reducing greenhouse gas emissions through technological means can exceed $46 per ton (Gillingham and Stock, 2018). CARB reports that emission allowances are consistently sold out at quarterly auctions, indicating the popularity of the "financial approach" and its enduring financial pressure on firms. Consequently, if purchasing emission allowances annually proves more economically viable, a sustained impact of the *California ETS* on safety violations would be a reasonable expectation.

5.3. Suggestive Evidence

The preceding discussion on regulatory focus, compliance mechanisms, and the availability of green technology in addressing pollution versus decarbonization offers potential explanations for why the impacts of *California ETS* are more enduring compared to the transient effects of the *CAAA* and *NAAQS Revisions*. Empirical investigation of this hypothesis is challenging, yet we attempt to provide some suggestive evidence through additional tests. In Table OA8 of the Online Appendix, we document a significant drop in green innovations and no change in safety versus environmental labor preferences under *California ETS*, while emission levels remained unaffected for the treated plants compared to controls. This indicates that firms affected by *California ETS* do not engage in operational changes. In contrast, as reported in Table 5, firms impacted by *NAAQS Revisions* show an increase in green process patents and a higher adoption of abatement technology. These findings are consistent with the conjecture that *NAAQS Revisions* tend to rely on operational changes for compliance, whereas firms under *California ETS* primarily depend on a financial approach to meet their compliance obligations.

These findings, while suggestive, underscore the complexity of environmental regulation impacts on workplace safety. The distinct temporal patterns of safety violations between *CAAA/NAAQS Revisions* and *California ETS* enforcement highlight the need for further research to fully understand these dynamics. Understanding that different environmental policies can lead to varying short-term and long-term safety challenges is essential for developing more effective compliance strategies and support mechanisms to mitigate adverse effects on workplace safety.

6. Conclusion

The urgency of climate change has prompted governments to implement regulations aimed at reducing harmful emissions. However, the implications of these policies for labor rights and employee welfare have received less attention. Our research addresses this gap by analyzing the impact of environmental policies on workplace safety.

Using comprehensive data and various identification strategies, we find that stricter environmental policies are linked to an increase in safety infractions, especially in establishments that are financially constrained, undergoing significant operational changes, experiencing heightened stakeholder attention to climate change, and facing intense market competition. Our study reveals the underlying mechanisms that connect environmental regulation and workplace safety. Specifically, the interplay between the operational adjustments required for compliance with environmental mandates and financial resource limitations drives the adverse impact of environmental regulation on safety issues.

Moreover, we provide suggestive explanations for why the Clean Air Act causes a temporary spike in safety violations, while California's Cap-and-Trade system leads to a long-lasting increase in safety violations. The compliance requirements, the fundamental differences between reducing toxic chemicals and reducing carbon emissions, and the availability of green technology to achieve these goals drive the observed temporal pattern.

Our research illuminates the unintended consequences of environmental regulations and provides valuable insights for policymakers, businesses, and labor advocates. It highlights the necessity for balanced regulations that protect both the environment and worker welfare. Additionally, it contributes a critical perspective to the dialogue on sustainable corporate practices.

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Appendix A: Variable Definitions

This table provides definitions and data sources of the study's variables.

Variable	Definition	Source
Dependent Variable		
Violations	Number of violations reported by OSHA	OSHA
Climate Policies		
CAAA	Dummy variable that equals one for counties designated as nonattainment due to *CAAA* and zero otherwise	Constructed
Post_1990	Dummy variable that equals one after 1990 and zero otherwise	Constructed
NA	Dummy variable that equals one for counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise	Constructed
Post_NA	Dummy variable that equals one after a county is classified as nonattainment due to *NAAQS Revisions* and zero otherwise	Constructed
Cal	Dummy variable that equals one for plants in California and zero otherwise	Constructed
Post_2012	Dummy variable that equals one after 2012 and zero otherwise	Constructed
Plant Characteristics		
Log Emp.	Natural logarithm of the number of employees	OSHA
Union	Dummy variable that equals one if employees have a union representation and zero otherwise	OSHA
Firm Characteristics		
Firm Size	Natural logarithm of total assets	Capital IQ
Cash Holding	Cash and cash equivalents scaled by total assets	Capital IQ
Profitability	Operating income before depreciation divided by total assets	Capital IQ
Tangible Assets	Net property, plant, and equipment divided by total assets	Capital IQ
Leverage	Total debt divided by total assets	Capital IQ
Log Plant	Natural logarithm of the number of plants owned by a firm	Capital IQ

WW Index	Whited and Wu's (2006) financial constraint index computed as − 0.091(Cash Flow/Total Assets) − 0.062(Positive Dividend) + 0.021 (Long-term Debt/Total Assets) − 0.044(Ln(Total Assets)) + 0.102 (Industry Sales Growth) − 0.035 (Sales Growth)	Capital IQ
Dividend	Amount of dividend paid	Capital IQ
Safety Employees	Number of safety workers	EMSI
Safety/Env. Jobs	Safety-related job postings scaled by environment-related job postings	Lightcast
Green Process Patents	Number of granted green patents with process claims, where process claims are defined by Bena and Simintzi's (2024) process-related patent claims data	PatentsView; Bena and Simintzi (2024)
Abatement Tech Changes	Dummy variable that equals one if a plant makes adjustments to the source of its toxic emissions and zero otherwise	EPA P2
Other Variables		
WVS Env. Attention	The ratio of World Values Survey respondents in the United States that (1) would do voluntary work for unpaid environment, conservation, and animal rights; (2) are active members of an environmental organization; (3) believe that it is important for a person to look after the environment; (4) would give part of their income for the environment; or (5) think that protecting the environment has priority in contrast to economic growth	World Values Survey
Env. Regulation Opinion	Yale Climate Opinion Maps' state-level score on the estimated percentage who think regulators should be doing more/much more to address global warming	Yale Climate Opinion Maps
Sales HHI	Herfindahl-Hirschman Index based on firms' sales at the industry level	Capital IQ
Oligopoly	Proportion of sales in a firm's industry that is accounted for by the two largest firms	Capital IQ

Appendix B: Determination of Final Samples

This table presents an overview of the steps used to obtain our final samples.

Step	No. of Obs.
Panel A: CAAA	
OSHA and AFS (1970 – 2021)	79,515
Restrict to sample period (1987 – 1993)	11,920
Drop non-polluters of the regulated toxics	8,336
Drop abnormal observations	**3,531**
Panel B: NAAQS Revisions	
OSHA and TRI (1970 – 2021)	85,594
Restrict to sample period (1987 – 2021)	65,219
Drop non-polluters of the regulated toxics	45,753
Drop counties designated as NA before 1987	21,558
Drop abnormal observations	**13,945**
Panel C: California ETS	
OSHA and TRI (1970 – 2021)	85,594
Restrict to sample period (2009 – 2015)	12,457
Drop non-emitters of greenhouse gas	1,748
Drop abnormal observations	**1,052**

Table 1: Summary Statistics

This table presents the summary statistics of the variables used in the study. Panels A, B, and C focus on *CAAA*, *NAAQS Revisions*, and *California ETS*, respectively. Detailed variable definitions are provided in Appendix A.

Variable	N	Mean	St. Dev	P25	Median	P75
Panel A: CAAA (1987 – 1993)						
Violations	3,531	7.720	9.695	1.000	4.000	11.00
Log Emp.	3,531	4.998	1.479	3.932	4.868	5.979
Union	3,531	0.479	0.500	0.000	0.000	1.000
Panel B: NAAQS Revisions (1987 – 2021)						
Violations	13,945	5.609	7.562	1.000	3.000	7.000
Log Emp.	13,945	5.223	1.316	4.382	5.220	6.064
Union	13,945	0.283	0.451	0.000	0.000	1.000
Log Plant	4,635	0.813	0.246	0.693	0.693	0.693
Firm Size	4,635	6.391	3.561	5.094	7.225	8.926
Cash Holding	4,635	0.060	0.071	0.006	0.037	0.089
Profitability	4,635	0.095	0.078	0.030	0.091	0.144
Tangible Assets	4,635	0.246	0.182	0.100	0.243	0.362
Leverage	4,635	0.211	0.174	0.042	0.205	0.325
Panel C: California ETS (2009 – 2015)						
Violations	1,052	4.442	7.033	0.000	2.000	5.000
Log Emp.	1,052	5.899	1.558	4.844	5.861	7.003
Union	1,052	0.471	0.499	0.000	0.000	1.000
Log Plant	452	0.874	0.306	0.693	0.693	1.099
Firm Size	452	8.380	2.810	7.515	8.965	10.09
Cash Holding	452	0.067	0.052	0.026	0.062	0.094
Profitability	452	0.121	0.127	0.057	0.102	0.147
Tangible Assets	452	0.326	0.190	0.181	0.333	0.468
Leverage	452	0.254	0.154	0.150	0.252	0.341

Table 2: The 1990 Clean Air Act Amendments and Workplace Safety

This table presents the effect of the 1990 Clean Air Act Amendments (*CAAA*) on workplace safety. The first and last two columns show the baseline and dynamic DiD results, respectively. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *CAAA* is a dummy variable equal to one for plants in counties designated as nonattainment due to the 1990 Clean Air Act Amendments and zero otherwise. *Post_1990* is a dummy variable that equals one after 1990 and zero otherwise. $Post\_1990_n$ is one if the year is n years relative to 1990 and zero otherwise. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables and plant-fixed effects. The first and third columns include year-fixed effects. The second and fourth columns include industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Violations	(2) Violations	(3) Violations	(4) Violations
CAAA × Post_1990	0.652**	0.605**		
	(2.317)	(2.070)		
CAAA × $Post\_1990_{-3}$			0.289	0.293
			(0.762)	(0.757)
CAAA × $Post\_1990_{-2}$			0.386	0.407
			(1.014)	(1.065)
CAAA × $Post\_1990_{-1}$			0.109	0.110
			(0.212)	(0.212)
CAAA × $Post\_1990_{+1}$			0.521	0.505
			(0.981)	(0.952)
CAAA × $Post\_1990_{+2}$			1.319***	1.362***
			(3.149)	(3.231)
CAAA × $Post\_1990_{+3}$			0.605	0.623
			(1.474)	(1.515)
Log Emp.	0.238***	0.242***	0.231***	0.221***
	(3.096)	(3.409)	(3.024)	(2.889)
Union	0.122	0.262*	0.138	0.180
	(0.712)	(1.718)	(0.800)	(1.006)
Observations	3,531	3,531	3,531	3,531
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes

Pseudo R-Squared	0.321	0.376	0.323	0.331

Figure 1: The Effect of the 1990 Clean Air Act Amendments on Workplace Safety
This figure shows the trend of safety violations around *CAAA*.

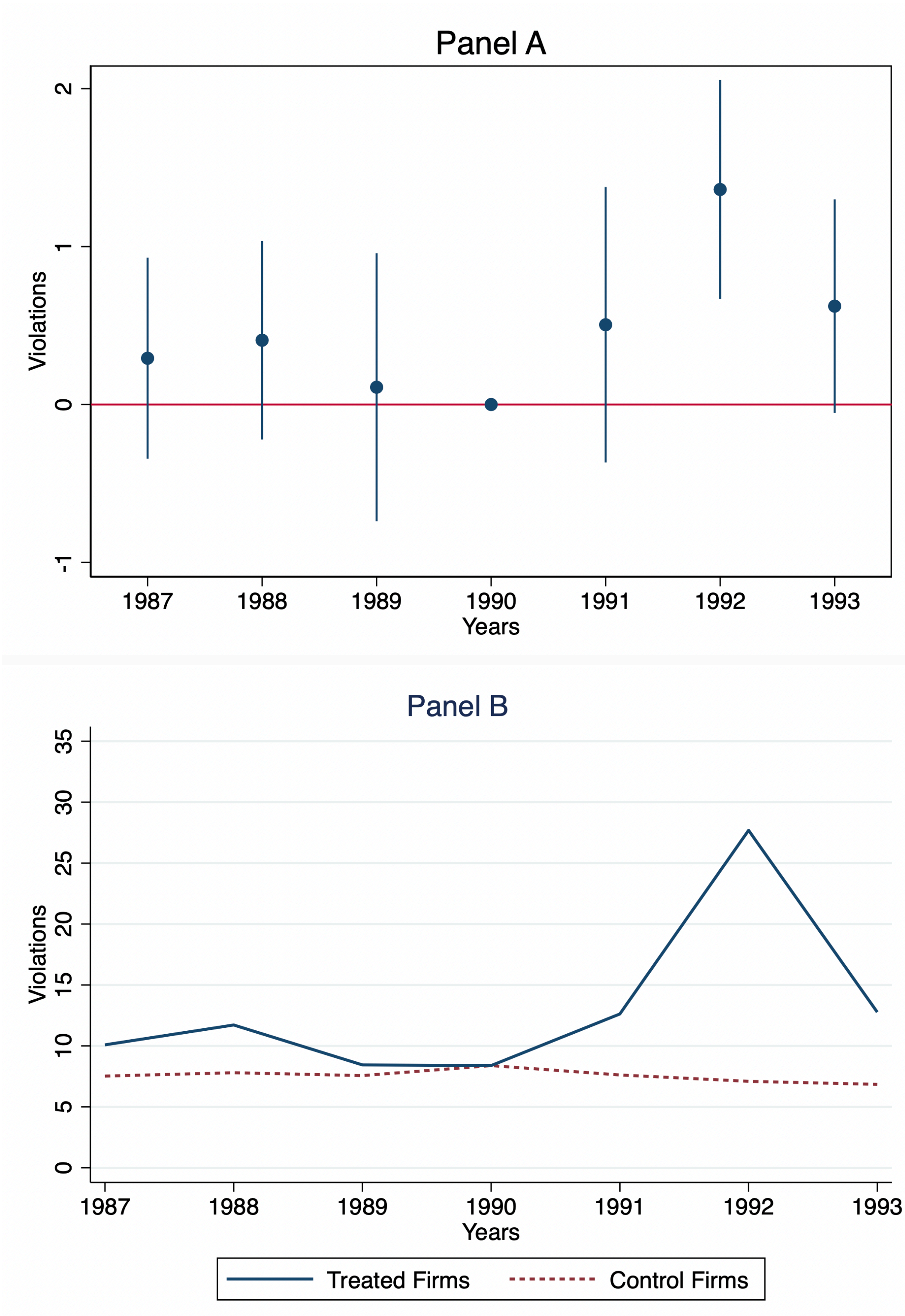

Table 3: NAAQS Revisions and Workplace Safety

This table presents the effect of *NAAQS Revisions* on workplace safety. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is a dummy variable that equals one after nonattainment designation and zero otherwise. *Post_NA$_n$* is a dummy variable equal to one if the year is n years relative to the year of nonattainment designation and zero otherwise. Detailed variable definitions are provided in Appendix A. Columns (1) and (3) include plant-level control variables, while Columns (2) and (4) include both plant and firm-level control variables. All regressions include plant-fixed effects and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Violations	(2) Violations	(3) Violations	(4) Violations
NA × Post_NA	0.245***	0.416***		
	(3.544)	(3.277)		
NA × Post_NA$_{\leq -4}$			0.209	0.209
			(1.090)	(0.644)
NA × Post_NA$_{-3}$			0.141	0.052
			(0.627)	(0.154)
NA × Post_NA$_{-2}$			-0.001	0.0700
			(-0.005)	(0.172)
NA × Post_NA$_{-1}$			0.140	0.059
			(0.638)	(0.179)
NA × Post_NA$_{+1}$			0.536**	0.414
			(2.204)	(0.884)
NA × Post_NA$_{+2}$			0.465**	0.612*
			(2.232)	(1.667)
NA × Post_NA$_{+3}$			0.511**	0.767**
			(2.086)	(1.982)
NA × Post_NA$_{\geq +4}$			0.268	0.255
			(1.368)	(0.855)
Log Emp.	0.493***	0.516***	0.439***	0.486***
	(23.56)	(12.74)	(22.15)	(13.29)
Union	0.124	0.155	0.237***	0.329*
	(1.483)	(0.909)	(2.834)	(1.943)
Log Plant		-0.079		0.011

		(-0.575)		(0.078)
Firm Size		0.021		-0.012
		(0.796)		(-0.566)
Cash Holding		0.079		0.424
		(0.150)		(0.922)
Profitability		-0.181		-0.687
		(-0.365)		(-1.456)
Tangible Assets		-0.603*		-0.253
		(-1.873)		(-0.912)
Leverage		0.561**		0.272
		(2.292)		(1.221)
Observations	13,945	4,635	13,945	4,635
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.356	0.428	0.294	0.298

Figure 2: The Effect of NAAQS Revisions on Workplace Safety
This figure shows the trend of safety violations around *NAAQS Revisions*.

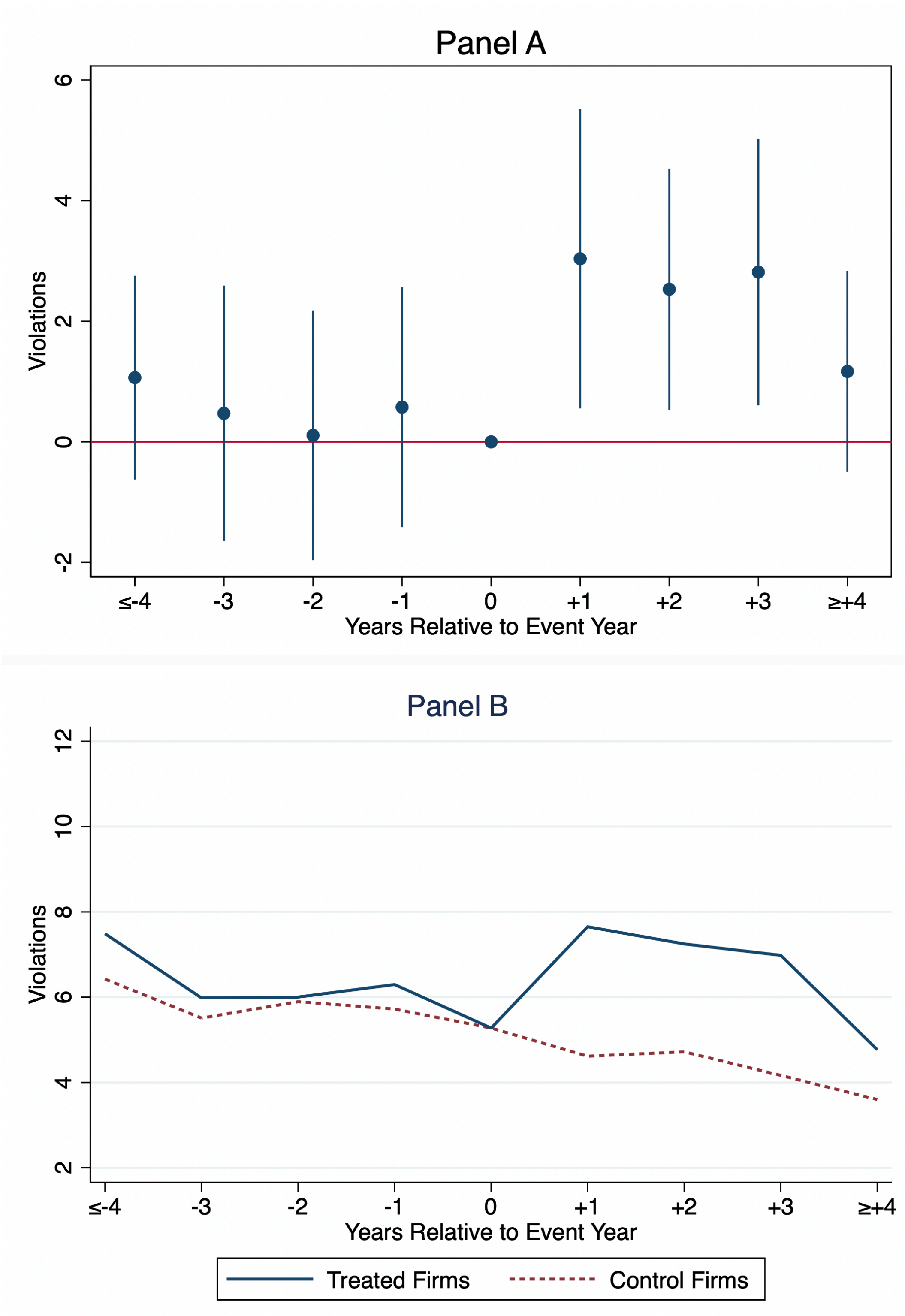

Table 4: California ETS and Workplace Safety

This table presents the effect of *California ETS* on safety violations. The first and last two columns show the baseline and dynamic DiD results, respectively. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *Cal* is a dummy variable that equals one for plants in California and zero otherwise. *Post_2012* is a dummy variable that equals one after 2012 and zero otherwise. $Post\_2012_n$ is equal to one if the year is n years relative to 2012 and zero otherwise. Detailed variable definitions are provided in Appendix A. The first two columns include plant-level control variables, while the last two columns include both plant- and firm-level control variables. All regressions include plant-fixed effects and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the state level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Violations	(2) Violations	(3) Violations	(4) Violations
Cal × Post_2012	1.612***	2.069***		
	(9.992)	(3.976)		
Cal × $Post\_2012_{-3}$			-0.203	0.526
			(-0.801)	(0.873)
Cal × $Post\_2012_{-2}$			-0.312	-0.008
			(-1.247)	(-0.014)
Cal × $Post\_2012_{-1}$			-0.421	0.186
			(-1.464)	(0.346)
Cal × $Post\_2012_{+1}$			0.896***	1.288**
			(3.836)	(2.463)
Cal × $Post\_2012_{+2}$			1.533***	2.394***
			(6.525)	(4.927)
Cal × $Post\_2012_{+3}$			0.691**	0.985*
			(2.039)	(1.707)
Observations	1,052	452	1,052	452
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.491	0.589	0.413	0.459

Figure 3: The Effect of California ETS on Workplace Safety
This figure shows the trend of safety violations around *California ETS*.

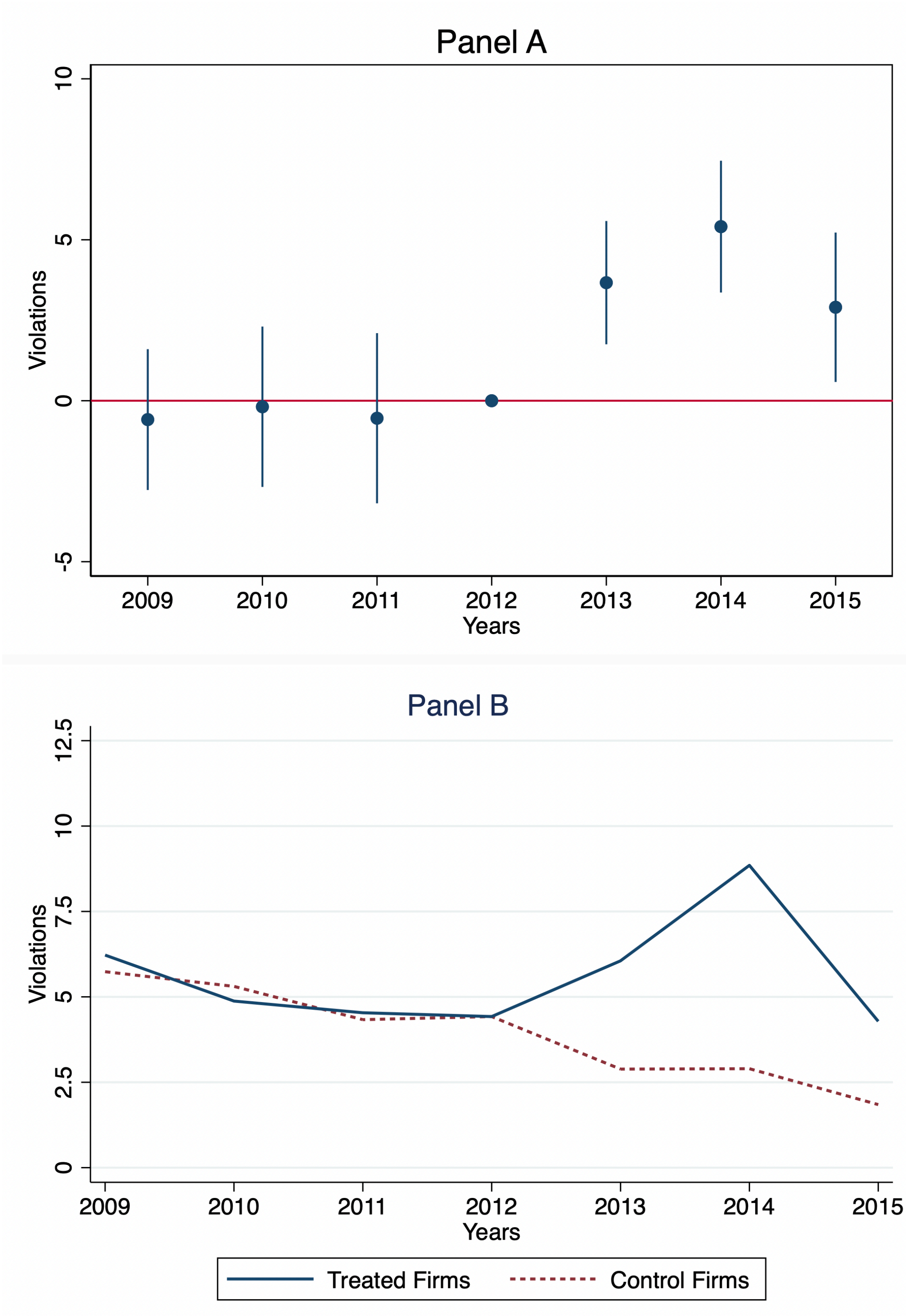

Table 5: Mechanism: Financial Constraints

This table presents the effect of *NAAQS Revisions* on workplace safety for subsamples partitioned based on financial constraints proxied by *Firm Size* (natural logarithm of total assets), *WW Index* (Whited and Wu's (2006) index), and *Dividend* (amount of dividend paid). Firms are grouped into high and low subsamples based on whether the financial constraints measure is above and below the sample median, respectively. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is one after nonattainment designation and zero otherwise. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables, firm-level control variables, plant-fixed effects, and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: Violations					
	(1) Small Firm	(2) Large Firm	(3) High WW Index	(4) Low WW Index	(5) High Dividend	(6) Low Dividend
NA × Post_NA	0.611***	0.111	0.560***	0.033	0.201	0.549**
	(4.258)	(0.447)	(3.904)	(0.146)	(1.294)	(2.417)
P-value of Difference	0.000		0.000		0.000	
Observations	2,320	2,315	2,312	2,323	2,311	2,324
Plant Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.475	0.508	0.501	0.486	0.482	0.481

Table 6: Resource Allocation and Safety Investments

This table presents the effect of *NAAQS Revisions* on resource allocation and safety investments proxied by labor changes. The dependent variable in Columns (1) and (2) is *Safety/Env. Jobs*, defined as safety-related job postings scaled by environment-related job postings. The dependent variable in Columns (3) and (4) is *Safety Employees*, defined as the number of safety-related workers. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is one after nonattainment designation and zero otherwise. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables, plant-fixed effects, and industry-year-fixed effects. Additionally, Columns (2) and (4) include firm-level control variables. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)
	Safety/Env. Jobs	Safety/Env. Jobs	Safety Employees	Safety Employees
NA × Post_NA	-0.080**	-0.078**	-1.979***	-1.585***
	(-2.476)	(-2.482)	(-3.662)	(-4.428)
Observations	4,635	4,635	4,635	4,635
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.474	0.475	0.858	0.861

Table 7: Mechanism: Operational Changes

This table presents the role of operational adjustments in the relationship between *NAAQS Revisions* and workplace safety. Panel A reports the effect of *NAAQS Revisions* on production process changes. In Columns (1) – (2), the dependent variable is *Green Process Patents*, which is defined as the number of granted green patents with process claims. The dependent variable in Columns (3) – (4) is *Abatement Tech Changes*, defined as a dummy variable that equals one if a plant makes a change to the source of its pollution and zero otherwise. All Panel A regressions include plant-level control variables, plant-fixed effects, and industry-year-fixed effects. Additionally, Columns (2) and (4) include firm-level control variables. Panel B reports the heterogeneous effects of climate policies on workplace safety based on production process changes. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. High and low groups are created based on the median of *Green Process Patents* and whether adjustments to pollution sources are made. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is one after nonattainment designation and zero otherwise. Detailed variable definitions are provided in Appendix A. All Panel B regressions include plant-level control variables, firm-level control variables, plant-fixed effects, and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: *NAAQS Revisions* and Production Process Changes

	(1)	(2)	(3)	(4)
	Green Process Patents	Green Process Patents	Abatement Tech Changes	Abatement Tech Changes
NA × Post_NA	0.457**	0.401*	1.107**	0.968**
	(2.022)	(1.871)	(2.480)	(2.157)
Observations	4,635	4,635	832	832
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.952	0.953	0.334	0.342

Panel B: Subsamples by Production Process Changes

	Dependent Variable: Violations			
	(1)	(2)	(3)	(4)

	High Green Process Patents	Low Green Process Patents	High Abatement Tech. Changes	Low Abatement Tech. Changes
NA × Post_NA	0.748***	0.293*	0.618***	0.212
	(3.296)	(1.787)	(3.151)	(1.266)
P-value of Difference	0.000		0.006	
Observations	1,467	3,168	1,868	2,767
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.517	0.462	0.492	0.488

Table 8: Financial Constraints and Operational Changes

This table presents the effect of *NAAQS Revisions* on workplace safety conditional on operational changes for financially constrained and unconstrained firms. *Firm Size* and *WW Index* are the proxies for financial constraints, while *Green Process Patents* is the measure of operational changes. High and low groups are created based on whether the respective measures are above or below the median. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is a dummy variable that equals one after nonattainment designation and zero otherwise. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables, firm-level control variables, plant-fixed effects, and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: Violations							
	Small Firm		Large Firm		High WW Index		Low WW Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High Green Process Patents	Low Green Process Patents	High Green Process Patents	Low Green Process Patents	High Green Process Patents	Low Green Process Patents	High Green Process Patents	Low Green Process Patents
NA × Post_NA	0.879***	0.408**	0.475	0.445	0.798**	0.352*	0.521	0.262
	(2.658)	(2.310)	(1.561)	(0.841)	(1.960)	(1.818)	(1.478)	(0.872)
P-value of Difference	0.019		0.358		0.010		0.217	
Observations	388	1,932	1,079	1,236	457	1,855	1,010	1,313
Plant Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Pseudo R-Squared	0.706	0.486	0.535	0.606	0.713	0.519	0.571	0.555

Table 9: Stakeholder Attention

This table presents the effect of *NAAQS Revisions* on workplace safety for subsamples partitioned based on stakeholders' attention to climate change. *WVS Env. Attention* (i.e., an index computed based on World Values Survey questions on environmental awareness) and *Env. Regulation Opinion* (i.e., Yale Climate Opinion Map score on environmental regulation) are the measures of stakeholders' attention to climate change in the first two and last two columns, respectively. High and low groups are created based on whether the measure is above or below the sample median. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is a dummy variable that equals one after nonattainment designation and zero otherwise. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables, firm-level control variables, plant-fixed effects, and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: Violations			
	(1) High WVS Env. Attention	(2) Low WVS Env. Attention	(3) High Env. Regulation Opinion	(4) Low Env. Regulation Opinion
NA × Post_NA	0.903***	-0.254	2.928***	1.185***
	(5.631)	(-1.318)	(4.544)	(4.180)
P-value of Difference	0.000		0.000	
Observations	2,256	2,379	828	828
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.510	0.443	0.633	0.594

Table 10: Product Market Competition

This table presents the effect of *NAAQS Revisions* on workplace safety for subsamples partitioned based on product market competition. *Sales HHI* (i.e., Herfindahl-Hirschman Index based on firms' sales at the industry level.) and *Oligopoly* (i.e., the proportion of sales in a firm's industry that is accounted for by the two largest firms.) are the measures of product market competition in the first two and last two columns, respectively. High and low groups are created based on whether the measure is above or below the sample median. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is a dummy variable that equals one after nonattainment designation and zero otherwise. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables, firm-level control variables, plant-fixed effects, and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: Violations			
	(1)	(2)	(3)	(4)
	Low Sales HHI	High Sales HHI	Low Oligopoly	High Oligopoly
NA × Post_NA	0.715***	0.353**	0.737***	0.344**
	(3.232)	(2.191)	(3.649)	(2.302)
P-value of Difference	0.026		0.020	
Observations	2,332	2,303	2,320	2,315
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.499	0.474	0.489	0.480

Table 11: Concentrated and Dispersed Firms

This table presents the effect of *NAAQS Revisions* on workplace safety for firms with all their plants in a single county (*Concentrated Firms*) and those with their plants spread across multiple counties (*Dispersed Firms*). *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is a dummy variable that equals one after nonattainment designation and zero otherwise. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables, plant-fixed effects, and industry-year-fixed effects. Additionally, Columns (3) and (4) include firm-level control variables. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: Violations			
	(1) Concentrated	(2) Dispersed	(3) Concentrated	(4) Dispersed
NA × Post_NA	0.958***	0.278*	0.970***	0.267*
	(3.029)	(1.859)	(2.962)	(1.782)
P-value of Difference	0.000		0.000	
Observations	764	3,871	764	3,871
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	No	No	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.658	0.436	0.661	0.438

Table 12: Private and Public Firms

This table presents the effect of *NAAQS Revisions* on workplace safety for private and public firms. *NA* is one for plants in counties designated as nonattainment due to *NAAQS Revisions* and zero otherwise. *Post_NA* is a dummy variable that equals one after nonattainment designation and zero otherwise. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. Detailed variable definitions are provided in Appendix A. All regressions include plant-level control variables, plant-fixed effects, and industry-year-fixed effects. Additionally, Columns (3) and (4) include firm-level control variables. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: Violations			
	(1) Private Firms	(2) Public Firms	(3) Private Firms	(4) Public Firms
NA × Post_NA	0.304***	0.184	0.936***	0.159
	(3.563)	(1.262)	(3.106)	(1.153)
P-value of Difference	0.000		0.000	
Observations	10,013	3,932	853	3,782
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	No	No	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.370	0.444	0.624	0.440

ONLINE APPENDIX

The Unseen Cost of Green Policies: The Impact of Environmental Regulation on Workplace Safety

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Table OA1: NAAQS Revision Dates

This table presents the years of *NAAQS Revisions* employed in this study. The first column displays the official names of the pollutants as provided by the EPA. The second column reports the dates on which the revisions became operational.

Pollutant	Effective Date
Sulfur Dioxide (1971)	15/11/1990
Carbon Monoxide (1971)	15/11/1990
Nitrogen Dioxide (1971)	15/11/1990
PM-10 (1987)	15/11/1990
Lead (1978)	06/01/1992
1-Hour Ozone (1979)[1]	06/01/1992
8-Hour Ozone (1997)[2]	15/06/2004
PM-2.5 (1997)[3]	05/04/2005
PM-2.5 (2006)	14/12/2009
Lead (2008)	31/12/2010
8-Hour Ozone (2008)	20/07/2012
Sulfur Dioxide (2010)[4]	04/10/2013
PM-2.5 (2012)	15/04/2015
8-Hour Ozone (2015)[5]	03/08/2018

[1] This is based on 40 CFR Part 81 designations. Original areas were designated on 15/11/1990. Also, this pollutant was revoked on 15/06/2005.

[2] Revoked on 06/04/2015.

[3] Revoked on 24/10/2016.

[4] Sulfur Dioxide (2010) has four other rounds of area designations on 12/09/2016, 17/01/2017, 09/04/2018, and 30/04/2021.

[5] An additional area was designated effective 24/09/2018. Other revisions occurred effective 14/07/2021 and 30/12/2021.

Table OA2: OSHA Violations vs. Violation Tracker Datasets

This table compares the coverage of the OSHA Violations and Violation Tracker datasets.

	OSHA (All Data)	OSHA	Violation Tracker
Years	1972 – 2021	2000 – 2021	2000 – 2021
No. of Obs.	2,880,820	1,272,134	177,148
No. of Plants	900,468	517,329	143,255

OA3: Defining Plants Subject to California ETS Using the TRI Database

This note explains how we define the establishments subjected to *California ETS*. The California Cap-and-Trade Program targets facilities that emit GHG exceeding 25,000 metric tons of CO_2 equivalent (MT CO_2e) annually. Existing studies such as Bartram et al. (2022) and Ivanov et al. (2024) use EPA's Greenhouse Gas Reporting Program (GHGRP) data, which provides GHG data from large U.S. GHG emission sources. GHGRP starts in 2010 while our analysis of *California ETS* commences in 2009. Given that EPA's Toxic Release Inventories (TRI) cover earlier years and have a wider range of pollutants, we rely on TRI to identify GHG polluters that fall under the *California ETS* regulation criteria.

TRI covers more than 800 toxic chemicals that threaten human health and the environment. First, we identify the GHG-related toxic chemicals using resources such as ChatGPT and DeepAI. We then verify our identification using Google searches and the official websites of significant environmental agencies (including the U.S. EPA, the California Air Resources Board (CARB), and the UK National Atmospheric Emissions Inventory (NAEI), among others). With this step, we recognize 68 out of the total 824 chemicals (as of 2021) as GHG.

Second, we calculate the CO_2 equivalent. The California Health and Safety Code Section 38505 outlines seven categories of GHG that CARB is tasked with regulating: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulfur hexafluoride (SF_6), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and nitrogen trifluoride (NF_3). Each category has an assigned global warming potential (GWP), which measures the heat-trapping capability of a GHG relative to CO_2 over a specified period. Thus, the GWP of CO_2 is set at one, and emissions of other GHGs are typically expressed in terms of MT CO_2e for easier comparison. Therefore, in our second step, we classify the 68 chemicals into the seven GHG groups. We then apply the GWP data provided by CARB (available at https://ww2.arb.ca.gov/ghg-gwps) to convert the emissions reported by facilities into CO_2e. The facilities that emit more than 25,000 MT CO_2e annually during our sample period fall into our *California ETS* sample.

As we show in Table OA5, our findings hold when we restrict the sample to plants covered in the GHGRP database.

Table OA4: Stacked DiD for Ozone NAAQS Revisions

This table presents the effect of climate policies on workplace safety using a stacked DiD design around *NAAQS Revisions* for Ozone. The dependent variable is *Violations*, defined as the number of safety violations committed at a plant. NA_{Ozone} is one for plants in counties that achieved nonattainment for Ozone and zero otherwise. $Post\_NA_{Ozone}$ is a dummy variable that equals one after nonattainment designation for Ozone and zero otherwise. Columns (1) – (2) include plant-level control variables, while Columns (3) – (4) include both plant and firm-level control variables. All regressions include plant-fixed effects and either year-fixed effects or industry-year-fixed effects. Detailed variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the county level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Violations	(2) Violations	(3) Violations	(4) Violations
$NA_{Ozone} \times Post\_NA_{Ozone}$	0.475*	0.582**	2.009***	2.413***
	(1.695)	(1.980)	(5.439)	(5.004)
Observations	6,078	6,078	1,961	1,961
Plant Level Controls	Yes	Yes	Yes	Yes
Firm Level Controls	No	No	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Pseudo R-Squared	0.377	0.427	0.380	0.504

Table OA5: Using The California ETS Sample Covered in the GHGRP Database

This table presents the effect of *California ETS* on safety violations restricting the sample to plants covered in the GHGRP database. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *Cal* is a dummy variable that equals one for plants in California and zero otherwise. *Post_2012* is a dummy variable that equals one after 2012 and zero otherwise. Detailed variable definitions are provided in Appendix A. The first column includes plant-level control variables, while the last column includes both plant- and firm-level control variables. All regressions include plant-fixed effects and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the state level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Violations	(2) Violations
Cal × Post_2012	2.455***	3.505**
	(3.420)	(2.142)
Observations	395	224
Plant Level Controls	Yes	Yes
Firm Level Controls	No	Yes
Plant FE	Yes	Yes
Industry-Year FE	Yes	Yes
Pseudo R-Squared	0.576	0.679

Table OA6: Placebo Test for California ETS Using Nonregulated Plants

This table presents the effect of *California ETS* on workplace safety, concentrating on plants that do not meet the threshold requirement to be regulated by the rule. The dependent variable is *Violations*, which is defined as the number of safety violations committed at a plant. *Cal* is a dummy variable that equals one for plants in California and zero otherwise. *Post_2012* is a dummy variable that equals one after 2012 and zero otherwise. Detailed variable definitions are provided in Appendix A. The first column includes plant-level control variables, while the last column includes both plant- and firm-level control variables. All regressions include plant-fixed effects and industry-year-fixed effects. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the state level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Violations	(2) Violations
Cal × Post_2012	0.000	-0.543
	(0.002)	(-0.617)
Observations	449	176
Plant Level Controls	Yes	Yes
Firm Level Controls	No	Yes
Plant FE	Yes	Yes
Industry-Year FE	Yes	Yes
Pseudo R-Squared	0.557	0.719

Table OA7: Industry Composition of Our Samples

This table presents the top 10 most dominant industries within our samples. Panels A, B, and C focus on *CAAA*, *NAAQS Revisions*, and *California ETS*, respectively. As indicated by the bolded industries (i.e., industries that are common across all three settings), the industrial composition of our samples is fairly comparable across the settings.

Panel A: CAAA

#	Industry	Obs.	Percent	Violations
1.	**Fabricated Metal Products, Except Machinery And Transportation Equipment**	**636**	**18.01**	**5,283**
2.	**Primary Metal Industries**	**475**	**13.45**	**4,609**
3.	**Rubber And Miscellaneous Plastics Products**	**234**	**6.63**	**1,774**
4.	**Transportation Equipment**	**234**	**6.63**	**2,039**
5.	**Industrial And Commercial Machinery And Computer Equipment**	**201**	**5.69**	**1,418**
6.	**Food And Kindred Products**	**199**	**5.64**	**1,259**
7.	Health Services	189	5.35	980
8.	**Lumber And Wood Products, Except Furniture**	**165**	**4.67**	**1,243**
9.	Electronic And Other Electrical Equipment And Components, Except Computer Equipment	158	4.47	1,211
10.	**Chemicals And Allied Products**	**151**	**4.28**	**1,184**
		2,642	74.82	

Panel B: NAAQS Revisions

#	Industry	Obs.	Percent	Violations
1.	**Fabricated Metal Products, Except Machinery And Transportation Equipment**	**2,327**	**16.69**	**13,621**
2.	**Primary Metal Industries**	**1,573**	**11.28**	**10,052**
3.	**Transportation Equipment**	**1,378**	**9.88**	**7,332**
4.	**Rubber And Miscellaneous Plastics Products**	**1,251**	**8.97**	**6,804**
5.	**Industrial And Commercial Machinery And Computer Equipment**	**1,215**	**8.71**	**6,506**
6.	**Lumber And Wood Products, Except Furniture**	**1,205**	**8.64**	**7,657**
7.	**Chemicals And Allied Products**	**832**	**5.97**	**4,409**
8.	Furniture And Fixtures	687	4.93	4,404

9.	Electronic And Other Electrical Equipment And Components, Except Computer Equipment	639	4.58	2,862
10.	**Food And Kindred Products**	**583**	**4.18**	**2,739**
		11,690	83.83	

Panel C: California ETS

#	Industry	Obs.	Percent	Violations
1.	**Food And Kindred Products**	**310**	**29.47**	**1,345**
2.	**Chemicals And Allied Products**	**137**	**13.02**	**633**
3.	**Primary Metal Industries**	**106**	**10.08**	**464**
4.	Petroleum Refining And Related Industries	74	7.03	486
5.	**Lumber And Wood Products, Except Furniture**	**46**	**4.37**	**249**
6.	Wholesale Trade-non-durable Goods	42	3.99	215
7.	**Transportation Equipment**	**37**	**3.52**	**79**
8.	**Rubber And Miscellaneous Plastics Products**	**36**	**3.42**	**187**
9.	**Industrial And Commercial Machinery And Computer Equipment**	**36**	**3.42**	**168**
10.	**Fabricated Metal Products, Except Machinery And Transportation Equipment**	**35**	**3.33**	**196**
		859	81.65	

Table OA8: California ETS and Operational Changes

This table presents the effect of *California ETS* on operational changes and emission levels. In Columns (1) – (2), the dependent variable is *Green Process Patents*, which is defined as the number of granted green patents with process claims. The dependent variable in Columns (3) – (4) is the ratio of safety to environmental job hiring. In Columns (5) – (6), the dependent variable is the natural log of GHG emissions. *Cal* is a dummy variable that equals one for plants in California and zero otherwise. *Post_2012* is one after 2012 and zero otherwise. All regressions include plant-level control variables, plant-fixed effects, and industry-year-fixed effects. In addition, Columns (2), (4), and (6) include firm-level control variables. Detailed variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the state level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Green Process Patents	(2) Green Process Patents	(3) Safety/Env. Jobs	(4) Safety/Env. Jobs	(5) GHG Emissions	(6) GHG Emissions
Cal ×Post_2012	-1.053***	-1.390***	-0.345	-0.349	0.414	0.676
	(-3.805)	(-3.093)	(-0.938)	(-0.977)	(0.676)	(0.823)
Observations	452	452	452	452	1,052	452
Plant Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Level Controls	No	Yes	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-Squared	0.919	0.923	0.618	0.626	0.776	0.831

Figure OA9: An Extended Post-Event Trend Graphs for CAAA and California ETS
This figure shows the trend of safety violations around *CAAA* (Panel A) and *California ETS* (Panel B), focusing on an extended post-event period.