Valuing Local Climate Policy: Evidence from Firm Behavior and Financial Markets

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Abstract

This paper examines the efficacy of state-level emissions regulations and their local economic effects. Using newly collected data, I find that regulation reduces employment, output, profitability and equity returns in affected industries, but also lowers emissions and emissions intensity, while increasing R&D and capital investment. To interpret these effects, I develop a spatial equilibrium model in which firms choose locations and emissions in response to local carbon taxes. I infer the implicit tax increase corresponding to each regulation from the stock-market reactions of exposed firms and use these values to estimate the model's structural parameters. I use the model to quantify the costs of individual regulations and compare them to the social benefits of reduced emissions. I find that policies targeting utilities and waste management are beneficial, unlike those focused on fossil fuel extraction and manufacturing. On average, endogenous technology switching contributes an additional 20 percent of emissions abatement, whereas relocation undoes about 10 percent of the reductions achieved within the regulated state.

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1 Introduction

Despite the global nature of climate change and the theoretical efficiency of international coordination, political constraints and other frictions have meant that, in practice, most climate policy is implemented at the national or subnational level. In the United States, federal regulation of greenhouse gas (GHG) emissions remains limited.[1] As a result, nearly all substantive efforts to regulate GHG emissions occur at the state level, leading to large variation in regulatory stringency across jurisdictions. In this paper, I study the net impact of emissions regulation, examining the mechanisms that generate variation in costs and benefits across policies and the distribution of those costs between investors and workers. Although many studies examine the effects of specific regulations, much less is known about the magnitude and distribution of costs and benefits once firms respond along realistic margins such as relocation and technology adoption.

Two concerns commonly arise in debates over emissions regulation. First, such policies may impose substantial economic costs, including stranded assets, job loss, and decreased profitability. Second, without coordination across jurisdictions, regulated activity may simply relocate to less regulated areas, producing economic costs without corresponding emissions reductions. These challenges are particularly acute in a decentralized system such as that in the United States, where firms can respond to new regulation by adjusting output, adopting cleaner technologies, or shifting production across state lines. These spatial responses complicate efforts to understand the full impact of emissions regulation. Moreover, variation in regulatory design creates another challenge: there is no standardized metric for comparing the degree of regulatory burden imposed on firms by different regulations. This makes it difficult to draw conclusions about the impacts of regulation from observed outcomes.

To address these challenges, I proceed in three parts. First, I document reduced-form effects of state-level emissions regulation. Second, I develop a methodology to infer the implicit carbon tax embedded in each regulation, placing diverse policies on a common quantitative scale. Third, I present a spatial general equilibrium model with endogenous location and technology choice. I use the inferred carbon tax estimates to recover the model's structural parameters and quantify economic and environmental impacts. An advantage of this research design is that the implicit tax estimates, coupled with the structural model, allow me to quantify cross-state spillovers that are central to assessing the efficacy of decentralized climate policy.

I begin by assembling a novel dataset of state-level GHG regulations. The dataset records the timing, policy type and the industries affected. Because these regulations can be enacted by many different regulatory bodies (including but not limited to the legislature, the executive and the environmental regulator in each state), no centralized database exists. I identify 140 state-level regulations that govern GHG emissions from

[1] Examples include the Clean Air Act, which has been applied to GHGs in a limited way, as well as some provisions of the Inflation Reduction Act, including tax credits for electric vehicles and solar panels.

the production process (scope 1 emissions).[2] The dataset covers regulations across four broad categories: GHG targets, renewable portfolio standards (RPS), industrial and short-lived climate pollutants (SLCP), and non-RPS electricity.[3] The regulations vary substantially in both design and scope, leading to meaningful variation in regulatory burden across both industries and states.

I use the state-level database to estimate the reduced-form effects of regulation at the industry/state- and firm-level. First, I use a staggered difference-in-difference design to estimate the impact of the introduction of state-level GHG targets. This setup takes advantage of the fact that the structure of GHG targets is common across states and, as discussed by Korganbekova (2025), GHG targets often lead to future prescriptive regulations. At the industry/state-level, I find that, as expected, regulation leads to both economic costs (reductions in employment, wages and output) and environmental benefits (reductions in emissions and emissions intensity).

Next, I focus on firm-level outcomes. Because firms can respond to regulation by shifting production to less regulated jurisdictions, firm-level outcomes provide a more complete picture of the effects of these regulations. I estimate the impact of new prescriptive GHG regulations on firm-level outcomes. I find that these regulations lead to lower profitability, emissions and emissions intensity. In addition, regulated firms increase investment in capital and R&D, suggesting that they respond by improving their production technology, not only by reducing output or relocating.

The reduced form estimates based on binary indicators conflate two distinct components: the average level of the emissions tax implicit in the regulations observed in the sample, and the responsiveness of outcomes to changes in that tax. Disentangling these requires assigning a quantitative value to the policy shock itself. Because I study a diverse set of policies, it is not obvious how to specify such a value directly from policy characteristics. Instead, I use equity returns of exposed firms to infer "policy intensity" for each regulation in my sample. Stock price reactions provide a market-based measure of the expected profit impact of regulation, aggregating all channels through which regulation affects firm value (compliance costs, demand shifts, relocation, etc.). Combining market reactions with firm-level measures of geographic exposure leads to estimates of intensity on a common scale, allowing for comparison across very different types of policies. I estimate policy-specific intensity using a hierarchical Bayesian methodology that allows for learning across policies with common characteristics. This circumvents potential measurement error arising from the small sample of firms affected by many of the policies I study. I show that my intensity measure exhibits a number

[2] I intentionally exclude regulations that govern emissions from customers using a firm's product (scope 3 emissions), such as electric vehicle mandates and bans on certain household refrigerants.

[3] GHG targets set broad goals (e.g. reduce emissions to 85% below their 1990 level by 2050), but do not impose specific requirements on firms. Renewable portfolio standards mandate that a set percentage of electricity be generated from renewable sources. I define the industrial+SLCP category to cover a range of regulations that apply to sectors other than utilities (oil and gas, waste management and manufacturing). The non-RPS electricity category contains any electricity sector regulations that are not renewable portfolio standards (e.g. mandated coal plant retirement, bans on certain types of equipment).

of intuitive features and that an increase in market-implied intensity leads to reductions in both emissions and economic activity and increases in R&D investment and capital expenditures.

The empirical evidence suggests that emissions regulation leads to both economic costs and social benefits. To interpret these patterns and quantify welfare effects, I develop a spatial general equilibrium model in which firms choose location and emissions technology and workers choose where to live and in which industry to work. Emissions regulation enters the firm's decision problem as a state- and industry-specific tax. The firm's location decision is based on the tax rate, as well as location-specific productivity and local wages. Since the tax is per unit of emissions and emissions technology is firm-specific, high emitting firms are more likely to relocate in response to an increase in the tax rate. However, firms can also choose to invest in green technology to reduce their emissions at a particular facility. The cost of the green technology is firm-specific, so that some firms will choose to adjust technology in response to the tax increase, while others will choose to relocate.

The model yields closed-form expressions for the incidence of environmental regulation on firm profits, wages, and environmental outcomes. Importantly, it also implies a functional relationship between equity returns and the implicit emissions tax. Because each state's emissions tax rate is not observable, I cannot estimate the model parameters directly. To overcome this obstacle, I use my equity-return-based measure of regulatory intensity as a proxy for shocks to the tax rate. I then estimate the model parameters, matching empirical moments for emissions, wages, employment, establishment counts, and investment across industries and states. Using a range of estimates for the social cost of carbon, I find that, while the median regulation is net beneficial (with benefits about twice as large as costs), there is substantial variation across industries and policy types. In utilities and waste management, the average regulation is net beneficial, while the costs exceed the benefits in fossil fuel extraction and manufacturing. Two margins of adjustment play a central role in shaping these results. First, endogenous technology switching amplifies emissions abatement: allowing firms to adopt cleaner technologies increases total emissions reduction by roughly 7 percent in manufacturing and by more than 50 percent in utilities. At the same time, the ability to adopt cleaner technology meaningfully lowers the economic burden of regulation. Second, relocation decisions create modest but non-negligible leakage, with 3 percent of utilities-sector reductions and up to 18 percent of manufacturing-sector reductions reappearing in other states. These margins help explain why some regulations generate large net benefits while others do not. The share of costs falling on workers ranges from 3 percent in utilities to 62 percent in manufacturing, with the remaining burden borne by investors.

1.1 Related Literature

My paper contributes to four main strands of literature. First, I contribute to the literature on the economic effects of emissions regulation. The empirical part of my paper is most closely related to Korganbekova (2025), who studies the effect of state-level GHG targets on corporate emissions. My reduced form results extend her work by incorporating a broader set of regulations and documenting the economic costs in addition to the environmental benefits. Hahn et al. (2024) also study a wide range of climate-related policies, but they aggregate results from separate empirical analyses using different data and methods, whereas my framework provides a unified empirical and structural approach that evaluates all policies on a consistent basis. Several other studies document the economic and financial impacts of either individual state-level emissions regulation or a particular category of regulations. Bartram et al. (2022) find that financially constrained firms respond to California's cap-and-trade program by shifting emissions to other states. Benincasa et al. (2024) find that the same policy led firms to lose customer relationships. Hong et al. (2024) find that state-level renewable portfolio standards lead both to more volatile electricity prices and bond yields of affected producers.

Second, my paper proposes a new method of measuring regulatory stringency. In a survey of the literature on this topic, Brunel and Levinson (2016) describe the measurement difficulties as stemming from four conceptual challenges: multidimensionality (regulations cannot generally be summarized using a single measure), simultaneity (more stringent regulations may be targeted toward jurisdictions where pollution is highest, so one cannot take observed high pollution to be evidence of lenient policy), industrial composition (the same regulation may be more or less costly in different locations) and capital vintage (regulatory standards that differ for existing and new equipment complicate stringency measurement). Existing studies have aimed to circumvent these challenges in several ways, but no approach is widely regarded as successfully addressing all four challenges.[4] Using equity returns of exposed firms as a proxy for stringency addresses all four challenges. The hierarchical Bayesian methodology I use to infer stringency from returns is closely related to that of Pástor and Stambaugh (2001), Jones and Shanken (2005) and Van Binsbergen et al. (2025). My methodology is conceptually very close to Kogan et al. (2017), who use equity market reactions to infer patent values.

My paper also relates to the literature broadly classified as climate finance. I primarily contribute to the subset of this literature that explores the impact of climate transition risk on asset prices. Hsu et al. (2023) document a "pollution premium" in the cross-section of equity returns and argue that the premium

[4] These include U.S. Pollution Abatement Costs and Expenditures (PACE) survey (e.g. Becker (2011), Shapiro and Walker (2018)), shadow costs (e.g. Van Soest et al. (2006)), direct assessment of a narrow set of regulations (e.g. Chay and Greenstone (2005), Haščič and Johnstone (2011)), composite indexes (e.g. Levinson (1996), Dasgupta et al. (2001)), inferring stringency from pollution levels (e.g. Smarzynska (2002)) and using data on enforcement expenditures (e.g. Gray et al. (2012)).

is explained by heterogeneous exposure to regulatory risk. Duchin et al. (2025) find that divesting pollutive plants is associated with positive equity returns. Bolton and Kacperczyk (2023) find that carbon risk premia are higher in countries with stricter climate policies. Building on this literature, my approach reverses the usual perspective by using the market response to climate policy as information about the policy itself rather than using policy as a test of how markets price climate risk. Conceptually, my framework parallels that of Chittaro et al. (2025), who link asset returns to implicit carbon taxes. I apply a similar mapping to quantify the intensity of state-level climate policies.

Finally, this paper relates to the literature studying the interaction between local policy and firm location choice. Agrawal et al. (2022) provide a detailed summary of this literature. Due to the challenges associated with measuring stringency across locations, much of this literature focuses on easily quantifiable policies such as local tax rates. My paper advances this literature by applying its methodologies to emissions policy. Fowlie and Reguant (2022) demonstrate that emissions regulation can induce cross-border leakage when firms relocate or adjust output across jurisdictions, motivating my focus on spatial reallocation as a key margin of adjustment. The particular model I use closely follows Suárez Serrato and Zidar (2016), who quantify the welfare incidence of state corporate tax cuts.

The paper is organized as follows. Section 2 describes emissions regulation in the U.S. as well as the data I use. Section 3 documents the reduced form impacts of state-level emissions regulation. Section 4 discusses how I use equity returns to infer the implicit emissions tax increase corresponding to individual emissions regulations. Section 5 introduces the spatial model and derives analytical expressions for the equilibrium impacts of local emissions regulation. Section 6 describes the procedure to estimate the parameters of the model using the return-based measure of the implicit carbon tax. Section 7 uses the estimated parameters to to decompose the economic costs, environmental benefits, and net welfare effects of regulation, highlighting the roles of technology switching, relocation, and wage adjustment. Section 8 concludes.

2 Institutional Background and Data Sources

2.1 Greenhouse Gas Emissions Regulation in the U.S.

In the U.S., legal and political constraints have prevented comprehensive federal GHG emissions regulation. As a result, the majority of the regulatory burden faced by emitting firms is due to state-level regulations. Economically, this matters because cross-state heterogeneity in regulatory stringency creates opportunities for firms to respond to regulation by relocating across state lines.[5] From a practical perspective, studying the

[5] While firms can and do move production internationally in response to regulation, the barriers to doing so (such as tariffs, transportation costs or country-specific knowledge) are much higher.

impact of emissions regulation in the U.S. requires assembling a unified database of state-level regulations.

To this end, I hand-collect a database of state-level GHG emissions regulation in the United States, recording the state, type of regulation, date enacted, and the industries affected.[6] I focus on regulations that govern emissions from the production process (scope 1 emissions) rather than those generated when customers use the product. The sample contains 140 such regulations, of which 96 require firms to take a specific action. I refer to these as prescriptive regulations. The remaining 44 are GHG targets that specify emissions reduction goals (either economy-wide or for specific industries) without imposing compliance requirements.

I group the prescriptive regulations into three categories: 51 renewable portfolio standards (RPS), 21 industrial and short-lived climate pollutant (SLCP) regulations, and 24 non-RPS electricity sector regulations. The full list of regulations can be found in Table A1. These regulations cover a wide range of economic activity. The most commonly regulated sector is electricity, followed by oil and gas, waste management and manufacturing.

2.2 Other Data Sources

Since 2011, facilities emitting more than 25,000 tons of CO2 equivalent GHGs (C02e) per year have been required to report their annual emissions to the EPA under the Greenhouse Gas Reporting Program (GHGRP). I match the parent companies of these facilities to Compustat and link the facilities themselves to the National Establishment Time Series (NETS). NETS provides employment and revenue data for U.S. facilities that have been owned by publicly traded firms at any time since 1990.

At the firm level, I draw on several additional sources. From Compustat and CRSP, I obtain accounting and financial market data. I also use the cost of capital measure developed by Gormsen and Huber (2023). Firm-level scope 1 emissions data come from Trucost, which reports both absolute emissions (in tons of CO2e) and emissions intensity (tons of CO2e per million USD of revenue).

For state- and industry-level variables, I use multiple datasets. From the Bureau of Economic Analysis (BEA), I collect real GDP by industry and state. Industries are defined at approximately the two-digit NAICS level, with some sectors (e.g., 44–45) combined. Because this classification is less granular than Bureau of Labor Statistics (BLS) data, I use BEA's industry definitions in my analysis. From the BLS, I use quarterly data on industry–state employment and wages, aggregating to annual averages for employment and total annual wages. For industry-state emissions, I use the EPA's GHG Inventory, which covers emissions from all facilities within an industry, not just those above the GHGRP reporting threshold.

[6] To assemble my list, I rely on information from National Conference of State Legislatures, American Council for an Energy Efficient Economy, Lexis Nexis, Climate XChange, U.S. Climate Alliance and Center for Energy and Climate Solutions.

2.3 Constructing Firm-State Exposure

Estimating the impacts of local policy on firm-level outcomes requires a measure of how exposed firm n is to state s. I use NETS facility-level employment to construct this measure. In particular, I define:

$$\text{Expos}_{nst} = \sum_{j \in J^{ns}} \frac{L_{jt}}{L_{nt}}, \tag{1}$$

where J^{ns} is the set of facilities owned by firm n located in state s, L_{jt} is the number of workers employed at facility j in year t, L_{nt} is total employment of firm n in year t (from Compustat). I scale by Compustat employment rather than the sum of NETS employment because NETS only covers U.S. facilities and firms with substantial international operations will be less exposed to state-level policy in the U.S. NETS also reports facility-level revenue, but I choose to use employment as my measure of exposure for two reasons. First, as noted by Crane and Decker (2019), almost all revenue data in NETS is imputed for multi-establishment firms. Second, many firms have establishments whose "customers" are establishments of the same firm (e.g. a firm has one factory making parts and one assembling the final product). Using employment avoids the conceptual question of how to assign from the sale of the final good to the establishments that took part in making it.

3 Reduced Form Impact of Emissions Regulation

3.1 Industry/State-Level

To estimate the impact of emissions regulation, I begin by focusing on economy-wide GHG targets.[7] While targets do not impose specific regulations on firms, states with targets are more likely to implement prescriptive GHG regulation in the future.[8] The advantage of using targets is that they provide a binary summary measure of the states climate policy stance.

To study the impact of targets on industry/state outcomes, I use a staggered difference-in-difference design based on the enactment of GHG targets. Focusing on six outcomes (all in logs): number of workers, wage per worker, output, emissions, emissions intensity (emissions scaled by output), and establishment counts, I run the following regression:

$$y_{ist} = \sum_{h=-8}^{10} \beta^h \text{Target}_{s,t-h} + \gamma_{it} + \gamma_{is} + \eta_{ist}, \tag{2}$$

[7] Figure A1 shows which states have such targets.
[8] Korganbekova (2025) discusses this in detail. Figure A2 shows the path of emissions relative to the target for states that announced targets prior to 2014.

where $\text{Target}_{s,t-h}$ is equal to one if state s enacted an economy-wide GHG target at time $t-h$. The specification includes industry-year fixed effects (γ_{it}), which control for national shocks to specific industries and industry-state fixed effects (γ_{is}), which capture time-invariant differences across industry-state pairs.

Figure 1 plots the dynamic response of industry/state-level outcomes to the introduction of GHG targets. At the industry/state-level, GHG targets have a statistically significant negative effect on employment, wages, output, emissions, emissions intensity and establishment counts. The magnitude of the emissions and emissions intensity responses is larger than for employment and output, suggesting that part of the adjustment comes through cleaner production processes rather than solely through economic contraction. To alleviate concerns about the validity of two-way fixed effects estimation in settings with staggered treatment, I also show the estimates from the procedures proposed by Sun and Abraham (2021) (Figure A3) and Callaway and Sant'Anna (2021) (Figure A4).

3.2 Firm-Level

Since most firms operate in multiple states, I must modify the definition of treatment for the firm-level analysis.[9] To estimate the effect of emissions regulation on firm-level outcomes over different time horizons, I use a local projections setup similar to that employed by Chodorow-Reich et al. (2021). For a given firm-level outcome y and horizon h, I estimate:

$$\Delta y_{n,t-1,t+h} = \beta^h \text{NewReg}_{n,t} + \Gamma' X_{n,t-1} + \gamma_{i(n),t} + \gamma_n + \eta_{n,t}, \tag{3}$$

where $\Delta y_{n,t-1,t+h}$ is the change in firm-level outcome y from $t-1$ to $t+h$.[10] $\text{NewReg}_{n,t}$ is equal to the sum of $\text{Expos}_{ns,t-1}$ for all states s that enacted a regulation affecting firm n at time t.[11] $X_{n,t-1}$ is a vector of controls (log-market value and book to market). The regression also includes firm fixed effects (γ_n), which absorb time-invariant firm characteristics and industry-year fixed effects ($\gamma_{i(n),t}$) which control for time-varying industry conditions.

Figure 2 indicates that, despite the evidence above that some firms shrink or relocate in response to new regulation, brown firms exhibit an overall decline in emissions intensity. Short-term reductions in profitability, combined with increases in capital expenditures and R&D, suggest that firms may be investing in new technologies and upgrading capital to make production processes greener. The observed reduction in

[9] In my merged Compustat/NETS sample, 64 percent of firm-year observations operate in multiple states. The mean (median) firm-year operates in 9 (3) states.

[10] I focus on six outcomes: profitability (net income over lagged assets), investment intensity (capex over lagged assets), the log of CO2 emissions, CO2 intensity (tons per million USD revenue) cost of capital (from Gormsen and Huber (2023)) and R&D intensity (R&D over lagged assets).

[11] Exposed means that firm n has a facility in the state that enacted the regulation and that the facility's SIC code is in the scope of the regulation.

the cost of capital aligns with existing literature on investor demand for green assets (e.g., Gormsen et al. (2024); Pástor et al. (2022)).

4 Quantifying Regulatory Intensity

The analysis in the previous section, which uses binary treatment variables, identifies the average effect of adopting "a regulation" in my sample. Concretely, let τ denote the implicit tax per unit of emissions imposed by regulation.[12]. Since the binary treatment variable is equal for all regulations, the estimate for outcome Y is a mix of $\mathbb{E}[\Delta \log \tau]$ (the average increase in the tax rate associated with the regulations in my sample) and $\frac{\partial \log Y}{\partial \log \tau}$ (the effect of a one percent increase in the tax rate, which is the economically relevant quantity). I use equity returns to infer "regulatory intensity," which proxies for $\Delta \log \tau$, allowing me to estimate $\frac{\partial \log Y}{\partial \log \tau}$.

Existing approaches to studying the effects of local policy changes typically rely either on variation in policies whose magnitudes are directly observable, such as changes in state corporate tax rates or minimum wages, or on analysis of a single policy, such as California's cap-and-trade program. In contrast, I study a wide range of state-level emissions regulations that vary in scope and form, and for which there is no obvious way to quantify regulatory intensity.[13] To overcome the challenges associated with quantifying regulatory intensity for a diverse set of regulations, I use equity market reactions to regulatory announcements as a measure of policy impact. Stock returns reflect expectations about how regulation will affect future profits, allowing me to infer the relative intensity of different policies in a consistent, data-driven way. In Appendix B.2, I show that the regulations in my sample have an observable impact on equity returns of affected firms.

To infer regulatory intensity from observed equity returns, I rely on the idea that the impact of a given regulation on firm value depends on the regulation's (unobserved) intensity and the firm's exposure to the regulated state. I formally derive the relationship between returns and the implicit emissions tax rate in Section 5.4.2.

Many regulations in my sample impact a very small number of firms.[14] To effectively infer intensity from realized returns over a window around enactment, I use a hierarchical Bayesian estimation approach. This allows the policy-specific estimates to learn from similar policies, which helps discipline the estimates when the sample of affected firms is small. The methodology is closely related to Pástor and Stambaugh (2001),

[12]This concept is formalized in Section 5 and is common practice in the literature. See for example Fraas and Lutter (2012), Fabra and Reguant (2014), Shapiro and Walker (2018) and Belfiori and Rezai (2024)

[13]Brunel and Levinson (2016) discuss the key challenges of measuring regulatory stringency, as well as the shortcomings of several existing approaches. The four issues they raise are: multidimensionality (complex design of regulation cannot easily be captured by a single measure), simultaneity (regulations are intended to affect emissions, but emissions levels can influence the decision to regulate), industrial composition (the average business faces more stringent regulation in a given location if that location has a more pollution-intensive industrial mix) and capital vintage (regulatory standards often have "grandfathering" provisions).

[14]For example, many states only have two electricity providers.

who apply it to learning across time, Jones and Shanken (2005) (learning across funds) and Van Binsbergen et al. (2025) (learning across countries).

Consider the following mapping from a regulatory shock Δ_p to the cumulative return of stock n over some window around the enactment of policy p:

$$\tilde{r}_{np} = \underbrace{\Delta_p}_{\substack{\text{unexpected}\\\text{intensity of}\\\text{policy } p}} \times \underbrace{\text{Expos}_{n,s(p),t(p)-1}}_{\substack{\text{geographic exposure}\\\text{of firm } n \text{ to state } s(p)}} + \varepsilon_{np}, \tag{4}$$

where $\tilde{r}_{np}$ is the cumulative abnormal return of stock n over the event window for policy p, $\text{Expos}_{n,s(p),t(p)-1}$ is the percentage of firm n's employment located in state $s(p)$ as of year $t(p)-1$ and $\varepsilon_{np} \sim \mathcal{N}(0, \sigma_r)$. I construct abnormal returns by removing the effects of the Fama and French (2015) factors, momentum and earnings surprises. Details are provided in Appendix C.1. The event window for each policy is from five months before until one month after the policy's enactment date.[15]

The goal of this exercise is to estimate Δ_p for each policy and correct for anticipation to obtain a final measure that reflects both expected and unexpected components of policy intensity. Based on equation (5), a natural approach to estimating Δ_p would be to run cross-sectional OLS regressions, which would identify Δ_p based on on return differentials between exposed and unexposed firms. However, the small sample of exposed firms for many policies makes this infeasible in practice. Instead, I propose that within each policy category c, Δ_p takes the form

$$\Delta_p = \alpha_{c(p)} + X_p' \lambda_{c(p)} + \eta_p, \tag{5}$$

where $\alpha_{c(p)}$ is the baseline impact of policies in category $c(p)$, $X_p'\lambda_{c(p)}$ is the effect of observable characteristics and $\eta_p \sim \mathcal{N}(0, \sigma^2_{c(p)})$ is the idiosyncratic effect of policy p. I estimate this separately for each of the four broad categories of regulations in my sample: GHG Targets, Industrial+SLCP, RPS and Non-RPS Electricity. For all categories, X_p includes indicators for the legal form of the regulation (legislation, administrative rule, executive order). I also include additional category-specific policy characteristics.[16]

For a given category c, let $\theta_c \equiv \{\alpha_c, \lambda_c, \sigma_c, \sigma_r, \{\Delta_p\}_{p \in c}\}$. Then, the hierarchical prior is given by:

$$\pi(\theta_c) = \pi(\alpha_c)\pi(\lambda_c)\pi(\sigma_c)\pi(\sigma_r) \prod_{p \in c} \mathcal{N}(\Delta_p | \alpha_c + X_p' \lambda_c, \sigma_c^2), \tag{6}$$

where the priors for the individual parameters are described in Table A4.[17] Over all firms n and policies p

[15] In Appendix C.3, I show that the estimates are robust to the choice of window.

[16] For GHG targets: percent reduction required, years to target, indicator for whether there are interim targets; for RPS: percent renewables required, years to enforcement,indicator equal to one if the state was controlled by Democrats, indicator equal to one if the state had a GHG target; for industrial+SLCP and non-RPS electricity: subcategory indicators.

[17] I choose weakly informative priors over each parameter and discuss robustness to the choice of priors in Appendix C.3.

in category c, the likelihood is:

$$\mathcal{L}(\tilde{r}_c|\theta_c) = \prod_{p \in c} \prod_{n \in N(p)} \mathcal{N}(\tilde{r}_{np}|\Delta_p \text{Expos}_{np}, \sigma_r). \tag{7}$$

Firm n is in the set $N(p)$ if its industry is affected by policy p. From Bayes' rule, the posterior is:

$$p(\theta_c|\tilde{r}_c) \propto \pi_c(\theta_c)\mathcal{L}(\tilde{r}_c|\theta_c), \tag{8}$$

which I estimate using Markov Chain Monte Carlo Simulation, as described in Appendix C.2. This approach addresses the problems caused by the small sample of exposed firms because the precision of the likelihood is inversely related to $\sum_n \text{Expos}_{np}^2$, which leads the posterior to put more weight on the $\alpha_{c(p)} + X_p'\lambda_c$ than on the idiosyncratic piece of the policy's own estimate.

4.1 Adjusting for Anticipation

There are two conceptually distinct sources of anticipation that may result in Δ_p not fully reflecting policy intensity. First, investors may learn information about the *specific policy* prior to the event window. This is addressed by choosing a sufficiently wide window and by verifying that the estimates are robust to using a window that starts from the first news mention of each policy, as discussed in Appendix C.3.[18] The second type of anticipation is more difficult to address. Investors may hold background expectations about a state's policy environment (e.g. if the state is controlled by Democrats or has a GHG target). These expectations can attenuate announcement-window returns even when all policy-specific information is released during the event window. The adjustment I discuss below targets the second type of anticipation.

In principle, one could estimate anticipation effects directly within each policy category by comparing return responses to otherwise identical regulations enacted in states with differing political environments. If the observable characteristics of the regulation fully capture differences in underlying policy intensity, then the coefficient on an indicator for Democratic control or the presence of a GHG target would identify the extent to which background expectations attenuate announcement-window returns. However, such a comparison is only credible when the set of controls is rich enough to make the "all else equal" assumption plausible. For many types of regulation, the relevant policy features are not quantifiable in a way that is comparable across policies. In those cases, the estimated coefficients would conflate anticipation with real differences in regulatory ambition, and using them to adjust the inferred tax change would risk removing genuine variation in policy intensity rather than isolating expectations-driven attenuation.

[18] I choose the window from five months before to one month after policy enactment because five months is the average length of the legislative process (from bill introduction to gubernatorial signing) for policies in my sample enacted through legislation.

To obtain anticipation-adjusted estimates, I rely on estimates from Renewable Portfolio Standards (RPS), the policy category for which an "all else equal" comparison is credible. RPS are requirements that a specified share of electricity generation come from renewable sources by a given year. Percent renewables required and years to enforcement are observable and controlling for them accounts for cross-state differences in actual regulatory intensity.[19] The coefficients on the Democratic control and GHG target indicators therefore measure how much smaller (in absolute value) announcement-window return responses are in states where stricter regulation is anticipated, conditional on the realized policy design. I interpret these coefficients as measuring the attenuation in observed returns due to expectations. I use these coefficients to construct adjustment factors:

$$\mathrm{Adj}^{\mathrm{Antic}} \equiv \frac{\hat{\lambda}^{\mathrm{Antic}}_{\mathrm{RPS}}}{\overline{\Delta}^{\mathrm{Antic}}_{\mathrm{RPS}}}, \tag{9}$$

for Antic $\in \{\mathrm{Dem}, \mathrm{Tgt}\}$, where $\hat{\lambda}^{\mathrm{Dem}}_{\mathrm{RPS}}$ is the estimated coefficient on the Democratic control indicator for the RPS category and $\overline{\Delta}^{\mathrm{Antic}}_{\mathrm{RPS}}$ is a precision-weighted average of the Δ_p estimates for RPS regulations passed in states controlled by Democrats (for Antic=Dem) or states with targets (for Antic=Tgt).[20] Then, for each policy in the sample, I construct the adjusted policy intensity:

$$\hat{\Delta}^{\mathrm{adj}}_p = \hat{\Delta}_p - \left(\underbrace{\mathrm{FullDem}_p \times \mathrm{Adj}^{\mathrm{Dem}} \times \overline{\Delta}^{\mathrm{Dem}}_{c(p)} + \mathrm{Tgt}_p \times \mathrm{Adj}^{\mathrm{Tgt}} \times \overline{\Delta}^{\mathrm{Tgt}}_{c(p)}}_{\text{anticipation adjustment, }>0} \right), \tag{10}$$

where $\mathrm{FullDem}_p$ (Tgt_p) is an indicator equal to one if the state that enacted policy p was controlled by Democrats (had a GHG target in place) at the time of enactment. This procedure corrects for differences in anticipation without also removing variation in actual policy stringency under the assumption that similar expectations about state-level policy environments generate comparable degrees of attenuation across policy types. Figure 3 plots both raw and adjusted Δ_p across policy categories and Figure 4 maps the cumulative policy intensity by industry and state. The map shows that the most regulated industry/state pairs are utilities in California and Colorado, whereas many states have no GHG regulation at all.

4.2 Example: Two Oil and Gas Regulations

To demonstrate why the return-based measure of regulatory intensity is informative, I will use two regulations affecting the oil and gas industry as an example. The first, which is estimated to be the most costly

[19]In principle, similar quantitative characteristics are available for GHG Targets. However, since the market impact of targets depends on the extent to which investors believe that prescriptive regulations arising from the targets will be costly, there could be a partisan stringency gap, even after controlling for the quantitative characteristics. This is less of a concern for RPS, since the quantitative characteristics reflect variation in *actual* requirements imposed on affected firms.

[20]Note that in practice, $\mathrm{Adj}^{\mathrm{Antic}} < 0$ because $\hat{\lambda}^{\mathrm{Antic}}_{\mathrm{RPS}} > 0$ (i.e. all else equal, anticipated policies have a less negative return impact than unanticipated polices) and $\overline{\Delta}^{\mathrm{Antic}}_{\mathrm{RPS}} < 0$ (i.e. return impact is negative on average even for anticipated policies).

regulation in the sample ($\hat{\Delta}_p = -0.158$, $\hat{\Delta}_p^{\text{adj}} = -0.171$), is Colorado's SB 19-181, which was enacted in 2019. This regulation gave local governments authority over oil and gas development (previously, permits had been granted by a statewide regulator). The second regulation, which I estimate to be much less costly ($\hat{\Delta}_p = -0.009$, $\hat{\Delta}_p^{\text{adj}} = -0.060$), is NM Admin. Rule 19.15.27, which was enacted in 2021. It banned routine venting and flaring of oil and gas.[21] Systematically ranking the intensity of these two regulations based purely on observable characteristics or regulatory text would be difficult without expert knowledge of the operations of affected firms.[22] My return-based measure aggregates the market's assessment of the complex details of each regulation, concluding that Colorado's regulation is much more costly than New Mexico's.

To understand whether the market reaction to these two regulations reveals differences in stringency, I examine media coverage in the years since enactment. Following the enactment of SB 19-181, many local governments enacted moratoria on oil and gas permits. This had substantial impacts on affected firms. For example, Fitch downgraded Extraction Oil & Gas in March 2020, citing "local regulatory risks" in Colorado (Extraction filed for bankruptcy in June 2020); the state seized property (including 151 gas wells) from PCR LLC and PetroShare's CEO cited "damage of Senate Bill 181" when discussing its bankruptcy. On the other hand, New Mexico's venting and flaring rule is widely considered ineffective. The rule has exceptions for emergencies, which firms have used to justify routine venting and flaring. In addition, the state only has funding for 14 inspectors (a very small number given that there are about 56,000 active wells in New Mexico), which means that enforcement relies on self-reported data about methane capture. Nonprofit groups have systematically documented flares even at facilities that claim to capture 100 percent of methane and the aggregate quantity of venting and flaring has actually increased since the regulation was enacted. Taken together, this narrative evidence lends support to the idea that the Colorado regulation is much more stringent than the New Mexico regulation and that the return-based estimates are capturing meaningful and difficult-to-measure variation.[23]

[21] Figure A6 plots the full posterior densities for the unadjusted $\hat{\Delta}_p$ for these two regulations.

[22] The difficulty is magnified further when considering doing the same exercise for over 100 regulations affecting a wide variety of industries.

[23] To understand why this would be difficult to measure in a systematic way (especially for 100+ regulations), consider the information that the market-based measure is aggregating. In Colorado, investors needed detailed knowledge of the policy stance of local authorities in each county (there was substantial variation in the way permits were handled across counties) and on the within-state geographic dispersion of operations, notably which facilities were already permitted and which would be subject to local government permitting authority. In New Mexico, investors understood that while 100 percent compliance with the regulation may be costly (an analysis by Synapse Energy on behalf of the Environmental Defense Fund estimated compliance costs at around $5.2 billion over 10 years, whereas the BEA reports annual oil and gas revenue in NM of about $8 billion), the particular structure of the regulation (exceptions for emergencies, self-reported data and limited funding for inspections) substantially reduced the actual regulatory burden faced by firms.

4.3 Role of Policy Characteristics

Table 1 reports the estimates of λ_c. Observable characteristics have an intuitive impact on the policy intensity estimates. Across all categories, policies enacted through legislation and ballot initiatives have a larger negative impact than executive orders or administrative rules (the baseline category). This is logical both because the scope of rules that executive branch and the environmental regulator can enact is generally limited and because executive orders and administrative rules are more likely to be repealed by a future administration or overturned in court. Quantitative characteristics are available only for GHG targets and RPS. For both categories, a longer horizon is associated with smaller (less negative) policy intensity estimates, while the opposite is true for the "ambition" of the policy (as measured by percent emissions reduction targeted or percent renewables required). For GHG targets, having an interim target is associated with a larger return impact.[24] Investors may view interim targets as increasing the likelihood of costly prescriptive regulations being enacted in the short term (holding the terminal target year and target percentage fixed).

4.4 Impact of Estimated Stringency on Real Outcomes

I test the impact of regulatory stringency on real outcomes using the same specification as Section 3. For a given industry-state-year (ist), I define $\text{Reg}_{ist} = -100 \times \sum_{p \in P_{ist}} \hat{\Delta}_p^{\text{adj}}$, where P_{ist} is the set of regulations enacted in year t that affect industry i in state s. The measure is scaled so that higher values reflect more stringent regulation. For a given outcome y_{is}, I regress the change from $t-1$ to $t+h$ on Reg_{ist}:

$$\Delta y_{is,t-1,t+h} = \beta^h \text{Reg}_{ist} + \alpha_{is} + \alpha_{it} + \alpha_{st} + \eta_{ist}. \tag{11}$$

As in the triple-difference specification discussed in Section 3, I include industry/state, industry/year and state/year fixed effects. The outcomes I study (all in logs) are: employees, output, wages, CO2 intensity, CO2 emissions and establishment counts.

Figure 5 shows that an increase in regulatory stringency (scaled to correspond to a 1 percent decline in market value for a fully exposed firm) leads to statistically significant declines in employment, wages, CO2 intensity, CO2 emissions and establishment counts.

I repeat the exercise for firm-level outcomes. I define the firm-level regulatory change $\text{Reg}_{nt} = -100 \times \sum_s \text{Expos}_{ns,t-1} \text{Reg}_{ist}$. I include the same set of controls and fixed effects as in equation (3). I find that, in the 6 years following the regulation, exposed firms have lower profitability, higher investment and lower

[24] An example of a state whose GHG target has interim targets is Massachusetts, whose target (enacted in 2021) is 50 percent below 1990 levels by 2030, 75 percent by 2040 and 85 percent by 2050.

emissions (both tons of CO2 and CO2 per unit of output). These effects are consistent with the reduced form results. Note that the impact on profitability is close to -1 percent (when the shock is scaled to represent a -1 percent return response), suggesting that markets are (on average) accurately forecasting the profit impact of these regulations.

5 Model

The reduced-form results document both economic costs (declines in employment, output, establishments, and profitability) and benefits (declines in emissions and intensity, increases in R&D and capital investment). I use a spatial equilibrium model to interpret these patterns and assess how the costs of regulation are distributed across firms and workers and how the magnitude of the economic costs compares to the societal benefit of reduced emissions.

The model characterizes the effect of an increase in the stringency of local emissions regulation on wages, employment and profits. The model environment builds on the setup of Suárez Serrato and Zidar (2016), replacing corporate income tax with state- and industry-specific carbon taxes and adding endogenous emissions technology. I consider an economy with locations $s \in S$ and industries $i \in I$. There are two types of agents: workers (who are also investors) and firm managers. Workers choose their location, industry and asset allocation to maximize expected utility. Firms choose establishment locations, input quantities and emissions technology to maximize profits. Aggregating these choices delivers equilibrium objects at the industry-state level: establishments, emissions, employment, and wages and technology switching costs. I derive elasticities of these outcomes with respect to the implicit emissions tax, decomposed into relocation, technology switching, and intensive margin channels. I next show how the model maps into the moments used for estimation and how equity returns identify policy intensity. I then derive expressions for the equilibrium welfare impacts: costs to affected firms and workers, global benefits of reduced emissions.

5.1 Household Problem

Household h, employed by sector i and located in state s maximizes expected utility over local amenities (A_{nis}) and a composite consumption good (X_h). The household inelastically supplies one unit of labor, earning wages w_{is} and can invest in a length N vector of equity assets. Taking wages, goods prices and expected returns as given, the household solves:

$$\max_{\theta_h, \{x_{hj}\}_{j \in J}} \quad \log A_{his} + \mathbb{E}\left[\log X_h\right] \quad \text{s.t.} \int_{j \in J} p_j x_{hj} dj = w_{is} \theta_h' R, \tag{12}$$

where X_h represents a composite consumption good and the sum of the vector of portfolio weights $\theta_h' \mathbf{1} = 1$. The gross return vector of equity assets is lognormally distributed such that $\log(R) \sim \mathcal{N}(\mu, \Sigma)$, where μ is a length N vector and Σ is an $N \times N$ covariance matrix.

Let J_i denote the set of products produced by sector i. The sectoral sub-composite good is defined:

$$X_{hi} = \left(\int_{j \in J_i} x_{hj}^{\frac{\varepsilon_i^D + 1}{\varepsilon_i^D}} \right)^{\frac{\varepsilon_i^D}{\varepsilon_i^D + 1}}, \tag{13}$$

where sector-specific product demand elasticity $\varepsilon_i^D < -1$. The composite consumption good is then given by:

$$X_h = \prod_i X_{hi}^{\beta_i}, \quad \sum_i \beta_i = 1, \beta_i > 0. \tag{14}$$

Households choose their location and industry to maximize their expected indirect utility, accounting for state- and industry-specific amenities $\log A_{his}$, which are comprised of a common term $\overline{A}_{is}$ and an idiosyncratic preference shock ξ_{his}. The preference shock follows an i.i.d. Type I Extreme Value distribution with dispersion σ^H. As shown in Appendix D.1, the share of households employed by sector i in state s, which will determine local labor supply, is given by:

$$H_{is} = \mathbb{P}\left(V_{his}^H = \max_{(is)'} \left\{ V_{h(is)'}^H \right\} \right) = \frac{\exp \frac{u_{is}}{\sigma^H}}{\sum_{(is)'} \exp \frac{u_{(is)'}}{\sigma^H}}, \tag{15}$$

where $u_{is} \equiv \log w_{is} + \overline{A}_{is}$. Note that the elasticity of labor supply with respect to wages is σ^H. This means that when σ^H is low (i.e. workers have less disperse tastes for location- and industry-specific amenities), labor supply will be more responsive to changes in wages.

In addition to choosing location and a vector of consumption goods, the household also chooses portfolio weights in the N equity assets. As shown in Appendix D.1.2, portfolio weights can be approximated using the standard mean-variance form. Importantly, since households share identical risk preferences and beliefs about asset returns, they all hold the market portfolio. As a result, equity market returns are independent of the household's location decision. [25]

[25] Relaxing the assumption of common preferences and beliefs opens the door to several interesting extensions. For example, one could introduce home bias, heterogeneous preferences for green assets or heterogeneous beliefs about expected return and risk of green versus brown firms. Such heterogeneity would create an additional channel through which the impact of local environmental regulation could vary across households.

5.2 Firm Problem

Firm n in industry i operates a continuum of monopolistically competitive establishments $j \in J^n$, each producing output (y_{js}) using a Cobb-Douglas technology with labor (l_{js}), capital (k_{js}) and emissions ($\mathcal{E}_{js}$). Establishment-level productivity has a firm-specific component η_n and a location-specific component ϕ_{js}. The production function in state s using technology T is:

$$y_{js}^T = \eta_n \phi_{js} l_{js}^{\gamma_i^l} \mathcal{E}_{js}^{\gamma_j^T} k_{js}^{1-\gamma_i^l-\gamma_j^{\mathcal{E}}}, \tag{16}$$

The firm-specific productivity shock is jointly lognormal across firms, $\log \eta \sim \mathcal{N}(0, \Sigma_\eta)$. Facility-specific reliance on emissions is $\gamma_j^{\mathcal{E}} \in \{\gamma_i^B, \gamma_i^G\}$. In other words, facilities can operate one of two industry-specific technologies (brown or green).

Taking location and emissions technology as given, firms choose inputs and prices to maximize expected profits.[26] Under CES demand, prices are set as a markup over marginal cost. The firm's intensive margin (fixed location and emissions technology) maximization problem is:

$$\pi_{js}^T = \max_{l_{js}, \mathcal{E}_{js}, k_{js}} \left\{ \mathbb{E}_\eta \left[p_j y_{js}^T \right] - w_{is} l_{js} - \tau_{is} \mathcal{E}_{js} - \kappa_i k_{js} \right\}, \tag{17}$$

where κ_i is the (exogenous and location-invariant) rental rate of capital and τ_{is} is the tax on one unit of emissions.[27] The T superscript is used to emphasize that the profit expression is conditional on operating technology T.

After solving the establishment problem, expected profits can be rewritten:

$$\pi_{js}^T = \nu_n^T w_{is}^{\gamma_i^l (1+\varepsilon_i^D)} \tau_{is}^{\gamma_i^T (1+\varepsilon_i^D)} \phi_{js}^{-(1+\varepsilon_i^D)}, \tag{18}$$

where ν_n^T is a constant across locations. The derivation can be found in Appendix D.3.

5.2.1 Location Choice

In this subsection, I consider the firm's location decision, holding emissions technology fixed. In the next subsection, I will discuss how the firm jointly chooses its location and emissions technology. The firm chooses the location of establishment j to maximize profits. Assume that $\log(\phi_{js}) = \log \overline{\phi}_{is} + \zeta_{js}$, where $\overline{\phi}_{is}$ is common

[26] Since the covariance matrix Σ_η is exogenous, maximizing profits is equivalent to maximizing the firm's market value, as shown in Appendix D.2.

[27] As discussed in Shapiro and Walker (2018), in a Cobb-Douglas production function, it is equivalent to model emissions as an input with a price, as a jointly produced output that is taxed, or as subject to a constraint. Additionally, the firm problem takes w_{is} and τ_{is} as given. Since the problem is static, the firm considers only current levels of these values, disregarding expectations about how they may change in the future. In other words, firms make decisions based on existing emissions regulation and do not change their behavior based on how they expect emissions regulation to change in the future.

to all firms in industry i and ζ_{js} follows an i.i.d. type I extreme value distribution with dispersion σ_i^F. The value function, conditional on operating emissions technology T, is determined by dividing log profits by $-(1+\varepsilon_i^D) \geq 1$:

$$V_{js}^T = \frac{\log \nu_n^T}{-(1+\varepsilon_i^D)} + \underbrace{\log \overline{\phi}_{is} - \gamma_i^l \log w_{is} - \gamma_i^T \log \tau_{is}}_{\equiv v_{is}^T} + \zeta_{js}, \tag{19}$$

As in the household problem, establishments will locate in state s if their value function there is higher than in any other state s'. Thus, the share of establishments of firms in industry i with emissions technology $T \in \{B, G\}$, located in state s is given by:

$$E_{is}^T = \mathbb{P}\left(V_{js}^T = \max_{s'}\{V_{js}^T\}\right) = \frac{\exp \frac{v_{is}^T}{\sigma_i^F}}{\sum_{s'} \exp \frac{v_{is'}^T}{\sigma_i^F}}. \tag{20}$$

Then, the total share of industry i establishments that choose to locate in state s is given by:

$$E_{is} = \mathbb{P}_i(G) E_{is}^G + (1 - \mathbb{P}_i(G)) E_{is}^B, \tag{21}$$

where $\mathbb{P}_i(\cdot)$ denotes $\mathbb{P}(\cdot|i)$. I discuss how the share of green firms in industry i is determined in Section 5.2.2.

5.2.2 Emissions Technology Choice

All facilities start with the brown technology ($T_0 = B$) and can pay a firm-specific proportional cost $\chi_n \overset{\text{i.i.d.}}{\sim} U[0, 1]$ in order to acquire the green technology.I assume that χ_n is independent of both ϕ_{js} and η_n. An establishment's net profits are equal to $\alpha_i(1 - \chi_n)\pi_{js}$, where π_{js} is given by equation (18) and $\alpha_i > 1$.[28] Expected establishment profits are given by:

$$\pi_j = \max\left\{\pi_j^B, \quad \alpha_i(1 - \chi_n)\pi_j^G\right\}, \tag{22}$$

where π_j^T refers to the expression in equation (18) using technology T and when state s is chosen according to Section 5.2.1.[29]

The probability that a facility in industry i operates the green technology conditional on being located

[28] The purpose of α_i is to offset the fact that, with CRS technology, an decrease in γ_i^T mechanically leads an increase in the capital share of output. As such, firms would never switch technologies when the rental rate of capital, κ_i is larger than τ_{is}. A further implication of this is that switching to the green technology reduces the marginal cost (because switching only occurs when $\kappa_i < \tau_{is}$), increasing output and actually leading emissions to increase (even though emissions per unit of output falls). While potentially interesting, this effect is a particular quirk of CRS technology and not the focus of this paper.

[29] It would also be reasonable to consider a fixed χ_n, i.e. net profits are $\pi_{js} - \chi_n$ if the firm chooses to operate the green technology in facility j. In that case, the derivation would proceed almost identically, and the propensity to invest in the green technology would increase with facility size.

in state s is given by:

$$\mathbb{P}_i(G|s) = 1 - \frac{\nu_i^B}{\alpha_i \nu_i^G} \tau_{is}^{-(1+\varepsilon_i^D)(\gamma_i^G - \gamma_i^B)}, \tag{23}$$

as shown in Appendix D.4. Recall that $\varepsilon_i^D < -1$ and $\gamma_i^G < \gamma_i^B$, so that the state-specific green technology share is increasing in τ_{is}.

5.3 Local Impacts of Emissions Regulation

In this subsection, I present the partial equilibrium impacts of an increase in local emissions regulation on outcomes in state s.[30] Detailed derivations are provided in Appendix D.5.

Establishments The share of establishments of industry i that choose to locate in state s is a weighted sum of the technology-specific shares, given by equation (21). Following Hopenhayn (1992), I assume that the number of states S is large enough that a change in τ_{is} does not affect the unconditional green technology probability, $\mathbb{P}_i(G)$. Then, the elasticity of the establishment share E_{is} with respect to τ_{is} is given by:

$$\frac{\partial \log E_{is}}{\partial \log \tau_{is}} = -\frac{1}{\sigma_i^F} \left(\mathbb{P}_i(G|s)\gamma_i^G + (1 - \mathbb{P}_i(G|s))\gamma_i^B \right). \tag{24}$$

This expression makes apparent that three forces may shape the impact of regulation on the local establishment share: (1) green technology share, (2) "technology gap," $\gamma_i^B - \gamma_i^G$ and (3) the dispersion of location-specific productivity, σ_i^F. If the green technology share is low, then establishments are more likely to leave state s in response to the regulation. This is because the same increase in τ_{is} is more costly for firms operating the brown technology. If the technology gap is small (i.e. the green and brown technologies are similar), establishments are also more likely to relocate. This is because the ability to mitigate the impact of the tax increase by switching to the green technology is limited.[31] Finally, if σ_i^F is low, there is more likely to be another state where the establishment is similarly productive, so the decline in the establishment share is larger.

Emissions The total emissions of firms in industry i and state s are given by a weighted sum of emissions from green and brown firms:

$$\begin{aligned} \mathcal{E}_{is} &= \mathbb{P}_i(G)\mathcal{E}_{is}^G + (1 - \mathbb{P}_i(G))\mathcal{E}_{is}^B \\ &= E_{is} \left[\mathbb{P}_i(G|s)\mathcal{E}_{is}^G + (1 - \mathbb{P}_i(G|s))\mathcal{E}_{is}^B \right], \end{aligned} \tag{25}$$

[30] For brevity, I write the expressions in partial equilibrium (omitting general equilibrium feedback from wages to the other variables). Section 6.1 discusses the full impacts when accounting for changes to wages.

[31] Oil and gas is a good example of an industry where this is the case because even the "greenest" oil and gas extraction firm is still very emissions intensive.

where the second line uses the equivalence between E_{is} and $\mathbb{P}_i(s)$. The effect of emissions regulation on local emissions can then be decomposed into three components: relocation, technology switching and intensive margin (fixed technology and location). Let $\psi_{is}^T \equiv \frac{\mathbb{P}_i(T|s)\mathbb{E}[\mathcal{E}_{jis}^T]}{\mathbb{P}_i(G|s)\mathbb{E}[\mathcal{E}_{jis}^G]+\mathbb{P}_i(B|s)\mathbb{E}[\mathcal{E}_{jis}^B]}$ for $T \in \{B, G\}$.[32] As shown in Appendix D.5, the elasticity of local emissions with respect to the emissions tax is then:

$$\frac{\partial \log(\mathcal{E}_{is})}{\partial \log \tau_{is}} = \underbrace{\frac{\partial \log E_{is}}{\partial \log \tau_{is}}}_{\text{relocation}} + \sum_{T\in\{B,G\}} \psi_{is}^T \left(\underbrace{\frac{\partial \log \mathbb{P}_i(T|s)}{\partial \log \tau_{is}}}_{\text{tech. switching}} + \underbrace{\gamma_i^T(1+\varepsilon_i^D) - 1}_{\substack{\text{intensive margin} \\ \text{(substitution and scale)}}} \right). \tag{26}$$

The relocation effect is given by equation (24) and $\frac{\partial \log \mathbb{P}_i(G|s)}{\partial \log \tau_{is}} = \frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}(1+\varepsilon_i^D)(\gamma_i^G - \gamma_i^B)$. Each term captures a distinct channel through which regulation affects emissions. The location effect represents firm relocation in response to local regulation, as discussed above. The technology switching effect arises because higher emissions taxes make the green technology profitable for a larger share of firms. The substitution effect ($\gamma_i^T - 1 < 0$) reflects firms shifting away from other inputs. The scale effect ($\gamma_i^T \varepsilon_i^D < 0$) captures the reduction in output due to higher costs.[33]

Employment Following the same logic, the elasticity of local labor demand is given by:

$$\frac{\partial \log(L_{is}^D)}{\partial \log \tau_{is}} = \underbrace{\frac{\partial \log E_{is}}{\partial \log \tau_{is}}}_{\text{relocation}} + \sum_{T\in\{B,G\}} \psi_{is}^T \left(\underbrace{\frac{\partial \log \mathbb{P}_i(T|s)}{\partial \log \tau_{is}}}_{\text{tech. switching}} + \underbrace{\gamma_i^T(1+\varepsilon_i^D)}_{\substack{\text{intensive margin} \\ \text{(substitution and scale)}}} \right). \tag{27}$$

The scale and location effects are identical to equation (26). The substitution effect (equal to γ_i^T) is positive because labor and emissions are substitutes: stricter emissions regulation induces firms to increase reliance on labor and other inputs. Empirically, Figure 1 shows that wages and employment fall after the introduction of emissions regulation, which suggests that the scale and firm location effects dominate.

Wages Equilibrium wages are determined by equating $H(w_{is}; \overline{A}_{is}) = L_{is}^D(w_{is}; \tau_{is}, \overline{\phi}_{is})$. As shown in Appendix D.5, the effect of an increase in the emissions tax rate on wages is given by:

$$\dot{w}_{is} \equiv \frac{\partial \log w_{is}}{\partial \log \tau_{is}} = \frac{\sum_{T\in\{B,G\}} \psi_{is}^T \left(\gamma_i^T + \gamma_i^T \varepsilon_i^D - \frac{\gamma_i^T}{\sigma_i^H}\right)}{\frac{1}{\sigma^H} - \left(\gamma_i^l + \gamma_i^l \varepsilon_i^D - 1 - \frac{\gamma_i^l}{\sigma_i^F}\right)}. \tag{28}$$

[32]Using the expressions for emissions and the state-specific technology probabilities, it is straightforward to show that $\psi_{is}^G = \frac{\mathbb{P}_i(G|s)}{\mathbb{P}_i(G|s)+[\mathbb{P}_i(B|s)]^2}$ and $\psi_{is}^B = 1 - \psi_{is}^G$.

[33]I follow the decomposition in Suárez Serrato and Zidar (2016) and abstract from the composition effect added by Malgouyres et al. (2023). The original decomposition allows for a more transparent mapping from firm-level decisions to aggregate emissions changes and facilitates interpretation of the relative importance of each behavioral margin. As Suárez Serrato and Zidar (2023) show, the quantitative implications of this abstraction are small in practice.

The numerator captures the effect of the regulatory change on labor demand as given by equation (27). The first term in the denominator, $\frac{1}{\sigma^H}$, is the elasticity of labor supply. If σ^H is large (i.e. preferences are more heterogeneous across locations and industries), labor supply is less elastic. Intuitively, when preferences are more dispersed, workers are less responsive to local wage changes because their outside options are less attractive. The second term in the denominator, $\left(\gamma_i^l + \gamma_i^l \varepsilon_i^D - 1 - \frac{\gamma_i^l}{\sigma_i^F}\right)$, is the elasticity of firms' labor demand with respect to a change in wages. It has the same three components (substitution, scale and firm location) as the elasticities discussed in the above.

Switching Costs The total switching costs paid by facilities of industry i in state s are given by:

$$SC_{is} = \int_{j \in J^i} \mathbb{1}\{T_j = G\}\mathbb{1}\{s_j = s\}\chi_{n(j)}\pi_j^G dj$$

As shown in Appendix D.5, the effect of an increase in the emissions tax rate on the total switching costs paid by facilities in industry i and state s is given by:

$$\frac{\partial \log SC_{is}}{\partial \log \tau_{is}} = \underbrace{\frac{\partial \log E_{is}}{\partial \log \tau_{is}}}_{\text{relocation}} + \underbrace{2\frac{\partial \log \mathbb{P}_i(G|s)}{\partial \log \tau_{is}}}_{\text{switching}}. \tag{29}$$

The first term reflects the decrease in industry i/state s switching costs due to some facilities relocating out of state s. The second term represents the increase in switching costs that arises because the higher tax makes the green technology attractive to a larger set of firms.

5.4 Full Equilibrium Impacts of Emissions Regulation

5.4.1 Emissions

Equation (26) shows the change in emissions of firms in industry i and state s resulting from a change in τ_{is}. However, this expression does not account for the fact that when considering total emissions, the firms that leave state s may increase emissions elsewhere. To derive the adjustment, I assume that when a firm relocates from state s to state s', $w_{is} = w_{is'}$ and $\phi_{js} = \phi_{js'}$. In other words, the two states only differ in their emissions regulatory stringency.[34] I further assume that facilities that relocate in response to the regulation do not switch technologies, reflecting the idea that relocation and technology adoption are

[34] This assumption simplifies the analysis by abstracting from the effects of wage and productivity differences on firm emissions. In reality, relocation could alter both the scale and input mix of production. However, if a destination state had significantly higher wages or lower productivity, relocation would be less likely (and if the opposite were true, state s' would have been optimal even before the regulatory change). Thus, emissions regulation is likely to be the primary driver of emissions intensity differences across locations for relocating firms.

alternative compliance strategies rather than complementary ones.[35] Under these assumptions, the effect of a change in local emissions regulation on industry-wide emissions is:

$$\dot{\mathcal{E}}_i = \sum_{T\in\{B,G\}} \psi_{is}^T \left[\underbrace{\frac{\partial \log \mathbb{P}_i(T|s)}{\partial \log \tau_{is}}}_{\text{tech. switching}} + \underbrace{\left(\gamma_i^T - 1 + \gamma_i^T \varepsilon_i^D - \frac{\gamma_i^T}{\sigma_i^F}\right)}_{\text{substitution + scale + relocation from } s} + \underbrace{\sum_{s'\neq s} \frac{\exp\left(\frac{v_{is'}^T}{\sigma_i^F}\right)}{\sum_{s''\neq s}\exp\left(\frac{v_{is''}^T}{\sigma_i^F}\right)} \left(\frac{\tau_{is'}}{\tau_{is}}\right)^{\gamma_i^T - 1} \frac{\gamma_i^T}{\sigma_i^F}}_{\text{relocation into } s'} \right] \tag{30}$$

The relocation term has three intuitive components. The first, $\frac{\exp\left(\frac{v_{is'}^T}{\sigma_i^F}\right)}{\sum_{s''\neq s}\exp\left(\frac{v_{is''}^T}{\sigma_i^F}\right)}$, captures the conditional probability that a relocating firm selects state $s' \neq s$ as its new location, given that it exits state s. The second, $\left(\frac{\tau_{is'}}{\tau_{is}}\right)^{\gamma_i^T - 1}$, reflects the change in emissions intensity that results from relocating to a state with different regulatory stringency; if $\tau_{is'}^{\mathcal{E}} < \tau_{is}$, then emissions intensity increases. The third term, $\frac{\gamma_i^T}{\sigma_i^F}$, reflects the volume of emissions that reappear elsewhere due to firms relocating out of s. Since these probabilities are conditional on relocation, they are normalized over $s' \neq s$ and thus sum to one. When all states have identical regulatory stringency (i.e., $\tau_{is'}^{\mathcal{E}} = \tau_{is}$ for all s'), emissions per firm are unchanged by relocation. In that case, the increase in emissions in other states exactly offsets the decrease in state s. In practice, firms that relocate from state s in response to regulation are likely to choose a state s' where $\tau_{is'} < \tau_{is}$, which means that the emissions of the relocated facility will be larger than those of the facility in the origin state prior to the regulatory change.

5.4.2 Corporate Profits and Equity Returns

Let $\omega_{ns} = \frac{\pi_{ns}}{\sum_{s'}\pi_{ns'}}$ denote the fraction of firm n's profits generated in state s. Then, the total impact on profits of a discrete change in regulation from τ_{is} to τ_{is}^{new} is given by:

$$\begin{aligned}
\dot{\pi}_n = \omega_{ns} \Bigg[& \mathbb{P}(\text{stay, no switch})(1+\varepsilon_i^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is})\Delta \log \tau_{is} \\
& + \mathbb{P}(\text{stay,switch}) \left[(1+\varepsilon_i^D)\left(\Delta \log \tau_{is}(\gamma_i^B + \gamma_i^l \dot{w}_{is}) + (\gamma_i^G - \gamma_i^B)\log \tau_{is}^{\text{new}}\right) + (\log \nu_i^G - \log \nu_i^B) + \log(1-\chi_n)\right] \\
& + \sum_{s'\neq s} \mathbb{P}(\text{move to } s')(1+\varepsilon_i^D)\left(\gamma_i^l(\log w_{is'} - \log w_{is}) + \gamma_i^{T_{ns}}(\log \tau_{is'} - \log \tau_{is}^{\text{old}}) - (\log \overline{\phi}_{is'} - \log \overline{\phi}_{is})\right) \Bigg],
\end{aligned} \tag{31}$$

[35] This assumption is reasonable for two main reasons. First, facilities that are already using the green technology have no incentive to switch back to brown after relocating, since they have already incurred the upfront cost (this is outside the static model). Second, brown facilities that choose to relocate are typically doing so to avoid stringent regulation. Relocating to a low-regulation state reduces the returns to green investment, making technology switching less likely.

where T_{ns} denotes the technology that firm n was operating in state s prior to the regulatory change., the probabilities of each outcome are derived in Appendix D.6.2 and $\dot{w}_{is}$ is given by equation (28). The probabilities are at the facility level and are conditional on the facility location in state s under τ_{is}^{old}. This expression reflects the different forces through which emissions regulation affects firm profits. The direct impact (without G.E. wage feedback, technology switching or relocation) is $(1+\varepsilon_i^D)\gamma_i^{T_{ns}}$. There are three ways that the direct profit impact is offset. First, if the regulation-induced change to labor demand leads to a decline in wages, then a reduction in labor costs serves to offset the increased cost of emitting.[36] This effect is larger in more labor-intensive industries (higher γ_i^l). The second way that the direct profit impact is offset is through technology switching. Instead of keeping the brown technology (in which case the direct impact is $(1+\varepsilon_i^D)\gamma_i^B$), firms can reduce this impact by switching to the green technology. The benefit to doing so depends on the technology gap, $\gamma_i^G - \gamma_i^B$ and on the switching cost, $1-\chi_n$.[37] When the technology gap is large (i.e. the green technology is much less emissions-dependent than the brown), the benefit of switching is larger. The third channel through which firms can offset the direct profit impact is relocation. Since we do not observe the idiosyncratic piece of location-specific productivity ϕ_{js}, relocation is summarized as a sum of probabilities over each state s'. The profit impact of relocating to s' depends on the difference in wages, emissions tax rates and productivity.

As shown in Appendix D.6.3, given the assumptions of local shocks and an exogenous covariance matrix, the realized equity return around the announcement of this policy change is equal to the profit impact. Importantly, it scales linearly with ω_{ns}, the share of firm n's profits generated in state s, consistent with the setup for the Bayesian estimation of policy intensity described in Section 4.

5.4.3 Goods Prices

The price of good j is the marginal cost times a markup:

$$p_j = \frac{\varepsilon_i^D}{\varepsilon_i^D+1} \underbrace{\frac{1}{\phi_{js}} \left(\frac{w_{is}}{\gamma_i^l}\right)^{\gamma_i^l} \left(\frac{\tau_{is}}{\gamma_i^T}\right)^{\gamma_i^T} \left(\frac{\kappa_i}{1-\gamma_i^l-\gamma_i^T}\right)^{1-\gamma_i^l-\gamma_i^T}}_{\equiv c_{js}}. \tag{32}$$

[36] Technically, the sign of $\dot{w}_{is}$ is ambiguous because if the substitution effect leads firms to replace emissions with labor, then labor demand would increase. However, my empirical results show that this is not the case in practice, consistent with the logical intuition that emissions and capital are more substitutable than emissions and labor.

[37] It also depends on ν_i^B/ν_i^G, which arises because in the CRS technology, switching to the green technology mechanically increases reliance on capital (since the Cobb Douglas weight on capital is $1-\gamma_i^l-\gamma_i^T$ and $\gamma_i^G < \gamma_i^B$). If the rental rate of capital, κ_i is large, this term can offset the benefits of switching to the green technology. One can think of this effect as essentially rescaling $1-\chi_n$ and I thus do not discuss it in detail.

The direct impact of emissions taxes on goods prices is:

$$\frac{\partial \log p_j}{\partial \log \tau_{is}} = \gamma_i^{T_j}, \tag{33}$$

where T_j is the technology used to produce good j. If firms relocate or adjust technology in response to regulation, these costs are also directly passed to consumers (because of monopolistic competition). It is important to note here that the model does not distinguish between tradable goods (where it is implausible that firms would be able to pass regulatory costs in a single state to consumers) and non-tradable goods (in particular utilities and waste management), where the monopolistic competition assumption is more reasonable.

5.4.4 Welfare

I discuss the welfare effects in two parts. First, I examine how regulatory changes impact the welfare of households through both labor and equity markets.[38] Then, I use social cost of carbon estimates from the literature to quantify the welfare benefit associated with the reduction in GHG emissions caused by new regulation.

I define the welfare of household n as $\mathcal{V}^H \equiv \mathbb{E}[\log(\theta' R) + \max_{is}\{u_{is} + \xi_{nis}\}]$. Separating the (location-invariant) investment income component and using standard properties of the T1EV distribution,

$$\mathcal{V}^H = \mathbb{E}\left[\log(\theta' R)\right] + \sigma^H \log\left(\sum_{(is)} \exp \frac{\log w_{is} + \overline{A}_{is}}{\sigma^H}\right). \tag{34}$$

It follows that the effect of an increase in regulatory stringency on the (expected) welfare of workers is given by:

$$\dot{\mathcal{V}}^H = \underbrace{\sum_{n\in F^i} \rho_n \dot{\pi}_n}_{\equiv \dot{\mathcal{V}}_\pi} + \underbrace{N_{is}\left(\mathbb{P}^{is}_{\text{stay}} \dot{w}_{is} + \sum_{(is)'\neq is} \mathbb{P}^{is\to(is)'}_{\text{move}} \Delta\mathcal{V}_{is\to(is)'}\right)}_{\equiv \dot{\mathcal{V}}_w} + \underbrace{\left(-H_s \beta_i \gamma_i^T\right)}_{\equiv \dot{\mathcal{V}}_P}, \tag{35}$$

where F^i are the set of firms in industry i, $\rho_n \equiv \frac{\theta_n e^{\mu_n}}{\sum_{n'} \theta_{n'} e^{\mu_{n'}}}$ is the fraction of the investors' expected return generated by firm $n$and H_s is the total share of households located in state s. The full expression for $\dot{\mathcal{V}}_w$ is derived in Appendix D.7. The structural estimation will allow me to compute the magnitudes of $\dot{\mathcal{V}}_\pi$ (firms' welfare incidence) to $\dot{\mathcal{V}}_w$ (workers' welfare incidence) and $\dot{\mathcal{V}}_P$ (consumers' welfare incidence) and to the costs to the benefits arising from emissions reduction.

[38] Even though I model these effects as impacting the same households, this decomposition captures the distinction between the effect on investors, workers and consumers.

The total welfare gain resulting from a discrete policy change $\Delta\tau_{is}$ can then be approximated:

$$\dot{\mathcal{V}}^{\mathcal{E}} \approx \Delta\tau_{is} \times \dot{\mathcal{E}}_i \times \text{SCC}, \tag{36}$$

where $\dot{\mathcal{E}}_i$ is given by equation (30) and SCC is the social cost of carbon. Note that agents in this model do not internalize the emissions externality. However, it is straightforward to imagine that climate change would affect welfare through local amenities, stock returns or productivity. These effects have been modeled extensively in the literature, leading to estimates of the SCC ranging from about \$50-\$250 per ton of CO2. The variation in these estimates is driven by assumptions about discount rates, damage functions and tipping points. This leads to a range for the welfare benefit associated with emissions reductions induced by regulatory changes. Additionally, given the broad disagreement about the SCC, equations (35) and (36) can be used to infer the value of SCC that will equate economic costs and environmental benefits.

5.5 Comparative Statics

Before proceeding to estimation, I illustrate the key mechanisms of the model by examining how emissions respond to a change in the tax rate under four comparative statics. The first varies the size of the tax shock, while the remaining exercises hold the shock fixed and assess how the response depends on alternative out-of-state tax environments, firm mobility, and technology gaps.

Magnitude of the Tax Change Figure 7 shows how the relative importance of technology switching and relocation evolves with the size of a change in the emissions tax rate. I simulate a scenario where all states are ex-ante identical and one state increases its emissions tax rate. Panel A shows that when the tax increase is small, technology switching (dashed line) drives a large share of the reduction in local emissions, as more firms adopt the cleaner production method (for the smallest tax changes in the plot, switching increases the magnitude of local emissions reduction by about 40 percent). The incremental gain from switching (dotted line) is largest for modest tax changes, but its effect diminishes as the tax becomes more stringent. Panel B shows that switching also mitigates leakage: because some firms become cleaner rather than relocating, the rise in emissions elsewhere is smaller when switching is allowed. At larger tax changes, however, relocation becomes the dominant adjustment margin because emissions in the regulated state continue to fall, but these reductions are offset by inflows to less-regulated states. Panel C combines these effects to show that total (global) emissions still decline, but the declines are smaller for larger tax changes. This is directly attributable to the increase in leakage caused by large increases in the tax rate. An important note is that in this particular scenario, emissions reduction goes to zero as τ_{is} goes to infinity (i.e. all state s production moves to other states), which is a direct result of the setting identical pre-regulation tax rates in all states. As discussed below, if the pre-regulation tax rate is higher in state s than in other states, total emissions can actually increase as a result of the tax.

Tax Rate in Other States Panel A of Figure 8 plots the impact of a 20 percent increase in the emissions tax in state s on local emissions, leakage and total emissions as a function of the tax rate in state $s' \neq s$.[39] When $\tau_{is'}$ is low, regulation in state s generates substantial leakage: production shifts toward the lower-tax location, offsetting part or all of the local emissions reduction. As the other state's tax rises, this relocation channel weakens and the local tax increase leads to a reduction in total emissions. This figure illustrates a potential shortcoming of decentralized emissions policy.

Firm Mobility Panel B of Figure 8 plots the impact of a 20 percent increase in the emissions tax in state s on local emissions, leakage and total emissions as a function of σ_i^F, which governs firm mobility. When mobility is high (σ_i^F is low), firms favor relocation over within-state emissions reduction, leading to larger emissions increases in unregulated states and smaller reductions in global emissions despite similar declines locally. As σ_i^F increases, firms remain largely in place and emissions decline mainly through within-state technology switching and scale reductions.

Technology Gap Panel C of Figure 8 plots the impact of a 20 percent increase in the emissions tax in state s on local emissions, leakage and total emissions as a function of the technology gap, $\gamma_i^B - \gamma_i^G$. The within-state reduction in emissions increases with the size of the gap because a wider gap makes switching more attractive and reduces per-facility emissions of those who do switch (the scenario is defined so that the mean emissions technology, $0.5 \times (\gamma_i^G + \gamma_i^B)$ is held constant).[40]

6 Estimation

6.1 Exact Structural Effects of Emissions Regulation

Following Suárez Serrato and Zidar (2016), I derive a simultaneous equation model to represent the general equilibrium impacts of a change in local emissions regulation. The five equations in the system are: establishment location (equation (24)), emissions (equation (26)), labor supply equation (equation (15)), labor demand equation (equation (27)) and technology switching costs (equation (29)). Stacking these five

[39] For illustrative purposes, the simulated economy only has two states.

[40] The positive relation between leakage and the technology gap arises because by fixing the average technology parameter and symmetrically varying the gap, I am increasing the per-facility emissions of those who do relocate (because brown facilities are more likely to relocate than green).

equations yields:

$$\boldsymbol{A}_i \boldsymbol{Y}_{is,t} = \boldsymbol{B}_i \boldsymbol{Z}_{is,t} + \boldsymbol{e}_{is,t}, \tag{37}$$

where $\boldsymbol{Y}_{is,t} \equiv \begin{bmatrix} \Delta \log w_{is,t} & \Delta \log L_{is,t} & \Delta \log \mathcal{E}_{is,t} & \Delta \log E_{is,t} & \Delta \log \mathrm{SC}_{is,t} \end{bmatrix}'$ is a vector of changes in the five endogenous variables (wages, employment, emissions, number of establishments and technology switching costs), $\boldsymbol{Z}_{is,t} = [\Delta \log \tau_{is,t}]$ is a vector of shocks to the emissions tax rate, $\boldsymbol{A}_i$ is a matrix that characterizes the relation between the endogenous variables, $\boldsymbol{B}_i$ captures the direct effects of regulatory shocks on each endogenous variable and $\boldsymbol{e}_{is,t}$ is a structural error term. $\boldsymbol{A}_i$ and $\boldsymbol{B}_i$ are given by:

$$\boldsymbol{A}_i = \begin{bmatrix} -\frac{1}{\sigma^H} & 1 & 0 & 0 & 0 \\ \gamma_i^l(1+\varepsilon_i^D) - 1 & -1 & 0 & 1 & 0 \\ -\gamma_i^l(1+\varepsilon_i^D) & 0 & 1 & -1 & 0 \\ \frac{\gamma_i^l}{\sigma^F} & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 & 1 \end{bmatrix} \quad \boldsymbol{B}_i = \begin{bmatrix} 0 \\ (1+\varepsilon_i^D)\left[\psi_{is}^G\left(\gamma_i^G - \frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}\dot{\gamma}_i\right) + \psi_{is}^B(\gamma^B + \dot{\gamma}_i)\right] \\ (1+\varepsilon_i^D)\left[\psi_{is}^G\left(\gamma_i^G - \frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}\dot{\gamma}_i\right) + \psi_{is}^B(\gamma^B + \dot{\gamma}_i)\right] - 1 \\ -\frac{\mathbb{P}_i(G|s)\gamma_i^G + \mathbb{P}_i(B|s)\gamma_i^B}{\sigma^F} \\ -2\frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}(1+\varepsilon_i^D)\dot{\gamma}_i \end{bmatrix}, \tag{38}$$

where $\dot{\gamma}_i \equiv \gamma_i^B - \gamma_i^G > 0$.

6.1.1 Substituting Returns For Unobserved Tax Shocks

Although the model treats emissions regulation as a proportional tax on pollution, most real-world emissions regulation (as described in Section 2) does not take the form of explicit taxes. However, these policies impose implicit costs on firms that affect equilibrium outcomes in ways analogous to a tax. Throughout, I use this shadow-price or implicit-tax representation as a device to gain comparability across heterogeneous policies. The magnitude of this implicit tax is not directly observable in the data, so I rely on the return-based measure of policy intensity discussed in Section 4.

By inverting the model's profit equation, I back out the implied change in the emissions tax rate that would have generated the observed returns, allowing me to trace out the full set of general equilibrium responses and welfare effects given by equation (37). I abstract from the relocation and technology switching terms when performing this inversion, treating the observed change in expected profits as if the firm were unable to change location or technology. This avoids a circular, parameter-dependent, and non-linear mapping in which the return–tax link would vary with pre-policy tax levels, technology gaps, and the cross-state surplus from relocation. Importantly, this restriction is used only to convert returns into tax units; once the tax shock is recovered, all subsequent simulations and counterfactuals in the paper allow for relocation and technology switching. Since the option to relocate or improve technology can only increase the firm's post-regulation value, the inversion that ignores those options maps a given return into a larger required tax change, so it delivers a conservative (lower-bound) measure of policy stringency.[41]

In addition, I abstract from changes in discount rates. In reality, regulations that make firms greener could reduce their cost of capital, either because greener firms are less exposed to future regulatory risk or because investors exhibit non-pecuniary preferences for greenness (Bolton and Kacperczyk (2021), Pástor et al. (2021)). Conversely, regulatory compliance may introduce cash flow risk, which could increase discount rates. However, the empirical evidence suggests that these regulations typically lower firms cost of capital (Hsu et al. (2023)). By abstracting from discount rates, the estimated change in the pollution tax needed to rationalize observed returns again reflects a conservative estimate of the regulation's actual stringency.

Using equation (31) and imposing the simplifying assumptions, I obtain:

$$\Delta \log \tau_{is} \approx \frac{\dot{\pi}_n}{\omega_{ns}(1+\varepsilon_i^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is})}, \tag{39}$$

where $\dot{\pi}_n$ denotes the expected profit impact inferred from returns and the denominator collects parameters that influence the slope of the relation between the tax shock and profits. My policy-intensity measure is built at the policy level as the profit impact per unit exposure, then aggregated to the industry–state–year level by summing across policies. This aggregate therefore reflects the impact for a fully exposed firm. When I map returns into tax-change units, a firm's profit change equals exposure times this fully exposed measure, so the exposure term (ω_{ns}) cancels. The mapping then depends only on model parameters and the model-implied wage response, not on firm-specific exposure. I use this mapping to modify the structural system given by equation (37):

$$\boldsymbol{A}_i \boldsymbol{Y}_{is,t} = \tilde{\boldsymbol{B}}_i \tilde{\boldsymbol{Z}}_{is,t} + \boldsymbol{e}_{is,t}, \tag{40}$$

where $\tilde{\boldsymbol{Z}}_{is,t}$ is a vector of return-based policy intensity estimates described in Section 4 and

$$\tilde{\boldsymbol{B}}_i \equiv \frac{1}{(1+\varepsilon_i^D)\left(\overline{\gamma_i^{\mathcal{E}}} + \gamma_i^l \dot{w}_{is}\right)} \boldsymbol{B}_i, \tag{41}$$

where $\overline{\gamma_i^{\mathcal{E}}}$ is the weighted average emissions technology operated by facilities of industry i in state s.[42]

[41] Ignoring relocation and technology switching in the inversion step yields a linear mapping from returns to the implicit tax that does not depend on pre-regulation taxes or on the option values of switching and moving. If those options were included, the denominator in (39) would contain additional terms that depend on pre-policy τ_{is}, the technology cost gap, relocation surpluses across states, and the associated choice probabilities, making the mapping heterogeneous and parameter-dependent. I use the simplification only for rescaling the return shock into tax units that are then fed into the model. The quantitative results and welfare calculations that follow fully incorporate technology switching, relocation, and general-equilibrium wage changes.

[42] In practice, $\overline{\gamma_i^{\mathcal{E}}}$ is time-varying, so I use pre-regulation values to construct the mapping for each policy.

The reduced form impact of regulation-induced return shocks is then given by:

$$\boldsymbol{Y}_{is,t} = \underbrace{\boldsymbol{A}^{-1}\tilde{\boldsymbol{B}}_i}_{\equiv \boldsymbol{\beta}^{Reg}(\boldsymbol{\theta}_i)} \tilde{\boldsymbol{Z}}_{is,t} + \boldsymbol{A}_i^{-1}\boldsymbol{e}_{is,t}, \tag{42}$$

where the vector of reduced form coefficients, $\boldsymbol{\beta}_i^{Reg} = \begin{bmatrix} \beta_i^W & \beta_i^L & \beta_i^{\mathcal{E}} & \beta_i^E & \beta_i^{SC} \end{bmatrix}'$ and $\boldsymbol{\theta_i}$ is industry-specific parameter vector.[43] In the next section, I use the policy intensity measure to estimate empirical counterparts to each element of $\boldsymbol{\beta}_i^{Reg}$ and then choose $\boldsymbol{\theta}_i$ to minimize the distance between the theoretical and empirical elasticities.

6.2 Structural Estimation

I estimate the model using data from four sectors: Oil and Gas Extraction, Utilities, Manufacturing and Waste Management.[44] I choose these sectors because they are the only four that are the focus of *prescriptive* regulations in my sample.[45] I focus the estimation on the two emissions technology parameters in each industry, γ_i^G and γ_i^B. In the baseline specification, I fix γ_i^l and σ_i^F using estimates based on data from 2003-2005 (when there was minimal emissions regulation) and fix ε_i^D using estimates from the literature.[46] I then use the observed impacts of return-implied regulatory intensity to estimate γ_i^G and γ_i^B for each industry.[47]

To construct the empirical counterpart to $\boldsymbol{\beta}_i^{Reg}$, I re-estimate equation (11) with industry-specific interaction terms and using a horizon $h = 6$. The results can be found in Table 2. I then use a classical minimum distance estimator to find the industry-specific parameter vector, $\boldsymbol{\theta}_i$, that best matches the theoretical moments with their empirical counterparts:

$$\hat{\boldsymbol{\theta}}_i = \underset{\boldsymbol{\theta}_i}{\operatorname{argmin}} [\hat{\boldsymbol{\beta}}_i - \boldsymbol{\beta}_i^{Reg}(\boldsymbol{\theta}_i)] \hat{\boldsymbol{V}}^{-1} [\hat{\boldsymbol{\beta}}_i - \boldsymbol{\beta}_i^{Reg}(\boldsymbol{\theta}_i)], \tag{43}$$

where $\hat{\boldsymbol{V}}^{-1}$ is the inverse covariance matrix of the OLS estimate. In the baseline specification, I hold γ_i^l, σ_i^F and ε_i^D fixed and choose $\begin{bmatrix} \gamma_i^B & \gamma_i^B \end{bmatrix}$ to minimize the objective.

Given a set of candidate parameters, the response of each endogenous variable to a one unit change in the

[43] $\boldsymbol{\theta}_i \equiv \begin{bmatrix} \gamma_i^B & \gamma_i^G & \gamma_i^l & \varepsilon_i^D & \sigma_i^F \end{bmatrix}$.

[44] The four sectors I study account for about 60 percent of emissions reported in the EPA's GHG Inventory. The only omitted sectors that contribute more than 5 percent of emissions are transportation (14 percent) and agriculture (6.5 percent).

[45] Because I focus on regulations affecting Scope 1 emissions, I exclude green building requirements (which impose requirements on the construction sector, but affect downstream emissions). I also do not include regulations affecting agriculture because I find that these are typically in the form of subsidies or technical assistance programs, rather than explicit requirements.

[46] Appendix E.3 discusses the estimation procedure for σ_i^F. My sector-specific values for ε_i^D are based on Oberfield and Raval (2021), Deryugina et al. (2020) and Podolsky and Spiegel (2017).

[47] In this baseline, I treat γ_i^l and σ_i^F as fixed using pre-period estimates (2003-2005) and I treat the return-implied regulation "tax shocks" as observed inputs. A fully formal two-step approach would propagate the sampling error from these preliminary objects into the CMD weight matrix and standard errors, following Murphy and Topel (1985). I plan to add this correction in a future draft and expect that it will affect standard errors, rather than point estimates.

tax follows directly from equation (37), with two complications. First, equilibrium responses to regulation depend on the pre-regulation technology share, $\mathbb{P}_i(G|s)$. I use the empirical distribution of CO2 intensity (emissions scaled by output) to proxy for green technology adoption. Specifically, for each industry, I rank all state/year observations by CO2 intensity (lower CO2 intensity implies higher green technology share) and use the percentiles of this distribution wherever the estimation depends on $\mathbb{P}_i(G|s)$.[48] For each industry i and policy p, I use the CO2 intensity distribution to compute $\hat{\mathbb{P}}_i(G|s(p), t(p)-1)$, which informs the equilibrium response of the endogenous variables to the policy as a function of the model parameters. Given a candidate set of parameters, I also use $\hat{\mathbb{P}}_i(G|s(p), t(p)-1)$ to construct $\overline{\gamma}_i^{\mathcal{E}}$, which I use to map between returns and changes to the implicit tax rate as described by equation (39). This allows me to convert the theoretical impacts of a tax shock into units of the return-based policy intensity, which I use to estimate the empirical $\hat{\boldsymbol{\beta}}_i$.

Having established the exact mapping between the model parameters and the empirical elasticities, I estimate the parameters for each sector by matching the model-implied responses of emissions, employment, establishments, wages, and switching costs to their empirical counterparts. Because the other parameters are either fixed from pre-period data or calibrated from the literature, identification comes from the relative magnitudes of these five moments across outcomes and industries. Intuitively, the slope of the observed relationship between return-implied policy intensity and each outcome traces out the equilibrium adjustment margins that the model attributes to differences in emissions technology.

Table 3 shows the estimates of γ_i^B and γ_i^G. The technology gap $\gamma_i^B - \gamma_i^G$ is largest for utilities, which reflects the availability of truly green technology in that industry. In contrast, although oil and gas firms can improve their emissions intensity on the margin, even the "greenest" oil and gas firms are still very emissions-dependent. The smaller gap between γ_i^G and γ_i^B reflects this. Because I estimate two parameters using five moments, the system is overidentified and the Hansen–Sargan test statistic (Hansen (1982), Sargan (1958)) is asymptotically $\chi^2(3)$ under the null, providing a valid test of the overidentifying restrictions. The p-values for the over-identification test (all above 0.6) suggest that the model is able to fit the data well.

7 Results

7.1 Costs and Benefits of Emissions Regulation by Industry

Benefits I use the estimated parameters and equation (30) to decompose the emissions benefit into intensive margin effects, relocation and technology switching. Figure 9 displays this decomposition for the

[48] I scale the percentiles so that $\mathbb{P}_i(G|s) \in [0.25, 0.75]$, which avoids running into corner solutions during estimation. The results are robust to alternative bands (e.g. [0.05,0.95], [0.2,0.8]. Intuitively, the bands imply that in the greenest (brownest) state/year observation in my dataset, 75 percent (25 percent) of facilities operate the green technology.

average regulation in each industry. Across all sectors, the majority of abatement is due to intensive margin effects. However, both endogenous technology switching and relocation impact the magnitude of the emissions response. Technology switching expands abatement by between 7% (manufacturing) and 56% (utilities). Leakage to other states, which is a key concern in policy circles, offsets between 3% (utilities) and 18% (manufacturing) of within-state reductions. In addition, the ability to adjust technology substantially reduces leakage. In particular, when technology is fixed, the quantity of emissions leaking to other states can be much larger than the emissions that relocate from the regulated state. This is because firms that relocate are likely to choose less regulated states (lower τ), which leads the quantity of emissions "leaked" to other states to exceed the quantity that left the regulated state. An important note is that it would not be possible (or at least be very difficult) to quantify the magnitude of this leakage for a broad set of regulations in reduced form.[49] An advantage of my setup, is that my return-based policy intensity measure, combined with the estimated structural model allows me to quantify these spillovers, which are a key focus in many debates about the efficacy of local climate policy.

Costs Using the estimated parameters and equation (31), I decompose the costs to firms into the direct impact (no adjustment) and the offset to this impact arising from endogenous technology switching, relocation and general equilibrium wage feedback. Figure 10 presents this decomposition for the average regulation in each industry. Technology switching offsets between 5% (manufacturing) and 94% (utilities) of the direct profit impact by allowing facilities to substitute toward cleaner production methods. The ability to relocate has a negligible effect on profits in utilities and waste management, but offsets 27% of the direct impact in oil and gas and 20% in manufacturing. General-equilibrium wage adjustment also affects the distribution of costs. In sectors where labor demand falls more steeply, wages in regulated states decline, which partially offsets firms' losses but imposes costs on workers. The net cost to firms is the sum of these four components and is reported in dollars below each industry. These magnitudes highlight that neither reduced-form estimates nor models that omit relocation or switching would capture the full economic incidence of regulation. In particular, technology switching and relocation both dampen the direct cost of the emissions tax, while wage adjustment redistributes part of the burden from firms to workers. My structural framework allows these channels to be quantified consistently across a diverse set of regulations, which would not be feasible in reduced form.

[49] This is because the quantity of emissions flowing to any particular state is likely small, so estimating the impacts requires a clean natural experiment. For example, Bartram et al. (2022) document within-firm/across-state leakage from California's cap and trade program, whereas Korganbekova (2025) documents positive within-firm spillovers from GHG targets.

Net Impact I combine the estimated cost components with the dollar value of emissions reductions to quantify the net impact of the average regulation in each industry. Figure 11 summarizes these impacts. The green bar reports the value of abatement, which I compute using an SCC of $150. The gray bar reports the total cost to firms, which incorporates the direct effect of the emissions tax as well as technology switching, relocation, and general-equilibrium wage adjustment. The blue bar reports the cost borne by workers, which reflects wage changes in regulated states and the reallocation of workers across locations. The teal bar plots the net impact, which is the difference between the benefits and the combined costs to firms and workers. This net value varies across industries for two reasons. First, the structure of production differs: emissions intensities, switching elasticities, and the potential for relocation all shape the cost side. Second, the value of emissions reductions depends on the underlying emissions baseline and the responsiveness of firms to regulation. Utilities and waste management yield positive net benefits, whereas manufacturing and oil and gas require a higher SCC to break even. The SCC values printed below each panel indicate the dollar value of carbon that would make the net impact equal to zero for the representative regulation in that sector. Consistent with the relocation channel, industries in which firms can more easily reallocate facilities across states place a larger share of the burden on workers rather than firms: workers bear 56 percent of costs in oil and gas and 62 percent in manufacturing, compared with only 3 percent in utilities and 10 percent in waste management. Ongoing work extends the analysis to incorporate household welfare more fully by quantifying the welfare impacts of changes in goods prices and worker relocation.

8 Conclusion

This paper uses a new dataset and a structural framework to evaluate the economic and environmental impacts of state-level greenhouse gas regulation in the United States. Using a hand-collected dataset of 140 regulations that govern scope 1 emissions, I document reduced-form effects of regulation at the industry–state, facility, and firm levels. The results show that regulation reduces both emissions and emissions intensity, but that these environmental gains come alongside economic costs in the form of lower employment, wages and output. At the firm level, regulated firms respond by investing in capital and R&D, consistent with technology upgrading rather than only reducing scale or exiting regulated states.

To interpret these reduced form results, I develop a spatial general equilibrium model in which firms choose location and emissions technology and workers choose location and industry. The model links equity returns to regulatory stringency, enabling me to infer the magnitude of policy shocks and to quantify the welfare incidence of regulation. Using a range of estimates for the social cost of carbon, I find that, while the median regulation is net beneficial (with benefits about twice as large as costs), there is substantial variation across industries and policy types. In utilities and waste management, the average regulation is net beneficial, while the costs exceed the benefits in fossil fuel extraction and manufacturing. I also show that endogenous technology adjustment and relocation are key mechanisms behind the wide variation in costs and benefits across industries.

Several extensions are currently in progress. I am adding changes in goods prices and worker relocation to the cost and benefit calculations in order to more fully reflect impacts to household welfare. I also use the model to quantify the costs of decentralized climate policy relative to the efficient benchmark of a global carbon tax and determine which frictions are responsible for the inefficiency of current policy. The model allows me to evaluate the existing set of policies as well as counterfactual sets of disaggregated policies against the efficient benchmark.

One area for future work is to better understand the innovation induced by emissions regulation. An important finding of my paper is that the regulations in my sample increase R&D investment of affected firms, an effect which has been widely debated in environmental economics (Ambec et al. (2013)) and is largely inconsistent with studies of other types of regulation (e.g. Aghion et al. (2023)). In my setting, regulation effectively subsidizes green investment for affected firms by raising the cost of remaining brown. A natural next step is to better understand the dynamic effects of this "regulation-induced innovation." An additional line of inquiry I plan to pursue focuses on the relation between environmental regulation and sustainable investing. Two particular questions of interest are how exposure to past regulations shapes a firm's exposure to future regulatory risk and how climate policy and green investor preferences (whether non-pecuniary or based on cash flow expectations or risk factors) jointly influence firm decisions.

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Figures

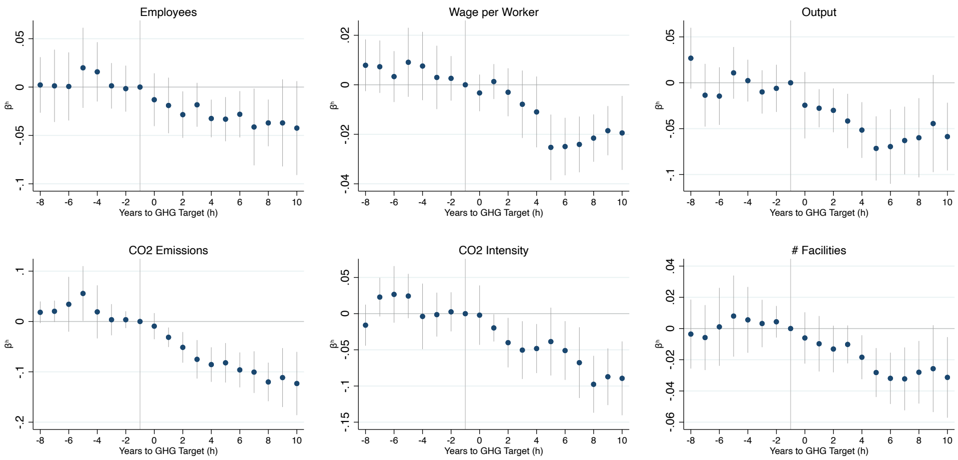

Figure 1: This figure plots the dynamic difference-in-difference estimates of the effect of adopting state-level GHG targets on industry/state outcomes. Each panel plots estimates of $\hat{\beta}_h$ from event-study regressions of the specified outcome on leads and lags of GHG target enactment. Standard errors are clustered by state and the lines show 95% confidence intervals.

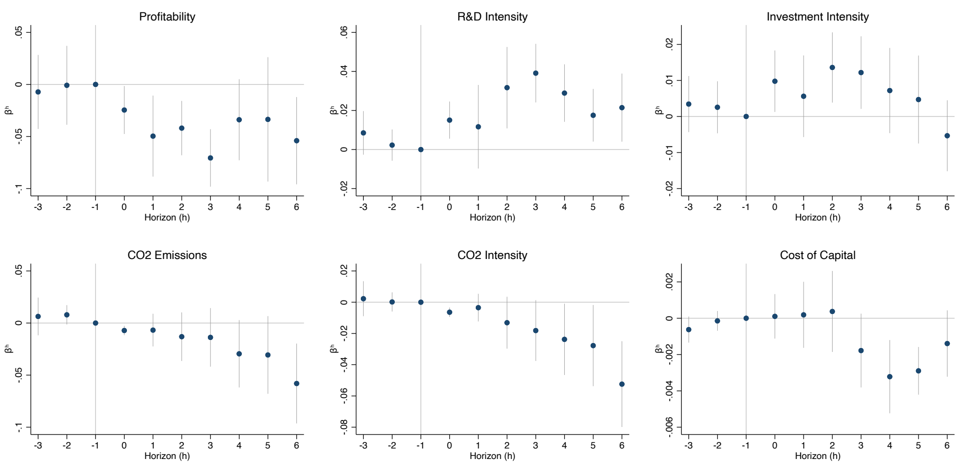

Figure 2: This figure shows estimates of β^h from the regression in equation 3, which capture the effect of new emissions regulations on firms with above-median emissions intensity. Standard errors are clustered by industry and year, and the lines show 95% confidence intervals.

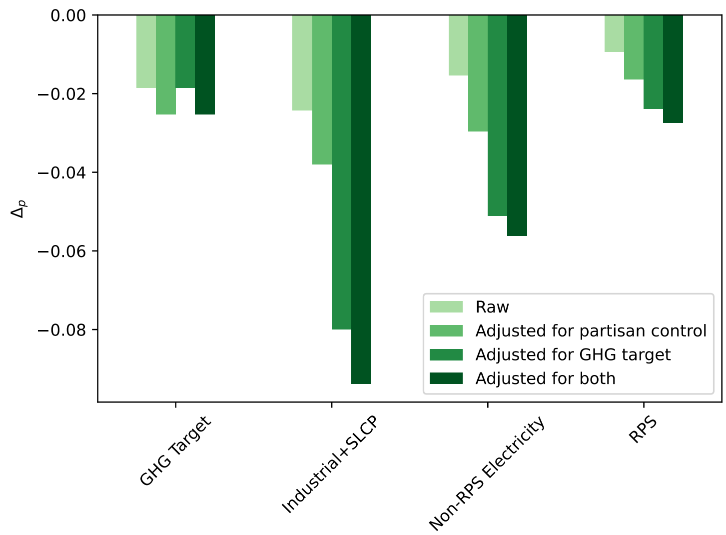

Figure 3: This figure plots the average estimates of policy intensity, Δ_p, within each category. The lightest bar represents the raw estimate, the middle bars depict the estimates adjusted for partisan control and GHG targets one at a time, and the darkest bar plots the fully adjusted estimates.

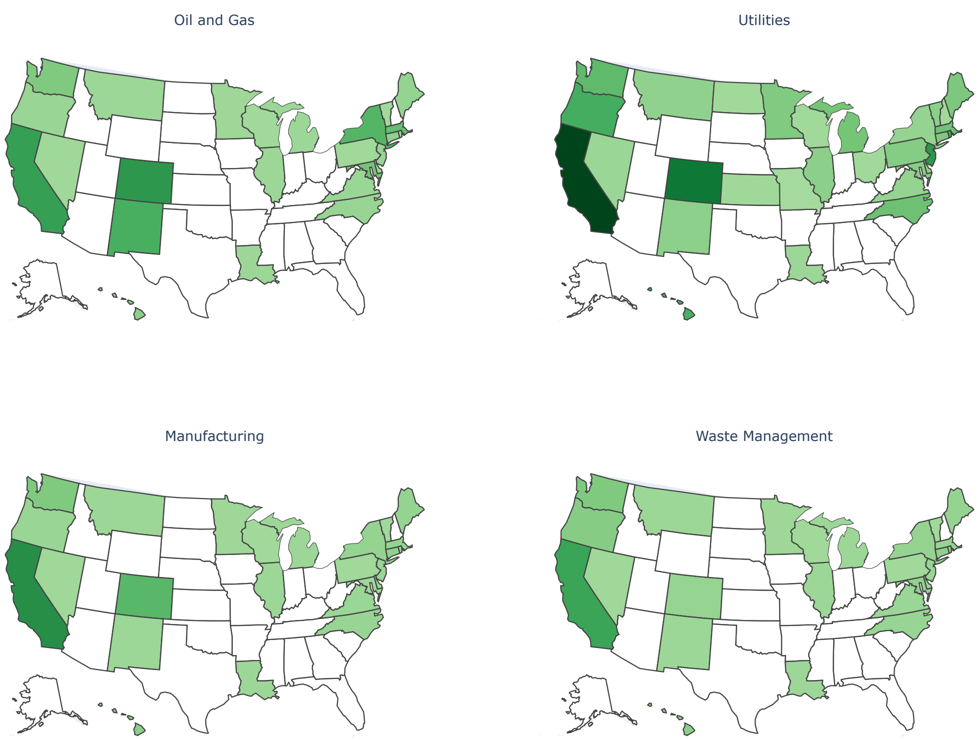

Figure 4: Each panel maps, for a given industry, the cumulative sum of policy-level intensities from all state regulations applying to that industry; GHG targets contribute to all four industries. Values are aggregated at the state–industry level, using a common color scale across panels and anchored at zero (white) so darker shades indicate larger cumulative intensity.

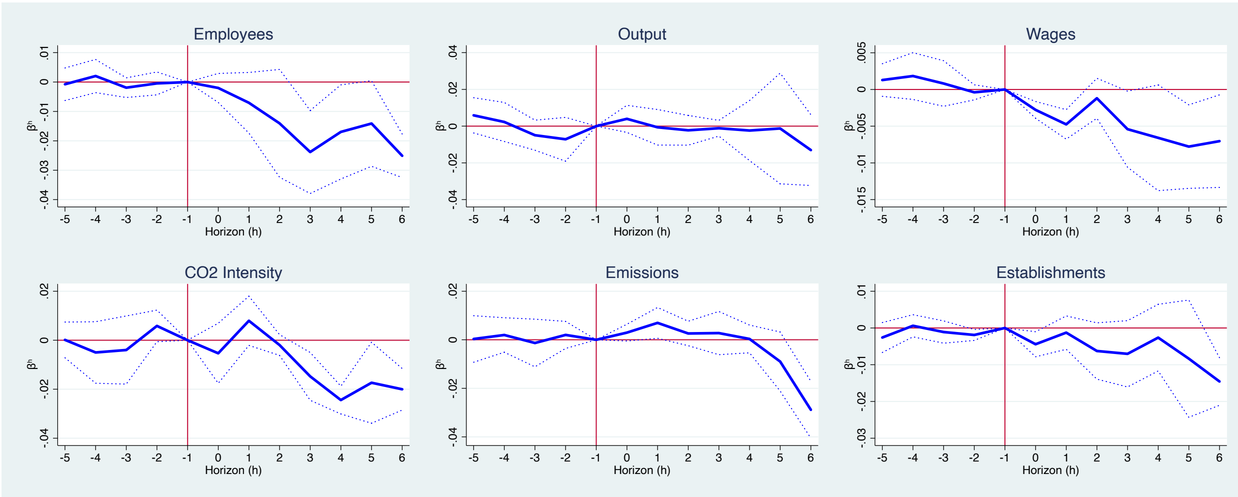

Figure 5: This figure plots the impact of a one unit increase in regulatory stringency on industry/state-level outcomes, as described in equation (11). The dotted lines represent 95% confidence intervals. Standard errors are clustered by state and year.

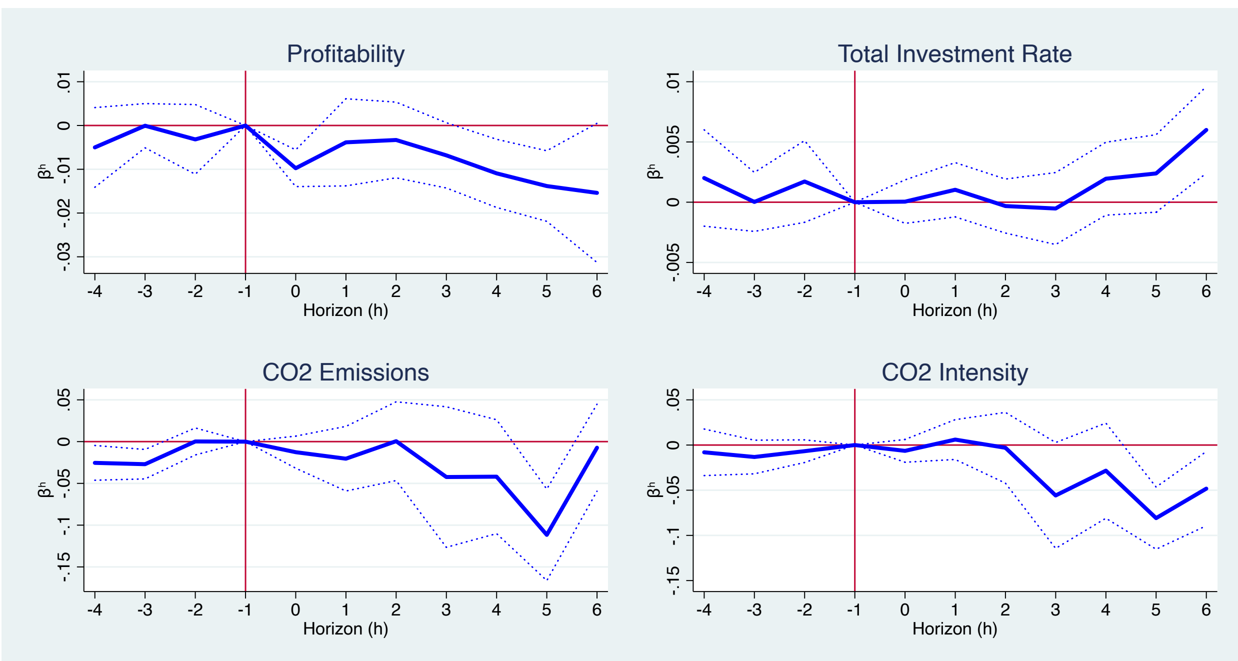

Figure 6: This figure plots the impact of a one unit increase in regulatory stringency on firm-level outcomes. The dotted lines represent 95% confidence intervals. Standard errors are clustered by industry and year.

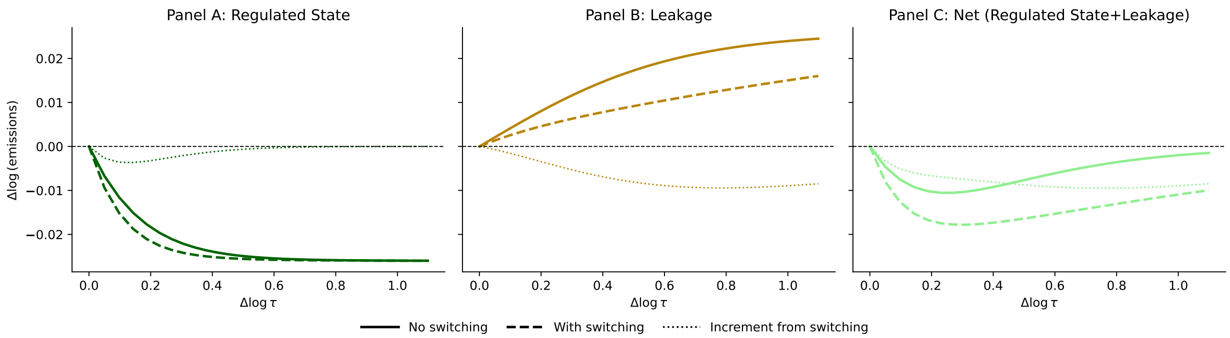

Figure 7: This figure plots the model-predicted changes in emissions as a function of the change in the emissions tax rate. Panel A plots the effect within the regulated state. Panel B plots the change in emissions in other states due to regulation-induced relocation. Panel C plots the net effect on global emissions. In each panel, the solid line represents the effect if the technology share was fixed at the baseline (firms cannot switch technologies), the dashed line depicts the effect when technology is optimally chosen and the dotted line plots the difference between the two scenarios. In all panels, the states start identical with $\tau_{is} = 1$. Parameters are: $\gamma_i^l = 0.1$, $\gamma_i^G = 0.05$, $\gamma_i^B = 0.85$, $\varepsilon_i^D = -4$, $\kappa_i = 3$, $\alpha_i = 1.1$, $\sigma_i^F = 1$.

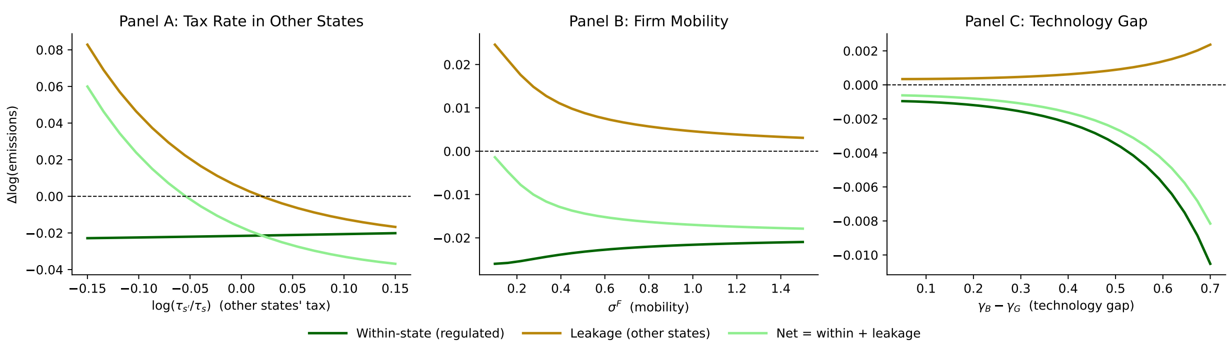

Figure 8: This figure plots the model-predicted change in emissions as a function of key structural parameters that shape firms' responses to regulation. In all panels, the regulated state experiences a fixed emissions tax increase of $\Delta \log \tau = 0.2$, and each line shows the model-implied change in emissions relative to the pre-policy equilibrium. Panel A varies the initial tax rate in the unregulated state, Panel B varies firm mobility (the dispersion of location preferences, σ_i^F), and Panel C varies the technology gap ($\gamma_i^B - \gamma_i^G$). Each panel plots changes in emissions within the regulated state (dark green), emissions leakage to the unregulated state (brown), and the net effect on total emissions across both states (light green). Parameter values are: $\gamma_i^l = 0.1$, $\gamma_i^B = 0.85$ (panels A and B), $\gamma_i^G = 0.05$ (panels A and B) $\epsilon_i^D = -4$, $\kappa_i = 3$, $\alpha_i = 1.1$, $\sigma_i^F = 1$ (panels A and C).

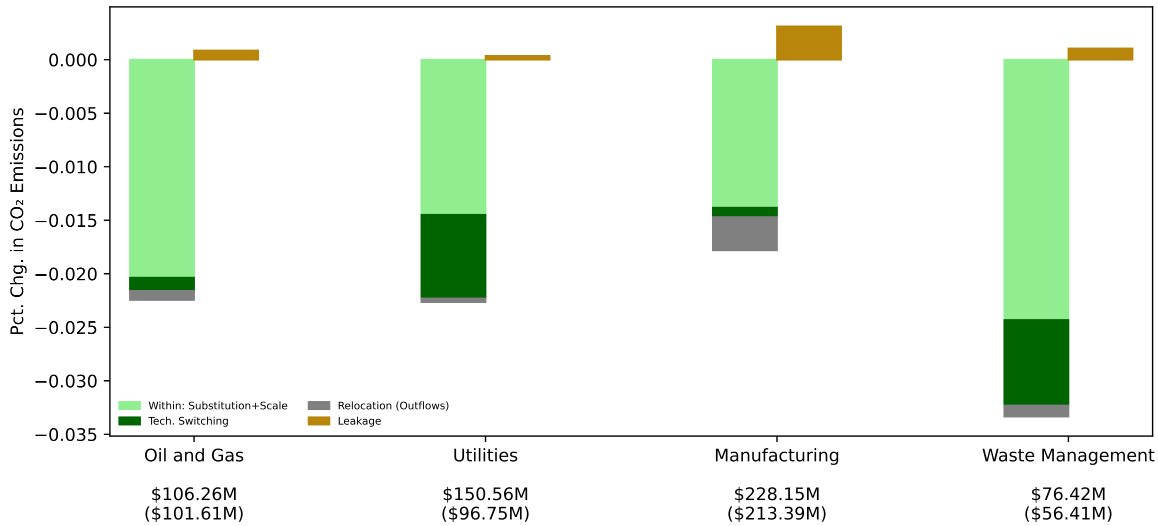

Figure 9: This figure presents a decomposition of regulation-induced emissions changes by sector. Light green represents intensive-margin reductions, dark green captures additional reductions from endogenous technology switching, and gray denotes further in-state reductions arising from relocation. Brown reports emissions that reappear elsewhere (leakage). The dollar amounts below each bar provide the social value of the emissions reductions at a $150 social cost of carbon, with parenthetical values giving the corresponding amounts absent technology switching.

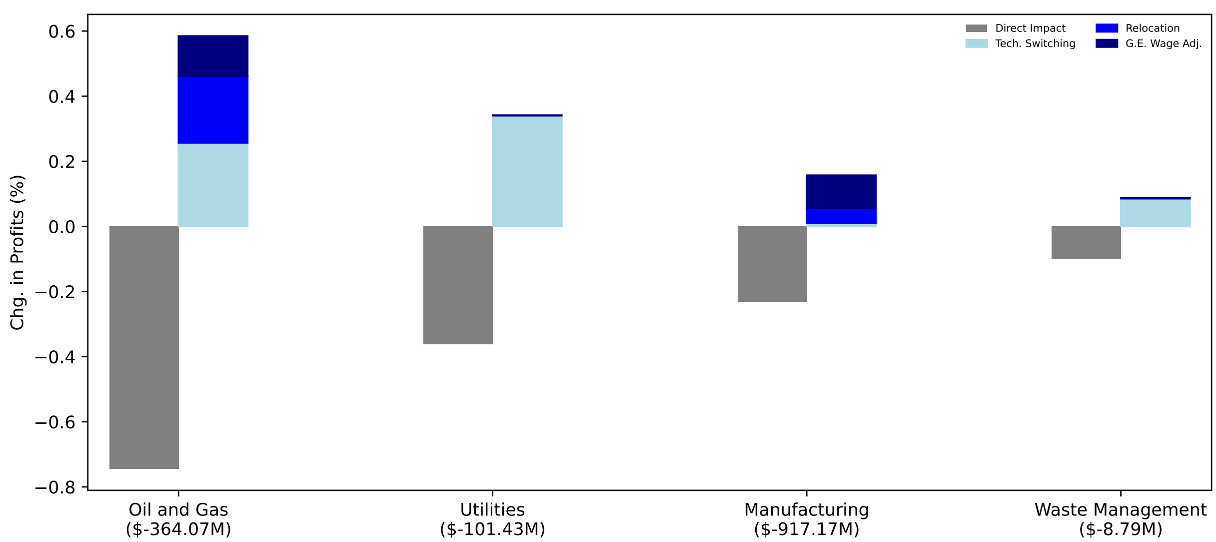

Figure 10: This figure shows the components of the average profit impact of regulation in each sector. The gray bar shows the direct effect of the emissions tax holding technology, location and wages fixed. The light–blue bar shows the offset from endogenous technology switching. The dark–blue bar shows the contribution of facility relocation. The navy bar shows the contribution of general–equilibrium wage adjustment. The total profit impact (reported in dollars below each industry label) is the sum of these four components multiplied by the pre-regulation gross operating surplus (in 2023 dollars) of the affected industry/state.

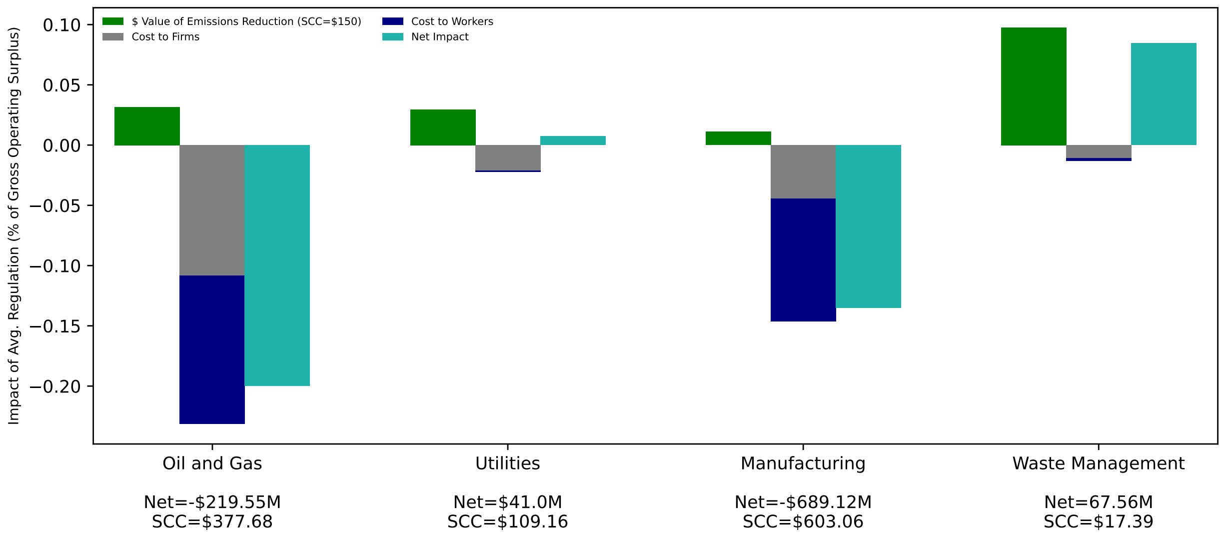

Figure 11: This figure shows the net impacts of the average regulation in each sector. The green bar reports the dollar value of emissions reductions (using an SCC of $150). The gray bar reports the cost to firms, which includes the direct impact, technology switching, relocation, and general–equilibrium wage adjustment. The dark–blue bar reports the cost to workers. The teal bar shows the net impact, which is the sum of the cost and benefit components and matches the net dollar values printed below each industry. The SCC values reported beneath each panel indicate the social cost of carbon that would make the net impact equal to zero for the average regulation in that industry.

Tables

Category	GHG Target	Industrial+SLCP	Non-RPS Electricity	RPS
Exec. Order	-0.002	0.006	-0.017	0.005
	(0.022)	(0.091)	(0.032)	(0.816)
Legislation	-0.002	-0.019	-0.023	-0.008
	(0.022)	(0.039)	(0.029)	(0.023)
Ballot Initiative				-0.004
				(0.032)
Pct. Renewables				-0.076
				(0.038)
Decades to RPS				0.026
				(0.013)
Target Pct.	-0.003			
	(0.001)			
Decades to Target	0.004			
	(0.002)			
Has Interim Target	-0.002			
	(0.012)			
α_c	-0.021	0.011	-0.014	-0.021
	(0.025)	(0.048)	(0.049)	(0.026)

Table 1: This table reports the posterior means of the estimated λ coefficients from the hierarchical Bayesian model, representing the average effect of observable policy characteristics on the inferred policy intensity within each category of regulation. Columns correspond to policy categories. Rows list the coefficients on specific policy features. Exec. Order, Legislation and Ballot Initiative are indicators representing the legal form of the policy (and should be interpreted as relative to administrative rules, which is the baseline category). Pct. Renewables, Decades to RPS, Target Pct. and Decades to Target are quantitative features available only for the RPS and GHG Target categories. Pct. Renewables and Target Pct. are in decimal units. Has Interim Target is an indicator equal to 1 if the GHG Target has intermediate goals. α_c is the estimated category baseline effect.

	$\Delta\log(L)$	$\Delta\log(w)$	$\Delta\log(\mathcal{E})$	$\Delta\log(E)$	$\Delta\log(SC)$
Oil and Gas × RegShock	-0.074**	-0.047***	-0.071***	-0.012	0.067
	(0.026)	(0.015)	(0.012)	(0.011)	(0.199)
Utilities × RegShock	-0.0634	-0.007	-0.133***	-0.009	0.341***
	(0.051)	(0.019)	(0.041)	(0.022)	(0.094)
Manufacturing × RegShock	-0.017***	-0.004	-0.005	-0.010**	0.059
	(0.005)	(0.005)	(0.011)	(0.004)	(0.043)
Waste × RegShock	0.026	-0.017	-0.142**	-0.102	0.145**
	(0.067)	(0.011)	(0.050)	(0.467)	(0.051)
State×Year FE	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes
Industry×State FE	Yes	Yes	Yes	Yes	Yes
Obs.	15200	14351	15000	15200	12751

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Estimates of $\boldsymbol{\beta}_i^{Reg}$ from equation (11) with industry-specific interaction terms. All variables are the changes in the log-outcome from the year prior to the regulation to 6 years after. L is number of employees, w is real wage per worker, $\mathcal{E}$ is tons of CO2 equivalent emissions, E is number of establishments and SC is the sum of firm-level capital investment and R&D expense weighted by firms' state-level employment shares. Standard errors clustered by industry and state are in parentheses.

	Estimated from Shocks		Estimated from Pre-Period		Calibrated		
Industry	γ_i^G	γ_i^B	γ_i^l	σ_i^F	ε_i^D	J	P-Val
Oil and Gas	0.047	0.077	0.251	1.217	-6	0.731	0.866
Utilities	0.001	0.679	0.321	0.994	-1.5	1.322	0.724
Manufacturing	0.411	0.441	0.559	0.574	-6	1.826	0.609
Waste	0.001	0.089	0.819	0.244	-1.5	1.020	0.796

Table 3: Parameter estimates by industry. γ_i^G and γ_i^B are estimated according to equation 43. γ_i^l and σ_i^F are estimated using pre-period data as described in Appendix E.3. $J \equiv (\hat{\boldsymbol{\beta}}_i - \boldsymbol{\beta}_i^{Reg}(\hat{\boldsymbol{\theta}}_i))\hat{\boldsymbol{V}}_i(\hat{\boldsymbol{\beta}}_i - \boldsymbol{\beta}_i^{Reg}(\hat{\boldsymbol{\theta}}_i))$, where $\hat{\boldsymbol{V}}_i^{-1}$ is the industry i block of the inverse of the bootstrapped empirical covariance matrix of the estimated moments. P-values are based on the χ^2 distribution with three degrees of freedom.

Appendix

A Supplementary Tables and Figures

A.1 Figures

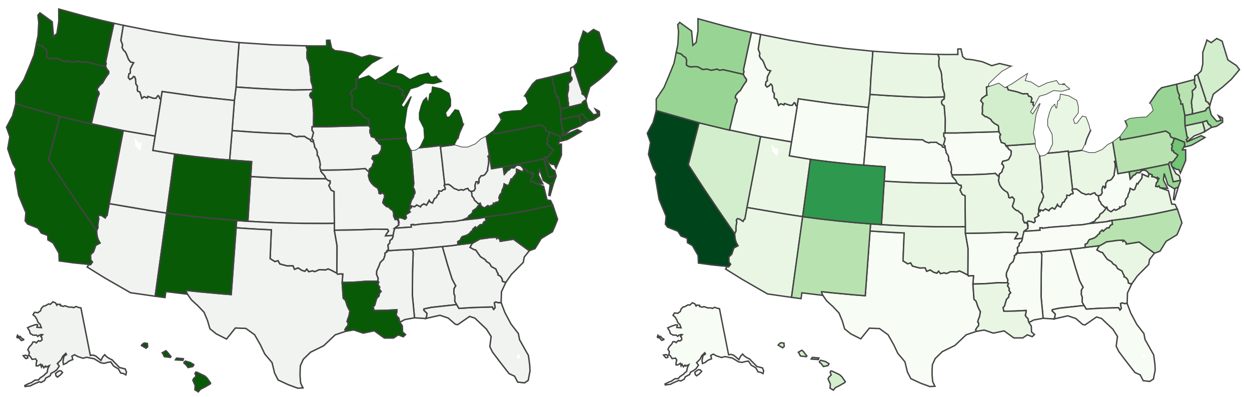

Figure A1: Left panel: states with economy-wide GHG targets. Right panel: number of prescriptive regulations by state.

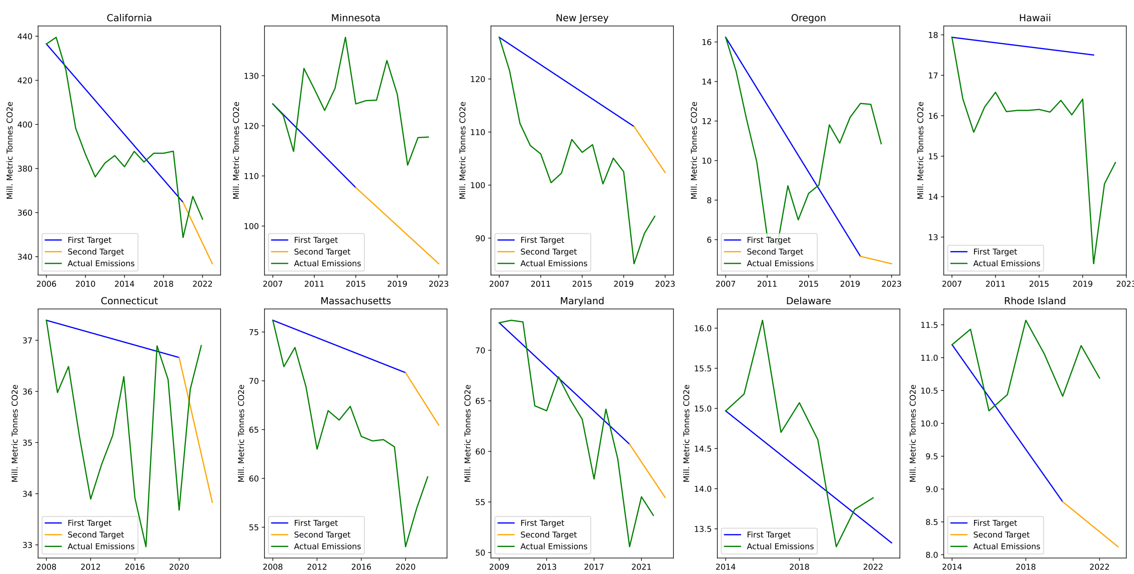

Figure A2: This figure shows targeted and actual emissions for states that passed targets before 2014. The blue and yellow lines show what emissions would be if the states were (linearly) adhering to their target. The green line plots actual statewide emissions since enactment of the target.

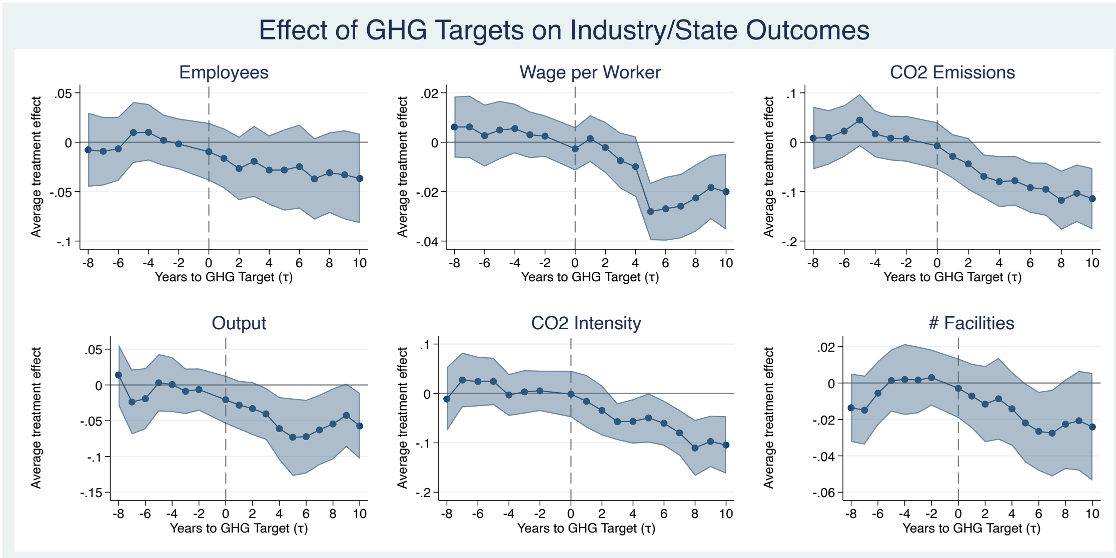

Figure A3: Sun and Abraham (2021) regressions of industry/state level outcomes on GHG target introduction.

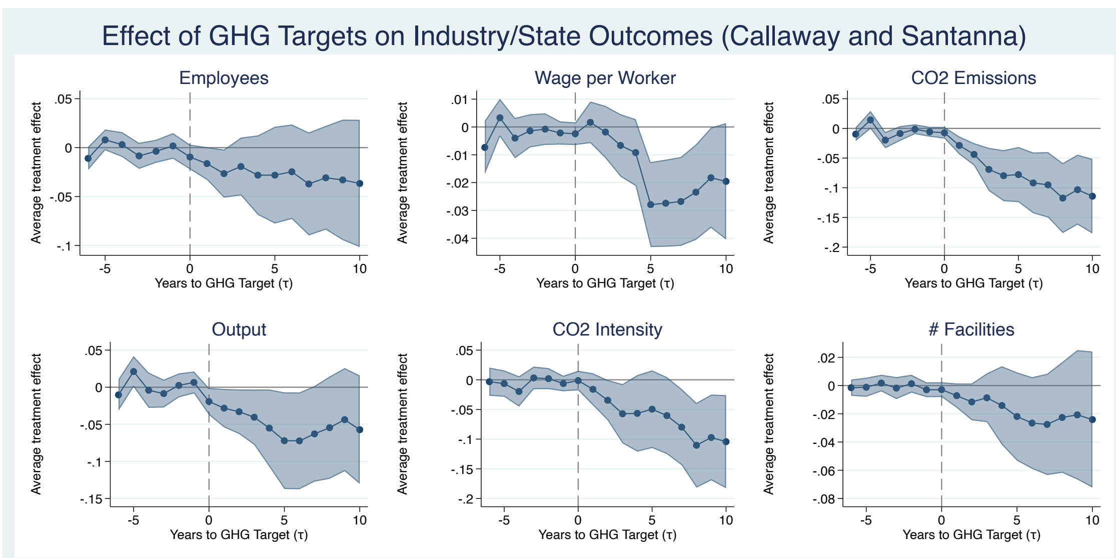

Figure A4: Callaway and Sant'Anna (2021) regressions of industry/state level outcomes on GHG target introduction.

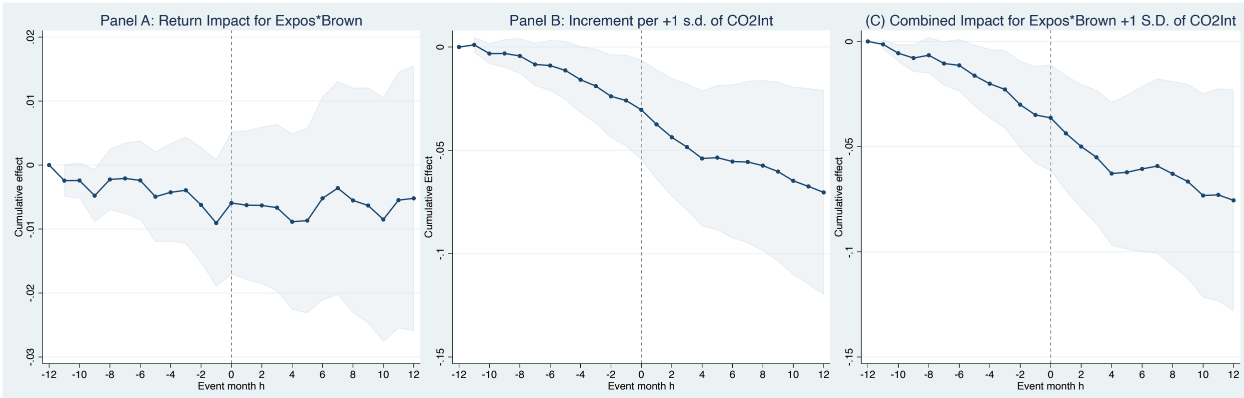

Figure A5: This figure plots cumulative effects by event month from regressions in equation (A3). Panel A shows the cumulative effect for firms that are exposed to the enacting state and operate in brown industries (Expos × Brown). Panel B shows the additional increment for a one standard deviation increase in firm carbon intensity (+1 s.d. in CO2Int). Panel C combines Panels A and B to show the cumulative effect for an exposed brown-industry firm with CO2Int one standard deviation above its two-digit industry mean. Shaded regions are 95% confidence intervals. Returns are adjusted for the Fama and French five factors, momentum, and earnings surprises. Exposure Expos_{np} is measured continuously as the employment share of firm n in the enacting state in the year prior to enactment, $\text{Expos}_{np} \equiv L_{ns}/L_n$. Stacks include only industries covered by each policy. All specifications include firm×policy and month×policy fixed effects. Observations overlapping multiple policies are excluded. The estimation window is ±12 months. Standard errors are two-way clustered by firm and policy.

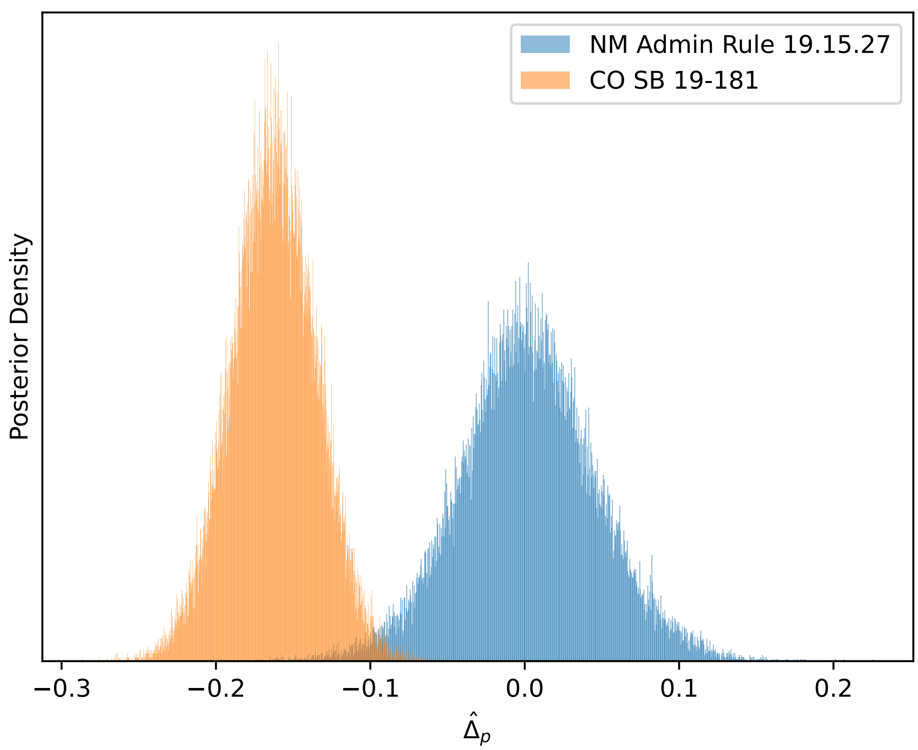

Figure A6: This figure plots the posterior density for the regulatory intensity, Δ_p for two oil and gas sector regulations.

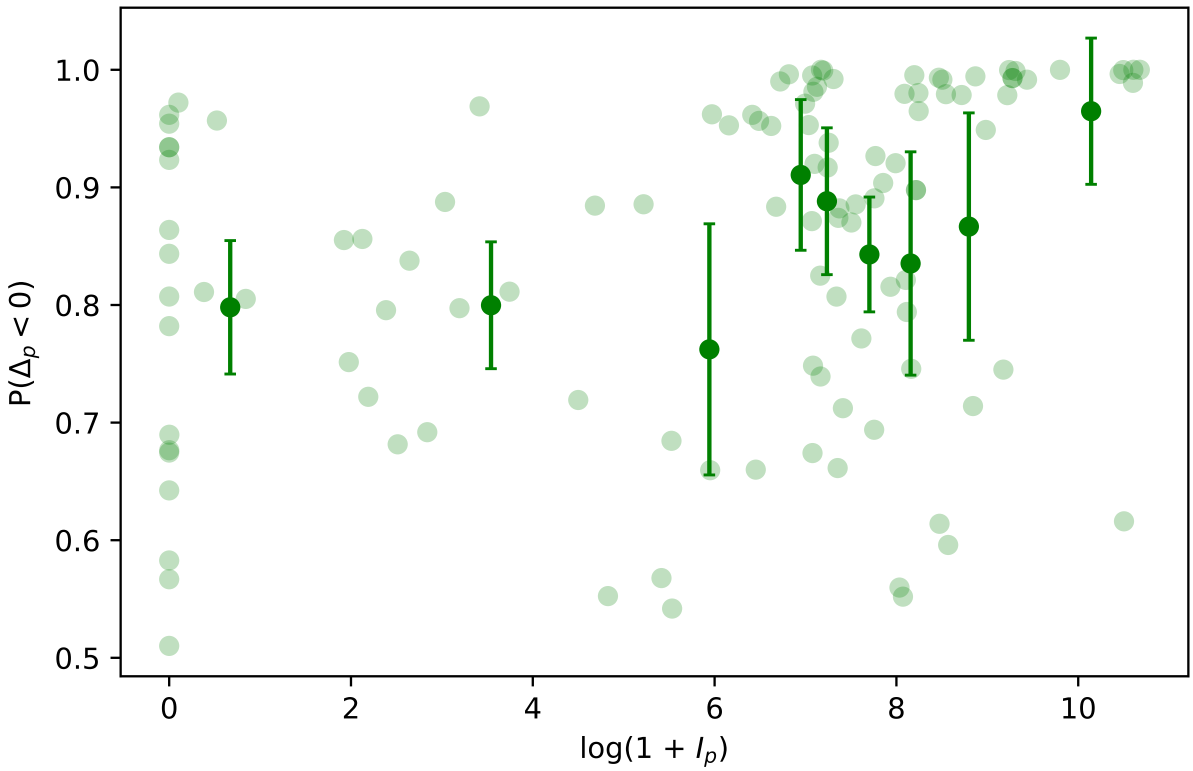

Figure A7: This figure plots the probability that a regulation's estimated effect $\hat{\Delta}_p$ is negative against the Fisher information, I_p. Each pale point represents one policy, and the dark points with error bars show binned averages with corresponding standard errors.

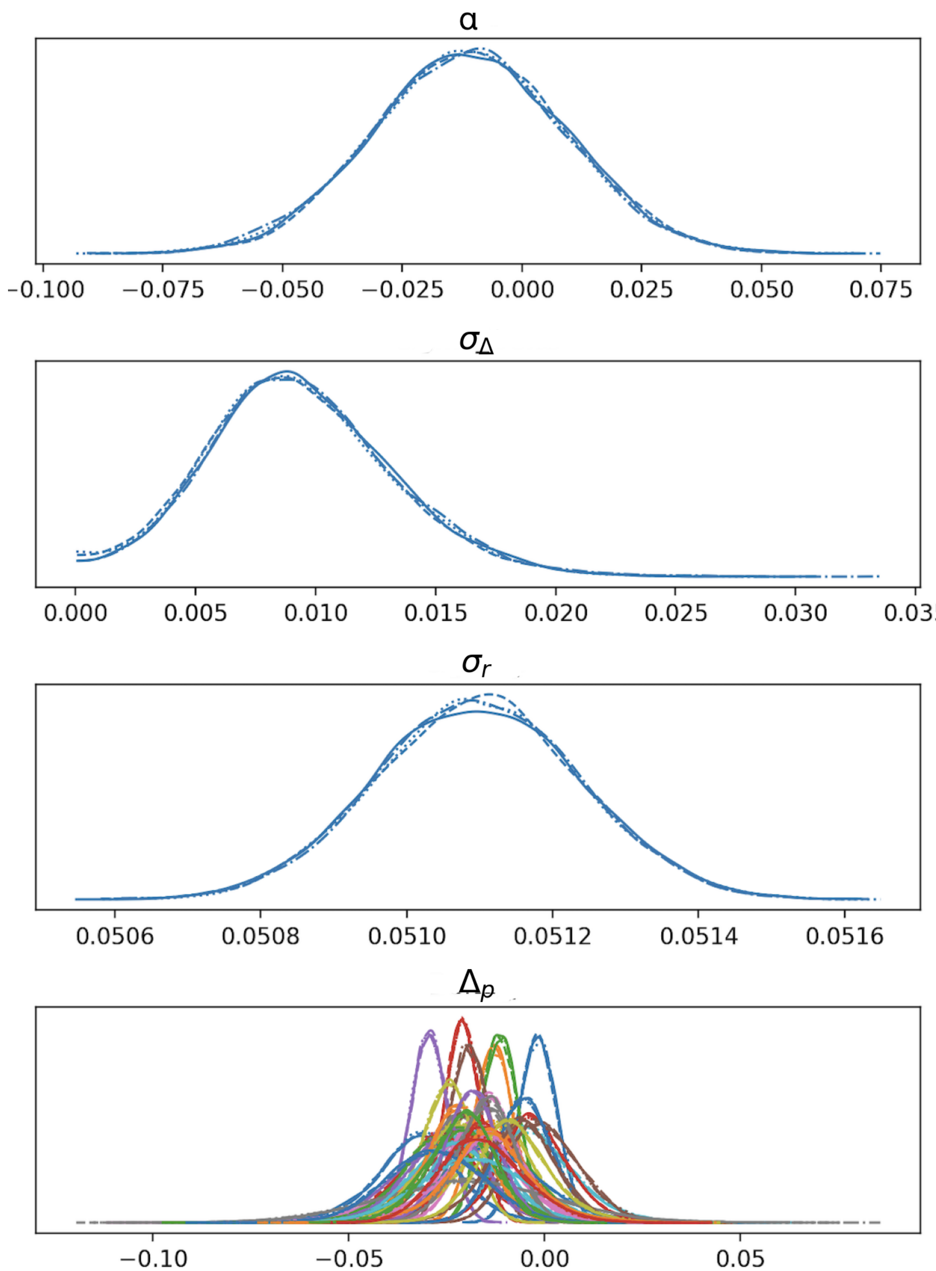

Figure A8: Posterior densities estimated on each of four chains. The estimated densities are for GHG Targets.

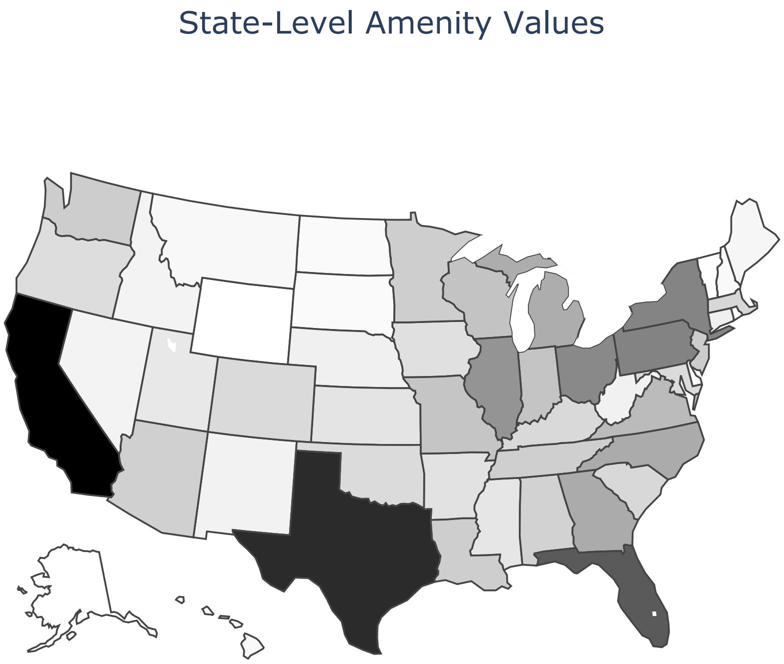

Figure A9: Industry-specific amenity values estimated from a fixed effects regression as described in equation (A79). Darker colors indicate higher values. Range is from 0.04 (WY) to 0.53 (CA).

A.2 Tables

Month/Year	State	Policy	Category	Legal Form
11/2006	AZ	Renewable Energy Standard and Tariff	RPS	Admin
6/2005	CA	S-3-05	GHG Target	Exec
9/2006	CA	California Global Warming Solutions Act (AB 32)	GHG Target	Legislation
6/2010	CA	Methane Emissions from Municipal Solid Waste Landfills	Industrial+SLCP	Admin
10/2010	CA	Refrigerant Management Program	Industrial+SLCP	Admin
2/2011	CA	Regulation for reducing sulfur hexafluoride emissions	Non-RPS Electricity	Admin
4/2011	CA	SB X1-2 (2011)	RPS	Legislation
12/2011	CA	California Cap and Trade Program	Cap and trade	Admin
4/2015	CA	EO B-30-15	GHG Target	Exec
10/2015	CA	Clean Energy and Pollution Reduction Act (SB 350)	RPS	Legislation
9/2016	CA	Short Lived Climate Pollutants Regulations (SB 1383)	Industrial+SLCP	Legislation
9/2016	CA	SB32	GHG Target	Legislation
3/2017	CA	Oil and Gas Methane Regulations	Industrial+SLCP	Admin
7/2017	CA	Community Air Protection Incentives (AB 617)	Industrial+SLCP	Legislation
9/2018	CA	EO B-55-18	GHG Target	Exec
9/2018	CA	Renewable Portfolio Standard (SB100)	RPS	Legislation
9/2021	CA	Net-Zero Emissions Strategy for the Cement Sector (SB 596)	Industrial+SLCP	Legislation
1/2022	CA	Amendments to the Regulation for Reducing Sulfur Hexafluoride Emissions from Gas Insulated Switchgear	Non-RPS Electricity	Admin
9/2022	CA	Embodied Carbon Law (AB 2446)	Industrial+SLCP	Legislation

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Month/Year	State	Policy	Category	Legal Form
9/2022	CA	California Climate Crisis Act (AB 1279)	GHG Target	Legislation
3/2007	CO	HB 07-1281	RPS	Legislation
3/2010	CO	HB 10-1001	RPS	Legislation
4/2019	CO	SB 19-181 (Oil and Gas)	Industrial+SLCP	Legislation
5/2019	CO	HB 19-1261	GHG Target	Legislation
5/2019	CO	SB 19-236	RPS	Legislation
6/2021	CO	SB 21-264 Clean Heat Plan	GHG Target	Legislation
7/2021	CO	HB 21-1266	GHG Target	Legislation
10/2021	CO	Greenhouse Gas Emissions and Energy Management for the Manufacturing Sector (Phase 1)	Industrial+SLCP	Admin
3/2023	CO	Nitrogen Oxide Target Oil and Gas (EO)	GHG Target	Exec
5/2023	CO	SB 23-016	GHG Target	Legislation
6/2023	CO	SB 23-198	GHG Target	Legislation
6/2023	CO	Greenhouse Gas Emissions and Energy Management for the Manufacturing Sector (Phase 2)	Industrial+SLCP	Admin
12/2005	CT	RGGI	Cap and trade	Legislation
10/2008	CT	GHG Target (HB 5600)	GHG Target	Legislation
5/2018	CT	GHG Target (SB 7)	GHG Target	Legislation
5/2018	CT	Renewable Portfolio Standard (SB 9)	RPS	Legislation
5/2022	CT	SB 10	GHG Target	Legislation
12/2005	DE	RGGI	Cap and trade	Legislation
2/2021	DE	Renewable Portfolio Standard (SB 33)	RPS	Legislation
8/2023	DE	GHG Target (HB 99)	GHG Target	Legislation
7/2007	HI	GHG Target (Act 234)	GHG Target	Legislation
6/2015	HI	Renewable Portfolio Standard HB 623 (Act 97) (2015)	RPS	Legislation

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Month/Year	State	Policy	Category	Legal Form
6/2018	HI	Act 15 HB 2182	GHG Target	Legislation
9/2020	HI	SB 2629	Non-RPS Electricity	Legislation
7/2022	HI	Act 238 HB 1800 CD2	GHG Target	Legislation
8/2007	IL	PA 95-0481 (2007)	RPS	Legislation
1/2019	IL	EO 2019-06	GHG Target	Exec
9/2021	IL	Clean Energy and Renewable Portfolio Standards (SB 2408)	RPS	Legislation
5/2009	KS	HB 2369	RPS	Legislation
8/2020	LA	Executive Order JBE 2020-18	GHG Target	Exec
1/2007	MA	RGGI	Cap and trade	Exec
8/2008	MA	Global Warming Solutions Act	GHG Target	Legislation
7/2017	MA	310 CMR 7.72	Non-RPS Electricity	Admin
3/2021	MA	S.9	GHG Target	Legislation
3/2021	MA	310 CMR 7.73	Industrial+SLCP	Admin
4/2007	MD	RGGI	Cap and trade	Legislation
5/2009	MD	Maryland Greenhouse Gas Emissions Reduction Act	GHG Target	Legislation
5/2019	MD	SB 516	RPS	Legislation
8/2020	MD	COMAR 26.11.41	Industrial+SLCP	Admin
4/2022	MD	SB 528 Climate Solutions Now	GHG Target	Legislation
6/2023	MD	Methane Emissions from Municipal Solid Waste Landfills	Industrial+SLCP	Admin
12/2005	ME	RGGI	Cap and trade	Legislation
6/2019	ME	LD 1679	GHG Target	Legislation
6/2019	ME	LD 1494	RPS	Legislation
3/2022	ME	LD 1429	GHG Target	Legislation
10/2008	MI	PA 295 (2008)	RPS	Legislation
7/2009	MI	ED 2009-4	GHG Target	Exec
12/2016	MI	SB 438	RPS	Legislation
9/2020	MI	Executive Directive 2020 - 10	GHG Target	Exec

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Month/Year	State	Policy	Category	Legal Form
11/2023	MI	SB 271	RPS	Legislation
5/2007	MN	SF 145	GHG Target	Legislation
5/2007	MN	Next Generation Energy Act (2007)	RPS	Legislation
2/2023	MN	HF 7	RPS	Legislation
5/2023	MN	HF 2310	GHG Target	Legislation
11/2008	MO	Mo. Rev. Stat. 393.1020	RPS	Ballot initiative
4/2005	MT	RPS	RPS	Legislation
4/2007	MT	HB 681	RPS	Legislation
7/2019	MT	US Climate Alliance	GHG Target	Exec
8/2007	NC	Gen Stat 62-133.8	RPS	Legislation
10/2018	NC	EO 80	GHG Target	Exec
10/2021	NC	HB 951	GHG Target	Legislation
1/2022	NC	EO 246	GHG Target	Exec
3/2007	ND	HB 1506	RPS	Legislation
12/2005	NH	RGGI	Cap and trade	Legislation
5/2007	NH	NH Rev. Stat. Ann. 362-F	RPS	Legislation
12/2005	NJ	RGGI	Cap and trade	Exec
7/2007	NJ	A3301	GHG Target	Legislation
5/2018	NJ	A3723	RPS	Legislation
6/2019	NJ	RGGI	Cap and trade	Admin
11/2021	NJ	EO 274	GHG Target	Exec
1/2023	NJ	N.J.A.C. 7:27F	Non-RPS Electricity	Admin
1/2019	NM	EO 2019-003	GHG Target	Exec
3/2019	NM	SB 489	RPS	Legislation
5/2021	NM	19.15.27 NMAC	Industrial+SLCP	Admin
8/2022	NM	20.2.50 NMAC	Industrial+SLCP	Admin
6/2013	NV	Sb 123	Non-RPS Electricity	Legislation
4/2019	NV	SB 358	RPS	Legislation
6/2019	NV	SB 254	GHG Target	Legislation
12/2005	NY	RGGI	Cap and trade	Exec

Continued on next page

Month/Year	State	Policy	Category	Legal Form
8/2016	NY	Clean Energy Standard	RPS	Admin
7/2019	NY	S6599	GHG Target	Legislation
7/2019	NY	S6599	RPS	Legislation
2/2022	NY	6 NYCRR Part 203, Oil and Natural Gas Sector	Industrial+SLCP	Admin
5/2008	OH	SB 221 (2008)	RPS	Legislation
5/2007	OR	SB 838	RPS	Legislation
8/2007	OR	HB 3543	GHG Target	Legislation
3/2016	OR	SB 1547	RPS	Legislation
3/2020	OR	EO 20-04	GHG Target	Exec
7/2021	OR	HB 2021	RPS	Legislation
10/2021	OR	DEQ 16-2021	Industrial+SLCP	Admin
1/2019	PA	EO 2019-01	GHG Target	Exec
4/2022	PA	RGGI	Cap and trade	Exec
7/2022	PA	Regulation 7-544	Industrial+SLCP	Admin
4/2023	PA	Regulation 7-580	Industrial+SLCP	Admin
4/2008	RI	RGGI	Cap and trade	Legislation
6/2014	RI	Resilient Rhode Island Act	GHG Target	Legislation
1/2020	RI	EO 20-01	GHG Target	Exec
4/2021	RI	Chapter 42-6.2-2021 Act on Climate	GHG Target	Admin
6/2022	RI	HB 7277A	RPS	Legislation
4/2020	VA	Virginia Energy Plan Chapter 1192	GHG Target	Admin
4/2020	VA	HB 1526	RPS	Legislation
12/2005	VT	RGGI	Cap and trade	Legislation
6/2015	VT	H 40	RPS	Legislation
9/2020	VT	Act 153	GHG Target	Legislation
11/2006	WA	RPS (I-937)	RPS	Ballot initiative
2/2018	WA	Ch. 173-407 Power Plant GHG Standards	Non-RPS Electricity	Admin
5/2019	WA	SB 5116	RPS	Legislation

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Month/Year	State	Policy	Category	Legal Form
3/2020	WA	Chapter 79, 2020	GHG Target	Legislation
5/2021	WA	Cap and Invest (SB 5126)	Cap and trade	Legislation
7/2005	WI	RPS	RPS	Legislation
8/2019	WI	Executive Order 38	GHG Target	Exec

Table A1: List of state-level greenhouse gas emissions regulations.

	$\log(L_{ist})$	$\log(w_{ist})$	$\log(Y_{ist})$	$\log(\mathcal{E}_{ist})$	$\log(\mathcal{E}_{ist}/Y_{ist})$
$\text{Target}_{st} \times \text{Brown}_i$	-0.011**	-0.019***	-0.026***	-0.053***	-0.048**
	(0.004)	(0.003)	(0.008)	(0.015)	(0.019)
State×Year FE	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes
Industry×State FE	Yes	Yes	Yes	Yes	Yes
Obs.	18050	20613	19398	18000	18000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	$\log(L_{ist})$	$\log(w_{ist})$	$\log(Y_{ist})$	$\log(\mathcal{E}_{ist})$	$\log(\mathcal{E}_{ist}/Y_{ist})$
$\#Reg_{ist}$	0.000	-0.003*	0.005	-0.011*	0.004
	(0.005)	(0.001)	(0.004)	(0.006)	(0.007)
State×Year FE	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes
Industry×State FE	Yes	Yes	Yes	Yes	Yes
Obs.	18050	20613	19398	18000	18000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	$\log(L_{ist})$	$\log(w_{ist})$	$\log(Y_{ist})$	$\log(\mathcal{E}_{ist})$	$\log(\mathcal{E}_{ist}/Y_{ist})$
$\#Reg_{ist}$	-0.300***	-0.020	-0.264***	-0.732***	-0.463**
	(0.098)	(0.032)	(0.085)	(0.220)	(0.192)
State×Year FE	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	18050	19916	19398	18000	18000
First-Stage F	6.436	7.59	7.105	5.206	5.206

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: This table presents results from regressions of industry/state-level outcomes on local emissions regulation. Panel A reports estimates from a triple-difference specification comparing brown industries in states with GHG targets to (i) non-brown industries in the same states, (ii) the same industries in states without targets, and (iii) pre-policy periods. Panel B reports results from an OLS regression where the dependent variable is the number of industry-specific regulations in state s, industry i, and year t. Panel C presents two-stage least squares estimates, instrumenting for $\#\text{REG}_{ist}$ using the interaction $\text{Target}_{st} \times \text{CO2Int}_i^{\text{Pre}}$, which captures variation in regulatory exposure driven by state-level GHG targets and industry emissions intensity. All standard errors are clustered by industry and state.

	(1)	(2)	(3)	(4)
$\text{TreatWindow}_{mp} \times \text{Expos}_{np}^{(\text{disc.})} \times \text{Brown}_n$	-0.012***	-0.002		
	(0.003)	(0.002)		
$\text{TreatWindow}_{mp} \times \text{Expos}_{np}^{(\text{disc.})} \times \text{Brown}_n \times \text{CO2Int}_{np}$		-0.028***		
		(0.008)		
$\text{TreatWindow}_{mp} \times \text{Expos}_{np}^{(\text{cont.})} \times \text{Brown}_n$			-0.015***	0.006
			(0.004)	(0.011)
$\text{TreatWindow}_{mp} \times \text{Expos}_{np}^{(\text{cont.})} \times \text{Brown}_n \times \text{CO2Int}_{np}$				-0.025***
				(0.009)
Firm×Policy FE	Yes	Yes	Yes	Yes
Month×Policy FE	Yes	Yes	Yes	Yes
Obs. (stacked)	4,477,397	3,241,885	4,477,397	3,241,885
Firm–months (unique)	457,667	316,741	457,667	316,741
Firms	4,076	3,788	4,076	3,788
Policies	112	112	112	112

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: This table presents results from stacked event time regressions of monthly abnormal returns on exposure to state-level emissions regulation, as described in equation (A3). The dependent variable is the return of stock n in month n adjusted for Fama and French (2015) factors, momentum and earnings surprises. $\mathbb{1}\{|m - m_p| \leq 4\}$ captures whether month m is in the treatment window for policy p. Exposure to policy p of firm n is measured in the year preceding enactment and is defined as either a discrete indicator $\text{Expos}_{np}^{(\text{disc.})} \equiv \mathbb{1}\left\{\frac{L_{ns(p)t}}{L_{nt}} > 0.1\right\}$ or as a continuous employment share $\text{Expos}_{np}^{(\text{cont.})} \equiv \frac{L_{ns(p)t}}{L_{nt}}$. Brown_n is equal to 1 if firm n is in a brown industry and CO2Int_{np} is the firm's CO2 intensity standardized within two-digit NAICS and year. All specifications contain firm×policy and firm×month fixed effects. Standard errors are clustered by firm and policy. Stacks include only industries covered by each policy and firm–months overlapping multiple policies are excluded. Each stack includes observations in a +/- 12 month window around policy enactment.

Parameter	Definition	Prior
α_c	Category baseline effect	$\mathcal{N}(0, 1)$
λ_c	Effect of observable policy characteristics	$\mathcal{N}(0, 1)$
σ_c	Variance of idiosyncratic part of Δ_p	Half-Normal(1)
σ_r	Variance of idiosyncratic portion of returns	Half-Normal(1)

Table A4: Priors for the parameters in the hierarchical Bayesian estimation.

	Pearson Correlation	Rank Correlation
Alt. Window	0.9791	0.9324
Policy-Specific Window	0.9717	0.9273
Student-t Likelihood	0.9173	0.8809
Heteroskedastic Likelihood	0.9566	0.9318
CO2 Interaction	0.9694	0.9297
Pooled Categories	0.9200	0.8760
Narrow Priors	0.9999	0.9992

Table A5: Pearson and rank correlation between baseline and alternative policy intensity estimates. The definition of each alternative specification is given in Appendix C.3.

Industry Name	NAICS	A_i	s.e.(A_i)
Mining, Quarrying, and Oil and Gas Extraction	21	0.155	0.032
Agriculture, Forestry, Fishing and Hunting	11	0.177	0.036
Utilities	22	0.193	0.025
Management of Companies and Enterprises	55	0.384	0.042
Information	51	0.705	0.070
Real Estate and Rental and Leasing	53	0.755	0.067
Educational Services	61	0.846	0.093
Finance and Insurance	52	0.970	0.128
Professional, Scientific, and Technical Services	54	1.001	0.132
Wholesale Trade	42	1.003	0.126
Transportation and Warehousing	48-49	1.045	0.117
Arts, Entertainment, and Recreation	71	1.112	0.106
Construction	23	1.461	0.199
Manufacturing	31-33	1.955	0.356
Other Services (except Public Administration)	81	1.986	0.248
Administrative and Support and Waste Management and Remediation Services	56	2.366	0.347
Health Care and Social Assistance	62	2.839	0.533
Retail Trade	44-45	4.349	0.821
Accommodation and Food Services	72	5.851	0.980

Table A6: Industry-specific amenity values estimated from a fixed effects regression as described in equation (A79). Standard errors are clustered by state.

Industry Name	NAICS	σ_i^F	s.e.(σ_i^F)
Health Care and Social Assistance	62	0.131	0.014
Professional, Scientific, and Technical Services	54	0.241	0.018
Administrative and Support and Waste Management and Remediation Services	56	0.244	0.016
Educational Services	61	0.263	0.030
Retail Trade	44-45	0.311	0.023
Wholesale Trade	42	0.318	0.022
Other Services (except Public Administration)	81	0.321	0.034
Accommodation and Food Services	72	0.339	0.021
Construction	23	0.343	0.030
Transportation and Warehousing	48-49	0.399	0.059
Manufacturing	31-33	0.574	0.072
Finance and Insurance	52	0.584	0.064
Information	51	0.800	0.040
Arts, Entertainment, and Recreation	71	0.817	0.291
Real Estate and Rental and Leasing	53	0.970	0.022
Utilities	22	0.994	0.137
Mining, Quarrying, and Oil and Gas Extraction	21	1.217	0.084
Management of Companies and Enterprises	55	4.115	8.023
Agriculture, Forestry, Fishing and Hunting	11	34.166	223.195

Table A7: Industry-specific relocation dispersion estimated from Poisson pseudo-maximum likelihood estimation, as described in equation (A83). Standard errors are clustered by state.

B Additional Reduced Form Analysis

B.1 Impacts of Prescriptive Regulations on Industry/State: IV Design

To test the impact of prescriptive regulations without relying on the return-based stringency measure, I regress the same six outcomes on the number of specific regulations that apply to industry i in state s at time t:

$$y_{ist} = \beta(\#REG_{ist}) + \gamma_{st} + \gamma_{it} + \gamma_{is} + \eta_{ist}, \tag{A1}$$

where $\#REG_{ist}$ is the number of GHG emissions regulations affecting industry i in state s as of year t. As above, I include state-year, industry-year and industry-state fixed effects.

Directly regressing industry-state outcomes on the number of regulations may lead to endogeneity, as policies could be targeted toward particular industries for reasons that are correlated with the outcome variables of interest. In addition, the number of regulations itself is a noisy measure of stringency, leading to measurement error. To address these concerns, I instrument for the number of regulations using the interaction between GHG targets and industry brownness. This instrument captures plausibly exogenous variation in regulatory exposure arising from the combination of a state's overall GHG policy stance and an industry's baseline emissions intensity. In particular, the first stage regression is:

$$\#REG_{ist} = \delta_1(\text{Target}_{st} \times \text{CO2Int}_i^{\text{Pre}}) + \delta_2\text{Target}_{st} + \gamma_{it} + \eta_{ist}, \tag{A2}$$

where $\text{CO2Int}_i^{\text{Pre}}$ is the average CO2 intensity (emissions scaled by output) of industry i in 2003.[50] This is a valid instrument because, as discussed in detail in Korganbekova (2025), targets themselves do not impose any restrictions on polluting activity. Instead, targets are meant as a goal for state regulators to consider when enacting new emissions regulation, so targets should only impact economic activity to the extent that they lead to specific regulations. Figure A2 shows that the extent to which states actual GHG emissions comply with their targets varies widely. This divergence suggests that the presence of a target is not mechanically linked to realized emissions, lending additional support to the exclusion restriction.

B.2 Effect of Regulation on Equity Returns: Stacked Event Study

Before measuring the market-implied stringency of each individual policy, I verify that the policies in my sample affect equity returns of exposed firms. I begin by estimating a stacked event regression for firm n,

[50] The first target was enacted in 2006.

calendar month m and policy p:

$$\tilde{r}_{mnp} = \beta \text{TreatWindow}_{mp} \times \text{Expos}_{np} \times \text{BrownInd}_n \times \text{CO2Int}_{np} + \alpha_{np} + \alpha_{mp} + \varepsilon_{mnp}, \tag{A3}$$

where $\tilde{r}_{mnp}$ is the return adjusted for the Fama and French (2015) five factors, momentum and earnings surprises (see Appendix C.1 for details), TreatWindow_{mp} is equal to 1 if month m is within [-5,2] months of the enactment month of policy p, Expos_{np} reflects firm n's operations in the state that enacted policy p, BrownInd_n is equal to 1 if firm n's industry is brown and CO2Int_{np} is the z-score of firm n's carbon intensity within its two-digit NAICS industry.[51] Expos_{np} and CO2Int_{np} are computed in the year prior to enactment of regulation p. α_{np} and α_{mp} are firm×policy and calendar-month×policy fixed effects, respectively. Each policy-specific stack only contains firms in industries affected by the policy.

C Estimating Policy Intensity: Details and Robustness

C.1 Constructing Abnormal Returns

In order to estimate the return impact of regulation, I first orthogonalize the return data with respect to the Fama and French (2015) five factors, momentum and earnings surprises. For each stock in my dataset of monthly returns, I run a time-series regression:

$$r_{nm} = \beta_1 \text{Mkt}_m + \beta_2 \text{SMB}_m + \beta_3 \text{HML}_m + \beta_4 \text{RMW}_m + \beta_5 \text{CMA}_m + \beta_6 \text{Mom}_m + \beta_7 \text{SUE}_{nm} + \tilde{r}_{nm}, \tag{A4}$$

where Mkt_m, SMB_m, HML_m, RMW_m, CMA_m and Mom_m are the monthly returns of the Fama-French and momentum factor portfolios and SUE_{nm} is the I/B/E/S earnings surprise of firm n in month m (equal to zero if the firm does not report earnings). The residual, $\tilde{r}_{nm}$ is the measure of abnormal returns that I use in my analysis.

An alternative approach to controlling for earnings surprises would be to recompute monthly returns excluding the earnings announcement day. The decision to use only the I/B/E/S earnings surprise is intentional because this measure summarizes the new information revealed by the firm about its *past* performance. On the other hand, the total announcement day return could reflect discussions about factors with the potential to influence the firm's *future* performance, notably state-level emissions regulations. Thus, by excluding the announcement-day return, I would be removing potentially important information about how the market

[51] Expos_{np} is either equal to $\frac{L_{nst}}{L_{ns}}$, where the numerator is computed by summing employment (from NETS) across firm n's facilities in state s at time t and the denominator comes from Compustat, or an indicator equal to 1 if that ratio is larger than 0.1.

perceives the firm's exposure to new regulation.

C.2 Bayesian Estimation Details

This appendix describes the baseline hierarchical Bayesian estimator used in the paper. Suppose that event–window abnormal returns of firm n are determined by:

$$\tilde{r}_{np} \;=\; \text{Expos}_{np}\,\Delta_p \;+\; \varepsilon_{np}, \qquad \varepsilon_{np} \overset{i.i.d.}{\sim} \mathcal{N}(0,\sigma_r^2), \tag{A5}$$

where $\tilde{r}_{np}$ is the abnormal return of firm n around the enactment of policy p, Expos_{np} is the (pre–event) exposure of firm n to policy p, and Δ_p is the unexpected component of the latent "policy intensity." For each policy p, define:

$$SZZ_p \equiv \sum_{n\in N(p)} \text{Expos}_{np}^2, \qquad SZR_p \equiv \sum_{n\in N(p)} \text{Expos}_{np}\,\tilde{r}_{np}. \tag{A6}$$

Within a policy category c,

$$\Delta_p \;=\; \alpha_{c(p)} + X_p'\lambda_{c(p)} + \eta_p, \qquad \eta_p \overset{i.i.d.}{\sim} \mathcal{N}(0,\sigma_{c(p)}^2), \tag{A7}$$

with independent priors on the common parameters. For a given category c, let $\theta_c \equiv \{\alpha_c,\lambda_c,\sigma_c,\sigma_r,\{\Delta_p\}_{p\in c}\}$. The hierarchical prior factorizes to:

$$\pi(\theta_c) = \pi(\alpha_c)\,\pi(\lambda_c)\,\pi(\sigma_c)\,\pi(\sigma_r)\prod_{p\in c}\mathcal{N}\big(\Delta_p \,\big|\, \alpha_c + X_p'\lambda_c,\ \sigma_c^2\big), \tag{A8}$$

with weakly informative priors on $(\alpha_c,\lambda_c,\sigma_c,\sigma_r)$ as reported in Table A4.

C.2.1 Posterior Densities

Policy shocks Δ_p For each policy p, the likelihood is given by:

$$\mathcal{L}(\Delta_p) = \prod_{n\in N(p)} \frac{1}{\sqrt{2\pi\sigma_r^2}} \exp\left(-\frac{(\tilde{r}_{np} - \text{Expos}_{np}\Delta_p)^2}{2\sigma_r^2}\right). \tag{A9}$$

Up to a constant, the log likelihood is:[52]

$$
\begin{aligned}
l(\Delta_p) \equiv \log(\mathcal{L}(\Delta_p)) &= -\sum_{n \in N(p)} \frac{(\tilde{r}_{np} - \text{Expos}_{np}\Delta_p)^2}{2\sigma_r^2} \\
&= -\frac{1}{2}\left(\frac{SZZ_p}{\sigma_r^2}\right)\Delta_p^2 + \left(\frac{SZR_p}{\sigma_r^2}\right)\Delta_p + \text{const},
\end{aligned}
\tag{A10}
$$

where the dropped constant is $-\frac{\sum_n \tilde{r}_{np}^2}{2\sigma_r^2}$.

Recall that the prior for Δ_p is normal with mean $\alpha_c + X_p'\lambda_c$ and variance σ_c^2. In logs, the prior density is:

$$
\begin{aligned}
\log \pi(\Delta_p) &= -\frac{\left(\Delta_p - (\alpha_c + X_p'\lambda_c)\right)^2}{2\sigma_c^2} - \frac{\log(2\pi\sigma_c^2)}{2} \\
&= -\frac{1}{2\sigma_c^2}\Delta_p^2 + \frac{\Delta_p(\alpha_c + X_p'\lambda_c)}{\sigma_c^2} + \text{const},
\end{aligned}
\tag{A11}
$$

where the dropped constant is $-\frac{\log(2\pi\sigma_c^2)}{2} - \frac{(\alpha_c + X_p'\lambda_c)^2}{2\sigma_c^2}$. Adding the log-likelihood and log-prior to obtain the (log) posterior:

$$
\begin{aligned}
\log p(\Delta_p|\alpha_c, \lambda_c, \sigma_c, \sigma_r, \tilde{r}_p) &= -\frac{1}{2}\left(\frac{SZZ_p}{\sigma_r^2}\right)\Delta_p^2 + \left(\frac{SZR_p}{\sigma_r^2}\right)\Delta_p - \frac{1}{2\sigma_c^2}\Delta_p^2 + \frac{\Delta_p(\alpha_c + X_p'\lambda_c)}{\sigma_c^2} + \text{const} \\
&= -\frac{1}{2}\underbrace{\left(\frac{SZZ_p}{\sigma_r^2} + \frac{1}{\sigma_c^2}\right)}_{\text{posterior precision}}\Delta_p^2 + \underbrace{\left(\frac{SZR_p}{\sigma_r^2} + \frac{\alpha_c + X_p'\lambda_c}{\sigma_c^2}\right)}_{\text{precision-weighted mean}}\Delta_p + \text{const}.
\end{aligned}
\tag{A12}
$$

Let $v_p \equiv \left(\frac{SZZ_p}{\sigma_r^2} + \frac{1}{\sigma_c^2}\right)^{-1}$ and $m_p \equiv v_p\left(\frac{SZR_p}{\sigma_r^2} + \frac{\alpha_c + X_p'\lambda_c}{\sigma_c^2}\right)$. Then,

$$
\begin{aligned}
\log p(\Delta_p|\alpha_c, \lambda_c, \sigma_c, \sigma_r, \tilde{r}_p) &\propto -\frac{\Delta_p^2}{2v_p} + \frac{m_p}{v_p}\Delta_p - \frac{(\alpha_c + X_p'\lambda_c)^2}{2\sigma_c^2} \\
\implies \log p(\Delta_p|\alpha_c, \lambda_c, \sigma_c, \sigma_r, \tilde{r}_p) &\propto -\frac{1}{2}\frac{(\Delta_p - m_p)^2}{2v_p},
\end{aligned}
\tag{A13}
$$

which is proportional to the (log) density of a normal distribution with mean m_p and variance v_p.

To see concretely why the Bayesian estimator particular useful for policies with weak signals (low SZZ_p), note that the OLS estimate of Δ_p from equation (A5) is $\hat{\Delta}_p^{\text{OLS}} \equiv \frac{SZR_p}{SZZ_p}$. Then, the posterior mean m_p can be written as a weighted average of $\hat{\Delta}_p^{\text{OLS}}$ and $(\alpha_c + X_p'\lambda_c)$:

$$
m_p = \frac{\sigma_c^2}{\sigma_c^2 + \frac{\sigma_r^2}{SZZ_p}}\hat{\Delta}_p^{\text{OLS}} + \left(1 - \frac{\sigma_c^2}{\sigma_c^2 + \frac{\sigma_r^2}{SZZ_p}}\right)(\alpha_c + X_p'\lambda_c).
\tag{A14}
$$

[52] The dropped constant is $-\frac{1}{2}|N(p)| \times \log(2\pi\sigma_r^2)$.

This expression makes explicit that the posterior mean puts more weight on the OLS estimate when SZZ_p is high (i.e. the data is more informative) and more weight on the characteristics when SZZ_p is low.

Coefficients λ_c and α_c Stack the $P(c)$ policies in category c and let $\tilde{\boldsymbol{X}}_c \equiv [\mathbf{1}, X]$ and $\tilde{\boldsymbol{\lambda}}_c \equiv (\alpha_c, \lambda_c')'$. Let $\boldsymbol{\Delta}_c$ denote the $P(c) \times 1$ vector of $\{\Delta_p\}_{p \in c}$. For each category,

$$\boldsymbol{\Delta}_c = \tilde{\boldsymbol{X}}_c \tilde{\boldsymbol{\lambda}}_c + \boldsymbol{\eta}_c, \qquad \boldsymbol{\eta}_c \sim \mathcal{N}(0, \sigma_c^2 I_{P(c)}), \tag{A15}$$

with prior $\tilde{\boldsymbol{\lambda}}_c \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, I_{k(c)+1})$, where $k(c)$ is the number of policy characteristics used for category c.

The likelihood (up to a constant) is:

$$\mathcal{L}(\tilde{\boldsymbol{\lambda}}_c) \propto \exp\left(-\frac{1}{2\sigma_c^2}||\boldsymbol{\Delta}_c - \tilde{\boldsymbol{X}}_c \tilde{\boldsymbol{\lambda}}_c||^2\right) \tag{A16}$$

Combine the prior and likelihood to obtain the (log) posterior:

$$\log p(\tilde{\boldsymbol{\lambda}}_c | \boldsymbol{\Delta}_c, \sigma_c^2) \propto -\frac{1}{2}\tilde{\boldsymbol{\lambda}}_c' \underbrace{\left(\frac{1}{\sigma_c^2}\tilde{\boldsymbol{X}}_c' \tilde{\boldsymbol{X}}_c + I_{k(c)+1}\right)}_{\equiv \boldsymbol{V}_\lambda^{-1}} \tilde{\boldsymbol{\lambda}}_c + \tilde{\boldsymbol{\lambda}}_c' \underbrace{\left(\frac{\mathbf{1}}{\boldsymbol{\sigma_c^2}}\tilde{\boldsymbol{X}}_c{}' \boldsymbol{\Delta}_c\right)}_{\equiv \boldsymbol{V}_\lambda^{-1}\boldsymbol{\mu}_\lambda}, \tag{A17}$$

which is equivalent to a multivariate normal:

$$\tilde{\boldsymbol{\lambda}}_c | \boldsymbol{\Delta}_c, \sigma_c^2 \sim \mathcal{N}\left(\boldsymbol{\mu}_\lambda, \boldsymbol{V}_\lambda\right). \tag{A18}$$

Intuitively, the posterior will put more weight on the characteristics when there is more variation in $\tilde{\boldsymbol{X}}_c$. When there is less information in $\tilde{\boldsymbol{X}}_c$, the posterior will shrink toward zero (which is the prior mean). In addition, the form of the posterior for $\tilde{\boldsymbol{\lambda}}_c$ makes the hierarchical structure apparent. The "data" for the coefficient estimation are the policy shocks $\boldsymbol{\Delta}_c$, treated as observed in this conditional step.

Variances σ_c and σ_r I place Half-Normal priors (with variance 1) on σ_r and σ_c. Under these priors, there is no closed form expression for the posterior. It would be possible to yield closed-form posteriors using the inverse-Gamma distribution, but doing so can lead to computational issues (Gelman (2006), Betancourt (2017)).

Figure A7 shows how the probability that a regulation's estimated effect $\hat{\Delta}_p$ is negative varies with the precision of that estimate, summarized by the Fisher information, $I_p \equiv \frac{\sum_n \text{Expos}_{np}^2}{\sigma_r^2}$.[53] As information increases, the probabilities move closer to 1. For high-information policies, the probability is above 0.8.

[53] σ_r^2 is the posterior for the variance of idiosyncratic returns.

C.2.2 Computational Details

I estimate each category's model with the No-U-Turn Sampler (NUTS), a variant of Hamiltonian Monte Carlo developed by Hoffman et al. (2014). I draw 5,000 tuning iterations and then 10,000 estimating iterations per chain. During tuning, the sampler chooses the step size, but does not retain draws for inference. I run this estimation (5,000 tuning and 10,000 estimating draws) on four chains in parallel. Whether the four chains agree is an important diagnostic. Figure A8 shows the convergence for GHG Targets. Importantly, the densities look very similar across all four chains. The same is true for the other categories (unreported). Convergence is confirmed by noting that $\widehat{R}$ close to 1 (specifically $\widehat{R} < 1.01$) for all estimated parameters in all categories and that there are no divergences.[54] Finally, I confirm that effective sample size (ESS) is larger than 1,000 for all estimates.[55]

C.3 Robustness of Bayesian Estimates

I verify that my estimates of policy intensity, Δ_p are robust to a range of modeling choices. In each of the specifications described below, I fix all the other estimation details at the baseline.

1. Define the event window from four months prior to enactment until the month of enactment. (In the baseline, the window is -5 to +1 months).

2. Use a policy-specific event window beginning at the earliest news mention of the policy and ending one month after.

3. Use a student-t likelihood for returns with an Exponential(0.05) prior on the degrees of freedom parameter, ν. (The baseline is normal).

4. Allow for heteroskedasticity in the likelihood for returns. Specifically, $\tilde{r}_{np} \sim \mathcal{N}(\Delta_p \text{Expos}_{np}, \sigma^2_{rp})$, where $\log \sigma_{rp} = \mu_{\sigma_r} + \nu_{\sigma_r} \varepsilon_p$ and $\varepsilon_p \sim \mathcal{N}(0, 1)$. This allows for the possibility that return volatility is not constant across policies.

5. Modify the mapping from policy intensity to returns to reflect firm-specific "brownness." Define $z(\text{CO2Int}_{n,t(p)-1})$ as the z-score of firm n's CO2 Intensity within its industry in the year prior to the regulation. I interact this variable with Expos_{np}. This structure allows for the fact that firms within an industry may be differentially affected by a regulation depending on how emissions intensive they are, consistent with Figure A5.

[54] $\widehat{R}$ is the ratio of between-chain variance to within-chain variance.
[55] ESS quantifies the number of independent samples, accounting for autocorrelation.

6. Estimate policy intensity jointly for all categories. To account for the fact that the characteristic set varies by category, I interact the category-specific characteristics with indicator variables for each category.

7. Use narrower priors. Specifically, $\alpha_c, \lambda_c \sim \mathcal{N}(0, 0.3)$ and $\sigma_c, \sigma_r \sim$ Half-Normal(0.3). (In the baseline, the variance of all priors is equal to 1).

Table A5 reports the correlation between the baseline estimates of $\hat{\Delta}_p$ with those estimated in each of the 6 alternative setups. I report both the Pearson correlation of the estimates and the rank correlation. The correlations are all above 87%, suggesting that the estimates are robust to any of these design choices.

D Derivations and Proofs

D.1 Solution to the Household's Problem

D.1.1 Consumption and Location Choice

After returns are realized, the household's intensive margin (within-state and industry) optimization problem:

$$\max_{\{x_{hj}\}_{j\in J}} \quad \log A_{his} + \log X_h \quad \text{s.t.} \int_{j\in J} p_j x_{hj} dj = w_{is}\theta'_h R, \tag{A19}$$

where $X_h = \prod_i \left[\left(\int_{j\in J_i} x_{hj}^{\frac{\varepsilon_i^D+1}{\varepsilon_i^D}} dj\right)^{\frac{\varepsilon_i^D}{\varepsilon_i^D+1}}\right]^{\beta_i}$. The Lagrangian is:

$$\mathcal{L}_1 = \log A_{his} + \sum_i \beta_i \frac{\varepsilon_i^D}{\varepsilon_i^D+1} \log\left(\int_{j\in J_i} x_{hj}^{\frac{\varepsilon_i^D+1}{\varepsilon_i^D}} dj\right) + \lambda_1 \left(w_{is}\theta'_h R - \int_{j\in J} p_j x_{hj} dj\right). \tag{A20}$$

Let $P_i = \left(\int_{j\in J_i} p_j^{1+\varepsilon_i^D} dj\right)^{\frac{1}{1+\varepsilon_i^D}}$ denote the CES price index for goods in sector i and $P = \prod_i P_i^{\beta_i}$ denote the aggregate price index. The first order conditions are:

$$[x_{hj}]: \quad x_{hj} = \beta_i^{-\varepsilon_i^D} \lambda_1^{\varepsilon_i^D} p_j^{\varepsilon_i^D} X_{hi}^{\varepsilon_i^D+1} \tag{A21}$$

$$[X_{hi}]: \quad X_{hi} = \frac{\beta_i}{\lambda_1 P_i} \tag{A22}$$

$$[\lambda_1]: \quad w_{is}\theta'_h R = \int_{j\in J} p_j x_{hj} dj \tag{A23}$$

For notational clarity distinguish the employment sector $i(h)$ from the sector producing good j, $i(j)$. Combine the first order conditions to obtain the household's demand for good j:

$$x_{hj} = \beta_{i(j)} w_{i(h)s} \theta_h' R \left(\frac{p_j}{P_{i(j)}} \right)^{\varepsilon^D_{i(j)}} \frac{1}{P_{i(j)}}. \tag{A24}$$

Normalize $P = 1$ so that $X_h = w_{i(h)s}\theta_h' R$. The household's indirect utility from locating in state s and working in industry i is then:

$$V^H_{his} = \log(\theta_h' R) + \log w_{is} + \log A_{his}. \tag{A25}$$

Decompose $\log A_{his} = \log \overline{A}_{is} + \xi_{his}$, where ξ_{his} is drawn from a type I extreme value distribution with dispersion σ^H. Define $u_{is} = \log w_{is} + \overline{A}_{is}$, so that the share of households working in sector i and living in state s is given by:

$$H_{is} = \mathbb{P}\left(V^H_{his} = \max_{(is)'} \left\{ V^H_{h(is)'} \right\} \right) = \frac{\exp \frac{u_{is}}{\sigma^H}}{\sum_{(is)'} \exp \frac{u_{(is)'}}{\sigma^H}}. \tag{A26}$$

Note that equity market returns do not depend on location choice, so the location decision is equivalent regardless of whether it is made before or after returns are realized.

D.1.2 Portfolio Choice

Using $X_h = w_{is}\theta_h' R$, the household's maximization problem prior to returns being realized is:

$$\max_{\theta_h} \quad \mathbb{E}[\log(\theta_h' R)] \quad \text{ s.t. } 1 = \theta_h' \mathbf{1}. \tag{A27}$$

Using the standard mean-variance approximation,

$$\mathbb{E}[\log(\theta_h' R)] \approx \theta_h' \mu - \frac{1}{2}\theta_h' \Sigma \theta_h. \tag{A28}$$

The Lagrangian for the (approximated) portfolio choice problem is:

$$\mathcal{L}_2 = \theta_h' \mu - \frac{1}{2}\theta_h' \Sigma \theta_h + \lambda_2(1 - \theta_h' \mathbf{1}). \tag{A29}$$

The first order condition for the weight on firm n is:

$$[\theta_{h,n}]: \quad \theta_h = \Sigma^{-1}(\mu - \lambda_2 \mathbf{1}). \tag{A30}$$

Solve for λ_2 using the constraint $\theta_h'\mathbf{1} = 1$:

$$\lambda_2 = \frac{\mathbf{1}\Sigma^{-1}\mu - 1}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}, \tag{A31}$$

so that:

$$\theta_h = \Sigma^{-1}\left(\mu - \frac{\mathbf{1}\Sigma^{-1}\mu - 1}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}\mathbf{1}\right). \tag{A32}$$

Note that as a result of identical preferences and beliefs, $\theta_h = \theta \ \forall \ h$, so we can drop the h subscript for simplicity.

D.2 Profit- vs. Value-Maximizing Objective

The market value of the firm is given by:

$$\mathcal{M}_n = \mathbb{E}[m\pi_n], \tag{A33}$$

where $m = \frac{1}{\theta' R}$ is the stochastic discount factor and π_n denotes firm profits. Equivalently, firms maximize the log of market value. Because productivity shocks are assumed to be jointly lognormal, log market value is approximated by:

$$\log \mathcal{M}_n = \mathbb{E}[\log \pi_n] - \mathbb{E}[\log R_m] + \frac{1}{2}[\mathbb{V}\text{ar}(\log \pi_n) + \mathbb{V}\text{ar}(\log R_m)] - \mathbb{C}\text{ov}(\log \pi_n, \log R_m), \tag{A34}$$

where R_m is the market return.

In general, firm decisions may affect market value through three channels: $\mathbb{E}[\log \pi_n]$, $\mathbb{V}\text{ar}(\log \pi_n)$ and $\mathbb{C}\text{ov}(\log \pi_n, \log R_m)$. However, in the baseline model, I assume that the covariance matrix of productivity shocks Σ_η is exogenous, so that $\mathbb{V}\text{ar}(\log \pi_n)$ and $\mathbb{C}\text{ov}(\log \pi_n, \log R_m)$ fixed. Under this assumption, maximizing market value is equivalent to maximizing expected log profits. This framework can be easily extended to allow firm choices to affect the variance of profits (for example greener firms may have either more or less cash flow volatility) or the covariance with the market (for example green firms hedge against climate shocks).

D.3 Equilibrium Establishment Profits

The household problem implies that demand for good j is given by:

$$x_{hj} = \beta_{i(j)} w_h \theta' R \left(\frac{p_j}{P_{i(j)}}\right)^{\varepsilon^D_{i(j)}} \frac{1}{P_{i(j)}}. \tag{A35}$$

Market clearing implies that,

$$y_{js} = I_i P_i^{-(1+\varepsilon_i^D)} p_j^{\varepsilon_i^D},$$

where $I_i \equiv \beta_i \sum_h w_h \theta' R$ denotes aggregate household income (including both labor and investment income). Note that because establishments operate with CRS technology, each product, j, will only be produced in a single location, so that $y_{js} = y_j$. Using the market clearing expression, the profit function in equation (16) can be rewritten:

$$\pi_{js}^T = \max_{l_{js}, \mathcal{E}_{js}, k_{js}} \quad \mathbb{E}\left[I_i^{-\frac{1}{\varepsilon_i^D}} P_i^{\frac{1+\varepsilon_i^D}{\varepsilon_i^D}} y_{js}^{\frac{1}{\varphi_i}} \right] - w_{is} l_{js} - \tau_{is} \mathcal{E}_{js} - \kappa_i k_{js}, \tag{A36}$$

where $\varphi_i = \left[\frac{1}{\varepsilon_i^D{}_i} + 1\right]^{-1}$ is the markup. Rewrite this by decomposing the firm's revenue into stochastic and deterministic components (from the firm's perspective, i.e. η_n and the vector R are unknown and ϕ_{js} is known):

$$\pi_{js}^T = \max_{l_{js}, \mathcal{E}_{js}, k_{js}} \quad \underbrace{\mathbb{E}\left[I_i^{-\frac{1}{\varepsilon_i^D}} P_i^{\frac{1+\varepsilon_i^D}{\varepsilon_i^D}} \eta_n^{\frac{1}{\varphi_i}} \right]}_{\equiv \Theta_n} \Bigg(\underbrace{\phi_{js} l_{js}^{\gamma_i^l} \mathcal{E}_{js}^{\gamma_i^T} k_{js}^{1-\gamma_i^l-\gamma_i^T}}_{\equiv \tilde{y}_{js}} \Bigg)^{\frac{1}{\varphi_i}} - w_{is} l_{js} - \tau_{is} \mathcal{E}_{js} - \kappa_i k_{js}, \tag{A37}$$

where $\tilde{y}_{js}$ is the portion of revenue that is known to the firm and Θ_n is the expectation of the stochastic component. The first order conditions are:

$$[l_{js}]: \quad w_{is} = \frac{\Theta_n \gamma_i^l \tilde{y}_{js}^{\frac{1}{\varphi_i}}}{\varphi_i l_{js}} \tag{A38}$$

$$[\mathcal{E}_{js}]: \quad \tau_{is} = \frac{\Theta_n \gamma_i^T \tilde{y}_{js}^{\frac{1}{\varphi_i}}}{\varphi_i \mathcal{E}_{js}} \tag{A39}$$

$$[k_{js}]: \quad \kappa_i = \frac{(1-\gamma_i^l - \gamma_i^T) \tilde{y}_{js}^{\frac{1}{\varphi_i}}}{\varphi_i k_{js}}. \tag{A40}$$

Combine the first order conditions to obtain the ratio of emissions and capital to labor:

$$\frac{\mathcal{E}_{js}}{l_{js}} = \frac{w_{is}\gamma_i^T}{\tau_{is}\gamma_i^l} \quad \text{and} \quad \frac{k_{js}}{l_{js}} = \frac{w_{is}(1-\gamma_i^l-\gamma_i^T)}{\kappa_i \gamma_i^l}. \tag{A41}$$

Substitute these two ratios into the deterministic portion of the production function to obtain a new expression for labor:

$$\begin{aligned}\tilde{y}_{js} &= \phi_{js} l_{js}^{\gamma_i^l} \left(\frac{w_{is}\gamma_i^T}{\tau_{is}\gamma_i^l} l_{js}\right)^{\gamma_i^T} \left(\frac{w_{is}(1-\gamma_i^l-\gamma_i^T)}{\kappa_i \gamma_i^l} l_{js}\right)^{1-\gamma_i^l-\gamma_i^T} \\ \implies l_{js} &= \frac{\tilde{y}_{js}}{\phi_{js}} \left(\frac{w_{is}}{\gamma_i^l}\right)^{\gamma_i^l-1} \left(\frac{\gamma_i^T}{\tau_{is}}\right)^{-\gamma_i^T} \left(\frac{1-\gamma_i^l-\gamma_i^T}{\kappa_i}\right)^{-(1-\gamma_i^l-\gamma_i^T)}\end{aligned} \tag{A42}$$

Using this expression and the decomposition $\mathbb{E}[p_j y_{js}] = \Theta_n \tilde{y}_{js}^{\frac{1}{\varphi_i}}$, equation (A38) becomes:

$$w_{is} = \frac{\mathbb{E}[p_j y_{js}]\gamma_i^l}{\varphi_i \frac{\tilde{y}_{js}}{\phi_{js}} \left(\frac{w_{is}}{\gamma_i^l}\right)^{\gamma_i^l-1} \left(\frac{\gamma_i^T}{\tau_{is}}\right)^{-\gamma_i^T} \left(\frac{1-\gamma_i^l-\gamma_i^T}{\kappa_i}\right)^{-(1-\gamma_i^l-\gamma_i^T)}}, \tag{A43}$$

which implies that:

$$\mathbb{E}[p_j y_j] = \tilde{y}_{js}\varphi_i \underbrace{\frac{1}{\phi_{js}} \left(\frac{w_{is}}{\gamma_i^l}\right)^{\gamma_i^l} \left(\frac{\tau_{is}}{\gamma_i^T}\right)^{\gamma_i^T} \left(\frac{\kappa_i}{1-\gamma_i^l-\gamma_i^T}\right)^{1-\gamma_i^l-\gamma_i^T}}_{\equiv c_{js}}, \tag{A44}$$

which shows that prices are a markup over marginal cost. Combining this expression with equation (A38) yields:

$$w_{is} l_{js} = \gamma_i^l \tilde{y}_{js} c_{js}. \tag{A45}$$

Again using $\mathbb{E}[p_j y_{js}] = \Theta_n \tilde{y}_{js}^{\frac{1}{\varphi_i}}$ and collecting $\tilde{y}_{js}$ terms in equation (A44) implies that $\tilde{y}_{js} = \left(\frac{\varphi_i c_{js}}{\Theta_n}\right)^{\varepsilon_i^D}$, which can be plugged into equation (A45) to obtain:

$$w_{is} l_{js} = \frac{\gamma_i^l \varphi_i^{\varepsilon_i^D} c_{js}^{1+\varepsilon_i^D}}{\Theta_n^{\varepsilon_i^D}} \tag{A46}$$

Equations (A44) and (A45) imply that $\mathbb{E}[y_{js} p_j] = \frac{\varphi_i w_{is} l_{js}}{\gamma_i^l}$, which can be substituted into the original expression for expected profits:

$$\begin{aligned}\pi_{js}^T &= \frac{\varphi_i w_{is} l_{js}}{\gamma_i^l} - w_{is} l_{js} - \tau_{is} \frac{\mathcal{E}_{js}}{l_{js}} l_{js} - \kappa_i \frac{k_{js}}{l_{js}} l_{js} \\ &= \frac{\varphi_i w_{is} l_{js}}{\gamma_i^l} - w_{is} l_{js} - \tau_{is} \frac{w_{is}\gamma_i^T}{\tau_{is}\gamma_i^l} l_{js} - \kappa_i \frac{w_{is}(1-\gamma_i^l-\gamma_i^T)}{\kappa_i\gamma_i^l} l_{js} \\ &= w_{is} l_{js} \left(\frac{\varphi_i}{\gamma_i^l} - 1 - \frac{\gamma_i^T}{\gamma_i^l} - \frac{(1-\gamma_i^l-\gamma_i^T)}{\gamma_i^l}\right) \\ &= w_{is} l_{js} \left(\frac{\varphi_i - 1}{\gamma_i^l}\right).\end{aligned} \tag{A47}$$

Use equation (A46) and the definition of c_{js} to re-express the profit function:

$$\pi_{js}^T = \frac{\varphi_i^{\varepsilon_i^D}\left(\frac{1}{\phi_{js}}\left(\frac{w_{is}}{\gamma_i^l}\right)^{\gamma_i^l}\left(\frac{\tau_{is}}{\gamma_i^T}\right)^{\gamma_i^T}\left(\frac{\kappa_i}{1-\gamma_i^l-\gamma_i^T}\right)^{1-\gamma_i^l-\gamma_i^T}\right)^{1+\varepsilon_i^D}}{\Theta_n^{\varepsilon_i^D}}(\varphi_i - 1). \tag{A48}$$

Let $\nu_n^T \equiv \Theta_n^{-\varepsilon_i^D}\varphi_i^{\varepsilon_i^D}(\varphi_i-1)\left((\gamma_i^l)^{-\gamma_i^l}(\gamma_i^T)^{-\gamma_i^T}(1-\gamma_i^l-\gamma_i^T)^{-(1-\gamma_i^l-\gamma_i^T)}\kappa_i^{(1-\gamma_i^l-\gamma_i^T)}\right)^{1+\varepsilon_i^D}$ so that:

$$\pi_{js}^T = \nu_n^T w_{is}^{\gamma_i^l(1+\varepsilon_i^D)}\tau_{is}^{\gamma_i^T(1+\varepsilon_i^D)}\phi_{js}^{-(1+\varepsilon_i^D)}, \tag{A49}$$

which is the expression in equation (18). Note that ν_n^T is a firm-specific constant that does not vary across locations.

D.4 Probability of Switching to the Green Technology (Industry Level)

The probability that a facility located in state s will choose the green technology is equivalent to the probability that the profits from doing so are greater than the profits from remaining brown:

$$\begin{aligned}
\mathbb{P}_i(G|s) &= \mathbb{P}_i(\alpha_i(1-\chi_n)\pi_j^G > \pi_j^B|s) \\
&= \mathbb{P}_i\left(\alpha_i(1-\chi_n) < \frac{\pi_j^B}{\pi_j^G}\middle| s\right) \\
&= \mathbb{P}\left(\chi_n < 1 - \frac{\nu_i^B}{\alpha_i\nu_i^G}\tau_{is}^{-(1+\varepsilon_i^D)(\gamma_i^G-\gamma_i^B)}\right) \\
&= 1 - \frac{\nu_i^B}{\alpha_i\nu_i^G}\tau_{is}^{-(1+\varepsilon_i^D)(\gamma_i^G-\gamma_i^B)}.
\end{aligned} \tag{A50}$$

D.5 Effect of Regulation on State/Industry Emissions and Labor Demand

D.5.1 Emissions

Emissions of firms in industry i, technology T and location s (per unit of industry mass) are given by:

$$\begin{aligned}
\mathcal{E}_{is}^T &= \underbrace{E_{is}^T}_{\text{extensive margin}} \times \underbrace{\mathbb{E}_\zeta\left[\mathcal{E}_{js}^*(\zeta_{js})\middle| s,T\right]}_{\text{intensive margin}} \\
&= \underbrace{\frac{\exp\left(\frac{v_{is}^T}{\sigma_i^F}\right)}{\sum_{s'}\exp\left(\frac{v_{is'}^T}{\sigma_i^F}\right)}}_{E_{is}^T} w_{is}^{\gamma_i^l(1+\varepsilon_i^D)}\tau_{is}^{\gamma^T(1+\varepsilon_i^D)-1}C_{\mathcal{E}}^T\exp(-(1+\varepsilon_i^D)\overline{\phi}_{is})z_i,
\end{aligned} \tag{A51}$$

where $C^T_{\mathcal{E}}$ is constant across locations and $z_i \equiv \mathbb{E}_\zeta\left[\exp(-(1+\varepsilon_i^D)\zeta_{js})\right]$. The total emissions of firms in industry i and state s are given by $\mathcal{E}_{is} = \mathbb{P}_i(B)\mathcal{E}^B_{is} + \mathbb{P}_i(G)\mathcal{E}^G_{is}$, which directly implies that the elasticity of local emissions with respect to a change in regulatory stringency is:

$$\frac{\partial \log(\mathcal{E}_{is})}{\partial \log \tau_{is}} = \underbrace{\frac{\mathcal{E}^G_{is} - \mathcal{E}^B_{is}}{\mathcal{E}_{is}} \frac{\partial \mathbb{P}_i(G)}{\partial \log \tau_{is}}}_{\text{technology switching}} + \underbrace{\frac{\mathcal{E}^G_{is}\mathbb{P}_i(G)}{\mathcal{E}_{is}} \frac{\partial \log(\mathcal{E}^G_{is})}{\partial \log \tau_{is}}}_{\text{chg. in emissions of green firms}} + \underbrace{\frac{\mathcal{E}^B_{is}(1-\mathbb{P}_i(G))}{\mathcal{E}_{is}} \frac{\partial \log(\mathcal{E}^B_{is})}{\partial \log \tau_{is}}}_{\text{chg. in emissions of brown firms}}. \tag{A52}$$

The within-technology elasticities follow directly from equation A51:[56]

$$\frac{\partial \log \mathcal{E}^T_{is}}{\partial \log \tau_{is}} = \underbrace{\gamma^T - 1}_{\text{substitution}} + \underbrace{\gamma^T \varepsilon_i^D}_{\text{scale}} - \underbrace{\frac{\gamma^T}{\sigma_i^F}}_{\text{firm location}}. \tag{A53}$$

It remains to compute the effect of a change in regulatory stringency on the switching probability. With the $\lambda_g = 0$ simplification, $\mathbb{P}_i(G) = \Delta_i$, so:

$$\frac{\partial \mathbb{P}_i(G)}{\partial \log \tau_{is}} = \frac{\partial \Delta_i}{\partial \log \tau_{is}} = \frac{\nu_i^B}{\nu_i^G}(1+\varepsilon_i^D)\sigma_i^F \left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-(1+\varepsilon_i^D)\sigma_i^F - 1} \frac{\frac{\partial \overline{\pi}_i^B}{\partial \log(\tau_{is})}\overline{\pi}_i^G - \frac{\partial \overline{\pi}_i^G}{\partial \log(\tau_{is})}\overline{\pi}_i^B}{(\overline{\pi}_i^G)^2}. \tag{A54}$$

Note that the only term in $\overline{\pi}_i^T$ that depends on τ_{is} is the state s term of the sum, so that:

$$\begin{aligned}
\frac{\partial \overline{\pi}_i^T}{\partial \log(\tau^{\mathcal{E}}_{is})} &= \frac{1}{S} \frac{\partial \exp\left(\frac{v^T_{is}}{\sigma_i^F}\right)}{\partial \log(\tau_{is})} \\
&= -\frac{1}{S} \exp\left(\frac{v^T_{is}}{\sigma_i^F}\right) \frac{\gamma_i^T}{\sigma_i^F} \\
&= -\frac{\sum_{s'} \exp\left(\frac{v^T_{is'}}{\sigma_i^F}\right)}{S \sum_{s'} \exp\left(\frac{v^T_{is'}}{\sigma_i^F}\right)} \exp\left(\frac{v^T_{is}}{\sigma_i^F}\right) \frac{\gamma_i^T}{\sigma_i^F} \\
&= -\overline{\pi}_i^T E^T_{is} \frac{\gamma_i^T}{\sigma_i^F},
\end{aligned} \tag{A55}$$

[56] With many states S, the denominator of $E^T_{is} = \exp(v^T_{is}/\sigma_i^F)/\sum_{s'}\exp(v^T_{is'}/\sigma_i^F)$ can be approximated by its law-of-large-numbers limit:

$$\sum_{s'} \exp\left(\frac{v^T_{is'}}{\sigma_i^F}\right) \approx S\,\overline{\pi}_i^T, \qquad \overline{\pi}_i^T \equiv \frac{1}{S}\sum_{s'} \exp\left(\frac{v^T_{is'}}{\sigma_i^F}\right).$$

Under this large-S (thin-share) approximation, changes in $\log \tau_{is}$ affect only the numerator locally, so

$$\frac{\partial \log E^T_{is}}{\partial \log \tau_{is}} \approx -\frac{\gamma_i^T}{\sigma_i^F}.$$

The exact log-share derivative is $-(1-E^T_{is})\,\gamma_i^T/\sigma_i^F$; the approximation replaces $(1-E^T_{is})$ by 1, which is accurate when each E^T_{is} is small.

where the last line uses the definitions of $\overline{\pi}_i^T$ and E_{is}^T. Substituting this into the expression for $\frac{\partial \mathbb{P}_i(G)}{\partial \log \tau_{is}}$ yields:

$$\frac{\partial \mathbb{P}_i(G)}{\partial \log \tau_{is}} = (1+\varepsilon_i^D)(1-\mathbb{P}_i(G))(E_{is}^G \gamma_i^G - E_{is}^B \gamma_i^B). \tag{A56}$$

Then, the elasticity of local emissions can be rewritten:

$$\begin{aligned}\frac{\partial \log(\mathcal{E}_{is})}{\partial \log \tau_{is}} = & \underbrace{\frac{\mathcal{E}_{is}^G - \mathcal{E}_{is}^B}{\mathcal{E}_{is}}(1+\varepsilon_i^D)(1-\mathbb{P}_i(G))(E_{is}^G \gamma_i^G - E_{is}^B \gamma_i^B)}_{\text{technology switching}} \\ & + \underbrace{\frac{\mathcal{E}_{is}^G \mathbb{P}_i(G)}{\mathcal{E}_{is}}\left(\underbrace{\gamma_i^G - 1}_{\text{substitution}} + \underbrace{\gamma_i^G \varepsilon_i^D}_{\text{scale}} - \underbrace{\frac{\gamma_i^G}{\sigma_i^F}}_{\text{firm location}}\right)}_{\text{chg. in emissions of green firms}} \\ & + \underbrace{\frac{\mathcal{E}_{is}^B (1-\mathbb{P}_i(G))}{\mathcal{E}_{is}}\left(\underbrace{\gamma^B - 1}_{\text{substitution}} + \underbrace{\gamma_i^B \varepsilon_i^D}_{\text{scale}} - \underbrace{\frac{\gamma_i^B}{\sigma_i^F}}_{\text{firm location}}\right)}_{\text{chg. in emissions of brown firms}}.\end{aligned} \tag{A57}$$

D.5.2 Labor Demand

Labor demand of firms in industry i, technology T and location s (per unit of industry mass) is given by:

$$L_{is}^{D,T} = \underbrace{\frac{\exp\left(\frac{v_{is}^T}{\sigma^F}\right)}{\sum_{s'} \exp\left(\frac{v_{is'}^T}{\sigma^F}\right)}}_{E_{is}^T} w_{is}^{\gamma_i^l(1+\varepsilon_i^D)-1} \tau_{is}^{\gamma_i^T(1+\varepsilon_i^D)} C_L^T \exp(-(1+\varepsilon_i^D)\overline{\phi}_{is}) z_i, \tag{A58}$$

where C_L^T is constant across locations. The derivation of the elasticity of labor demand with respect to $\tau_{is}^{\mathcal{E}}$ follows the exact logic laid out for emissions elasticity in the previous subsection.

D.6 Effect of Regulation on Profits

D.6.1 Effect of a Marginal Change in τ_{is}

Because location and technology are both chosen discretely, the profit impact of a marginal change in τ_{is} is derived under fixed location and technology. As a result, I can use gross profits, $\tilde{\pi}_n \equiv \int_{j \in J^n} \pi_j dj$, to derive the continuous piece of the profit impact.[57] Define $\tilde{\pi}_{ns} = \int_{j \in J_s^n} \pi_j dj$, where J_s^n is the set of firm n's facilities optimally located in state s. Only facilities located in state s are directly impacted by the change in τ_{is}, so

[57] By gross profits, I mean total firm profits without adjusting for technology switching costs.

I approximate $\frac{\partial \tilde{\pi}_n}{\partial \log \tau_{is}} \approx \frac{\partial \tilde{\pi}_{ns}}{\partial \log \tau_{is}}$.[58] The impact on gross profits, is then given by:

$$\begin{aligned}\frac{\partial \log \tilde{\pi}_n}{\partial \log \tau_{is}} &= \frac{1}{\tilde{\pi}_n}\frac{\partial \tilde{\pi}_n}{\partial \log \tau_{is}} \\ &\approx \frac{1}{\tilde{\pi}_n}\frac{\partial \tilde{\pi}_{ns}}{\partial \log \tau_{is}} \\ &= \frac{\tilde{\pi}_{ns}}{\tilde{\pi}_n}\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}} \\ &= \omega_{ns}\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}},\end{aligned} \tag{A59}$$

where the second line uses the no out-of-state profit impacts approximation and $\omega_{ns} \equiv \frac{\tilde{\pi}_{ns}}{\tilde{\pi}_n}$ is the share of the firm's gross profits generated in state s.

The next step is to derive an expression for $\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}}$,

$$\begin{aligned}\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}} &= \int_{j \in J_s^n} \frac{\pi_j}{\tilde{\pi}_{ns}}\frac{\partial \log \pi_j}{\partial \log \tau_{is}} dj \\ &= (1+\varepsilon_i^D)\int_{j \in J_s^n} \frac{\pi_j}{\tilde{\pi}_{ns}}\left[\mathbb{1}\{T_j = G\}\gamma_i^G + \mathbb{1}\{T_j = B\}\gamma_i^B + \gamma_i^l \dot{w}_{is}\right] dj,\end{aligned} \tag{A60}$$

where $\dot{w}_{is}$ is given by equation (**??**). The decision rule for choosing the green technology implies that all facilities of firm n within state s will operate the same technology, so this expression further simplifies to:[59]

$$\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}} = (1+\varepsilon_i^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is}), \tag{A61}$$

where T_{ns} denotes the technology operated by facility j in state s. Using the equivalence between marginal changes in gross and actual profits, this implies that the profit impact is:

$$\frac{\partial \log \pi_n}{\partial \log \tau_{is}} = \omega_{ns}(1+\varepsilon_i^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is}). \tag{A62}$$

D.6.2 Effect of a Discrete Change in τ_{is}: Relocation and Technology Adjustment

Consider a discrete increase in regulatory stringency from τ_{is}^{old} to τ_{is}^{new}. Define the change in expected log profits, $\dot{\pi}_n \equiv \log \pi_n(\tau_{is}^{\text{new}}) - \log \pi_n\left(\tau_{is}^{\text{old}}\right)$, where π_n denotes the total profits of the firm including an adjustment for switching costs. The discrete policy change may lead to technology switching or relocation.

[58] This approximation is valid as long as firm relocation to any particular state s' is not large enough to significantly impact $w_{is'}$.

[59] Recall the decision rule for choosing the green technology at a particular facility j (conditional on the facility being located in state s). A facility j, located in state s and owned by firm n will choose the green technology if $(1-\chi_n(g_n))\pi_j^G > \pi_j^B$. Taking logs of both sides and using the facility-level profit expression in equation (18), this condition becomes $\log \nu_n^G - \log \nu_n^B + (1+\varepsilon_i^D)\log \tau_{is}(\gamma_i^G - \gamma_i^B) > \log(1-\chi_n(g_n))$, which does not depend on any facility level characteristics. As a result, all facilities operated by firm n located in state s will operate the same technology.

Recall that because there is no within-firm/state heterogeneity in switching costs, all facilities of firm n in state s will operate the same technology. Denote this technology by $T_{ns} \in \{B, G\}$. Facilities do differ in productivity ϕ_{js}, so the relocation decision may vary by facility. With that in mind, there are three distinct cases to consider for facilities of firm n.[60]

(Case 1) The facility stays in s and keeps its technology T_{ns}. For these facilities, the profit impact is: $\dot{\pi}_j^{\text{Case 1}} = \Delta \log \tau_{is} \times (1+\varepsilon_i^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is})$. Using the location decision problem, $\mathbb{P}(\text{stay in } s|T) \approx \exp\left(-\frac{\gamma_i^T}{\sigma_i^F} \Delta \log \tau_{is}\right)$. For green facilities, $\mathbb{P}(\text{case 1}|G) = \mathbb{P}(\text{stay in } s|G)$. For brown facilities, $\mathbb{P}(\text{case 1}|B) = \mathbb{P}(\text{stay in } s|B) \times \mathbb{P}(\text{stay B}|s)$, where $\mathbb{P}(\text{stay B}|s) = \frac{\nu_i^B}{\nu_i^G}(\tau_{is}^{\text{new}})^{(\gamma_i^B - \gamma_i^G)(1+\varepsilon_i^D)}$.[61]

(Case 2) The facility stays in s and switches technology (this only applies to firms who were operating the brown technology in state s under τ_{is}^{old}). For these facilities, the profit impact is $\dot{\pi}_j^{\text{Case 2}} = (1+\varepsilon_i^D)\left[\Delta \log \tau_{is}(\gamma_i^B + \gamma_i^l \dot{w}_{is}) + (\gamma_i^G - \gamma_i^B)\log \tau_{is}^{\text{new}}\right] + (\log \nu_i^G - \log \nu_i^B) + \log(1-\chi_n^0)$, where the last term represent switching costs. For brown facilities, $\mathbb{P}(\text{case 2}|B) = \mathbb{P}(\text{stay in } s|B) - \mathbb{P}(\text{case 1}|B)$.

(Case 3) The facility relocates (and does not switch technology). For a facility that relocates to state s', the expected profit impact is $\dot{\pi}_j^{\text{Case 3}} = -(1+\varepsilon_i^D)\left((\log \overline{\phi}_{is'} - \log \overline{\phi}_{is}) - \gamma_i^l(\log w_{is'} - \log w_{is}) - \gamma_i^{T_{ns}}(\log \tau_{is'} - \log \tau_{is})\right)$. Conditional on moving, the probability of relocating to s' is $\mathbb{P}(s'|\text{move}) = \frac{\exp \frac{v_{is'}^{T_{ns}}}{\sigma_i^F}}{\sum_{s'' \neq s} \exp \frac{v_{is''}^{T_{ns}}}{\sigma_i^F}}$. The unconditional probability of moving to s' is then $\mathbb{P}(s') = \mathbb{P}(\text{move})\mathbb{P}(s'|\text{move}) = \left(1 - \exp\left(-\frac{\gamma_i^T}{\sigma_i^F}\Delta \log \tau_{is}\right)\right) \frac{\exp \frac{v_{is'}^{T_{ns}}}{\sigma_i^F}}{\sum_{s'' \neq s} \exp \frac{v_{is''}^{T_{ns}}}{\sigma_i^F}}$, using the expression for $\mathbb{P}(\text{stay})$ from case 1 and the fact that $\mathbb{P}(\text{move}) = 1 - \mathbb{P}(\text{stay})$.

Considering all three cases, the impact of a discrete change in τ_{is} on profits of firm n is given by:

$$\begin{aligned}
\dot{\pi}_n = \omega_{ns} \Bigg[& \mathbb{P}(\text{stay, no switch})(1+\varepsilon_i^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is})\Delta \log \tau_{is} \\
& + \mathbb{P}(\text{stay,switch})\left[(1+\varepsilon_i^D)\left(\Delta \log \tau_{is}(\gamma_i^B + \gamma_i^l \dot{w}_{is}) + (\gamma_i^G - \gamma_i^B)\log \tau_{is}^{\text{new}}\right) + (\log \nu_i^G - \log \nu_i^B) + \log(1-\chi_n^0)\right] \\
& + \sum_{s' \neq s} \mathbb{P}(\text{move to } s')(1+\varepsilon_i^D)\left(\gamma_i^l(\log w_{is'} - \log w_{is}) + \gamma_i^{T_{ns}}(\log \tau_{is'} - \log \tau_{is}^{\text{old}}) - (\log \overline{\phi}_{is'} - \log \overline{\phi}_{is})\right) \Bigg],
\end{aligned} \tag{A63}$$

where the probabilities are defined in the definition of each case.

[60] I assume that relocating and technology switching are mutually exclusive choices. Intuitively, a brown facility that relocates in response to regulation would do so in part to avoid the cost of complying (by investing in green technology), so it wouldn't make sense to both relocate and switch. Although outside the bounds of this static framework, a green facility that moves has already paid the switching cost and thus it is unlikely that it would revert back to the brown technology.

[61] For brevity, I omit the bounds from the probability expressions, but it is implicit that the actual form of each expression is $\max\{0, \min\{1, \mathbb{P}(.)\}\}$.

D.6.3 Equity Returns

Consider an unanticipated regulatory shock affecting industry i in state s where the emissions tax rate increases from τ_{is}^{old} to τ_{is}^{new}. Let $\mathcal{M}_n$ and $\tilde{\mathcal{M}}_n$ denote the market value of firm n under τ_{is} and τ_{is}^{new}, respectively. Then, when the regulatory change is announced, the return of stock n is given by:

$$r_{n,\tau_{is}^{\text{old}} \to \tau_{is}^{\text{new}}} = \log(\mathcal{M}_n^{\text{new}}) - \log(\mathcal{M}_n^{\text{old}}), \tag{A64}$$

where $\log \mathcal{M}_n$ is given by equation (A34). Because the regulation is local, I assume that the market return is not affected. Then, the return can be written:

$$r_{n,\tau_{is}^{\text{old}} \to \tau_{is}^{\text{new}}} \approx \mathbb{E}[\log \pi_n^{\text{new}}] - \mathbb{E}[\log \pi_n^{\text{old}}] + \underbrace{\frac{1}{2}[\mathbb{V}\text{ar}(\log \pi_n^{\text{new}}) - \mathbb{V}\text{ar}(\log \pi_n^{\text{old}})] - [\mathbb{C}\text{ov}(\log \pi_n^{\text{new}}) - \mathbb{C}\text{ov}(\log \pi_n^{\text{old}})]}_{=0 \text{ by assumption}}. \tag{A65}$$

Throughout the paper, I assume that the covariance of productivity shocks Σ_η is exogenous, so the expression simplifies to the change in expected log profits, as given by equation (**??**).

D.7 Impact of Relocation on Welfare of Workers

If the regulation does not induce any workers to relocate (across industries or states), the welfare impact is driven purely by the change in wages. However, if the change in labor demand resulting from the regulation is large enough that some workers move from industry/state is to $(is)'$, then the welfare impact is given by:

$$\dot{\mathcal{V}}_w = N_{is} \left(\mathbb{P}_{\text{stay}}^{is} \dot{w}_{is} + \sum_{(is)' \neq is} \mathbb{P}_{\text{move}}^{is \to (is)'} \Delta \mathcal{V}_{is \to (is)'} \right). \tag{A66}$$

Let w_{is}^{new} denote the equilibrium wage in industry/state is following the regulatory change. Note that if $w_{is}^{\text{new}} \geq w_{is}$, then no workers would be induced to move, so I focus on the case where $w_{is}^{\text{new}} < w_{is}$, which is also consistent with the empirical evidence that wages fall as a result of new regulation. The probability that a worker stays in is is given by:

$$\mathbb{P}_{\text{stay}}^{is} = P\left(V_{nis}^H(w_{is}^{\text{new}}) = \max_{(is)'} \left\{ V_{n(is)'}^H(w_{is}^{\text{new}}) \right\} \middle| V_{nis}^H(w_{is}) = \max_{(is)'} \left\{ V_{n(is)'}^H(w_{is}) \right\} \right). \tag{A67}$$

For brevity, let D_1 denote the event $V^H_{nis}(w^{\text{new}}_{is}) = \max_{(is)'}\left\{V^H_{n(is)'}(w^{\text{new}}_{is})\right\}$ and D_2 denote the event $V^H_{nis}(w_{is}) = \max_{(is)'}\left\{V^H_{n(is)'}(w_{is})\right\}$, so that $\mathbb{P}^{is}_{\text{stay}} = \mathbb{P}(D_1|D_2)$. Using standard probability rules,

$$\mathbb{P}(D_1|D_2) = \frac{\mathbb{P}(D_1 \cap D_2)}{\mathbb{P}(D_2)} \equiv \mathbb{P}^{is}_{\text{stay}}. \tag{A68}$$

Now note that if (is) is optimal under the lower wage, w^{new}_{is}, then it must have also been optimal under the original higher wage w_{is}, which implies that $\mathbb{P}(D_1 \cap D_2) = \mathbb{P}(D_1)$. It immediately follows that,

$$\mathbb{P}(D_1|D_2) = \frac{\mathbb{P}(D_1)}{\mathbb{P}(D_2)}. \tag{A69}$$

Let u^{new}_{is} denote the common component of the household's indirect utility given wages are equal to w^{new}_{is}. Using the expression from equation (15):

$$\begin{aligned}\mathbb{P}^{is}_{\text{stay}} &= \frac{\frac{\exp\frac{u^{\text{new}}_{is}}{\sigma^H}}{\sum_{(is)'}\exp\frac{u^{\text{new}}_{(is)'}}{\sigma^H}}}{\frac{\exp\frac{u_{is}}{\sigma^H}}{\sum_{(is)'}\exp\frac{u_{(is)'}}{\sigma^H}}} \\ &\approx \exp\left(\frac{u^{\text{new}}_{is} - u_{is}}{\sigma^H}\right) \\ &= \exp\left(\frac{\dot{w}_{is}}{\sigma^H}\right),\end{aligned} \tag{A70}$$

where the second line is almost exact because, under the assumption that household relocation is not large enough to impact equilibrium wages in other industries/locations, the terms of the sum are identical for all $(is)' \neq (is)$.

To derive $\mathbb{P}^{is\to(is)'}_{\text{move}}$, first note that the probability of moving anywhere is $1 - \mathbb{P}^{is}_{\text{stay}}$ and the probability of moving to a particular location/industry is:

$$\mathbb{P}^{is\to(is)'}_{\text{move}} = \mathbb{P}(\text{move})\mathbb{P}((is)'|\text{move}). \tag{A71}$$

Since the idiosyncratic preference shocks are i.i.d. T1EV, the conditional probability term follows the standard logit form, so that:

$$\mathbb{P}^{is\to(is)'}_{\text{move}} = (1 - \mathbb{P}^{is}_{\text{stay}})\frac{\exp\frac{u'_{(is)}}{\sigma^H}}{\sum_{(is)''\neq is}\exp\frac{u_{(is)''}}{\sigma^H}}. \tag{A72}$$

Finally, the change in expected welfare from relocating from is to $(is)'$ is given by:

$$\Delta\mathcal{V}_{is\to(is)'} = \underbrace{\log w_{(is)'} - \log w_{is}}_{\text{wage effect}} + \underbrace{\log\overline{A}_{(is)'} - \log\overline{A}_{is}}_{\text{amenity effect}}. \tag{A73}$$

Putting these components together, I obtain the full expression for the impact of a change in regulation on workers' welfare:

$$\dot{\mathcal{V}}_w = \exp\left(\frac{\dot{w}_{is}}{\sigma^H}\right)\dot{w}_{is} + \left(1-\exp\left(\frac{\dot{w}_{is}}{\sigma^H}\right)\right)\sum_{(is)'\neq is}\frac{\exp\frac{u'_{(is)}}{\sigma^H}}{\sum_{(is)''\neq is}\exp\frac{u_{(is)''}}{\sigma^H}}(\log w_{(is)'} - \log w_{is} + \log\overline{A}_{(is)'} - \log\overline{A}_{is}). \tag{A74}$$

E Structural Estimation Details

E.1 Exact Structural Effects of Emissions Regulation

In this subsection, I show the exact form of the structural system that links shocks to the emissions tax rate with the endogenous outcomes of my model. These equations capture the general equilibrium feedback between labor markets, establishment location and technology choice.

The five equations in the system are: establishment location (equation (24)), emissions (equation (26)), labor supply equation (equation (15)), labor demand equation (equation (27)) and technology switching costs (equation (29)). Stacking these five equations yields:

$$\boldsymbol{A}_i\boldsymbol{Y}_{is,t} = \boldsymbol{B}_i\boldsymbol{Z}_{is,t} + \boldsymbol{e}_{is,t}, \tag{A75}$$

where $\boldsymbol{Y}_{is,t} \equiv \begin{bmatrix}\Delta\log w_{is,t} & \Delta\log L_{is,t} & \Delta\log\mathcal{E}_{is,t} & \Delta\log E_{is,t} & \Delta\log\mathrm{SC}_{is,t}\end{bmatrix}'$ is a vector of change in the five endogenous variables (wages, employment, emissions, number of establishments and technology switching costs), $\boldsymbol{Z}_{is,t} = [\Delta\log\tau_{is,t}]$ is a vector of shocks to local emissions regulation, $\boldsymbol{A}_i$ is a matrix that characterizes the relation between the endogenous variables, $\boldsymbol{B}$ captures the direct effects of regulatory shocks on each endogenous variable and $\boldsymbol{e}_{is,t}$ is a structural error term. $\boldsymbol{A}_i$ and $\boldsymbol{B}_i$ are given by:

$$\boldsymbol{A}_i = \begin{bmatrix} -\frac{1}{\sigma^H} & 1 & 0 & 0 & 0\\ \gamma_i^l(1+\varepsilon_i^D)-1 & -1 & 0 & 1 & 0\\ -\gamma_i^l(1+\varepsilon_i^D) & 0 & 1 & -1 & 0\\ \frac{\gamma_i^l}{\sigma^F} & 0 & 0 & 1 & 0\\ 0 & 0 & 0 & -1 & 1\end{bmatrix} \quad \boldsymbol{B}_i = \begin{bmatrix} 0\\ (1+\varepsilon_i^D)\left[\psi_{is}^G\left(\gamma_i^G - \frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}\dot{\gamma}_i\right) + \psi_{is}^B(\gamma^B+\dot{\gamma}_i)\right]\\ (1+\varepsilon_i^D)\left[\psi_{is}^G\left(\gamma_i^G - \frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}\dot{\gamma}_i\right) + \psi_{is}^B(\gamma^B+\dot{\gamma}_i)\right]-1\\ -\frac{\mathbb{P}_i(G|s)\gamma_i^G+\mathbb{P}_i(B|s)\gamma_i^B}{\sigma^F}\\ -2\frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}(1+\varepsilon_i^D)\dot{\gamma}_i\end{bmatrix}, \tag{A76}$$

where $\dot{\gamma}_i \equiv \gamma_i^B - \gamma_i^G > 0$.

After substituting returns for unobserved tax shocks, $\boldsymbol{B}_i$ is replaced by:

$$\tilde{\boldsymbol{B}}_i = \frac{1}{(1+\varepsilon_i^D)\left(\overline{\gamma_i^{\mathcal{E}}} + \gamma_i^l \dot{w}_{is}\right)} \begin{bmatrix} 0 \\ (1+\varepsilon_i^D)\left[\psi_{is}^G\left(\gamma_i^G - \frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}\dot{\gamma}_i\right) + \psi_{is}^B(\gamma^B + \dot{\gamma}_i)\right] \\ (1+\varepsilon_i^D)\left[\psi_{is}^G\left(\gamma_i^G - \frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}\dot{\gamma}_i\right) + \psi_{is}^B(\gamma^B + \dot{\gamma}_i)\right] - 1 \\ -\frac{\mathbb{P}_i(G|s)\gamma_i^G + \mathbb{P}_i(B|s)\gamma_i^B}{\sigma^F} \\ -2\frac{\mathbb{P}_i(B|s)}{\mathbb{P}_i(G|s)}(1+\varepsilon_i^D)\dot{\gamma}_i \end{bmatrix}. \tag{A77}$$

E.2 Amenity Values

Adding time subscripts to equation (15):

$$H_{ist} = \frac{\exp\left(\frac{\log w_{ist} + \log \overline{A}_{is}}{\sigma^H}\right)}{\sum_{(is)'} \exp\left(\frac{\log w_{(is)'t} + \log \overline{A}_{(is)'}}{\sigma^H}\right)}. \tag{A78}$$

H_{ist} and w_{ist} are observable (H_{ist} is the number of workers employed by industry i in state s in year t divided by the total number of workers in the U.S. in year t), while $\overline{A}_{is}$ and σ^H must be estimated. I assume that $\log \overline{A}_{is}$ is time-invariant and has additively separable location and industry components, $\log \overline{A}_{is} = \log \overline{A}_i + \log \overline{A}_s$. Let $\exp(\alpha_t) \equiv \sum_{(is)'} \exp\left(\frac{\log w_{(is)'t} + \log \overline{A}_{(is)'}}{\sigma^H}\right)$. Then, equation (A78) can be rewritten:

$$\log H_{ist} = \frac{1}{\sigma^H}\log w_{ist} + \frac{1}{\sigma^H}\log \overline{A}_i + \frac{1}{\sigma^H}\log \overline{A}_s - \alpha_t. \tag{A79}$$

As a result, σ^H, $\{\overline{A}_i\}$ and $\{\overline{A}_s\}$ are obtained directly from a regressing $\log H_{ist}$ on $\log w_{ist}$, including industry, state and year fixed effects. In practice, I use the years 2003-2005, during which time there was very little state-level emissions regulation. I obtain a value of $\sigma^H = 0.66$, which is consistent with the range of 0.17-0.892, estimated by Suárez Serrato and Zidar (2016).[62] The estimates of amenity values A_i and A_s can be found in Table A6 and Figure A9, respectively.

E.3 Industry- and Location-Specific Productivity

Computing the parameters of the firm location decision expression, necessitates a different approach for three reasons. First, in contrast to the amenity values, it is not reasonable to assume that $\overline{\phi}_{is}$ is composed of separable industry and state components. Second, I assume that σ_i^F varies by industry, consistent with the

[62]It is logical that my estimate is near the top of their range, as they focus only on preference dispersion over states, while I measure dispersion across both industries and states.

idea that some industries are similarly productive in many states, whereas other industries' productivity is much more place-dependent.[63] Third, establishment counts, which I use for estimation, are very persistent, meaning that I cannot use time-series variation for identification as above.

Assuming that all firms within an industry operate the same (brown) technology in the pre-period (2003) and since all firms within a state face the same input prices, then equation (A41) implies that the ratio of inputs is the same for all facilities within an industry/state. As a result, $\frac{l_j}{l_{is}} = \frac{k_j}{k_{is}} = \frac{\mathcal{E}_j}{\mathcal{E}_{is}} \equiv a_j$ for all j in industry i and state s. Then, because the technology is CRS, total output of industry i in state s is:

$$y_{is} = \sum_j \eta_{n(j)} \phi_j (a_j l_{is})^{\gamma_i^l} (a_j \mathcal{E}_{is})^{\gamma_i^{\mathcal{E}}} (a_j k_{is})^{1-\gamma_i^l-\gamma_i^{\mathcal{E}}} = \left(\sum_j \eta_{n(j)} a_j \phi_j \right) l_{is}^{\gamma_i^l} \mathcal{E}_{is}^{\gamma_i^{\mathcal{E}}} k_{is}^{1-\gamma_i^l-\gamma_i^{\mathcal{E}}} = \overline{\phi}_{is} l_{is}^{\gamma_i^l} \mathcal{E}_{is}^{\gamma_i^{\mathcal{E}}} k_{is}^{1-\gamma_i^l-\gamma_i^{\mathcal{E}}}. \tag{A80}$$

Define $\log \tilde{\phi}_{is} \equiv \log \overline{\phi}_{is} + C_{is}$, where $C_{is} = \gamma_i^{\mathcal{E}} \log \mathcal{E}_{is,Pre} + (1-\gamma_i^l-\gamma_i^{\mathcal{E}}) \log k_{is,Pre}$. Then, $\tilde{\phi}_{is}$ can be estimated using:

$$\tilde{\phi}_{is} = \log y_{is} - \gamma_i^l \log l_{is}, \tag{A81}$$

where γ_i^l is obtained from the BEA-BLS Integrated Industry-Level Production Accounts and wages and output are averaged across the 2003-2005 pre-period.[64]

If emissions regulation, τ_{is} is constant across states, then the expression for the establishment location share in equation (20) simplifies to (recall that I already assume that the rental rate of capital, κ_i is constant across states):

$$E_{is}^{Pre} = \frac{\exp\left(\frac{\tilde{\phi}_{is} - \gamma_i^l \log w_{is}^{Pre}}{\sigma_i^F}\right)}{\sum_{s'} \exp\left(\frac{\tilde{\phi}_{is'} - \gamma_i^l \log w_{is'}^{Pre}}{\sigma_i^F}\right)}. \tag{A82}$$

Since there was very little GHG emissions regulation in the US before 2006, constant τ_{is} is a reasonable assumption in the pre-period, 2003-2005. E_{ist} and w_{ist} are observable (E_{ist} is the number of establishments of industry i located in state s in year t divided by the total number of industry i establishments in year t), $\tilde{\phi}_{is}$ is estimated above and σ_i^F remains to be estimated.

I estimate σ_i^F from a single pre-period cross-section (average of 2003-2005). Let $E_{is}^{\#}$ denote the number of establishments in industry i and state s and $E_i^{\#}$ be the industry total. I then use Poisson pseudo-maximum likelihood (PPML) with an industry fixed effect (Gourieroux et al. (1984)) to estimate:

$$\log E_{is}^{\#} = \frac{1}{\sigma_i^F} \left(\tilde{\phi}_{is} - \gamma_i^l \log w_{is}^{Pre} \right) - \alpha_i^{Pre} + \log E_i^{\#}, \tag{A83}$$

[63] As an example, healthcare would belong to the first category, whereas orange farming would belong to the second.
[64] The specific series is the average value of $\frac{\text{College Labor Compensation+Non-College Labor Compensation}}{\text{Value Added}}$ from 2003-2005.

where $\exp(\alpha_i^{Pre}) \equiv \sum_{s'} \exp\left(\frac{\tilde{\phi}_{is'} - \gamma_i^l \log w_{is'}^{Pre}}{\sigma_i^F}\right)$. The coefficient on $\log E_i^{\#}$ is constrained to 1 to ensure that the fitted counts sum to the total number of establishments. The industry fixed effect captures α_i^{Pre} and I use industry dummies interacted with $\left(\tilde{\phi}_{is} - \gamma_i^l \log w_{is}^{Pre}\right)$ to obtain industry-specific estimates of σ_i^F.

Estimates of σ_i^F range from 0.13 (healthcare) to 34.2 (agriculture). The full list can be found in Table A7.