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- **Program:** University of Chicago, Joint Program in Financial Economics, expected 2026

- **Research Interests:** I am interested in studying the economic and financial impacts of policies designed to combat climate change. In addition to my job market paper, which studies a broad set of such policies in the US, I have coauthored work focusing on a particular sustainability disclosure regulation in Europe.

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Joanna Harris

Updated August 7, 2025

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Research Interests

Climate Change and Sustainable Finance, Regulation, Asset Pricing, Monetary Policy

Education

University of Chicago Booth School of Business — Chicago, IL
PhD, Joint Program in Financial Economics — 2020 – Present

University of Chicago — Chicago, IL
Bachelor of Arts (Honors) in Economics and Statistics — 2013 – 2017

Awards

Eugene F. Fama PhD Fellowship	2025–2026
Stigler Center PhD Dissertation Award	2024–2025
Bradley Fellowship	2022 – 2025
Yiran Fan Memorial Prize for Best Third Year Paper	2023
Fama-Miller Research Development Fellowship	2022 – 2023
Bradley Fellowship	2022 – 2023
Liew Fama-Miller PhD Fellowship	2020 – 2022

Work in Progress

Heterogeneous Impacts of Emissions Regulation (Job Market Paper)
I examine the effects of state-level emissions regulations on local economic and environmental outcomes. Using newly collected data, I find that regulation reduces employment, output, and profitability in affected industries, but also lowers emissions and emissions intensity, while increasing R&D and capital investment. To interpret these mixed effects, I develop a spatial equilibrium model in which firms choose location and emissions based on local regulatory stringency. I use observed stock returns of affected firms to quantify the stringency of individual regulations and use these values to recover the structural parameters of the model. I then use the model to assess how the costs of regulation are distributed across firms and workers, and how they compare to the social benefits of reduced emissions. Preliminary estimates suggest that, for the average regulation, the monetary value of the resulting emissions reduction is approximately 1.6 times the economic cost. Approximately 88% of the cost is borne by workers through reductions in wages, rather than by firms through lower profits.

Regulating ESG Disclosure, with Marina Emiris and François Koulischer
We use new data on the ownership of mutual funds in Europe to estimate how investors respond to regulations on the disclosure of Environmental, Social and Governance (ESG) performance. We find that the introduction of ESG disclosure rules for mutual funds led to strong flows into funds categorized as green. We show that investor rebalancing takes place through two channels: an uncertainty channel where investors value the lower uncertainty, and a greenness channel where funds respond to disclosure rules by increasing their greenness to attract flows. We find empirical support for both channels: green funds for which investors had little information before the regulation experience the strongest flows, and green funds that had a low ESG rating before the regulation decrease their emissions most under the new rules.

Fed-Implied Market Conditions, with Charles Calomiris, Harry Mamaysky and Cristina Tessari
We introduce FDIF, a measure of Fed policy surprise based on the text of FOMC statements and minutes. FDIF is defined as the difference between text-implied and actual values of several key market variables. Positive FDIF of countercyclical variables (e.g., credit spreads) is associated with negative contemporaneous revisions to macroeconomic forecasts, and represents bad news. FDIF risk is priced at the industry level. Industries that hedge bad FDIF shocks earn low returns on FOMC announcement days, and high returns on all other days. Interest-rate-based policy surprise measures are not priced in the cross-section of industry returns, after controlling for FDIF.

Asset Pricing Implications of Firm-Level Exposure to Climate Risk
I use the text of 10-K filings to measure firm-level exposure to physical and transition risks associated with climate change. I find that both physical and transition risks are associated with lower monthly returns. Following Pàstor, Stambaugh and Taylor. (2022), I also focus on the interaction between climate risk and shocks to climate concerns and find that physical and transition risks are both associated with underperformance in months following upward shocks to climate concerns. These effects are not driven purely by variation across industries, highlighting the importance of considering climate risk at the firm level.

Quantifying Monetary Policy Uncertainty Through Text
I explore the relationship between the content of FOMC speeches and the price of monetary policy uncertainty in the S&P 500 options market. I provide evidence that a) monetary policy uncertainty is priced in the options market and b) there are aspects of FOMC speeches that are significant predictors of the time series variation in the price of such uncertainty. I argue that these results are evidence in favor of the hypothesis that, between January 2011-December 2020, policy makers' speeches reflected market conditions, rather than shaped them.

Teaching

Portfolio Choice and Asset Pricing
TA for Stefan Nagel, Chicago Booth PhD 2023

Investments
TA for John Heaton, Chicago Booth MBA and Undergraduate 2021, 2023

Topics in Economics
Lecturer, University of Chicago MS in Financial Math 2022, 2023
Independently designed and taught the course. Student feedback:

> "One of the best classes I have taken in Uchicago Finmath"
>
> "Great lecturer and laid out the content efficiently and engagingly!"

Other Activities

Organizer, Economic Dynamics and Financial Markets Working Group 2023 – Present
Co-Organizer, Booth Finance Brownbag 2022 – 2023

Work Experience

Columbia Business School — New York, NY
Finance Research Associate — 2018 – 2020
Assisted faculty with projects on a wide range of topics in asset pricing and corporate finance. Responsibilities included conducting data analysis, presenting findings and proposing relevant data sources and methods by reviewing related literature.

Barclays — New York, NY
Emerging Markets Macro Trading Analyst — 2017 – 2018

Skills

Programming
Proficient in: Python, Stata, R, LaTeX, Excel (VBA). Familiar with: Matlab, Julia.

Languages
English (native), French (working proficiency)

Heterogeneous Impacts of Emissions Regulation

PRELIMINARY AND INCOMPLETE.

Joanna Harris

August 7, 2025

Abstract

This paper examines the effects of state-level emissions regulations on local economic and environmental outcomes. 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 mixed effects, I develop a spatial equilibrium model in which firms choose location and emissions based on local regulatory stringency. I use observed stock returns of affected firms to quantify the stringency of individual regulations and use these values to recover the structural parameters of the model. I then use the model to assess how the costs of regulation are distributed across firms and workers, and how they compare to the social benefits of reduced emissions. Preliminary estimates suggest that, for the average regulation, the monetary value of the resulting emissions reduction is approximately 1.7 times the economic cost. Approximately 88% of the cost is borne by workers through reductions in wages, rather than by firms through lower profits.

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. This paper asks: What is the net impact of emissions regulation? How do the economic costs compare to the environmental benefits, and how are those costs distributed between investors and workers?

Two concerns commonly arise in debates over emissions regulation. First, such policies may impose substantial economic costs, including stranded assets, job losses, and lower 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 like 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 stringency of different regulations, making it difficult to draw conclusions about the impact of regulation from observed outcomes.

To address these challenges, 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. Using this dataset, I estimate the reduced-form effects of regulation at three levels of aggregation: industry-state, facility and firm. I find that regulation leads to both economic costs (reductions in employment, wages, output and profitability) and environmental benefits (reductions in emissions and emissions intensity). In addition, regulated firms increase investment in capital and R&D, suggesting that firms respond by improving their production technology, rather than only reducing output or relocating.

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. The model yields closed-form expressions for the incidence of environmental regulation on firm profits, wages, and environmental outcomes. and it implies a functional relationship between equity returns and regulatory stringency. Because the magnitude of each regulatory shock is not observable, I cannot

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

estimate the model parameters directly. To overcome this obstacle, I exploit the theoretical mapping between stock returns and regulatory stringency to obtain a quantitative measure that I can use for estimation. I then estimate the model using simulated method of moments, matching empirical moments for emissions, wages, employment, establishment counts, and output across industries and states. Preliminary estimates suggest that, for the average regulation, the social value of emissions reduction exceeds the economic costs by roughly 60 percent, with the majority of costs borne by workers though lower wages, rather than firm owners through reduced profits.

2 Institutional Background and Data Sources

I hand-collect a database of state-level greenhouse gas (GHG) emissions regulation in the United States, recording the state, type of regulation, date enacted, and the industries affected. The focus is on regulations that govern emissions from the production process (scope 1 emissions) rather than those generated when customers use the product. The sample contains 133 such regulations, of which 89 require firms to take a specific action. I refer to these as prescriptive regulations.[2] The remaining 44 are abstract regulations, primarily GHG targets that specify emissions reduction goals (either economy-wide or for specific industries) without imposing compliance requirements.

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

[2]The most common types of prescriptive regulations are renewable portfolio standards (mandating that a given percentage of electricity be generated from renewable sources), cap-and-trade programs (including the RGGI, which applies to the electricity sector, and several economy-wide programs in individual states), and quantity limits for methane emissions.

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.

3 Reduced Form Impacts of Emissions Regulation

3.1 Empirical Strategy

I analyze the impact of state-level emissions regulation on economic outcomes at three levels of aggregation: industry×state, facility and firm.

3.1.1 Industry×State-Level Analysis

To estimate the impact of new emissions regulation on local economic outcomes, I use three empirical strategies. First, I run a triple-difference regression where treated units are (1) brown industries, (2) located in a state with a GHG target, (3) after the target was enacted. Industry i is classified as brown if any of its facilities appear in the GHGRP dataset. Focusing on six outcomes (all in logs): number of workers, wage per worker, output, emissions, emissions intensity and number of establishments, I run the following regression:

$$y_{ist} = \beta \text{Target}_{st} \times \text{Brown}_i + \gamma_{st} + \gamma_{it} + \gamma_{is} + \eta_{ist}, \tag{1}$$

where Target_{st} is equal to one if state s has a target in place at time t and Brown_i is equal to one if industry i is classified as brown. The specification includes state-year fixed effects (γ_{st}), which flexibly absorb any time-varying state-level shocks or trends, 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.

The second specification focuses on prescriptive regulations. I regress the same six outcomes on the number of specific regulations that apply to industry i in state s at time t:

$$y_{ist} = \beta(\#REG_{ist}) + \gamma_{st} + \gamma_{it} + \gamma_{is} + \eta_{ist}, \tag{2}$$

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:

$$\#REG_{ist} = \delta_1(\text{Target}_{st} \times \text{CO2Int}_i^{\text{Pre}}) + \delta_2 \text{Target}_{st} + \gamma_{it} + \eta_{ist}, \tag{3}$$

where $\text{CO2Int}_i^{\text{Pre}}$ is the average CO2 intensity (emissions scaled by output) of industry i in 2003.[3] 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 1 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.

3.1.2 Facility-Level Analysis

The empirical design at the facility level is almost identical to that industry×state level with one main distinction. Since the GHGRP data covers only high-emitting facilities, all facilities in the sample operate in brown industries. As a result, there is no longer a meaningful distinction between green and brown industries. Thus, when running the regressions in equations (1) and (3) at the facility level, I drop the interaction with Brown_i. To take advantage of the full granularity of the data and because there is no longer within-state exposure to targets, I use facility and NAICS×year fixed effects (replacing state×year and NAICS-2×year fixed effects above).

3.1.3 Firm-Level Analysis

Since most firms operate in multiple states, I must modify the definition of treatment for the firm-level analysis.[4] I consider a firm to be "treated" by a new regulation if the regulation applies to the firm's industry and is enacted in a state where that firm has non-zero revenue.[5] To estimate the effect of emissions regulation on firm-level outcomes over different time horizons, I follow the setup in Chodorow-Reich et al.

[3] The first target was enacted in 2006.

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

[5] In unreported robustness checks, I vary the definition in several ways. First, for 1%, 5% and 10% thresholds, I consider a firm as treated only if the percentage of its revenue generated in the enacting state is above the threshold. Second, I consider a continuous treatment variable using the percentage of the firm's revenue generated in that state. Since the findings are not meaningfully affected by this choice, I choose to focus on the simplest definition.

(2021). For a given firm-level outcome y and horizon h, I estimate:

$$\Delta_{n,t-1,t+h} y = \beta^h \text{NewReg}_{n,t} + \beta_B^h \text{NewReg}_{n,t} \times \text{Brown}_{n,t-1} + \Gamma' X_{n,t-1} + \gamma_{i(n),t} + \gamma_n + \eta_{n,t}, \tag{4}$$

where $\Delta_{n,t-1,t+h} y$ is the change in outcome y from $t-1$ to $t+h$.[6] $\mathbb{1}\{\text{NewReg}_{n,t}\}$ equals 1 if firm n was subject to any new (prescriptive) emissions regulation at time t and $\mathbb{1}\{\text{Brown}_{n,t-1}\}$ equals to 1 if firm f had above-median emissions intensity at time $t-1$. $X_{n,t-1}$ 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.

In addition to the longer-horizon outcomes, I estimate the impact of local emissions regulation on monthly equity returns of brown firms in affected states:

$$r_{nm} = \sum_{h=-4}^{4} \left(\beta^h \text{NewReg}_{n,m-h} + \beta_B^h \text{NewReg}_{n,m-h} \times \text{Brown}_{n,Y(m)-1}\right) + \beta_B \text{Brown}_{n,Y(m)-1} + \gamma_n + \gamma_{i(n),m} + \varepsilon_{nm}, \tag{5}$$

where r_{nm} is the return of stock n in month m and $\text{NewReg}_{n,m-\tau}$ is an indicator equal to 1 if a regulation affecting firm n was enacted τ months from month m. As above, $\text{Brown}_{n,Y(m)-1}$ is equal to 1 if firm n had above median emissions intensity in the year prior to month m. The regression also includes firm (γ_n) and industry-month ($\gamma_{i(n),m}$) fixed effects.

3.2 Results

3.2.1 Industry×State-Level

Table 1 shows that GHG targets have a statistically significant negative effect on employment, wages, output, emissions, and emissions intensity in brown industries. 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 pure contraction. In contrast, using the raw number of regulations (Panel B) yields small and often insignificant coefficients, which is not surprising given that simple counts of regulations are difficult to interpret when regulatory measures vary substantially in their stringency. The IV results (Panel C), which use predicted exposure based on targets and pre-period emissions intensity, are substantially larger for output and emissions outcomes, consistent with attenuation bias in OLS from measurement error in regulation counts. 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

[6] 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).

Sun and Abraham (2021) (Figure 6) and Callaway and Sant'Anna (2021) (Figure 7).

3.2.2 Facility-Level

Table 2 shows that facility-level estimates using state-level GHG targets (Panel A) mirror the industry–state results: regulation is associated with significant reductions in employment, emissions, and emissions intensity, while the effect on revenue is negative but statistically insignificant, likely reflecting noise in the NETS revenue data. When replacing targets with the raw number of regulations (Panel B), the estimates are small and imprecise, reinforcing that simple counts of regulations are a poor proxy for regulatory stringency. Instrumental variables estimates (Panel C), which use predicted regulatory exposure from targets interacted with pre-period emissions intensity, yield larger effects, particularly for emissions and emissions intensity, suggesting attenuation bias in the OLS results due to measurement error in regulation counts. The employment effects are smaller in magnitude than the emissions effects, consistent with part of the emissions reduction coming from technology upgrades or process changes rather than only from scaling back production.

3.2.3 Firm-Level

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 the cost of capital aligns with existing literature on investor demand for green assets (e.g., Gormsen et al. (2024); Pástor et al. (2022)). In addition, Figure 3 shows that the stock returns of affected firms are 2–5 percentage points lower in the three months leading up to the enactment of new regulation.

4 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).

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. I compare outcomes before and after a change in emissions regulation and abstract from the transition between the two equilibria.

4.1 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:

$$\max_{\theta_h, \{x_{hj}\}_{j \in J}} \quad \log A_{his} + \mathbb{E}\left[\log X_h\right] \quad \text{s.t.} \int_{j \in J} p_j x_{hj} dj = w_{is} \theta_h' R, \tag{6}$$

where $X_h = \left(\int_{j \in J} x_{hj}^{\frac{\varepsilon^D + 1}{\varepsilon^D}} \right)^{\frac{\varepsilon^D}{\varepsilon^D + 1}}$, with product demand elasticity $\varepsilon^D < -1$ 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.

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 B.1, the share of households employed by sector i in state s, which will determine local labor supply, is given by:

$$H_{is} = \mathbb{P}\left(V_{his}^H = \max_{(is)'} \left\{ V_{h(is)'}^H \right\} \right) = \frac{\exp \frac{u_{is}}{\sigma^H}}{\sum_{(is)'} \exp \frac{u_{(is)'}}{\sigma^H}}. \tag{7}$$

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 B.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. [7]

4.2 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 is:

$$y_{js} = \eta_n \phi_{js} l_{js}^{\gamma_i^l} \mathcal{E}_{js}^{\gamma_j^{\mathcal{E}}} k_{js}^{1-\gamma_i^l-\gamma_j^{\mathcal{E}}}, \tag{8}$$

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.[8] 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:

$$\pi_{js}^T = \max_{l_{js}, \mathcal{E}_{js}, k_{js}} \left\{ \mathbb{E}[p_j y_{js}] - w_{is} l_{js} - \tau_{is}^{\mathcal{E}} \mathcal{E}_{js} - \kappa_i k_{js} \right\}, \tag{9}$$

where κ_i is the (exogenous and location-invariant) rental rate of capital and $\tau_{is}^{\mathcal{E}}$ is the tax on one unit of emissions.[9] 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:

$$\pi_{js}^T = \nu_n^T w_{is}^{\gamma_i^l (1+\varepsilon^D)} (\tau_{is}^{\mathcal{E}})^{\gamma_i^T (1+\varepsilon^D)} \phi_{js}^{-(1+\varepsilon^D)}, \tag{10}$$

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

[7] 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.

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

[9] 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.

4.2.1 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 $\log(\phi_{js}) = \overline{\phi}_{is} + \zeta_{js}$, where $\overline{\phi}_{is}$ is common 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 (i.e. $\gamma_j^{\mathcal{E}} = \gamma_i^T$), is determined by dividing log profits by $-(1+\varepsilon^D) \geq 1$:

$$V_{js}^T = \frac{\log \nu_i^T}{-(1+\varepsilon^D)} + \underbrace{\overline{\phi}_{is} - \gamma_i^l \log w_{is} - \gamma_i^T \log \tau_{is}^{\mathcal{E}}}_{\equiv v_{is}^T} + \zeta_{js}, \tag{11}$$

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:

$$E_{is}^T = \mathbb{P}\left(V_{js}^T = \max_{s'}\{V_{js}^T\}\right) = \frac{\exp \frac{v_{is}^T}{\sigma_i^F}}{\sum_{s'} \exp \frac{v_{is'}^T}{\sigma_i^F}}. \tag{12}$$

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

$$E_{is} = \mathbb{P}_i(T = G) E_{is}^G + (1 - \mathbb{P}_i(T = G)) E_{is}^B, \tag{13}$$

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 4.2.2.

4.2.2 Emissions Technology Choice

All facilities start with the brown technology ($\gamma_{0,j}^{\mathcal{E}} = \gamma_i^B$) and can pay a firm-specific cost $\chi_n(g_n)$ in order to acquire the green technology. χ_n is a decreasing and convex function of firm greenness g_n, which is equivalent to the portion of firm n's facilities already operating the green technology.[10] I assume this cost structure because it reflects the facility-specific nature of many technology upgrades, while still allowing for within-firm technology spillovers (as documented by Korganbekova (2025)). The cost is proportional to profits, so that an establishment's net profits are equal to $(1 - \chi_n)\pi_{js}$, where π_{js} is given by equation (10).[11] Expected

[10] The intuition behind this cost function is that it should be more costly to switch to the green technology if the firm has not done so before (i.e. g_n is low) because of learning, economies of scale or fixed organizational costs.

[11] 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.

establishment profits are given by:

$$\pi_j = \max\left\{\pi_j^B, \quad (1-\chi_n)\pi_j^G\right\}, \tag{14}$$

where π_j^T refers to the expression in equation (10) when $\gamma_j^{\mathcal{E}} = \gamma_i^T$ and state s is chosen according to Section 4.2.1.

Let the greening cost be given by $\chi_n(g_n) = \chi_n^0 \exp(-\lambda_g g_n)$, where $\chi_n^0 \overset{\text{i.i.d.}}{\sim} \text{U}[0,1]$ and $\lambda_g > 0$. Assume that χ_n^0 is independent of both ϕ_{js} and η_n. Panel A of Figure 4 plots the switching cost as a function of g_n.

Assume that χ_n^0 is independent of both ϕ_{js} and η_n. As derived in Appendix B.4, the proportion of facilities within industry i that operate the green technology is given by:

$$\mathbb{P}_i(G) = -\frac{W\left(-\lambda_g\left[1-\left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-(1+\varepsilon^D)\sigma_i^F}\right]\right)}{\lambda_g}, \tag{15}$$

where $\overline{\pi}_i^T \equiv \frac{1}{S}\sum_s \exp\left(\frac{v_{is}^T}{\sigma_i^F}\right)$ and $W(.)$ denotes the Lambert W function. Panel B of Figure 4 plots the probability of switching as a function of the profit ratio $\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}$. As λ_g increases and the switching cost declines more quickly with g_n, firms will choose a higher g_n for a given profit ratio.

4.3 Effect of Regulation on Local Emissions and Labor Demand

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

$$\mathcal{E}_{is} = \mathbb{P}_i(B)\mathcal{E}_{is}^B + \mathbb{P}_i(G)\mathcal{E}_{is}^G. \tag{16}$$

This gives rise to an intuitive decomposition of the elasticity of local emissions with respect to regulatory stringency:

$$\frac{\partial \log(\mathcal{E}_{is})}{\partial \log(\tau_{is}^{\mathcal{E}})} = \underbrace{\psi_{is}^{\mathcal{E},G}\frac{\partial \log(\mathcal{E}_{is}^G)}{\partial \log(\tau_{is}^{\mathcal{E}})}}_{\substack{\text{chg. in emissions}\\ \text{from green firms}}} + \underbrace{\psi_{is}^{\mathcal{E},B}\frac{\partial \log(\mathcal{E}_{is}^B)}{\partial \log(\tau_{is}^{\mathcal{E}})}}_{\substack{\text{chg. in emissions}\\ \text{from brown firms}}} + \underbrace{\frac{\mathcal{E}_{is}^G - \mathcal{E}_{is}^B}{\mathcal{E}_{is}}\frac{\partial \mathbb{P}_i(G)}{\partial \log(\tau_{is}^{\mathcal{E}})}}_{\text{technology switching}}, \tag{17}$$

where $\psi_{is}^{\mathcal{E},T} \equiv \frac{\mathcal{E}_{is}^T \mathbb{P}_i(T)}{\mathcal{E}_{is}}$ for $T \in \{B,G\}$ denotes the share of total emissions in industry i and state s attributable to technology T.

As shown in Appendix B.5, the within-technology elasticities consist of three components:

$$\frac{\partial \log \mathcal{E}_{is}^T}{\partial \log \tau_{is}^{\mathcal{E}}} = \underbrace{\gamma_i^T - 1}_{\text{substitution}} + \underbrace{\gamma_i^T \varepsilon^D}_{\text{scale}} - \underbrace{\frac{\gamma_i^T}{\sigma_i^F}}_{\text{firm location}}. \tag{18}$$

Each term captures a distinct channel through which regulation affects emissions. The substitution effect ($\gamma_i^T - 1 < 0$) reflects firms shifting away from other inputs. The scale effect ($\gamma_i^T \varepsilon^D < 0$) captures the reduction in output due to higher costs. The location effect ($-\gamma_i^T/\sigma_i^F < 0$) represents firm relocation in response to local regulation. The scale and location effects are larger in magnitude for brown firms, since $\gamma_i^B > \gamma_i^G$, while the substitution effect is larger for green firms.[12]

In addition to adjusting input mix and location, firms may also respond to regulation by investing in the green technology. This response gives rise to the third term in equation (17). Intuitively, stricter emissions regulation increases the share of firms that adopt the green technology. See Appendix B.5 for the full derivation of the emissions elasticity.

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

$$\frac{\partial \log(L_{is}^D)}{\partial \log(\tau_{is}^{\mathcal{E}})} = \underbrace{\psi_{is}^{L,G} \frac{\partial \log(L_{is}^{D,G})}{\partial \log(\tau_{is}^{\mathcal{E}})}}_{\text{chg. in labor from green firms}} + \underbrace{\psi_{is}^{L,B} \frac{\partial \log(L_{is}^{D,B})}{\partial \log(\tau_{is}^{\mathcal{E}})}}_{\text{chg. in labor from brown firms}} + \underbrace{\frac{L_{is}^{D,G} - L_{is}^{D,B}}{L_{is}^D} \frac{\partial \mathbb{P}_i(G)}{\partial \log(\tau_{is}^{\mathcal{E}})}}_{\text{technology switching}}, \tag{19}$$

where $\psi_{is}^{L,T} \equiv \frac{L_{is}^{D,T} \mathbb{P}_i(T)}{L_{is}^D}$ for $T \in \{B, G\}$ denotes the share of total labor demand in industry i and state s attributable to technology T.

The within-technology elasticities follow the same structure as emissions and consist of substitution, scale, and firm relocation effects:

$$\frac{\partial \log L_{is}^{D,T}}{\partial \log \tau_{is}^{\mathcal{E}}} = \underbrace{\gamma_i^T}_{\text{substitution}} + \underbrace{\gamma_i^T \varepsilon^D}_{\text{scale}} - \underbrace{\frac{\gamma_i^T}{\sigma_i^F}}_{\text{firm location}}, \tag{20}$$

The scale and location effects are identical to equation (18). The substitution effect is positive because labor and emissions are substitutes: stricter emissions regulation induces firms to increase reliance on labor and other inputs. Empirically, Table 1 shows that wages and employment fall after the introduction of emissions regulation, which suggests that the scale and firm location effects dominate.

The sign of the technology switching term is ambiguous. While $\frac{\partial \mathbb{P}_i(G)}{\partial \log(\tau_{is}^{\mathcal{E}})} > 0$, the net effect depends on whether green firms are more or less labor-intensive than brown firms i.e. whether $L_{is}^{D,G} > L_{is}^{D,B}$. For tractability, I assume that $L_{is}^{D,G} \approx L_{is}^{D,B}$, so that:

$$\frac{\partial \log(L_{is}^D)}{\partial \log(\tau_{is}^{\mathcal{E}})} = \psi_{is}^{L,G} \left(\gamma_i^G + \gamma_i^G \varepsilon^D - \frac{\gamma_i^G}{\sigma_i^F} \right) + \psi_{is}^{L,B} \left(\gamma_i^B + \gamma_i^B \varepsilon^D - \frac{\gamma_i^B}{\sigma_i^F} \right). \tag{21}$$

[12] 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.

4.4 Equilibrium Incidence of Emissions Regulation

4.4.1 Emissions

Equation (17) shows the change in emissions of firms in industry i and state s resulting from a change in $\tau_{is}^{\mathcal{E}}$. 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 $\phi_{fs} = \phi_{fs'}$. In other words, the two states only differ in their emissions regulatory stringency.[13] 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 alternative compliance strategies rather than complementary ones.[14] Under these assumption, the effect of a change in local emissions regulation on industry-wide emissions is:

$$\dot{\mathcal{E}}_i = \underbrace{\frac{\mathcal{E}_{is}^G - \mathcal{E}_{is}^B}{\mathcal{E}_{is}} \frac{\partial \mathbb{P}_i(G)}{\partial \log(\tau_{is}^{\mathcal{E}})}}_{\text{technology switching}} + \sum_{T \in \{B,G\}} \psi_{is}^{\mathcal{E},T} \left[\underbrace{\left(\gamma_i^T - 1 + \gamma_i^T \varepsilon^D - \frac{\gamma_i^T}{\sigma_i^F} \right)}_{\text{substitution + scale + relocation from } s} + \underbrace{\sum_{s' \neq s} \frac{\exp\left(\frac{v_{is'}^T}{\sigma_i^F}\right)}{\sum_{s'' \neq s} \exp\left(\frac{v_{is''}^T}{\sigma_i^F}\right)} \left(\frac{\tau_{is'}}{\tau_{is}}\right)^{\gamma_i^T - 1} \frac{\gamma_i^T}{\sigma_i^F}}_{\text{relocation into } s'} \right] \tag{22}$$

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 $\tau_{is'}^{\mathcal{E}} < \tau_{is}^{\mathcal{E}}$, 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., $\tau_{is'}^{\mathcal{E}} = \tau_{is}^{\mathcal{E}}$ 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.

[13] 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. Thus, emissions regulation is likely to be the primary driver of emissions intensity differences across locations for relocating firms.

[14] 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.

4.4.2 Labor Markets

Since workers inelastically supply one unit of labor, $L_{is} = N_{is}$. Wages are implicitly defined by equating

$$N_{is}(w_{is}; \overline{A}_{is}) = \mathbb{P}_i(G) L_{is}^{D,G}(w_{is}; \tau_{is}^{\mathcal{E}}, \overline{\phi}_{is}, z_{is}) + (1 - \mathbb{P}_i(G)) L_{is}^{D,B}(w_{is}; \tau_{is}^{\mathcal{E}}, \overline{\phi}_{is}, z_{is}),$$

where labor demand is a weighted average of green and brown firm demand and the weights endogenously respond to regulation.

The effect of stricter emissions regulation on wages is:

$$\dot{w}_{is} \equiv \frac{\partial \log w_{is}}{\partial \log \tau_{is}^{\mathcal{E}}} = \frac{\frac{\partial \log L_{is}^{D}}{\partial \log \tau_{is}^{\mathcal{E}}}}{(\varepsilon^{LS} - \varepsilon^{LD})}, \tag{23}$$

where ε^{LS} and ε^{LD} denote the wage elasticity of labor supply and demand, respectively. The numerator of this expression follows directly from equation (21). From the household problem, $\varepsilon^{LS} = \frac{1}{\sigma^H}$. From equation (65), $\varepsilon^{LD} = \gamma_i^l + \gamma_i^l \epsilon^D - 1 - \frac{\gamma_i^l}{\sigma_i^F}$, so the change in wages is given by:

$$\dot{w}_{is} = \frac{\psi_{is}^{L,G} \left(\gamma_i^G + \gamma_i^G \varepsilon^D - \frac{\gamma_i^G}{\sigma_i^F} \right) + \psi_{is}^{L,B} \left(\gamma_i^B + \gamma_i^B \varepsilon^D - \frac{\gamma_i^B}{\sigma_i^F} \right)}{\frac{1}{\sigma^H} - \left(\gamma_i^l + \gamma_i^l \varepsilon^D - 1 - \frac{\gamma_i^l}{\sigma_i^F} \right)}. \tag{24}$$

The numerator of $\dot{w}_{is}$ captures the effect of the regulatory change on labor demand as given by equation (21). The first term in the denominator, ε^{LS} captures the worker's response to the change in labor demand. If σ^H parameter 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, ε^{LD} captures 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 previous section.

4.4.3 Corporate Profits and Equity Returns

Let $\omega_{fs} = \frac{\pi_{ns}}{\sum_{s'} \pi_{ns'}}$ 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 $\tau_{is}^{\mathcal{E}}$ to τ_{is}^{new} is given by:

$$\dot{\pi}_n \approx \omega_{ns} \Bigg(\underbrace{-\frac{\chi_n(g_n)(1-\lambda_g)}{(1-\chi_n(g_n)g_n)} \frac{\partial \mathbb{P}_n(G)}{\partial \log \tau_{is}^{\mathcal{E}}}}_{\text{chg. in switching costs}} + (1+\varepsilon^D) \Bigg[\underbrace{\frac{\exp \frac{v_{is}^{T_{ns}}(\tau_{is}^{\text{new}})}{\sigma_i^F}}{\sum_{s'} \exp \frac{v_{is'}^{T_{ns}}}{\sigma_i^F}}}_{\mathbb{P}(\text{stay in } s)} \underbrace{\left(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is}\right) \Delta \log \tau_{is}^{\mathcal{E}}}_{\text{chg. in gross profits in } s}$$
$$- \sum_{s' \neq s} \underbrace{\frac{\exp \frac{v_{is'}^{T_{ns}}}{\sigma_i^F}}{\sum_{s''} \exp \frac{v_{is''}^{T_{ns}}}{\sigma_i^F}}}_{\mathbb{P}(\text{move to } s')} \underbrace{\left((\overline{\phi}_{is'} - \overline{\phi}_{is}) - \gamma_i^l (\log w_{is'} - \log w_{is}) - \gamma_i^{T_{ns}} (\log \tau_{is'}^{\mathcal{E}} - \log \tau_{is}^{\mathcal{E}}) \right)}_{\substack{\text{expected chg. in} \\ \text{gross profits from} \\ \text{moving to } s'}} \Bigg] \Bigg). \tag{25}$$

This expression captures the three channels through which emissions regulation affects firm profits. First, increased regulatory stringency may induce firms to operate the green technology in a larger proportion of their facilities (higher g_n), which comes with an associated increase in switching costs. Second, profits of facilities that remain in state s are affected by the change in emissions tax directly through γ_i^T and indirectly through the change in wages. Third, some facilities may relocate in response to the regulation, and their profits will change based on differences between the origin and destination states.

Since the initial choice of location was profit maximizing, it must be that the expected change in profits from moving to s' is negative. Thus, all else equal, the decrease in expected profits should be larger for firms that choose to move. In other words, the magnitude of the decrease in profits conditional on staying is a lower bound on the total (within-technology) effect.

As shown in Appendix B.6.2, 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.

4.4.4 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.[15] 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-

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

invariant) investment income component and using standard properties of the T1EV distribution,

$$\mathcal{V}^H = \mathbb{E}\left[\log(\theta' R)\right] + \sigma^H \log\left(\sum_{(is)} \exp \frac{\log w_{is} + \overline{A}_{is}}{\sigma^H}\right). \tag{26}$$

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

$$\dot{\mathcal{V}}^H = \underbrace{\sum_{n \in N^i} \rho_n \dot{\pi}_n}_{\equiv \dot{\mathcal{V}}_\pi} + \underbrace{N_{is}\left(\mathbb{P}^{is}_{\text{stay}} \dot{w}_{is} + \sum_{(is)' \neq is} \mathbb{P}^{is \to (is)'}_{\text{move}} \Delta \mathcal{V}_{is \to (is)'}\right)}_{\equiv \dot{\mathcal{V}}_w}, \tag{27}$$

where N^i are the set of firms in industry i and $\rho_n \equiv \frac{\theta_n e^{\mu_n}}{\sum_{n'} \theta_{n'} e^{\mu_{n'}}}$ is the fraction of the investors' expected return generated by firm n. The full expression for $\dot{\mathcal{V}}_w$ is derived in Appendix B.7. The goal of the quantitative exercise that follows is to compute the magnitudes of $\dot{\mathcal{V}}_\pi$ and $\dot{\mathcal{V}}_w$ and compare them both to each other and to the magnitude of the welfare benefit arising from emissions reduction.

The total welfare gain resulting from a discrete policy change $\Delta\tau^{\mathcal{E}}_{is}$ can then be approximated:

$$\dot{\mathcal{V}}^{\mathcal{E}} \approx \Delta\tau^{\mathcal{E}}_{is} \times \dot{\mathcal{E}}_i \times \text{SCC}, \tag{28}$$

where $\dot{\mathcal{E}}_i$ is given by equation (22) 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 (27) and (28) can be used to infer the value of SCC that will equate economic costs and environmental benefits.

5 Estimation

5.1 Exact Structural Effects of Emissions Regulation

Following Suárez Serrato and Zidar (2016), I use the log-labor supply equation (equation (7)), the log of the establishment location equation (equation (12)), the log of firm emissions (equation (76)) and the log-labor demand equation (equation (83)) to derive a simultaneous equations model that captures the equilibrium

effects of emissions regulation. Stacking these four equations yields:

$$\boldsymbol{A}\boldsymbol{Y}_{is,t} = \boldsymbol{B}\boldsymbol{Z}_{is,t} + \boldsymbol{e}_{is,t}, \tag{29}$$

where $\boldsymbol{Y}_{is,t}$ is a vector of the four endogenous variables (wage changes, employment changes, emissions changes and change in the number of establishments), $\boldsymbol{Z}_{is,t} = [\Delta \log \tau^{\mathcal{E}}_{is,t}]$ is a vector of shocks to local emissions regulation, $\boldsymbol{A}$ 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. The exact form of $\boldsymbol{Y}_{is,t}$, $\boldsymbol{A}$ and $\boldsymbol{B}$ is:

$$\boldsymbol{Y}_{is,t} = \begin{bmatrix} \Delta \log w_{is,t} \\ \Delta \log N_{is,t} \\ \Delta \log \mathcal{E}_{is,t} \\ \Delta \log E_{is,t} \end{bmatrix} \quad \boldsymbol{A} = \begin{bmatrix} -\frac{1}{\sigma^H} & 1 & 0 & 0 \\ \gamma_i^l(1+\varepsilon^D) - 1 - \frac{\gamma_i^l}{\sigma^F} & -1 & 0 & 0 \\ \gamma_i^l(1+\varepsilon^D) & 0 & -1 & 1 \\ \frac{\gamma_i^l}{\sigma^F} & 0 & 0 & 1 \end{bmatrix} \quad \boldsymbol{B} = \begin{bmatrix} 0 \\ \bar{\gamma}_i^{\mathcal{E}}\left(1+\varepsilon^D - \frac{1}{\sigma^F}\right) \\ \bar{\gamma}_i^{\mathcal{E}}(1+\varepsilon^D) - 1 \\ -\frac{\bar{\gamma}_i^{\mathcal{E}}}{\sigma^F}, \end{bmatrix} \tag{30}$$

where $\bar{\gamma}_i^{\mathcal{E}} = \mathbb{P}_i(G)\gamma_i^G + (1 - \mathbb{P}_i(G))\gamma_i^B$.

5.1.1 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. The magnitude of this implicit tax is not directly observable in the data. To evaluate the incidence and welfare effects of regulation within the structural model, I use abnormal stock returns of affected firms to recover an equivalent change in the implicit pollution tax rate.

By inverting the model's profit equation, I back out the implied change in the pollution 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 (29). I abstract from the relocation and technology switching terms in(25), treating the observed change in expected profits as if the firm were unable to change location or technology.[16] Since the option to relocate or improve technology can only improve the firm's post-regulation value, this simplification leads to a lower bound on the regulation's true stringency.

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

[16]Ignoring relocation is useful because without it, I would need to estimate $\overline{\phi}_{is'} - \overline{\phi}_{is}$ and $\log \tau^{\mathcal{E}}_{is'} - \log \tau^{\mathcal{E}}_{is}$ for each state $s' \neq s$.

because investors exhibit non-pecuniary preferences for greenness. 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. 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.

Finally, I set $\dot{w}_{is} = 0$. This simplification reflects the fact that while average wages at the industry–state level tend to fall following the enactment of environmental regulations, firms generally do not reduce wages for incumbent workers. As a result, from the perspective of a firm evaluating the profitability of continuing operations in a regulated location, it is reasonable to assume that wage costs remain largely unchanged in the short run.[17] In the model, falling wages partially offset the regulatory burden on firms, so this assumption reinforces the interpretation of the estimated tax change as a conservative measure of regulatory stringency. Overall, the resulting estimates should be interpreted as the minimum change in implicit emissions tax consistent with market valuation.

Using equations (**??**) and (**??**) and imposing the simplifying assumptions, I obtain:

$$\Delta \log \tau_{is}^{\mathcal{E}} \approx \frac{\dot{\pi}_n}{(1+\varepsilon^D)\omega_{ns}\gamma_n^{\mathcal{E}}}. \tag{31}$$

I use this expression to modify the structural system given by equations (29) and (30):

$$\boldsymbol{A}\boldsymbol{Y}_{is,t} = \tilde{\boldsymbol{B}}\tilde{\boldsymbol{Z}}_{is,t} + \tilde{\boldsymbol{e}}_{is,t}, \tag{32}$$

where $\tilde{\boldsymbol{Z}}_{is,t}$ is a vector of abnormal equity returns of exposed firms around enactment of new regulations. Equation (31) implies that when replacing the vector of tax shocks $\boldsymbol{Z}_{is,t}$ with the vector of returns $\tilde{\boldsymbol{Z}}_{is,t}$, the coefficient vector becomes:

$$\tilde{\boldsymbol{B}} = \frac{1}{(1+\varepsilon^D)\overline{\omega_{is}\gamma_i^{\mathcal{E}}}} \begin{bmatrix} 0 \\ \bar{\gamma}_i^{\mathcal{E}}\left(1+\varepsilon^{PD}-\frac{1}{\sigma^F}\right) \\ \bar{\gamma}_i^{\mathcal{E}}(1+\varepsilon^{PD})-1 \\ -\frac{\bar{\gamma}_i^{\mathcal{E}}}{\sigma^F} \end{bmatrix}, \tag{33}$$

where $\overline{\omega_{is}\gamma_i^{\mathcal{E}}}$ is the average of $\omega_{fs}\gamma_f^{\mathcal{E}}$ across firms in industry i.

[17] This is consistent with the large literature documenting wage stickiness. For a recent example, see Davis and Krolikowski (2025).

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

$$\boldsymbol{Y}_{is,t} = \underbrace{\boldsymbol{A}^{-1}\tilde{\boldsymbol{B}}}_{\equiv \boldsymbol{\beta}^{Reg}} \tilde{\boldsymbol{Z}}_{is,t} + \boldsymbol{A}^{-1}\boldsymbol{e}_{is,t}, \tag{34}$$

where the vector of reduced form coefficients, $\boldsymbol{\beta}^{Reg}$ is given by:

$$\boldsymbol{\beta}^{Reg} = \begin{bmatrix} \beta^W \\ \beta^N \\ \beta^{\mathcal{E}} \\ \beta^E \end{bmatrix} = \frac{1}{(1+\varepsilon^{PD})\overline{\omega_{is}\gamma_i^{\mathcal{E}}}} \begin{bmatrix} \dot{w} \\ \frac{\dot{w}}{\sigma^W} \\ \overline{\gamma}_i^{\mathcal{E}}(1+\varepsilon^{PD}) - 1 - \frac{\overline{\gamma}_i^{\mathcal{E}}}{\sigma_i^F} \\ -\frac{\overline{\gamma}_i^{\mathcal{E}}}{\sigma_i^F} - \frac{\gamma_i^l}{\sigma_i^F} \cdot \dot{w} \end{bmatrix}, \tag{35}$$

where $\dot{w}$ is given by equation (23). The expression for β^N comes from the fact that the elasticity of labor supply is $\frac{1}{\sigma^W}$ (i.e. labor supply is less elastic when σ^W is large because workers are less willing to move locations or industries). The expression for $\beta^{\mathcal{E}}$ follows directly from equation 18. The change in the number of establishments is the change that would result if wages were held constant (first term) and an adjustment that captures the effect of the equilibrium change in wages. The scalar multiplier, $\frac{1}{(1+\varepsilon^{PD})\overline{\omega_{is}\gamma_i^{\mathcal{E}}}}$, rescales the structural response to express the impact of a one-unit change in observed returns, rather than a one-unit change in the unobserved emissions tax.

5.1.2 Quantifying Regulatory Stringency from Equity Returns

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, well-defined policy shock, such as California's cap-and-trade program, where quantifying the size of the shock is less critical because the focus is on one event. 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 measure stringency directly. To overcome this challenge, 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 stringency of different policies in a consistent, data-driven way.

To infer policy stringency from observed equity returns, I rely on the idea that the impact of a given regulation on firm value depends on three factors: the regulation's (unobserved) stringency, the firm's exposure to the regulated state, and the firm's emissions intensity. While stringency is unobserved, both geographic exposure and emissions intensity can be measured using firm-level data, enabling me to recover stringency

from cross-sectional variation in returns. I formally derive the relationship between returns and stringency in Section 4.4.3.

For each regulation, r, I run the following cross-sectional regression using the set of firms in industries affected by the regulation:

$$\tilde{R}_{n,r} = \delta_{1,r}\text{RevShare}_{ns(r),t(r)-1} \times \text{CO2Int}_{n,t(r)-1} + \delta_{2,r}\text{RevShare}_{ns(r),t(r)-1} + \delta_{3,r}\text{CO2Int}_{n,t(r)-1} + \epsilon_{n,r}, \quad (36)$$

where $\tilde{R}_{n,r}$ is the monthly abnormal return of stock n during the event window for regulation r, $\text{RevShare}_{ns(r),t(r)-1}$ is the proportion of firm n's revenue generated in state $s(r)$ and $\text{CO2Int}_{n,t(r)-1}$ is firm n's carbon intensity, both measured in the year prior to enactment of regulation r. Abnormal returns are constructed by removing the effects of the Fama and French (2015) factors, momentum and earnings surprises. Where available, I define the event window from bill introduction to gubernatorial signing. For regulations enacted by the state environmental regulator or for legislation with missing timing data, I use a four month window prior to enactment.[18] I standardize $CO2Int_{n,t(r)-1}$ to have mean zero and unit variance across firms in the industries affected by regulation r.[19] I use the estimate of $\delta_{1,r} + \delta_{2,r}$ is a proxy for the stringency of regulation r. This captures the total effect of the regulation on a fully exposed firm that is one standard deviation more emissions-intensive than average, making it a useful measure of how costly the policy is for a representative "brown" firm. Figure 5 shows how the estimates of $\delta_{1,r} + \delta_{2,r}$ vary by policy type. The ordinal ranking of the policy types is consistent with intuition.

5.2 Reduced Form Incidence Estimates

As a first pass at using the model intuition to assess the welfare impacts of local emissions regulation, I first estimate the vector of reduced form effects, $\boldsymbol{\beta}^{Reg}$. For each industry–state outcome $y_{is,t}$, I estimate:

$$y_{is,t} = \sum_{h=1}^{5} \beta_h^{\text{Reg},y} \cdot \tilde{Z}_{is,t-h} + \gamma_{it} + \gamma_{st} + \epsilon_{is,t} \quad (37)$$

and then sum over horizons to obtain a cumulative five year effect. The coefficient estimates can be found in Table 4.

As a back-of-the-envelope welfare calculation, I observe the following:

1. **Investors:**

[18] I use four months because it matches the average window length observed for regulations with available legislative timing data.

[19] For regulations that target a single industry, I standardize within that industry. For regulations that apply to multiple industries, I standardize across all firms in the affected industries.

- Regulatory shock is scaled to represent a 1% decline in firm value for a firm that operates entirely in the regulated state
- Average industry/state/year profits≈ $850 million
- 1% decline≈ $8.5 million per year

2. **Workers:**
   - Average industry/state/year total wage ≈ $13 billion ($74,000 per worker)
   - 2% reduction over five years≈ $68 million per year
3. **Emissions:**
   - Average industry/state/year emissions≈64 million tons
   - 20.6% reduction over five years≈2.6 million tons per year
   - SCC estimates range from $50-$250 $\implies$ $130 million-$650 million welfare benefit (per year)

With the caveat that these calculations are a major simplification (among other reasons, they ignore migration, job loss, changes in discount rates, firm relocation, spillovers, etc.), these estimates suggest that, using the conservative estimate of $SCC = \$50$, the welfare benefit of reduced emissions is about 1.7 times the welfare loss. In addition, the welfare loss falls is borne primarily by workers.

5.3 Structural Estimation

While this reduced form estimation exercise was loosely informed by the model, I am working on using simulated method of moments to estimate the key parameters, which will allow me to much more thoughtfully quantify the impacts of emissions regulation. In addition, estimation will enable me to analyze policy counterfactuals in order to better understand what characteristics of regulation best balance the tradeoff of economic costs and environmental benefits. For example, the model suggests that emissions reduction is larger when σ_i^F is large (alternative locations are less attractive), χ_n^0 is low (technology switching is less costly) or $\tau_{is'}$ is high (other states already have strict regulation). Combining the general equilibrium model with return based stringency estimates will allow me to better understand when emissions regulation can be effective even in the absence of coordination across jurisdictions.

6 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 133

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. I then 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. Preliminary estimates indicate that, on average, the social value of emissions reduction exceeds the economic costs, with most of these costs borne by workers through lower wages rather than by firm owners through reduced profits.

Several extensions are currently in progress. To supplement my reduced-form analyss, I am developing a Bartik-style IV strategy for firm-level outcomes, using revenue exposure to state GHG targets as an instrument for exposure to actual regulations. I am also working on a more detailed analysis of the extensive margin, including facility-level logit models of plant closure and firm-level analysis of openings, closures, and the characteristics predicting exit in response to regulation. In addition, I am exploring heterogeneity in effects along dimensions such as financial constraints (Bartram et al., 2022) and tradability. I am also working on a more detailed analysis of the impact of regulations on equity returns.

After completing the structural estimation, I will use the model to better understand what characteristics of regulation are associated with the largest net welfare gains. I would also like to address normative policy questions, such as which industries and states should be prioritized for regulation to maximize net benefits, and assessing whether state-level regulators are effectively trading off global emissions benefits against the local economic costs that fall disproportionately on their own constituents.

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Figures

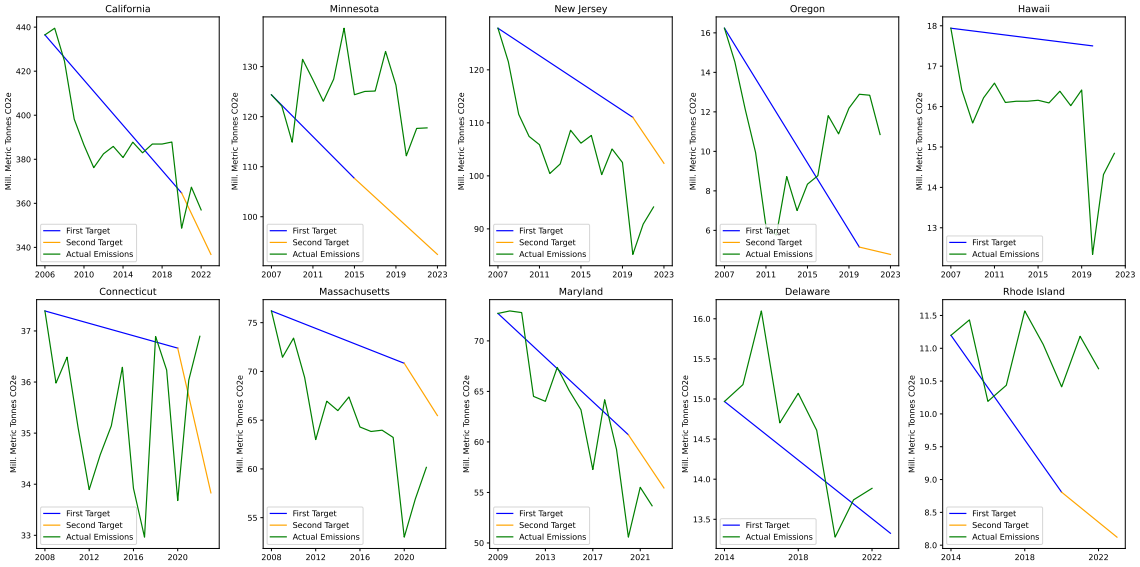


Figure 1: This figure shows targeted and actual emissions for states that passed targets before 2014. The blue and yellow lines show what emissions would be if the states were (linearly) adhering to their target. The green line plots actual statewide emissions since enactment of the target.

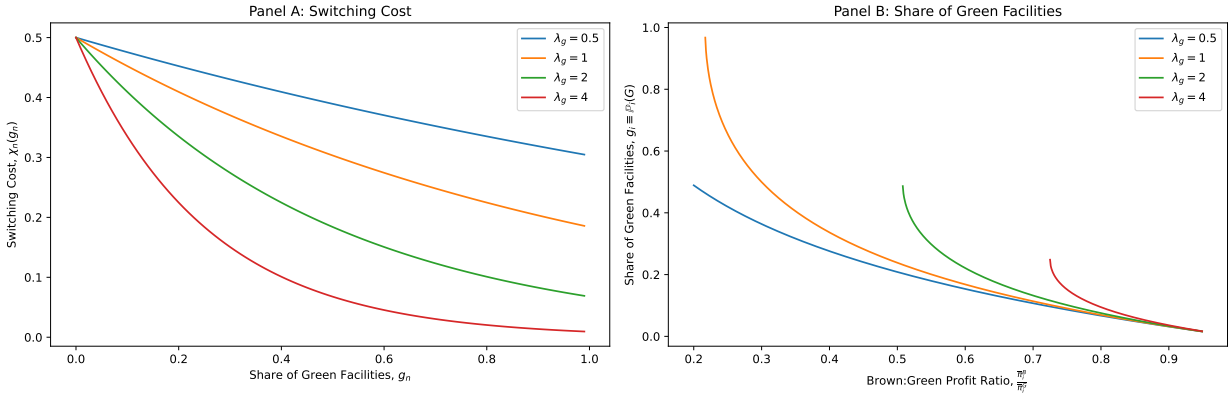


Figure 4: Panel A plots the switching cost, $\chi_n(g_n)$ as a function of the proportion of green facilities. Panel B plots the share of green facilities as a function of the ratio between brown and green profits. Both panels fix $\chi_n^0 = 0.5$. Panel B uses $\sigma_i^F = 0.2$ and $\varepsilon^D = -2.5$.

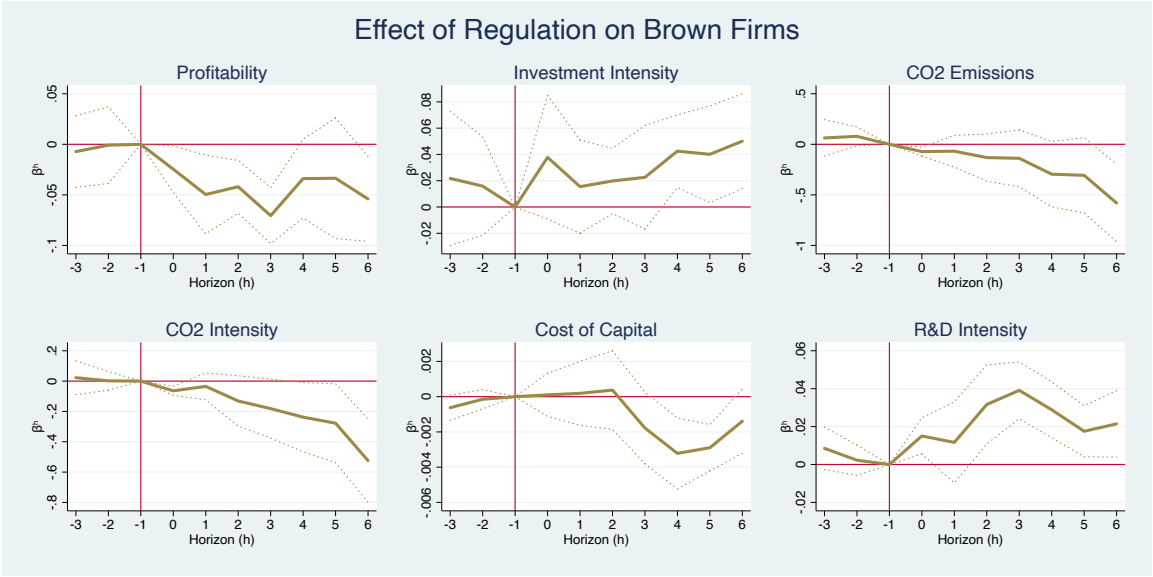


Figure 2: This figure shows estimates of β_B^h from the regression in equation 4, which capture the effect of new emissions regulations on firms with above-median emissions intensity. A firm is considered treated if the regulation applies to its industry and is enacted in a state where the firm has non-zero revenue. Standard errors are clustered by year, and the dotted lines show 95% confidence intervals.

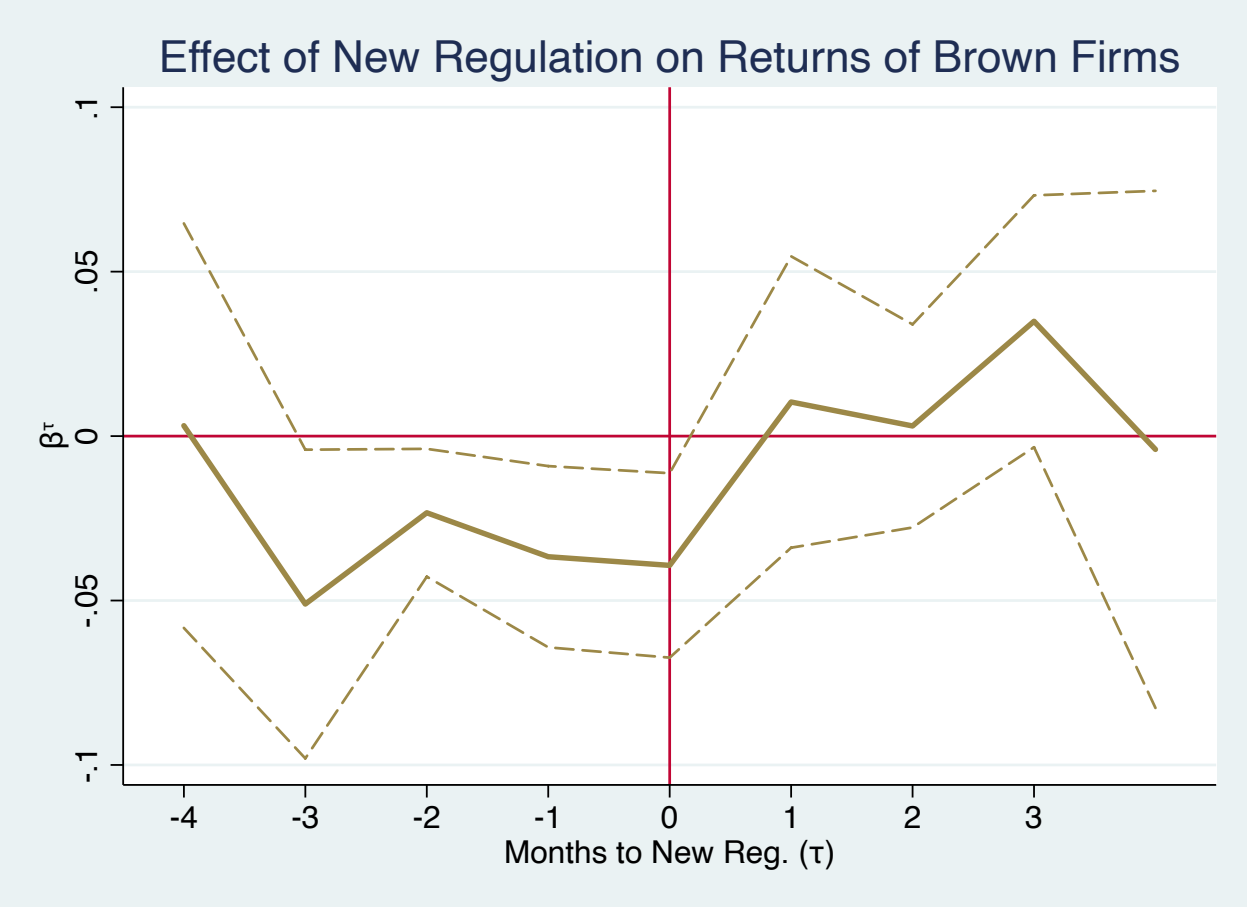


Figure 3: This figure plots estimates of β_B^h from the regression in equation (5), which capture the effect of new emissions regulation on monthly stock returns of affected firms. A firm is considered treated if it has above median emissions intensity and if the regulation applies to its industry and is enacted in a state where the firm has non-zero revenue. Standard errors are clustered by month, and the dotted lines show 95% confidence intervals.

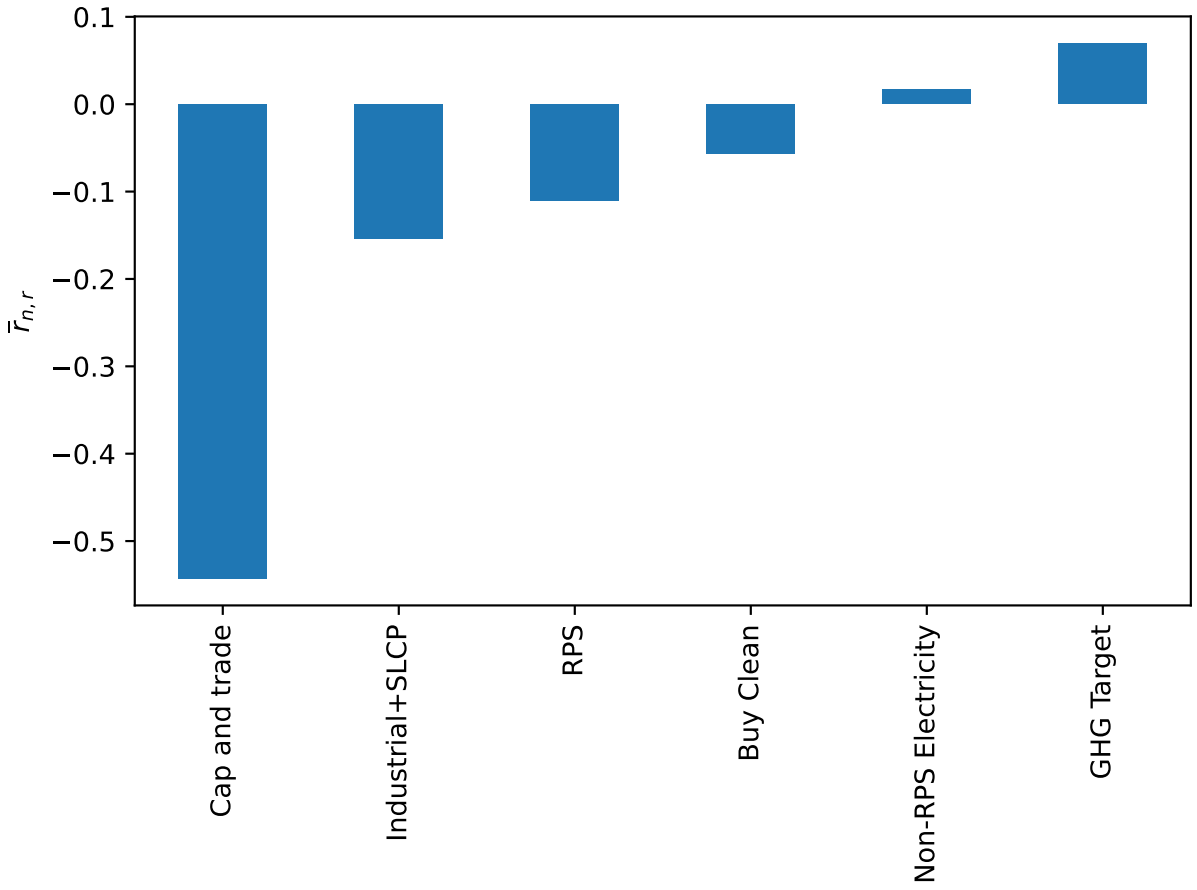


Figure 5: This figure plots the average value of $\delta_{1,r} + \delta_{2,r}$ from equation (36) by policy category.

Tables

	$\log(L_{ist})$	$\log(w_{ist})$	$\log(Y_{ist})$	$\log(\mathcal{E}_{ist})$	$\log(\mathcal{E}_{ist}/Y_{ist})$
$\text{Target}_{st} \times \text{Brown}_i$	-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 1: 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.

Panel A: GHG Targets

	$\log(L_{jst})$	$\log(Rev_{jst})$	$\log(\mathcal{E}_{jst})$	$\log\left(\frac{\mathcal{E}_{jst}}{Rev_{jst}}\right)$
Target_{st}	-0.029**	-0.011	-0.082***	-0.071**
	(0.011)	(0.025)	(0.017)	(0.030)
Const.	3.511***	16.909***	11.617***	-5.293***
	(0.002)	(0.005)	(0.004)	(0.006)
Facility FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
Obs.	19656	19656	19656	19656

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

Panel B: Number of Regulations (OLS)

	$\log(L_{jst})$	$\log(Rev_{jst})$	$\log(\mathcal{E}_{jst})$	$\log\left(\frac{\mathcal{E}_{jst}}{Rev_{jst}}\right)$
$\#REG_{jst}$	-0.035	-0.065	-0.008	0.057
	(0.020)	(0.037)	(0.041)	(0.047)
Const.	3.513***	16.923***	11.601***	-5.321***
	(0.005)	(0.009)	(0.010)	(0.011)
Facility FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
Obs.	19656	19656	19656	19656

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

Panel C: Number of Regulations (IV)

	$\log(L_{jst})$	$\log(Rev_{jst})$	$\log(\mathcal{E}_{jst})$	$\log\left(\frac{\mathcal{E}_{jst}}{Rev_{jst}}\right)$
$\#REG_{jst}$	-0.375*	-0.150	-1.078***	-0.928*
	(0.182)	(0.329)	(0.266)	(0.423)
Facility FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
Obs.	19656	19656	19656	19656
First-Stage F	29.24	29.24	29.24	29.24

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

Table 2: This table presents results from regressions of facility-level outcomes on local emissions regulation. Panel A reports estimates from a difference-in-difference using state-level GHG targets. 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-level emissions intensity. All standard errors are clustered by industry and state.

Table 4: Estimates of $\boldsymbol{\beta}^{Reg}$ from equation (37)

Appendix

A Supplementary Tables and Figures

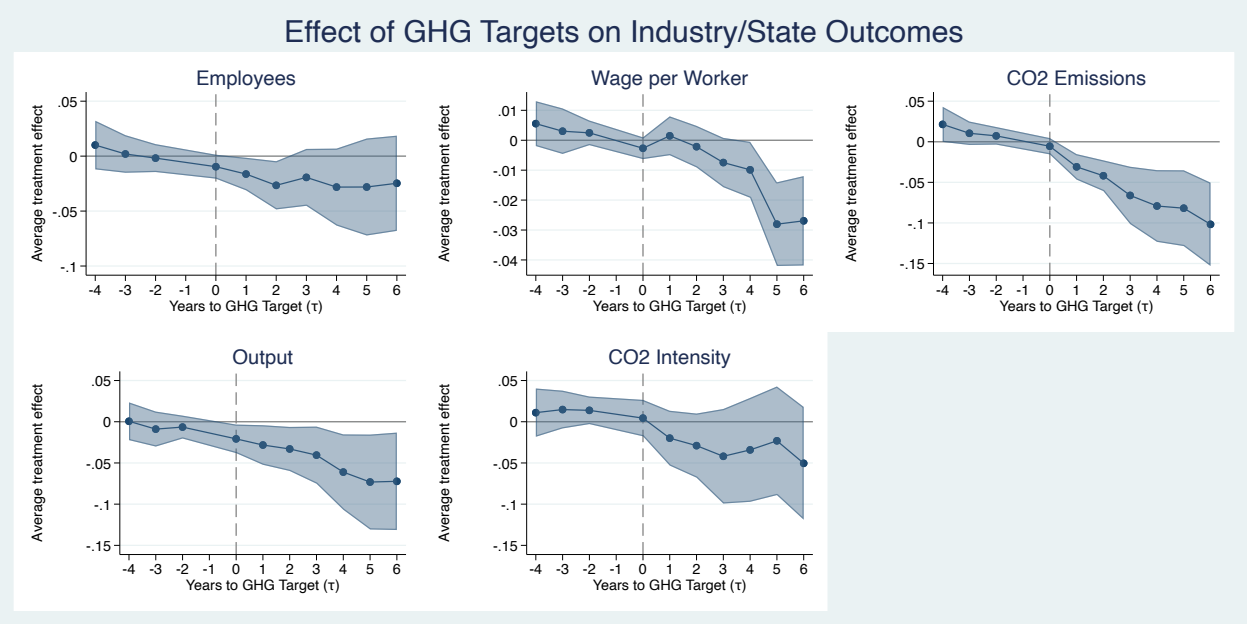


Figure 6: Sun and Abraham (2021) regressions of industry/state level outcomes on GHG target introduction.

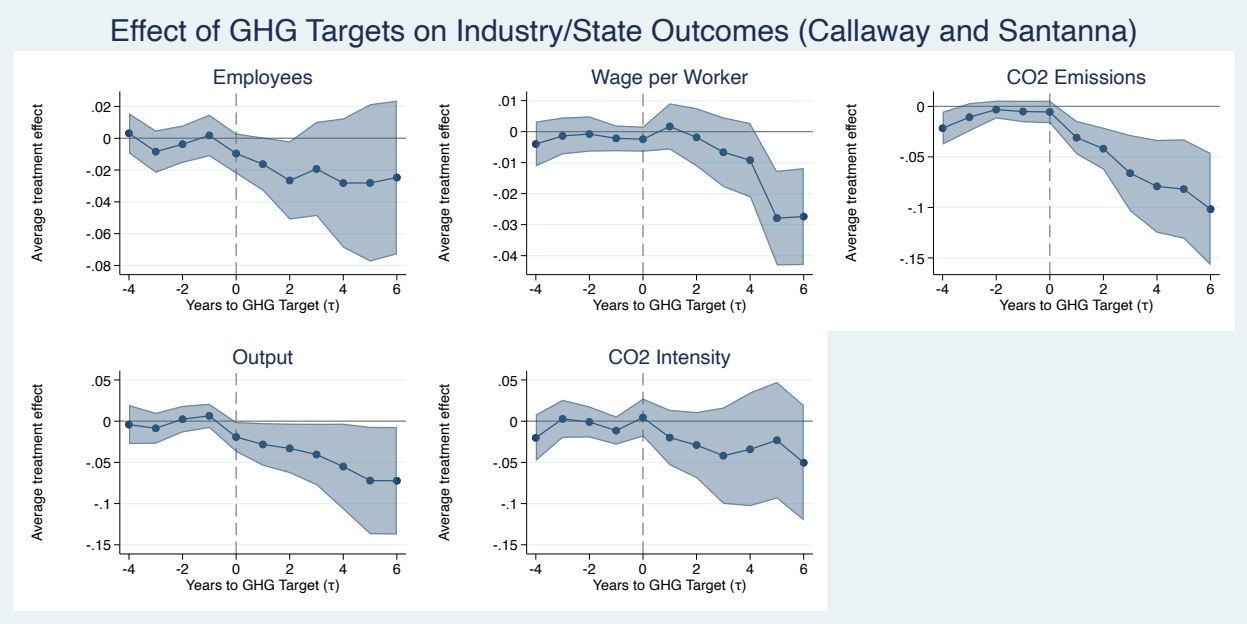


Figure 7: Callaway and Sant'Anna (2021) regressions of industry/state level outcomes on GHG target introduction.

B Derivations and Proofs

B.1 Solution to the Household's Problem

B.1.1 Consumption and Location Choice

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

$$\max_{\{x_{hj}\}_{j\in J}} \quad \log A_{his} + \log X_h \quad \text{s.t.} \int_{j\in J} p_j x_{hj} dj = w_{is}\theta_h' R, \tag{38}$$

where $X_h = \left(\int_{j\in J} x_{hj}^{\frac{\varepsilon^D+1}{\varepsilon^D}} dj\right)^{\frac{\varepsilon^D}{\varepsilon^D+1}}$. The Lagrangian is:

$$\mathcal{L}_1 = \log A_{his} + \frac{\varepsilon^D}{\varepsilon^D+1}\log\left(\int_{j\in J} x_{hj}^{\frac{\varepsilon^D+1}{\varepsilon^D}} dj\right) + \lambda_1\left(w_{is}\theta_h' R - \int_{j\in J} p_j x_{hj} dj\right). \tag{39}$$

Let $P = \left(\int_{j\in J} p_j^{1+\varepsilon^D} dj\right)^{\frac{1}{1+\varepsilon^D}}$ denote the CES price index. The first order conditions are:

$$[x_{hj}]: \quad x_{hj} = \lambda_1^{\varepsilon^D} p_j^{\varepsilon^D} X_h^{\varepsilon^D+1} \tag{40}$$

$$[X_h]: \quad X_h = \frac{1}{\lambda_1 P} \tag{41}$$

$$[\lambda_1]: \quad w_{is}\theta_h' R = \int_{j\in J} p_j x_h j dj \tag{42}$$

Normalize $P = 1$ and combine the three first order conditions to obtain:

$$x_{hj} = w_{is}\theta_h' R p_j^{\varepsilon^D}, \tag{43}$$

which (again using the $P = 1$ normalization) implies that $X_h = w_{is}\theta_h' R$.

The household's indirect utility from locating in state s and working in industry i is then:

$$V_{his}^H = \log(\theta_h' R) + \log w_{is} + \log A_{his}. \tag{44}$$

Decompose $\log A_{his} = \overline{A}_{is} + \xi_{his}$, 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:

$$H_{is} = \mathbb{P}\left(V_{his}^H = \max_{(is)'}\left\{V_{h(is)'}^H\right\}\right) = \frac{\exp\frac{u_{is}}{\sigma^H}}{\sum_{(is)'}\exp\frac{u_{(is)'}}{\sigma^H}}. \tag{45}$$

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.

B.1.2 Portfolio Choice

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

$$\max_{\theta_h} \quad \mathbb{E}[\log(\theta_h' R)] \quad \text{s.t. } 1 = \theta_h' \mathbf{1}. \tag{46}$$

Using the standard mean-variance approximation,

$$\mathbb{E}[\log(\theta_h' R)] \approx \theta_h' \mu - \frac{1}{2}\theta_h' \Sigma \theta_h. \tag{47}$$

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

$$\mathcal{L}_2 = \theta_h' \mu - \frac{1}{2}\theta_h' \Sigma \theta_h + \lambda_2(1 - \theta_h' \mathbf{1}). \tag{48}$$

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

$$[\theta_{h,n}]: \quad \theta_h = \Sigma^{-1}(\mu - \lambda_2 \mathbf{1}). \tag{49}$$

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

$$\lambda_2 = \frac{\mathbf{1}\Sigma^{-1}\mu - 1}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}, \tag{50}$$

so that:

$$\theta_h = \Sigma^{-1}\left(\mu - \frac{\mathbf{1}\Sigma^{-1}\mu - 1}{\mathbf{1}'\Sigma^{-1}\mathbf{1}}\mathbf{1}\right). \tag{51}$$

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

B.2 Profit- vs. Value-Maximizing Objective

The market value of the firm is given by:

$$\mathcal{M}_n = \mathbb{E}[m\pi_n], \tag{52}$$

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:

$$\log \mathcal{M}_n = \mathbb{E}[\log \pi_n] - \mathbb{E}[\log R_m] + \frac{1}{2}[\mathbb{V}\text{ar}(\log \pi_n) + \mathbb{V}\text{ar}(\log R_m)] - \mathbb{C}\text{ov}(\log \pi_n, \log R_m), \tag{53}$$

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).

B.3 Equilibrium Establishment Profits

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

$$x_{hj} = w_h \theta'_h R p_j^{\varepsilon^D}. \tag{54}$$

Market clearing implies that,

$$y_{js} = I p_j^{\varepsilon^D},$$

where $I = \sum_h w_h \theta' R$ 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 (8) can be rewritten:

$$\pi_{js}^T = \max_{l_{js}, \mathcal{E}_{js}, k_{js}} \quad \mathbb{E}\left[I^{-\frac{1}{\varepsilon^D}} y_{js}^{\frac{1}{\varphi}}\right] - w_{is} l_{js} - \tau_{is}^{\mathcal{E}} \mathcal{E}_{js} - \kappa_i k_{js}, \tag{55}$$

where $\varphi = \left[\frac{1}{\varepsilon^D} + 1\right]^{-1}$ 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):

$$\pi_{js}^{T} = \max_{l_{js},\mathcal{E}_{js},k_{js}} \underbrace{\mathbb{E}\left[I^{-\frac{1}{\varepsilon^{D}}}\eta_{n}^{\frac{1}{\varphi}}\right]}_{\equiv\Theta_{n}} \left(\underbrace{\phi_{js} l_{js}^{\gamma_{i}^{l}} \mathcal{E}_{js}^{\gamma_{i}^{T}} k_{js}^{1-\gamma_{i}^{l}-\gamma_{i}^{T}}}_{\equiv\tilde{y}_{js}}\right)^{\frac{1}{\varphi}} - w_{is} l_{js} - \tau_{is}^{\mathcal{E}} \mathcal{E}_{js} - \kappa_{i} k_{js}, \tag{56}$$

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:

$$[l_{js}]: \quad w_{is} = \frac{\Theta_{n}\gamma_{i}^{l}\tilde{y}_{js}^{\frac{1}{\varphi}}}{\varphi l_{js}} \tag{57}$$

$$[\mathcal{E}_{js}]: \quad \tau_{is}^{\mathcal{E}} = \frac{\Theta_{n}\gamma_{i}^{T}\tilde{y}_{js}^{\frac{1}{\varphi}}}{\varphi \mathcal{E}_{js}} \tag{58}$$

$$[k_{js}]: \quad \kappa_{i} = \frac{(1-\gamma_{i}^{l}-\gamma_{i}^{T})\tilde{y}_{js}^{\frac{1}{\varphi}}}{\varphi k_{js}}. \tag{59}$$

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

$$\frac{\mathcal{E}_{js}}{l_{js}} = \frac{w_{is}\gamma_{i}^{T}}{\tau_{is}^{\mathcal{E}}\gamma_{i}^{l}} \quad \text{and} \quad \frac{k_{js}}{l_{js}} = \frac{w_{is}(1-\gamma_{i}^{l}-\gamma_{i}^{T})}{\kappa_{i}\gamma_{i}^{l}}. \tag{60}$$

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

$$\begin{aligned} \tilde{y}_{js} &= \phi_{js} l_{js}^{\gamma_{i}^{l}} \left(\frac{w_{is}\gamma_{i}^{T}}{\tau_{is}^{\mathcal{E}}\gamma_{i}^{l}} l_{js}\right)^{\gamma_{i}^{T}} \left(\frac{w_{is}(1-\gamma_{i}^{l}-\gamma_{i}^{T})}{\kappa_{i}\gamma_{i}^{l}} l_{js}\right)^{1-\gamma_{i}^{l}-\gamma_{i}^{T}} \\ \implies l_{js} &= \frac{\tilde{y}_{js}}{\phi_{js}} \left(\frac{w_{is}}{\gamma_{i}^{l}}\right)^{\gamma_{i}^{l}-1} \left(\frac{\gamma_{i}^{T}}{\tau_{is}^{\mathcal{E}}}\right)^{-\gamma_{i}^{T}} \left(\frac{1-\gamma_{i}^{l}-\gamma_{i}^{T}}{\kappa_{i}}\right)^{-(1-\gamma_{i}^{l}-\gamma_{i}^{T})} \end{aligned} \tag{61}$$

Using this expression and the decomposition $\mathbb{E}[p_j y_{js}] = \Theta_n \tilde{y}_{js}^{\frac{1}{\varphi}}$, equation (57) becomes:

$$w_{is} = \frac{\mathbb{E}[p_j y_{js}]\gamma_{i}^{l}}{\varphi \frac{\tilde{y}_{js}}{\phi_{js}} \left(\frac{w_{is}}{\gamma_{i}^{l}}\right)^{\gamma_{i}^{l}-1} \left(\frac{\gamma_{i}^{T}}{\tau_{is}^{\mathcal{E}}}\right)^{-\gamma_{i}^{T}} \left(\frac{1-\gamma_{i}^{l}-\gamma_{i}^{T}}{\kappa_{i}}\right)^{-(1-\gamma_{i}^{l}-\gamma_{i}^{T})}}, \tag{62}$$

which implies that:

$$\mathbb{E}[p_j y_j] = \tilde{y}_{js}\varphi \underbrace{\frac{1}{\phi_{js}} \left(\frac{w_{is}}{\gamma_{i}^{l}}\right)^{\gamma_{i}^{l}} \left(\frac{\tau_{is}^{\mathcal{E}}}{\gamma_{i}^{T}}\right)^{\gamma_{i}^{T}} \left(\frac{\kappa_{i}}{1-\gamma_{i}^{l}-\gamma_{i}^{T}}\right)^{1-\gamma_{i}^{l}-\gamma_{i}^{T}}}_{\equiv c_{js}}, \tag{63}$$

which shows that prices are a markup over marginal cost. Combining this expression with equation (57) yields:

$$w_{is} l_{fs} = \gamma_i^l \tilde{y}_{js} c_{js}. \tag{64}$$

Again using $\mathbb{E}[p_j y_{js}] = \Theta_n \tilde{y}_{js}^{\frac{1}{\varphi}}$ and collecting $\tilde{y}_{js}$ terms in equation (63) implies that $\tilde{y}_{js} = \left(\frac{\varphi c_{js}}{\Theta_n}\right)^{\varepsilon^D}$, which can be plugged into equation (64) to obtain:

$$w_{is} l_{js} = \frac{\gamma_i^l \varphi^{\varepsilon^D} c_{js}^{1+\varepsilon^D}}{\Theta_n^{\varepsilon^D}} \tag{65}$$

Equations (63) and (64) imply that $\mathbb{E}[y_{js} p_j] = \frac{\varphi w_{is} l_{js}}{\gamma_i^l}$, which can be substituted into the original expression for expected profits:

$$\begin{aligned}
\pi_{js}^T &= \frac{\varphi w_{is} l_{js}}{\gamma_i^l} - w_{is} l_{js} - \tau_{is}^{\mathcal{E}} \frac{\mathcal{E}_{js}}{l_{js}} l_{js} - \kappa_i \frac{k_{js}}{l_{js}} l_{js} \\
&= \frac{\varphi w_{is} l_{js}}{\gamma_i^l} - w_{is} l_{js} - \tau_{is}^{\mathcal{E}} \frac{w_{is} \gamma_i^T}{\tau_{is}^{\mathcal{E}} \gamma_i^l} l_{js} - \kappa_i \frac{w_{is}(1-\gamma_i^l-\gamma_i^T)}{\kappa_i \gamma_i^l} l_{js} \\
&= w_{is} l_{js} \left(\frac{\varphi}{\gamma_i^l} - 1 - \frac{\gamma_i^T}{\gamma_i^l} - \frac{(1-\gamma_i^l-\gamma_i^T)}{\gamma_i^l} \right) \\
&= w_{is} l_{js} \left(\frac{\varphi - 1}{\gamma_i^l} \right).
\end{aligned} \tag{66}$$

Use equation (65) and the definition of c_{js} to re-express the profit function:

$$\pi_{js}^T = \frac{\varphi^{\varepsilon^D} \left(\frac{1}{\phi_{js}} \left(\frac{w_{is}}{\gamma_i^l} \right)^{\gamma_i^l} \left(\frac{\tau_{is}^{\mathcal{E}}}{\gamma_i^T} \right)^{\gamma_i^T} \left(\frac{\kappa_i}{1-\gamma_i^l-\gamma_i^T} \right)^{1-\gamma_i^l-\gamma_i^T} \right)^{1+\varepsilon^D}}{\Theta_n^{\varepsilon^D}} (\varphi - 1). \tag{67}$$

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

$$\pi_{js}^T = \nu_n^T w_{is}^{\gamma_i^l (1+\varepsilon^D)} (\tau_{is}^{\mathcal{E}})^{\gamma_i^T (1+\varepsilon^D)} \phi_{js}^{-(1+\varepsilon^D)}, \tag{68}$$

which is the expression in equation (10). Note that ν_n^T is a firm-specific constant that does not vary across locations.

B.4 Probability of Switching to the Green Technology

The probability that a facility will switch to the green technology is equivalent to the probability that the profits from doing so are greater than the profits from remaining brown:

$$\begin{aligned}\mathbb{P}_i(G|g_n) &= \mathbb{P}_i((1-\chi_n)(g_n)\pi_j^G > \pi_j^B) \\ &= \mathbb{P}_i\left(\chi_n(g_n) < 1 - \exp(\log \pi_j^B - \log \pi_j^G)\big|g_n\right)\end{aligned} \tag{69}$$

Because the facility-specific ϕ_{js} unobserved and $\zeta_{js} \perp\!\!\!\perp \chi_n$, I compute the switching probability using the expected difference in log profits across the two technologies, integrating over the location-specific shocks. The expected difference in log profits is given by:

$$\begin{aligned}\mathbb{E}\left[\log \pi_j^B - \log \pi_j^G\right] &= -(1+\varepsilon^D)\left(\mathbb{E}\left[\max_s V_{js}^B\right] - \mathbb{E}\left[\max_s V_{js}^G\right]\right) \\ &= -(1+\varepsilon^D)\sigma_i^F\left[\log \sum_s \exp\left(\frac{v_{is}^G}{\sigma_i^F}\right) - \log \sum_s \exp\left(\frac{v_{is}^B}{\sigma_i^F}\right)\right].\end{aligned} \tag{70}$$

Define $\overline{\pi}_i^T \equiv \frac{1}{S}\sum_s \exp\left(\frac{v_{is}^T}{\sigma_i^F}\right)$. Then, the switching probability can be written:

$$\mathbb{P}_i(G|g_n) = \mathbb{P}_i\left(\chi_n(g_n) < \underbrace{1 - \left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-(1+\varepsilon^D)\sigma_i^F}}_{\equiv \Delta_i}\middle| g_n\right) \tag{71}$$

Recall that $\chi_n(g_n) = \chi_n^0 e^{-\lambda_g g_n}$, where $\chi_n^0 \overset{\text{i.i.d}}{\sim} \text{U}[0,1]$ and $\lambda_g > 0$. Use this definition to rewrite the switching probability:

$$\mathbb{P}_i(G|g_n) = \mathbb{P}_i\left(\chi_n^0 < \Delta_i e^{\lambda_g g_n}\big|g_n\right). \tag{72}$$

Note that for a particular firm n, this expression defines a fixed point condition that its share of green facilities must satisfy:

$$g_n = \Delta_i e^{\lambda_g g_n}. \tag{73}$$

To generalize this to the industry level, I rely on the fact that firms are ex-ante identical, which leads to an analogous fixed point expression:

$$\mathbb{P}_i(G) = g_i = \Delta_i e^{\lambda_g g_n}. \tag{74}$$

The solution to this fixed point problem is:

$$g_i = -\frac{W(-\lambda_g \Delta_i)}{\lambda_g}, \tag{75}$$

where $W(.)$ denotes the Lambert W function. Note that this expression is a simplification of the true g_i since by aggregating to the industry level, the fixed point expression implies that each firm is using the industry-level g_i rather than their own g_n as an argument to the cost function $\chi_n(g)$.

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

B.5.1 Emissions

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

$$\begin{aligned}\mathcal{E}_{is}^T &= \underbrace{E_{is}^T}_{\text{extensive margin}} \times \underbrace{\mathbb{E}_\zeta\left[\mathcal{E}_{js}^*(\zeta_{fs})\middle|s,T\right]}_{\text{intensive margin}} \\ &= \underbrace{\frac{\exp\left(\frac{v_{is}^T}{\sigma_i^F}\right)}{S\bar{\pi}_i(\gamma^T)}}_{E_{is}^T} w_{is}^{\gamma_i^l(1+\varepsilon^D)}(\tau_{is}^{\mathcal{E}})^{\gamma^T(1+\varepsilon^D)-1} C_1^T \exp(-(1+\varepsilon^D)\overline{\phi}_{is}) z_{is},\end{aligned} \tag{76}$$

where S is the number of states, C_1^T is constant across locations and $z_{is} \equiv \mathbb{E}_\zeta\left[\exp(-(1+\varepsilon^D)\zeta_{js})\middle|s\right]$. The total emissions of firms in industry i and state s are given by $\mathcal{E}_{is} = \mathbb{P}_i(B)\mathcal{E}_{is}^B + \mathbb{P}_i(G)\mathcal{E}_{is}^G$, which directly implies that the elasticity of local emissions with respect to a change in regulatory stringency is:

$$\frac{\partial\log(\mathcal{E}_{is})}{\partial\log(\tau_{is}^{\mathcal{E}})} = \underbrace{\frac{\mathcal{E}_{is}^G - \mathcal{E}_{is}^B}{\mathcal{E}_{is}}\frac{\partial\mathbb{P}_i(G)}{\partial\log(\tau_{is}^{\mathcal{E}})}}_{\text{technology switching}} + \underbrace{\frac{\mathcal{E}_{is}^G\mathbb{P}_i(G)}{\mathcal{E}_{is}}\frac{\partial\log(\mathcal{E}_{is}^G)}{\partial\log(\tau_{is}^{\mathcal{E}})}}_{\text{chg. in emissions of green firms}} + \underbrace{\frac{\mathcal{E}_{is}^B(1-\mathbb{P}_i(G))}{\mathcal{E}_{is}}\frac{\partial\log(\mathcal{E}_{is}^B)}{\partial\log(\tau_{is}^{\mathcal{E}})}}_{\text{chg. in emissions of brown firms}}. \tag{77}$$

The within-technology elasticities follow directly from equation 76:

$$\frac{\partial\log\mathcal{E}_{is}^T}{\partial\log\tau_{is}^{\mathcal{E}}} = \underbrace{\gamma^T - 1}_{\text{substitution}} + \underbrace{\gamma^T\varepsilon^D}_{\text{scale}} - \underbrace{\frac{\gamma^T}{\sigma_i^F}}_{\text{firm location}}. \tag{78}$$

It remains to compute the effect of a change in regulatory stringency on the switching probability:

$$\begin{aligned}\frac{\partial\mathbb{P}_i(G)}{\partial\log(\tau_{is}^{\mathcal{E}})} &= \frac{W(-\lambda_g\Delta_i)}{\lambda_g\Delta_i(1+W(-\lambda_g\Delta_i))}\frac{\partial\Delta_i}{\partial\log\tau_{is}^{\mathcal{E}}} \\ &= \frac{W(-\lambda_g\Delta_i)}{\lambda_g\Delta_i(1+W(-\lambda_g\Delta_i))}(1+\varepsilon^D)\sigma_i^F\left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-(1+\varepsilon^D)\sigma_i^F-1} \times \frac{\partial\left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)}{\partial\log\tau_{is}^{\mathcal{E}}} \\ &= \frac{W(-\lambda_g\Delta_i)}{\lambda_g\Delta_i(1+W(-\lambda_g\Delta_i))}(1+\varepsilon^D)\sigma_i^F\left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-(1+\varepsilon^D)\sigma_i^F-1} \frac{\frac{\partial\overline{\pi}_i^B}{\partial\log(\tau_{is}^{\mathcal{E}})}\overline{\pi}_i^G - \frac{\partial\overline{\pi}_i^G}{\partial\log(\tau_{is}^{\mathcal{E}})}\overline{\pi}_i^B}{(\overline{\pi}_i^G)^2}.\end{aligned} \tag{79}$$

Now note that the only term in $\overline{\pi}_i^T$ that depends on $\tau_{is}^{\mathcal{E}}$ is the state s term of the sum, so that:

$$\begin{aligned}\frac{\partial \overline{\pi}_i^T}{\partial \log(\tau_{is}^{\mathcal{E}})} &= \frac{1}{S}\frac{\partial \exp\left(\frac{v_{is}^T}{\sigma_i^F}\right)}{\partial \log(\tau_{is}^{\mathcal{E}})} \\ &= -\frac{1}{S}\exp\left(\frac{v_{is}^T}{\sigma_i^F}\right)\frac{\gamma_i^T}{\sigma_i^F} \\ &= -\frac{\sum_{s'}\exp\left(\frac{v_{is'}^T}{\sigma_i^F}\right)}{S\sum_{s'}\exp\left(\frac{v_{is'}^T}{\sigma_i^F}\right)}\exp\left(\frac{v_{is}^T}{\sigma_i^F}\right)\frac{\gamma_i^T}{\sigma_i^F} \\ &= -\overline{\pi}_i^T E_{is}^T \frac{\gamma_i^T}{\sigma_i^F},\end{aligned} \tag{80}$$

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

$$\begin{aligned}\frac{\partial \mathbb{P}_i(G)}{\partial \log(\tau_{is}^{\mathcal{E}})} &= \frac{W(-\lambda_g\Delta_i)}{\lambda_g\Delta_i(1+W(-\lambda_g\Delta_i))}(1+\varepsilon^D)\sigma_i^F\left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-(1+\varepsilon^D)\sigma_i^F-1}\frac{-\overline{\pi}_i^B E_{is}^B\frac{\gamma_i^B}{\sigma_i^F}\overline{\pi}_i^G + \overline{\pi}_i^G E_{is}^G\frac{\gamma_i^G}{\sigma_i^F}\overline{\pi}_i^B}{(\overline{\pi}_i^G)^2} \\ &= \frac{W(-\lambda_g\Delta_i)}{\lambda_g\Delta_i(1+W(-\lambda_g\Delta_i))}(1+\varepsilon^D)\sigma_i^F\left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-\frac{(1+\varepsilon^D)}{\sigma_i^F}}\left(E_{is}^G\gamma_i^G - E_{is}^B\gamma_i^B\right).\end{aligned} \tag{81}$$

Then, the elasticity of local emissions can be rewritten:

$$\begin{aligned}\frac{\partial \log(\mathcal{E}_{is})}{\partial \log(\tau_{is}^{\mathcal{E}})} = &\underbrace{\frac{W(-\lambda_g\Delta_i)}{\lambda_g\Delta_i(1+W(-\lambda_g\Delta_i))}(1+\varepsilon^D)\sigma_i^F\left(\frac{\overline{\pi}_i^B}{\overline{\pi}_i^G}\right)^{-\frac{(1+\varepsilon^D)}{\sigma_i^F}}\left(E_{is}^G\gamma_i^G - E_{is}^B\gamma_i^B\right)}_{\text{technology switching}} \\ &+\underbrace{\frac{\mathcal{E}_{is}^G\mathbb{P}_i(G)}{\mathcal{E}_{is}}\left(\underbrace{\gamma^G-1}_{\text{substitution}}+\underbrace{\gamma^G\varepsilon^D}_{\text{scale}}-\underbrace{\frac{\gamma^G}{\sigma_i^F}}_{\text{firm location}}\right)}_{\text{chg. in emissions of green firms}} \\ &+\underbrace{\frac{\mathcal{E}_{is}^B(1-\mathbb{P}_i(G))}{\mathcal{E}_{is}}\left(\underbrace{\gamma^B-1}_{\text{substitution}}+\underbrace{\gamma^B\varepsilon^D}_{\text{scale}}-\underbrace{\frac{\gamma^B}{\sigma_i^F}}_{\text{firm location}}\right)}_{\text{chg. in emissions of brown firms}}.\end{aligned} \tag{82}$$

B.5.2 Labor Demand

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

$$L_{is}^{D,T} = \underbrace{\frac{1}{S\overline{\pi}_i^T}\exp\left(\frac{v_{is}^T}{\sigma^F}\right)}_{E_{is}^T} w_{is}^{\gamma_i^l(1+\varepsilon^D)-1}(\tau_{is}^{\mathcal{E}})^{\gamma_i^T(1+\varepsilon^D)}C_2^T\exp(-(1+\varepsilon^D)\overline{\phi}_{is})z_{is}, \tag{83}$$

where C_2^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.

B.6 Effect of Regulation on Expected Returns and Profits

B.6.1 Profits

Let $\omega_{ns} = \frac{\pi_{ns}}{\sum_{s'} \pi_{ns'}}$ denote the fraction of firm n's profits generated in state s. Let $\tilde{\pi}_n = \int_{j \in J^n} \pi_j dj$ denote the firm's total profits excluding switching costs. Each π_j refers to the profits of establishment j under its optimal choice of location and technology. Because each firm operates a continuum of establishments, total firm profits (including the adjustment for the switching cost) can be approximated by:[20]

$$\pi_n \approx (1 - \chi_n(g_n) g_n) \tilde{\pi}_n. \tag{84}$$

Then, the elasticity of firm profits with respect to the emissions tax rate is given by:

$$\frac{\partial \log \pi_n}{\partial \log \tau_{is}^{\mathcal{E}}} = \underbrace{\frac{\partial \log(1 - \chi_n(g_n) g_n)}{\partial \log \tau_{is}^{\mathcal{E}}}}_{\text{switching costs}} + \underbrace{\frac{\partial \log \tilde{\pi}_n}{\partial \log \tau_{is}^{\mathcal{E}}}}_{\text{chg. in gross profits}} \tag{85}$$

I first derive the impact of the emissions tax change on switching costs:

$$\begin{aligned}
\frac{\partial \log(1 - \chi_n(g_n) g_n)}{\partial \log \tau_{is}^{\mathcal{E}}} &= \frac{1}{(1 - \chi_n(g_n) g_n)} \frac{\partial (1 - \chi_n(g_n) g_n)}{\partial \log \tau_{is}^{\mathcal{E}}} \\
&= \frac{1}{(1 - \chi_n(g_n) g_n)} \left(- \frac{\partial \chi_n(g_n)}{\partial \log \tau_{is}^{\mathcal{E}}} g_n - \frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}} \chi_n(g_n) \right) \\
&= \frac{1}{(1 - \chi_n(g_n) g_n)} \left(- \frac{\partial \chi_n(g_n)}{\partial g_n} \frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}} - \frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}} \chi_n(g_n) \right) \\
&= - \frac{1}{(1 - \chi_n(g_n) g_n)} \frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}} \left(\frac{\partial \chi_n(g_n)}{\partial g_n} + \chi_n(g_n) \right) \\
&= - \frac{\chi_n(g_n)(1 - \lambda_g)}{(1 - \chi_n(g_n) g_n)} \frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}},
\end{aligned} \tag{86}$$

where $\frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}}$ is given by equation (81).

Now turning to the change in gross profits, first 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

[20] The continuum of establishments assumption is useful because the exact expression for net profits is $\pi_n = \int_{j \in J^n} [\mathbb{1}\{T_j = G\}(1 - \chi_n(g_n))\pi_j^G + \mathbb{1}\{T_j = B\}\pi_j^B] dj$, so the approximation is exact when the share of establishments using the green technology is equal to the share of profits generated by those establishments, which is reasonable when there are a continuum of establishments.

in $\tau_{is}^{\mathcal{E}}$, so I approximate $\frac{\partial \tilde{\pi}_n}{\partial \log \tau_{is}^{\mathcal{E}}} \approx \frac{\partial \tilde{\pi}_{ns}}{\partial \log \tau_{is}^{\mathcal{E}}}$.[21] The impact on gross profits is then given by:

$$\begin{aligned}\frac{\partial \log \tilde{\pi}_n}{\partial \log \tau_{is}^{\mathcal{E}}} &= \frac{1}{\tilde{\pi}_n} \frac{\partial \tilde{\pi}_n}{\partial \log \tau_{is}^{\mathcal{E}}} \\ &\approx \frac{1}{\tilde{\pi}_n} \frac{\partial \tilde{\pi}_{ns}}{\partial \log \tau_{is}^{\mathcal{E}}} \\ &= \frac{\tilde{\pi}_{ns}}{\tilde{\pi}_n} \frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}^{\mathcal{E}}} \\ &= \omega_{ns} \frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}^{\mathcal{E}}},\end{aligned} \tag{87}$$

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 $\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}^{\mathcal{E}}}$,

$$\begin{aligned}\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}^{\mathcal{E}}} &= \int_{j \in J_s^n} \frac{\pi_j}{\tilde{\pi}_{ns}} \frac{\partial \log \pi_j}{\partial \log \tau_{is}^{\mathcal{E}}} dj \\ &= (1+\varepsilon^D) \int_{j \in J_s^n} \frac{\pi_j}{\tilde{\pi}_{ns}} \left[\mathbb{1}\{T_j = G\} \gamma_i^G + \mathbb{1}\{T_j = B\} \gamma_i^B + \gamma_i^l \dot{w}_{is} \right] dj,\end{aligned} \tag{88}$$

where $\dot{w}_{is}$ is given by equation (23). 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:[22]

$$\frac{\partial \log \tilde{\pi}_{ns}}{\partial \log \tau_{is}^{\mathcal{E}}} = (1+\varepsilon^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is}), \tag{89}$$

where T_{ns} denotes the technology operated by facility j in state s.

Returning to equation (85), the elasticity of firm profits with respect to a particular states emissions tax is given by:

$$\frac{\partial \log \pi_n}{\partial \log \tau_{is}^{\mathcal{E}}} = \underbrace{-\frac{\chi_n(g_n)(1-\lambda_g)}{(1-\chi_n(g_n)g_n)} \frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}}}_{\text{switching costs}} + \underbrace{\omega_{ns}(1+\varepsilon^D)(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is})}_{\text{chg. in gross profits}}. \tag{90}$$

This elasticity captures the marginal effect of a change in $\tau_{is}^{\mathcal{E}}$, holding location fixed. The effect is larger in magnitude for firms that generate a greater share of profits in state s (higher ω_{fs}) or who operate the brown technology in state s. It is also larger for firms with larger adjustment costs (higher χ_n, which could be due to higher χ_n^0 or lower g_n). However, this expression does not account for discrete relocation as a

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

[22] 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 (10), this condition becomes $\log \nu_n^G - \log \nu_n^B + (1+\varepsilon^D) \log \tau_{is}^{\mathcal{E}}(\gamma_i^G - \gamma_i^B) > \log(1-\chi_n(g_n))$, 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.

result of the change in regulation.

Consider a discrete increase in regulatory stringency from τ_{is}^{old} to τ_{is}^{new}. Define the change in expected log profits, $\dot{\pi}_n \equiv \log \pi_n\left(\tau_{is}^{\text{new}}\right) - \log \pi_n\left(\tau_{is}^{\text{old}}\right)$, where π_n denotes the total profits of the firm including an adjustment for switching costs. The discrete policy change may also cause some firms to relocate. Because of the i.i.d. T1EV distribution of idiosyncratic productivity, the fixed-technology change in expected log profits is given by:[23]

$$\begin{aligned}\dot{\pi}_n \approx -\frac{\chi_n(g_n)(1-\lambda_g)}{(1-\chi_n(g_n)g_n)}\frac{\partial g_n}{\partial \log \tau_{is}^{\mathcal{E}}} + (1+\varepsilon^D)\omega_{ns}\Bigg[\underbrace{\frac{\exp\frac{v_{is}^{T_{ns}}(\tau_{is}^{\text{new}})}{\sigma_i^F}}{\sum_{s'}\exp\frac{v_{is'}^{T_{ns'}}}{\sigma_i^F}}}_{\mathbb{P}(\text{stay in } s)}\underbrace{\left(\gamma_i^{T_{ns}} + \gamma_i^l \dot{w}_{is}\right)\Delta\log\tau_{is}^{\mathcal{E}}}_{\text{chg. in profits in } s} \\ - \sum_{s'\neq s}\underbrace{\frac{\exp\frac{v_{is'}^{T_{ns}}}{\sigma_i^F}}{\sum_{s''}\exp\frac{v_{is''}^{T_{ns}}}{\sigma_i^F}}}_{\mathbb{P}(\text{move to } s')}\underbrace{\left((\overline{\phi}_{is'} - \overline{\phi}_{is}) - \gamma_i^l(\log w_{is'} - \log w_{is}) - \gamma_i^{T_{ns}}(\log\tau_{is'}^{\mathcal{E}} - \log\tau_{is}^{\mathcal{E}})\right)}_{\substack{\text{expected chg. in}\\ \text{profits from}\\ \text{moving to } s'}}\Bigg].\end{aligned} \tag{91}$$

Since the initial choice of location was profit maximizing, it must be that the expected change in profits from moving to s' is negative. Thus, all else equal, the decrease in expected profits should be larger for firms that choose to move. In other words, the magnitude of the decrease in profits conditional on staying (given by equation (90) is a lower bound on the total effect.

B.6.2 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 $\tau_{is}^{\mathcal{E}}$ and τ_{is}^{new}, respectively. Then, when the regulatory change is announced, the return of stock n is given by:

$$r_{n,\tau_{is}^{\text{old}}\to\tau_{is}^{\text{new}}} = \log(\mathcal{M}_n^{\text{new}}) - \log(\mathcal{M}_n^{\text{old}}), \tag{92}$$

where $\log \mathcal{M}_n$ is given by equation (53). Because the regulation is local, I assume that the market return is not affected. Then, the return can be written:

$$r_{n,\tau_{is}^{\text{old}}\to\tau_{is}^{\text{new}}} \approx \mathbb{E}[\log\pi_n^{\text{new}}] - \mathbb{E}[\log\pi_n^{\text{old}}] + \underbrace{\frac{1}{2}[\mathbb{V}\text{ar}(\log\pi_n^{\text{new}}) - \mathbb{V}\text{ar}(\log\pi_n^{\text{old}})] - [\mathbb{C}\text{ov}(\log\pi_n^{\text{new}}) - \mathbb{C}\text{ov}(\log\pi_n^{\text{old}})]}_{=0 \text{ by assumption}}. \tag{93}$$

[23] This is an approximation because I approximate the discrete change in within-location profits using the derivative.

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 (91).

B.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:

$$\dot{\mathcal{V}}_w = N_{is}\left(\mathbb{P}^{is}_{\text{stay}}\dot{w}_{is} + \sum_{(is)'\neq is}\mathbb{P}^{is\to(is)'}_{\text{move}}\Delta\mathcal{V}_{is\to(is)'}\right). \tag{94}$$

Let w^{new}_{is} denote the equilibrium wage in industry/state is following the regulatory change. Note that if $w^{\text{new}}_{is} \geq w_{is}$, then no workers would be induced to move, so I focus on the case where $w^{\text{new}}_{is} < w_{is}$, 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:

$$\mathbb{P}^{is}_{\text{stay}} = P\left(V^H_{nis}(w^{\text{new}}_{is}) = \max_{(is)'}\left\{V^H_{n(is)'}(w^{\text{new}}_{is})\right\}\middle| V^H_{nis}(w_{is}) = \max_{(is)'}\left\{V^H_{n(is)'}(w_{is})\right\}\right). \tag{95}$$

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,

$$\mathbb{P}(D_1|D_2) = \frac{\mathbb{P}(D_1\cap D_2)}{\mathbb{P}(D_2)} \equiv \mathbb{P}^{is}_{\text{stay}}. \tag{96}$$

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,

$$\mathbb{P}(D_1|D_2) = \frac{\mathbb{P}(D_1)}{\mathbb{P}(D_2)}. \tag{97}$$

Let u_{is}^{new} denote the common component of the household's indirect utility given wages are equal to w_{is}^{new}. Using the expression from equation (7):

$$\begin{aligned}\mathbb{P}_{\text{stay}}^{is} &= \frac{\exp\frac{u_{is}^{\text{new}}}{\sigma^H}}{\frac{\sum_{(is)'}\exp\frac{u_{(is)'}^{\text{new}}}{\sigma^H}}{\exp\frac{u_{is}}{\sigma^H}}} \\ &\approx \exp\left(\frac{u_{is}^{\text{new}} - u_{is}}{\sigma^H}\right) \\ &= \exp\left(\frac{\dot{w}_{is}}{\sigma^H}\right),\end{aligned} \tag{98}$$

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

$$\mathbb{P}_{\text{move}}^{is\to(is)'} = \mathbb{P}(\text{move})\mathbb{P}((is)'|\text{move}). \tag{99}$$

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

$$\mathbb{P}_{\text{move}}^{is\to(is)'} = (1 - \mathbb{P}_{\text{stay}}^{is})\frac{\exp\frac{u'_{(is)}}{\sigma^H}}{\sum_{(is)''\neq is}\exp\frac{u_{(is)''}}{\sigma^H}}. \tag{100}$$

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

$$\Delta\mathcal{V}_{is\to(is)'} = \underbrace{\log w_{(is)'} - \log w_{is}}_{\text{wage effect}} + \underbrace{\log \overline{A}_{(is)'} - \log \overline{A}_{is}}_{\text{amenity effect}}. \tag{101}$$

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

$$\dot{\mathcal{V}}_w = \exp\left(\frac{\dot{w}_{is}}{\sigma^H}\right)\dot{w}_{is} + \left(1 - \exp\left(\frac{\dot{w}_{is}}{\sigma^H}\right)\right)\sum_{(is)'\neq is}\frac{\exp\frac{u'_{(is)}}{\sigma^H}}{\sum_{(is)''\neq is}\exp\frac{u_{(is)''}}{\sigma^H}}(\log w_{(is)'} - \log w_{is} + \log \overline{A}_{(is)'} - \log \overline{A}_{is}). \tag{102}$$