Taxing Carbon, Not Competition: Optimizing Market and Environment in a World of Imperfections

Yağmur Menzilcioğlu*

July 21, 2025†

Abstract

Externalities from carbon emissions and market power work in opposite directions: emissions lead to overproduction, while market power leads to underproduction. Addressing only one failure can worsen outcomes. I develop a dynamic general equilibrium model to derive an optimal output tax formula that depends on firm-level market power and carbon intensity. Calibrated to the top five carbon-intensive US sectors, the optimal tax gets significantly smaller than the tax without considering market power, as competition decreases. In a set of policy experiments, I show that policies designed for incorrect market structures could be more detrimental than not intervening at all.

JEL Codes: E62, H21, H23, L13, L52, Q48, Q54, Q58.

Keywords: Carbon taxes, Market power, Climate change, Externalities, Optimal taxation, Industrial policy, Dynamic integrated assessment modeling, Heterogeneous firms.

*Department of Economics, Georgetown University, email: ym406@georgetown.edu.

†I am deeply grateful for the guidance and support of my advisor, Toshihiko Mukoyama. I also thank Arik Levinson, Mark Huggett, Jan Eeckhout, Per Krusell, John Hassler, Basile Grassi, Vincent Sterk, Pablo Ottonello, Mark Bils, Tiago Cavalcanti, Joseph Hanna, and Tsolmon Otgon for their valuable feedback and suggestions. All errors are my own.

1 Introduction

For some time now, the theory of optimal environmental policy has been concerned with the implications of market power in polluting industries; however, the literature on optimal climate change policy has not yet addressed this issue. When a production externality, such as pollution, is the only economic distortion, the Pigouvian tax, equal to marginal external damages or the difference between marginal social and private costs, is the first-best policy. However, when polluting firms have market power, the Pigouvian tax is no longer the first-best policy. Indeed, imposing the Pigouvian tax on an unregulated, imperfectly competitive industry may lead to welfare loss by reducing the output by more than the socially optimal amount. In this case, the optimal policy should include two policy instruments: a subsidy on output to increase production to competitive levels and a tax on pollution to reduce production to the socially optimal level. However, competition and environmental authorities are often separate, and thus, these policies are uncoordinated. In the absence of industrial policy to regulate product market distortions, the environmental policy should account for market power since the Pigouvian tax is only efficient when implemented with the second policy insturment, i.e., the output subsidy. How different is the optimal policy needed to regulate an imperfectly competitive carbon-emitting industry from the optimal policy to regulate a competitive carbon-emitting industry when only one policy instrument is available? How much the policy must be adjusted depends on market structure, characterized by the elasticity of demand and industry size.

This simple theoretical observation, studied for local pollutants' regulation in the past, e.g., Buchanan (1969), Barnett (1980), Levin (1985), Shaffer (1995), Simpson (1995), Katsoulacos and Xepapadeas (1996), Lee (1999), and Requate (2006), has been overlooked in the literature on climate change policy. Unlike local pollutants, greenhouse gases, measured in carbon dioxide (CO_2) equivalent units, in the atmosphere do not cause immediate damage; instead, the accumulation of global greenhouse gas emissions drives climate change, which increases the frequency and influences the magnitude of extreme weather events, such as hurricanes, heat waves, and droughts. Thus, regulating carbon emissions has dynamic implications, and the optimal policy should account for the intertemporal nature of climate change. The literature on optimal carbon policy has focused on the intertemporal nature of climate change and the uncertainty surrounding the damages caused by carbon emissions, e.g., Nordhaus (1994), Manne and Richels (2005), Anthoff and Tol (2013), and Golosov et al. (2014). However, it has not yet addressed the intratemporal tradeoff between lack of competition and climate damage. I address this gap by analyzing the implications of market power in the context of the design of a carbon policy.

First, I theoretically derive the optimal policy for an imperfectly competitive and unregulated carbon-intensive industry in the context of climate change. Furthermore, I quantitatively evaluate the implications of market power on the optimal policy. Using a seminal dynamic general equilibrium climate change model, I show that when industry size is fixed, the optimal carbon tax gets smaller as competition decreases. The underlying mechanism is that since the equilibrium output is lower with market power, the optimal tax does not have to be as high as it would be in a competitive industry to achieve the same reduction in emissions. This result depends on the assumption that the industry structure is exogenous, does not change over time, and is not affected by policy.

The literature on optimal climate change policy has focused on the assumption that carbon-intensive industries are perfectly competitive when designing optimal policy. Market power is a valid concern in the context of climate change policy due to the concentrated structure of carbon-intensive industries, which could give firms pricing power over their products. I begin by examining data on market power in carbon-intensive industries in the US.

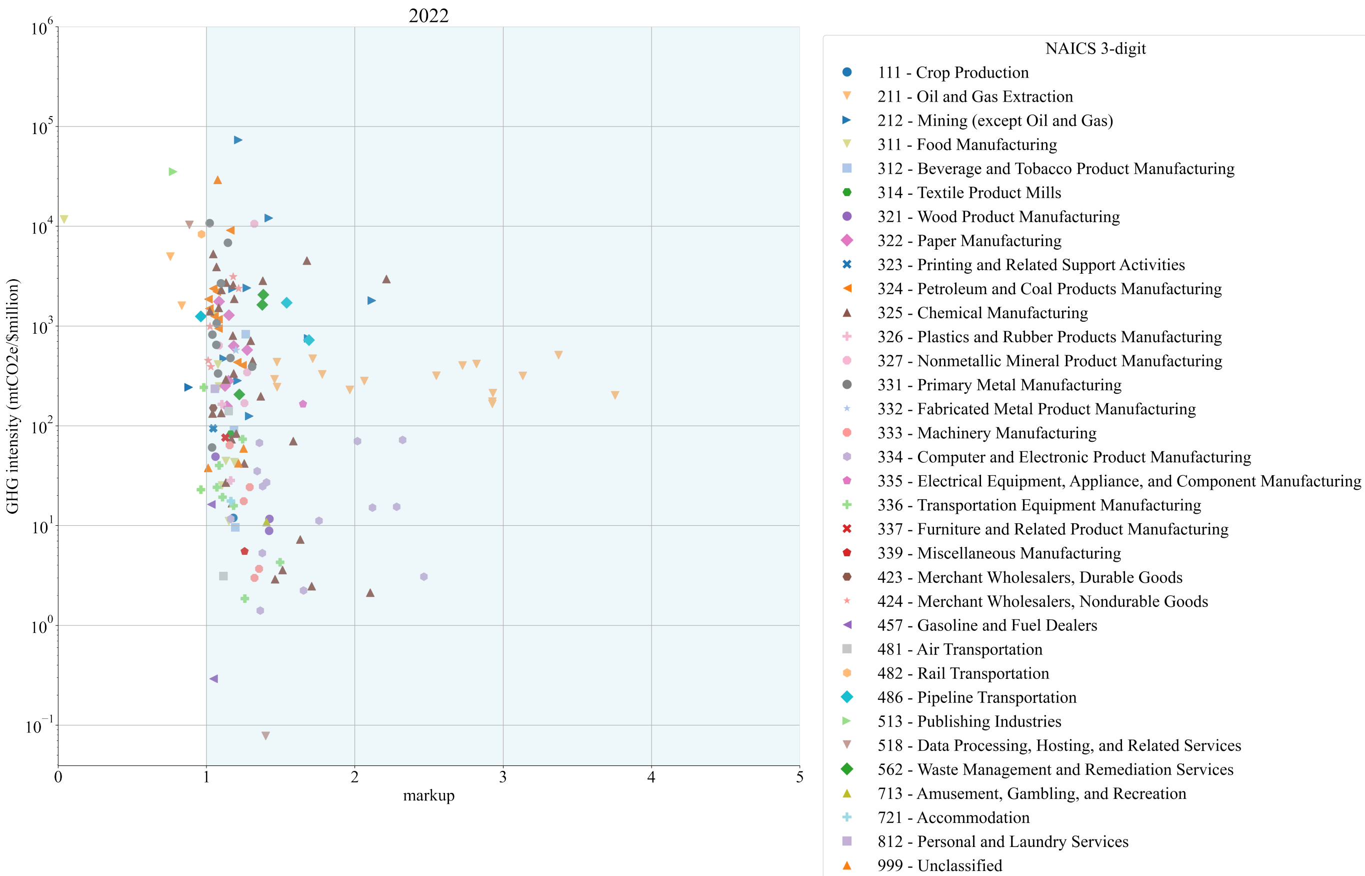
I present descriptive evidence that most carbon-intensive industries have markups greater than unity, indicating that they charge prices greater than their marginal costs, and also have positive economic profit rates. I calculate industry-level greenhouse gas (GHG) intensity (i.e., carbon intensity) as the ratio of the industry's total GHG emissions using data from the US Environmental Protection Agency's Greenhouse Gas Reporting Program (GHGRP) and the industry's value added, which I calculate as the difference between the industry's revenue and cost of goods sold using data from the S&P Global Market Intelligence's (2023) Compustat database. To calculate industry-level markups, I use Compustat data and follow the methodology of Traina 2018 using the production function approach. To calculate industry-level economic profit rates, I also use Compustat data and follow the methodology of Eeckhout (2025). I provide details about the data sources and methodology I used to calculate firm-level markups, economic profit rates, and greenhouse gas intensity (i.e., carbon intensity) in Supplementary Appendix A.

In Figure 1, I plot the carbon intensity of US publicly-traded firms with reported carbon emissions against their markups in 2022. The vertical axis shows the carbon intensity of the firm, which is the ratio of the firm's greenhouse gas emissions, measured in metric tons of CO_2 equivalent (mtCO2e), and the firm's value added, in units of millions of dollars, measured as the difference between the firm's revenue and cost of goods sold. The horizontal axis shows the firm's markup, which is the ratio of the firm's price over the marginal cost of production. The majority of the firms in the scatter plot lie in the right shaded area, indicating that they have prices greater than their marginal costs, i.e., they charge marked up prices.

In addition to the carbon-intensive firms' ability to charge prices greater than their marginal costs, I also find that the majority of the carbon-intensive firms have positive economic profit rates. Figure 2 plots the carbon intensity against the economic profit rate of US publicly-traded firms with reported carbon emissions in 2022. The economic profit rate is the ratio of the firm's economic profit, which is the difference between the firm's accounting profits, i.e., net income, and the shareholder's equity times the discount factor, and the firm's revenues. As it can be seen from the scatter plot, the majority of the firms lie in the right shaded area, indicating that they have positive economic profit rates.

For both figures, the scatter points are color coded to indicate the three-digit 2022 North American Industry Classification System (NAICS) code the business belongs to, mapped on the legend. In addition to the this cross-sectional evidence, I also find that market power and imperfect competition have been prevalent and increasing in the US carbon-intensive industries over the past

Figure 1: Markups and carbon intensity of US publicly-traded and carbon emitting firms in 2022.



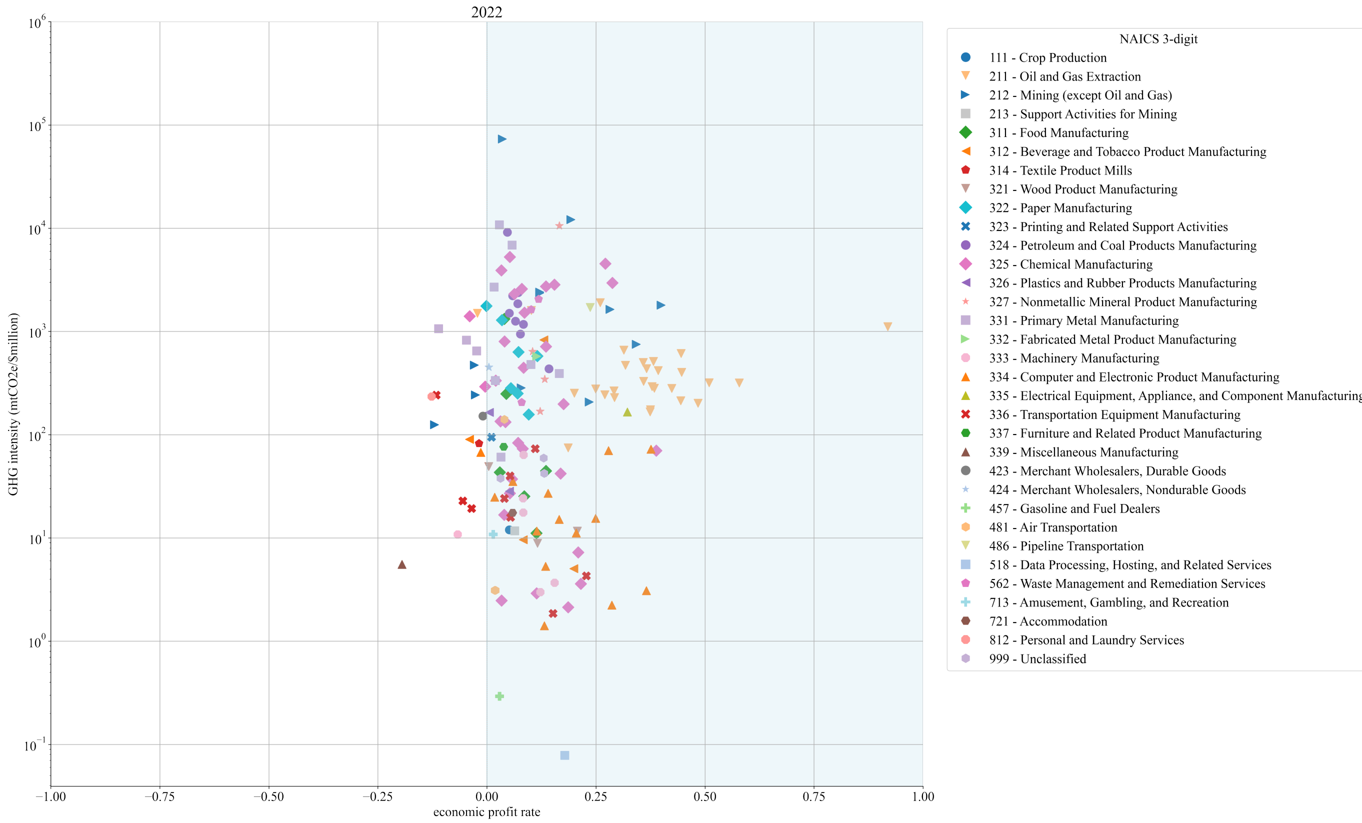
Sources: Markups are calculated using the S&P Global Market Intelligence (2023) and carbon intensities are calculated using data from US Environmental Protection Agency (2024) and S&P Global Market Intelligence (2023).

decade. I plot the sales-weighted average markup and economic profit rate of the US carbon-intensive industries in Figures 3 and 4, respectively, for the years 2010 to 2023.

Based on this evidence, I develop a theoretical model to derive the optimal policy for an oligopolistic and unregulated carbon-intensive industry in the context of climate change. I build this model on the dynamic general equilibrium model with climate change from Golosov et al. (2014). I extend their model to allow for imperfect competition and quantitatively evaluate the implications of market power on the optimal policy when regulation is restricted to a single policy instrument.

I extend Golosov et al.'s (2014) dynamic general equilibrium climate model to allow for imperfect competition in carbon-intensive intermediate input sectors. Throughout the paper, I refer to carbon-intensive intermediate input sectors with imperfect competition as carbon-intensive sectors for brevity. Each sector has a fixed number of firms producing differentiated inputs under Cournot competition, with firm-specific productivity and emissions intensity. Sector output is a constant elasticity of substitution (CES) aggregate. This framework features the Cournot oligopoly compe-

Figure 2: Economic profit rates and carbon intensity of US publicly-traded and carbon emitting firms in 2022.



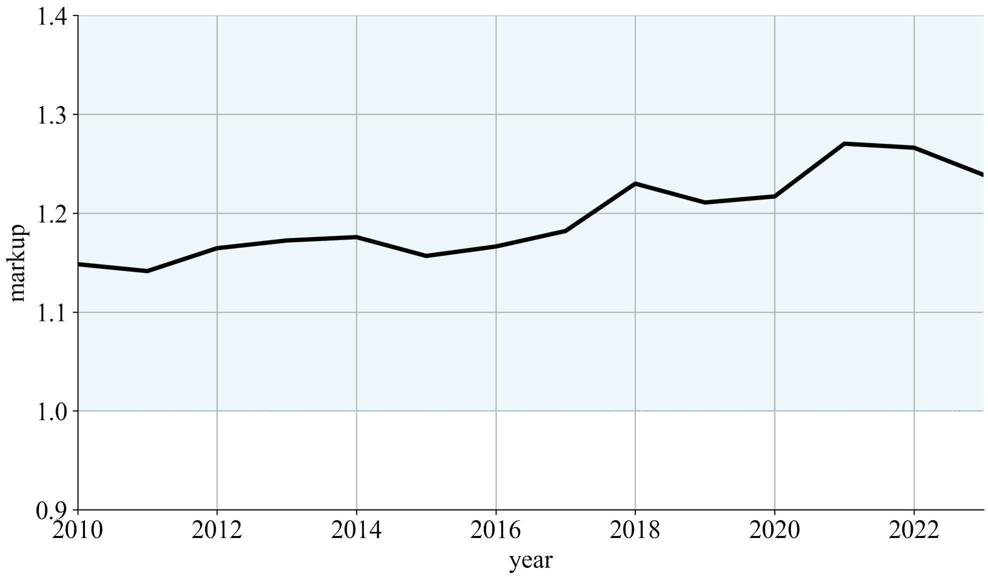
Sources: Economic profit rates are calculated using the S&P Global Market Intelligence (2023) and carbon intensities are calculated using data from US Environmental Protection Agency (2024) and S&P Global Market Intelligence (2023).

tition modeled in Atkeson and Burstein (2008). Finally, I also introduce fixed costs of intermediate goods production, which are paid in units of the final good, in order to reflect the capital intensity of carbon-intensive industries.

Under this generalized model, I derive a firm-specific optimal output tax formula for the oligopolistic and unregulated carbon-intensive producers. The optimal output tax is the sum of the differences between the marginal social cost and the marginal private cost of carbon emissions associated with a unit of firm output and between the marginal revenue and the marginal cost of intermediate good production. The latter difference is a simple function of the intermediate good price and the producer's price elasticity of demand. By the law of demand, the elasticity of demand is negative; thus, this output tax formula implies that the optimal output tax is less than the optimal tax for perfectly competitive producers, equal to the marginal external damage at the optimal allocation.

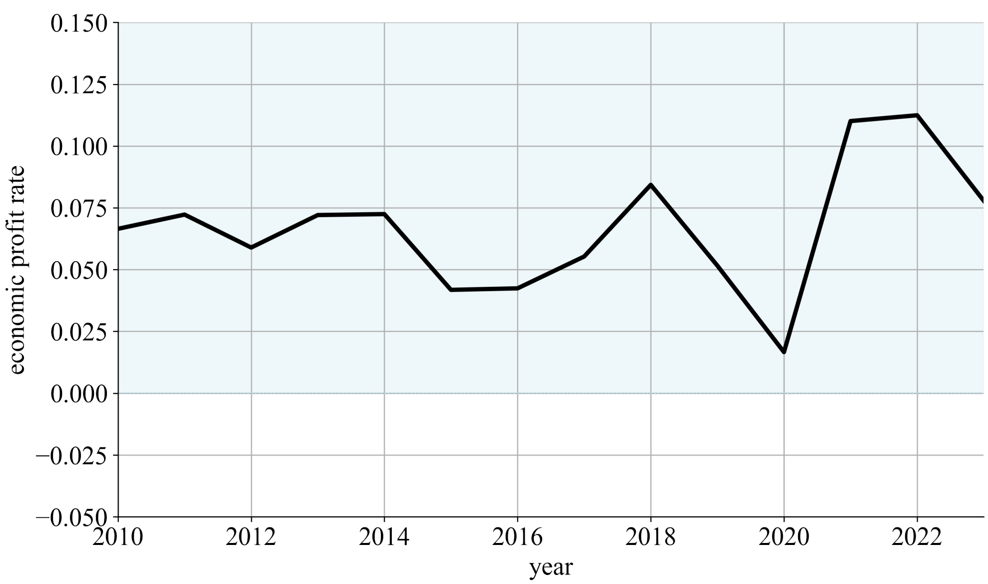
I focus on the design of an optimal output tax instead of a carbon tax. The output tax is more versatile than the emissions tax, as it can regulate both the output and emissions of carbon-intensive

Figure 3: Sales-weighted average markups of US carbon-intensive industries from 2010 to 2023.



Note: The blue shaded area indicates markups greater than unity.

Figure 4: Sales-weighted average economic profit rates of US carbon-intensive industries from 2010 to 2023.



Note: The blue shaded area indicates positive economic profit rates.

producers, while the emissions tax can only regulate emissions. While a carbon tax cannot provide incentives for firms with both zero-carbon emissions and market power to increase their output, a negative output tax can encourage these firms to produce more.

I quantitatively evaluate the adjustment of the optimal tax formulation by calibrating parameters governing the generalized model to match characteristics of publicly traded and carbon-intensive firms in the US. I calibrate the size of each industry to match its the Herfindahl-Hirschman Index (HHI), the elasticity of demand to match each industry's average markups given its effective size, and the carbon intensity of each intermediate good producer to industry averages. Furthermore, I adjust the benchmark calibration of the output shares in the final goods production to incorporate the variety of intermediate production factors used in final good production, rather than energy inputs. My quantitative model replicates the benchmark results from Golosov et al. (2014) as a special case and shows that when an industry's market structure is exogenous the optimal output tax gets smaller as market power increases. On the other hand, the effect of moving along the firm productivity distribution within a sector on the optimal output tax is ambigious and depends on the relative rates of change of the firm's marginal cost and its markups.

Finally, I conduct a series of policy experiments to evaluate the welfare implications of alternative policy designs. First, I evaluate the welfare loss associated with imposing the optimal output tax for perfectly competitive carbon-intensive producers on oligopolistic producers. This case is equivalent to imposing an economy-wide uniform tax on marginal emissions of all carbon-intensive producers, regardless of their market power. I find that the welfare loss associated with this policy is larger than the welfare loss associated with not intervening at all when the regulated industries are oligopolistic. Second, I evaluate the welfare loss associated with imposing a uniform sector-wide output tax on all producers within the same sector, regardless of their emissions intensity and markup heterogeneity. I set the sector-wide output tax equal to the optimal output tax implied for the oligopolistic producers that are homogeneous within the sector. I find that the welfare loss associated with this policy is smaller than the welfare loss associated with imposing the economy-wide uniform carbon tax on oligopolistic producers, but larger than the welfare loss associated with not intervening at all. Finally, I also evaluate the welfare loss associated with imposing the optimal output tax for oligopolistic carbon-intensive producers on perfectly competitive producers. I find that the welfare loss associated with this policy experiment is the largest among all policy experiments, as it could subsidize the output of perfectly competitive producers, which could lead to even more overproduction beyond the socially optimal level. These results imply that the design of the optimal policy that regulates carbon-intensive industries should carefully account for the market structure of the industry, as the optimal output tax is not a one-size-fits-all policy.

This study bridges two strands of literature. First is the extensive literature on optimal policy to control the problem of climate change while maintaining economic growth. Many macroeconomic studies of optimal carbon taxes focus on the climate externality as the only distortion in the modeled economy, e.g., Nordhaus (1994), Manne and Richels (2005), Anthoff and Tol (2013), and Golosov et al. (2014). In such a setting, the optimal carbon tax is equal to the marginal damage of carbon emissions, which is Pigouvian, named after the seminal work of Pigou (1920). Few optimal carbon tax studies consider other pre-existing distortions, e.g., Acemoglu et al. (2012) consider a static monopoly distortion in the market for machines used in carbon-intensive intermediate production, and Barrage (2019) considers other taxes on labor and capital. However, these analyses do not consider monopoly distortions in carbon-intensive industries. If implemented, carbon taxes will interact with the market structure of carbon-intensive industries. On the one hand, carbon taxes reduce the production of carbon-intensive goods. On the other hand, carbon taxes could exacerbate monopoly distortions in carbon-intensive industries by increasing costs and reducing competition. I contribute to this literature by considering the interaction between carbon taxes and monopoly distortions in carbon-intensive industries by incorporating imperfect competition into a dynamic integrated assessment model.

Second, several studies have considered the interaction between environmental policy and market structure. Buchanan (1969) was the first to consider the implications of monopoly distortions in the context of environmental policy. He argued that the optimal tax on a polluting monopolist should be lower than the Pigouvian tax because the monopolist's output is lower than the competitive level. He graphically illustrated the welfare loss associated with levying a Pigouvian tax on a polluting monopolist. Barnett (1980) formalized Buchanan's insight in a general equilibrium model. He describes that the ideal policy solution for a polluting monopolist would incorporate two policy actions: One device increases the monopolist's production, and another controls the external diseconomic effects of the monopolist's production. Instead, Barnett (1980) assumes that policymakers cannot directly correct the product market distortion, and the pollution tax is the only tool available to achieve the socially optimal allocation. He concludes that the optimal pollution tax on an unregulated monopolist is smaller than marginal external damages, and the difference between the two increases as the price elasticity of demand for the polluter's product decreases, i.e., the demand is more inelastic. Baumol and Oates (1988) summarizes that the optimal tax on an unregulated monopolist depends on the marginal external damages, the demand elasticity, and the abatement cost function of the monopolist's production.

Beyond the polar cases of perfect competition and monopoly, the analysis of optimal environmental policy under an oligopoly market structure has been carried out extensively. Levin (1985) examines various forms of taxation to control pollution from a Cournot oligopoly of homogenous goods. He uses the insight that the optimal tax on polluting, imperfectly competitive, and unregulated firms is less than the marginal external damages and asks its implications for regulating stock pollutants driving climate change.

The study of optimal tax on polluting oligopolists further developed from a static setting to a dynamic setting. Shaffer (1995), Katsoulacos and Xepapadeas (1996), and Lee (1999) extend the analysis to a Cournot oligopoly of homogenous goods to incorporate the possibility of endogenous market structure, i.e., the possibility of entry and exit of firms. Imposing a tax on polluting firms may affect the number of firms in the industry, affecting the optimal tax rate. Under the endogenous market structure setting, the optimal tax on polluting oligopolists may be lower, equal, or higher than the Pigouvian tax because now the regulator has to consider three effects: the beneficial effect of reducing pollution, the negative effect of reducing already distorted output due to imperfect competition, and a third positive effect of bringing the number of firms closer to the second-best optimum. If the regulator omits the third effect, the optimal tax is less than the marginal external damages. However, if the third effect is taken into account, the result depends on the curvature of market demand. The intuition behind this internalization result is that the equilibrium number of firms may be above (or below) the socially optimal level, resulting in an additional distortion. The optimal tax could reduce this distortion by raising (or lowering) its rate, which is why it may be optimal to have a tax greater (or less) than marginal external damages. Finally, Requate (2006) provides a comprehensive review of the literature on environmental policy under imperfect competition and summarizes optimal policies for oligopoly models, such as Bertrand competition with homogenous goods, price competition with differentiated goods, and monopolistic competition. I build a foundational model to study the dynamic interaction between carbon taxes and market structure in a dynamic general equilibrium model.

The rest of the paper is organized as follows: In Section 2, I introduce a generalized version of the dynamic general equilibrium climate change model from Golosov et al. 2014 and introduce extensions to include market power in the carbon-intensive intermediate input industries. Once I introduce the generalized and extended model and its assumptions, I review the derivation of Golosov et al.'s (2014) constant optimal social cost of carbon formula. Then, I look at the decentralized equilibrium outcomes under my new assumption of market power and derive the optimal output tax formula for the oligopolistic and unregulated carbon-intensive intermediate input sectors. Section 3 outlines my quantitative analysis and computation strategy. In Section 4, I calibrate the model to match the top five carbon-intensive intermediate input characteristics in the US and quantitatively evaluate the implications of market power on the optimal policy. Section 5 presents welfare implications of alternative policy experiments, such as uniform economy- or sector-wide output taxes, and the standard Pigovian carbon tax when the carbon-intensive intermediate input sectors are oligopolistic and have heterogeneous markups. Finally, Section 6 concludes.

2 Model

Consider a version of the multi-sector neoclassical growth model outlined in Golosov et al. (2014). Time is discrete and the time horizon is infinite. There is a representative household with a utility function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t),$$

where U is the strictly increasing and concave one-period utility function, C_t is consumption at period t, $\beta \in (0, 1)$ is the discount factor, and $\mathbb{E}_0$ is the mathematical expectation conditioned on the consumer's time 0 information.

There are multiple production sectors in the economy: a final goods sector, and M intermediate goods sectors. The final goods sector produces the consumption and investment good Y_t, and each intermediate goods sector $m \in \{1, ..., M\}$ produces a composite input $X_{m,t}$ for use in the final goods sector.

The feasibility constraint in the final goods sector, denoted as sector 0, is:

$$C_t + K_{t+1} = Y_t + (1-\delta)K_t, \tag{1}$$

where K_t is capital stock and $\delta \in (0,1)$ is the depreciation rate. The following aggregate production function describes output in the final goods sector:

$$Y_t = F_{0,t}\left(K_{0,t}, N_{0,t}, \{X_{m,t}\}_{m=1}^{M}, S_t\right), \tag{2}$$

where $K_{0,t}$ and $N_{0,t}$ are capital and labor used in sector 0 at time t, $X_{m,t}$ is the intermediate composite input of sector $m \in \{1, ..., M\}$ used in final-goods production at time t, and S_t is the climate variable which affects output. The production function $F_{0,t}$ depends on $K_{0,t}$, $N_{0,t}$, $\{X_{m,t}\}_{m=1}^{M}$, and S_t. This model views climate as sufficiently well represented by one variable, S_t, which is the amount of carbon in the atmosphere. In studies from natural sciences, for example, Schneider (1989), National Research Council (2010), and IPCC (2021), the current atmospheric carbon concentration is considered to be approximating the current climate well. Assume that S_t affects final goods production only. The amount of carbon in the atmosphere, S_t, is measured as atmospheric carbon concentration above pre-industrial times in billions of tons of carbon (GtC) units.

The intermediate input sectors each produce a composite input $X_{m,t}$ for use in the final goods sector, and there are a finite number of sectors M. These intermediate production factors could be carbon-intensive industries such as coal ($m = 1$), steel ($m = 2$), cement ($m = 3$), fertilizer ($m = 4$), and also zero-emissions sectors, such as renewable energy. I assume that each intermediate input composite m is produced by J_m number imperfectly substitutable products. Each intermediate product $j = 1, \ldots, J_m$ in sector m has its own technology $F_{m,j,t}$ to produce the intermediate good $X_{m,j,t}$ at time t by employing variable labor input $N_{m,j,t}^{var}$ to produce output, and a fixed cost $\Omega_{m,j,t}$, paid in units of labor, incurred regardless of the level of output $X_{m,j,t}$ produced. I proceed to assume that production remains linear in labor input $N_{m,j,t}^{var}$:

$$X_{m,j,t} = F_{m,j,t}(N_{m,j,t}^{var}) \geq 0, \tag{3}$$

with total labor demanded by firm j in sector m is:

$$N_{m,j,t} = N_{m,j,t}^{var} + \Omega_{m,j,t}. \tag{4}$$

In each period, production factors are mobile across sectors. The final goods sector is perfectly competitive, whereas studying different intermediate goods market structures is this paper's objective.

I assume that some intermediate production factors emit carbon to the atmosphere. Let $E_{m,j,t}$ be the amount of carbon emitted by firm j in sector m at time t. I generalize Golosov et al.'s (2014) modeling assumption by letting firm-level emissions $E_{m,j,t}$ be a general function of the intermediate input $X_{m,j,t}$ produced by firm j in sector m at time t, instead of assuming that the intermediate inputs are in one-to-one correspondence with its carbon emissions. The firm-specific emission function is generalized to allow for a nonlinearities and firm-specific carbon intensities:

$$E_{m,j,t} = g_{m,j}(X_{m,j,t}), \tag{5}$$

where $g_{m,j}(X_{m,j,t})$ is a general function that captures the relationship between the intermediate input $X_{m,j,t}$ and the emissions $E_{m,j,t}$ for firm j in sector m at time t.

At the sector level, total emissions $E_{m,t}$ are defined as the sum of emissions from all firms in sector m at time t. Thus, for each sector m, emissions are given by:

$$\begin{aligned} E_{m,t} &= \sum_{j=1}^{J_m} E_{m,j,t}, \\ &= \sum_{j=1}^{J_m} g_{m,j}(X_{m,j,t}). \end{aligned} \tag{6}$$

Finally, aggregate emissions at the economy-wide level, denoted E_t, are defined as the sum of sector-level emissions across al sectors $m = 1, \ldots, M$ at time t. Thus, aggregate emissions are given by:

$$\begin{aligned} E_t &= \sum_{m=1}^{M} E_{m,t}, \\ &= \sum_{m=1}^{M} \sum_{j=1}^{J_m} g_{m,j}(X_{m,j,t}). \end{aligned} \tag{7}$$

The climate variable S_t is affected by the aggregate carbon emissions, E_t, and the carbon cycle. To describe the evolution of the climate, let $\tilde{S}_t$ be a function that maps a history of human-made (anthropogenic) emissions into the current atmospheric concentration level, S_t. History is defined to start at the time of industrialization, denoted as T periods before period 0:

$$S_t = \tilde{S}_t \left(E_{-T}, E_{-T+1}, ..., E_t \right). \tag{8}$$

2.1 Additional Assumptions

In this section, I summarize the three key assumptions outlined in Golosov et al. (2014) that simplify the planning problem analyzed in the next section. Then, I introduce two additional assumptions that simplify the carbon tax formulation in the presence of imperfect competition in the energy sector. Golosov et al. (2014) discuss the plausibility of their three assumptions. First, households have a logarithmic utility function:

Assumption 1 $U(C) = \log(C)$.

Second, they assume that production damages are multiplicative:

Assumption 2 *The production technology can be represented as:*

$$F_{0,t}\left(K_{0,t}, N_{0,t}, \{X_{m,t}\}_{m=1}^{M}, S_t\right) = [1 - D(S_t)]\tilde{F}_{0,t}\left(K_{0,t}, N_{0,t}, \{X_{m,t}\}_{m=1}^{M}\right), \tag{9}$$

where $1 - D(S_t) = \exp[-\gamma_t(S_t - \bar{S})]$ *with* $\bar{S}$ *being the pre-industrial atmospheric* CO_2 *concentration, and* γ_t *is the marginal damage measured as a share of GDP per marginal unit of carbon in the atmosphere assumed to be constant, and before damages production function* $\tilde{F}_{0,t}$ *is strictly increasing and strictly concave in all its inputs* $K_{0,t}, N_{0,t}$*, and* E_t *and it exhibits constant returns to scale.*

Third, they assume a simplified carbon cycle:

Assumption 3 *The function* $\tilde{S}_t$ *is linear with the following depreciation structure:*

$$S_t - \bar{S} = \sum_{s=0}^{t+T}(1 - d_s)E_{t-s},$$

where $d_s \in [0, 1]$ *for all* s *and* T *denotes the number of periods since industrialization and* E_{t-s} *follows equations (6) and (7).*

The fraction $1 - d_s$ represents the amount of carbon left in the atmosphere s periods in the future. A three-parameter family determines the depreciation structure, where (i) ψ_L is the share of carbon emitted into the atmosphere that stays in it forever; (ii) $1 - \psi_0$ is the share of the remaining emissions exiting the atmosphere immediately, and (iii) ψ is the geometric decay rate of the remaining share of emissions. This parameterization corresponds to a linear system with the depreciation rate at horizon s given by:

$$1 - d_s = \psi_L + (1 - \psi_L)\psi_0(1 - \psi)^s. \tag{10}$$

Golosov et al. (2014) show that this depreciation structure is consistent with the existence of two "virtual carbon stocks" S_1 (the part that remains in the atmosphere forever) and S_2 (the part that depreciates at rate ψ), with $S_{1,t} = S_{1,t-1} + \psi_L E_t$ and $S_{2,t} = \psi S_{2,t-1} + \psi_0(1 - \psi_L)E_t$, and $S_t = S_{1,t} + S_{2,t}$. Golosov et al. (2014) use these three assumptions to obtain a closed-form solution to the optimal aggregate SCC to output ratio. This expression simplifies the computation of the model. I introduce two additional assumptions as an extension to the Golosov et al. (2014) model and yield simplifiable intermediate goods markup formulations:

Assumption 4 *The intermediate goods sectors are imperfectly competitive and in differing degrees. Each sector* m*'s intermediate good composite production combines imperfectly substitutable intermediate goods* j *in the sector using a constant elasticity of substitution (CES) technology with an elasticity of substitution parameter,* η_m*, greater than one. So, the monopoly problem of each intermediate good producer is well-defined.*

Assumption 5 *Each intermediate goods sector m's market structure is a Cournot oligopoly and in each sector m a finite number of firms $j = 1, \ldots, J_m$ produces intermediate inputs to a CES intermediate good composite production function:*

$$X_{m,t} = \left[\sum_{j=1}^{J_m} \kappa_{m,j} X_{m,j,t}^{\frac{\eta_m - 1}{\eta_m}}\right]^{\frac{\eta_m}{\eta_m - 1}}, \tag{11}$$

where $\kappa_{m,j}$ is the share parameter of firm j in sector m good production and $\sum_{j=1}^{J_m} \kappa_{m,j} = 1$.

Following Atkeson and Burstein (2008), I assume that the intermediate good is small compared to the entire economy, and none of the firms considers the influence of its production decision on the final goods production (or the general price level). Nevertheless, each producer j is sufficiently large within each sector m so that it is aware of its influence on sectoral composite good $X_{m,t}$ (and the intermediate sector price composite $p_{m,t}$).

2.2 The Planning Problem

The social planner's problem is to maximize the representative household's discounted lifetime expected utility subject to technology, feasibility, and carbon cycle constraints of the economy. The social planner's problem is:

$$\max_{\left\{C_t, K_{t+1}, N_{0,t}, \left\{X_{m,t}, \{N_{m,j,t}, E_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}, E_t, S_t, Y_t\right\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t)$$

subject to (1), (2), (3), (4) (5), (6), (7), (8), (11), and $N_t = N_0 + \sum_{m=1}^{M} \sum_{j=1}^{J_m} N_{m,j,t}$, where N_t is the inelastic and exogenous labor supply at period t (normalized to unity). Importantly, the social planner accounts for the climate externality in the planning problem.

2.3 The Social Cost of Carbon

Following Hassler, Krusell, and Smith (2016), I define the social cost of carbon (SCC) as the marginal externality damage of carbon emissions, keeping constant behavior in the given allocation. If one further assumes that the saving rate is constant (which does not tend to vary so much over time in the data), then the SCC expression simplifies significantly.

Assumption 6 *The planner's solution yields a constant saving rate $s \in (0, 1)$ over time.*

Proposition 1 of Golosov et al. (2014) shows under Assumptions 1-3 and 6, the SCC simplifies be a constant fraction of aggregate output:

$$\frac{\text{SCC}_{m,j,t}}{Y_t} = \bar{\gamma}_t \left(\frac{\psi_L}{1 - \beta} + \frac{(1 - \psi_L)\psi_0}{1 - (1 - \psi)\beta} \right). \tag{12}$$

I provide the full derivation of equation (12) in Supplementary Appendix B.1.

The optimal SCC (OSCC), denoted by $\Lambda_{m,j,t}$, is the marginal external damage of a unit of carbon emissions from firm j in sector m evaluated at the optimal allocation and is equal to the marginal external damage from a unit of carbon emissions. Let $\hat{\Lambda}_{m,j,t}$ denote the optimal SCC to output ratio, or $\hat{\Lambda}_{m,j,t} \equiv \Lambda_{m,j,t}/Y_t$. Finally, since aggregate emissions are the sum of firm-level emissions, $\Lambda_{m,j,t}$ is equal across all firms and sectors.

2.4 Decentralized Equilibrium

2.4.1 Consumers

The representative individual solves the problem:

$$\max_{\{C_t,K_{t+1}\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta^t \log(C_t)$$

subject to

$$\sum_{t=0}^{\infty} q_t(C_t + K_{t+1}) = \sum_{t=0}^{\infty} q_t((1 + r_t - \delta)K_t + w_t N_t + T_t) + \Pi,$$

where r_t is the net rental rate of capital at time t, w_t is the wage rate at time t, N_t is the inelastic labor supply at time t, T_t is the government transfer at time t, Π is the present value of all production sectors' profits from the future, and q_t are the Arrow-Debreu prices (i.e., probability-adjusted state-contingent prices of the consumption good) at time t.

2.4.2 Producers

All output and input markets are assumed to be competitive. The representative firm in the final good sector solves the following:

$$\Pi_0 \equiv \max_{\left\{Y_t,K_t,N_{0,t},\left\{X_{m,t},\{X_{j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} q_t \left[Y_t - r_t K_t - w_t N_{0,t} - \sum_{m=1}^{M} p_{m,t} X_{m,t}\right],$$

subject to nonnegativity constraints and technology constraints (9) and (11), where the price $p_{m,t}$ is the price of the intermediate sector composite at time t, and Π_0 is the present value of all maximized profits of the final-goods producer from the future. The cost-minimization of final goods producer 0 implies that:

$$\frac{p_{m,j,t}}{p_{m,t}} = \kappa_{m,j} X_{m,j,t}^{-\frac{1}{\eta_m}} X_{m,t}^{\frac{1}{\eta_m}}, \tag{13}$$

where $p_{m,j,t}$ is the price of intermediate producer j in sector m at time t and the intermediate sector composite price $p_{m,t}$ is the CES aggregator of the intermediate producers' prices at time t for every sector m:

$$p_{m,t} = \left[\sum_{j=1}^{J_m} \kappa_{m,j}^{\eta_m} p_{m,j,t}^{1-\eta_m}\right]^{\frac{1}{1-\eta_m}}.$$

The first-order condition of the final goods producer 0 and the intermediate sector composite price index implies that $p_{m,t}X_{m,t} = \sum_{j=1}^{J_m} p_{m,j,t}X_{m,j,t}$.

The problem of the producer j in sector m is to maximize the discounted value of its profits given the per-unit tax $\tau_{m,j,t}$ on its output given its fixed costs $\Omega_{m,j,t}$:

$$\Pi_{m,j} \equiv \max_{\{X_{m,j,t}, N_{m,j,t}, N^{var}_{m,j,t}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} q_t \left[(p_{m,j,t} - \tau_{m,j,t})X_{m,j,t} - w_t N_{m,j,t}\right],$$

subject to nonnegativity, intermediate production technologies (3), (4), intermediate sector m composite production technology (11) constraints, and the inverse input j in sector m demand in equation (13). Here, $\Pi_{m,j}$ is the present value of all maximized profits of the producer j in sector m from the future. Total profits are $\Pi = \Pi_0 + \sum_{m=1}^{M}\sum_{j=1}^{J_m}\Pi_{m,j}$.

In the absence of taxes, the first-order condition of the producer j in sector m and inverse input j demand function (13) implies:

$$p_{m,j,t} = \frac{\sigma_m(s_{m,j,t})}{\sigma_m(s_{m,j,t}) - 1}\frac{w_t}{F'_{m,j,t}(N^{var}_{m,j,t})},$$

where $F'_{m,j,t}$ is the marginal product (i.e., the derivative) of the producer j's production function at time t with respect to its variable input, $w_t/F'_{m,j,t}(N^{var}_{m,j,t})$ is the marginal cost of input j production, and $\sigma_m(s_{m,j,t})$ is the price elasticity of sector m input j demand, expressed as a function of producer j's sector m sales share $s_{m,j,t} = p_{m,j,t}X_{m,j,t}/p_{m,t}X_{m,t} = p_{m,j,t}X_{m,j,t}/\sum_{j=1}^{J_m} p_{m,j,t}X_{m,j,t}$ and elasticities following Atkeson and Burstein (2008). Specifically, $\sigma_m(s_{m,j,t})$ has the following expression:

$$\sigma_m(s_{m,j,t}) = \left[\frac{1}{\eta_m}(1 - s_{m,j,t}) + \frac{X_{m,t}/p_{m,t}}{|\partial X_{m,t}/\partial p_{m,t}|}s_{m,j,t}\right]^{-1}, \quad (14)$$

where $\frac{X_{m,t}/p_{m,t}}{|\partial X_{m,t}/\partial p_{m,t}|}$ is the absolute value of inverse price elasticity of sector m composite demand. In other words, $\frac{\sigma_m(s_{m,j,t})}{\sigma_m(s_{m,j,t})-1}$ is the markup of the intermediate producer j in sector m. Supplementary Appendix B provides a detailed derivation of the expression for $\sigma_m(s_{m,j,t})$ given by equation (14).

2.4.3 Market Clearing

The final goods market clears:

$$Y_t = C_t + K_{t+1} - (1 - \delta)K_t.$$

The labor market clears:

$$N_t = N_0 + \sum_{m=1}^{M}\sum_{j=1}^{J_m} N_{m,j,t}.$$

Finally, the intermediate good markets clears by Assumption 5.

2.4.4 Government

The government taxes output, $X_{m,j,t}$ of the intermediate producers at different rates, $\tau_{m,j,t}$, and these taxes target correcting both the climate externality and the market distortion. The effective tax rate on the intermediate producer j in sector m is a function of the marginal externality damage from input j in sector m, the input j price, and the price elasticity of input j demand, as shown in equation (15). Moreover, the effective firm-specific tax rate, $\tau_{m,j,t}$, could be negative, i.e., a subsidy, which would be the case when the marginal externality damage is smaller than the marginal social cost of the market distortion.

The government collects the tax proceeds from the intermediate producers and rebates the representative consumer with a lump-sum, T_t. In the case that the government's net tax proceeds from the intermediate producers are negative, i.e., the government subsidizes the intermediate producers, the government collects the negative tax proceeds from the representative consumer.

The government runs a balanced budget at time-0:

$$\sum_{t=0}^{\infty} q_t T_t = \sum_{t=0}^{\infty} q_t \sum_{m=1}^{M} \sum_{j=1}^{J_m} \tau_{m,j,t} X_{m,j,t},$$

where the left-hand side is the time-0 sum value of the lump-sum transfers to the representative consumer, and the right-hand side is the time-0 sum value of tax proceeds collected from all intermediate producers in all sectors m at time t.

2.4.5 Market Structure

Golosov et al. (2014) assume that all production sectors are perfectly competitive. When the climate externality is the only distortion, the optimal policy is to tax carbon emissions at the marginal externality damage at the optimal output level, i.e., the OSCC, Λ_t, known as the Pigouvian tax.

However, as argued in the introduction, imperfect competition is a more realistic market structure assumption for carbon-intensive production sectors. Under an imperfectly competitive carbon-intensive intermediate production sectors, there will be two different distortions in each producer's optimal decision: a climate externality and a market distortion, and two policy instruments will be needed to correct these two distortions, known as the Tinbergen rule, named after Tinbergen (1952).

2.5 Optimal Output Tax

Unless environmental and competition regulators operate harmoniously, a regulator is restricted with a constrained policy tool to improve aggregate welfare. Each carbon-intensive and imperfectly competitive intermediate sector subject society to two costs. The first is the external costs associated with climate change, and the second is the costs resulting from the output restriction. The simple Pigouvian tax, while reducing the climate externality, also increases the welfare loss resulting from reduced production. Thus, the net social welfare effect is uncertain, but likely negative. The optimal output tax will combine the policies that address each distortion individually: the Pigouvian tax and the output subsidy. I formally show this result by finding the optimal output tax in the presence of imperfect competition in the intermediate sector m.

Accounting for the pricing power changes the carbon tax formulation when competition policy is constrained. Let $\tau^*_{m,j,t}$ denote the optimal output tax on intermediate producer j in sector m. The optimal output tax, $\tau^*_{m,j,t}$ is firm-specific and depends on the marginal externality damages from input j in sector m, the input j price, and the price elasticity of input j demand:

$$\tau^*_{m,j,t} = \frac{dE_{m,j,t}}{dX_{m,j,t}}\Lambda_{m,j,t} - \frac{p_{m,j,t}}{\sigma_m(s_{m,j,t})}, \tag{15}$$

where $\sigma_m(s_{m,j,t})$ is the price elasticity of sector m input j demand defined in equation (14). Thus, the optimal output tax is always smaller than the Pigouvian tax and can even be negative, i.e., a subsidy, in the presence of market power.

Proposition 1 *Suppose that $\tau_{m,j,t}$ follows equation (15) and that the tax proceeds and firm profits are rebated lump-sum to the representative consumer. Then, the oligopoly equilibrium allocation coincides with the solution to the social planner's problem.*

Proof.

To derive the optimal output tax formula, I solve for the first-order conditions of the social planner's problem and the oligopolistic producer's problem with respect to variable input choice for each firm j in sector m at time t. Then evaluate the oligopolistic producer's first-order condition at the optimal allocation quantities implied by the social planner's problem. Under Assumptions 1, 2, 3, and 6 the planner's first-order condition simplifies to:

$$\frac{dX_{m,j,t}}{dN^{var}_{m,j,t}}\left[\frac{\partial Y_t}{\partial X_{m,t}}\frac{\partial X_{m,t}}{\partial X_{m,j,t}} + \frac{dE_{m,j,t}}{dX_{m,j,t}}\Lambda_{m,j,t}\right] = \frac{\partial Y_t}{\partial N_{0,t}}. \tag{16}$$

Under Assumption 4, the oligopolistic producer's first-order condition with respect to variable input choice is:

$$\frac{dX_{m,j,t}}{dN^{var}_{m,j,t}}\left[p_{m,j,t}\frac{\sigma_m(s_{m,j,t})-1}{\sigma_m(s_{m,j,t})} - \tau_{m,j,t}\right] = \frac{\partial Y_t}{\partial N_{0,t}}. \tag{17}$$

In order to obtain the optimal output tax $\tau^*_{m,j,t}$, I evaluate the first-order condition of the sector m producer j's problem with respect to its variable labor input choice, equation (17), at the allocation quantities implied by the social planner's problem, i.e., when the first-order condition of the social planner's problem with respect to the variable labor input employed by sector m producer j is satisfied, equation (16).

The first-order condition of the social planner's problem with respect to the variable labor input employed by sector m producer j is the same as the first-order condition of the sector m producer j's problem with respect to its variable labor input choice when $\tau_{m,j,t}$ is equal to the optimal tax formula given by equation (15):

$$\tau^*_{m,j,t} = \frac{dE_{m,j,t}}{dX_{m,j,t}}\Lambda_{m,j,t} - \frac{p_{j,t}}{\sigma_m(s_{m,j,t})},$$

where all the variables are evaluated at the optimal allocation quantities implied by the social planner's problem, including $\sigma_m(s_{m,j,t})$ given by equation (14). □

The optimal tax on oligopolistic carbon-intensive producers is a linear combination of the optimal tax on competitive producers and the optimal output subsidy on oligopolistic producers with zero carbon emissions. The optimal tax on competitive producers is $\frac{dE_{m,j,t}}{dX_{m,j,t}}\Lambda_{m,j,t}$, as shown in Golosov et al. (2014), where $\frac{dE_{m,j,t}}{dX_{m,j,t}}$ is marginal carbon emissions from a unit of sector m input j production. The optimal output subsidy on oligopolistic producers in the absence of carbon externality is equal to $\frac{p_{m,j,t}}{\sigma_m(s_{m,j,t})}$, where both $p_{m,j,t}$ and $\sigma_m(s_{m,j,t})$ are evaluated at the optimal allocation quantities implied by the social planner's problem. It can be shown that this is the optimal output subsidy by considering the first-order condition with respect to sector m producer j's variable labor input choice. Absent the carbon externality, the marginal external damages from a unit of sector m input j production term, i.e., $\frac{dE_{m,j,t}}{dX_{m,j,t}}\Lambda_{m,j,t}$, is absent from the planner's first-order condition, equation (16). Thus, the optimal output tax on an oligopolistic sector m producer j should equate its first-order condition (17) with the planner's first-order condition (16).

3 Quantitative Analysis

In this section, I completely characterize the generalized multi-sector model used for the quantitative analysis in Golosov et al. (2014) described above. Assume that Assumptions 1, 2, 3, 4, 5, and 6 hold. I present quantitative model results for a baseline calibration. I explain the calibration process of the new components of my extension of the Golosov et al.'s (2014) model to match the structure of major carbon-intensive intermediate production sectors in the US in 2010.

Assume that there are M intermediate production sectors each with differing degrees of carbon intensity. Further, suppose that within each sector there are J_m firms that produce imperfectly substitutable types of the intermediate production factor, which is a reasonable assumption given these intermediate sectors face varying qualities of goods and high transportation costs. Within in sector m type j producer produces its output using the following constant returns to scale technology:

$$X_{m,j,t} = \chi_{m,j,t}N^{var}_{m,j,t}, \tag{18}$$

where $\chi_{m,j,t}$ is the exogenous labor productivity of the producer j in sector m that grows at a constant rate $g_{\chi_{m,j}}$ and $N^{var}_{m,j,t}$ is the variable labor input used in j's production. In addition to the variable labor input, each producer j in sector m faces a fixed exogenous production cost, denoted in units of labor, $\Omega_{m,j,t}$, that it has to pay in order to produce, regardless the level of output it produces. The fixed costs represent the overhead that must be paid regardless of the output level, e.g., maintenance of physical plants, regulatory compliance, and upfront capital recovery. In oligopolistic sectors, these costs can explain limited firm entry. Thus, the total labor demand of producer j in sector m is given by:

$$N_{m,j,t} = N^{var}_{m,j,t} + \Omega_{m,j,t}. \tag{19}$$

Deviating further from Golosov et al. (2014), I assume that carbon emissions from each intermediate input production are a general, and potentially nonlinear, function of total production of the intermediate input $X_{m,j,t}$ and the carbon intensity of the production process $\theta_{m,j,t}$. The carbon emissions from the production of intermediate input j in sector m are given by:

$$E_{m,j,t} = \theta_{m,j,t} X^{\zeta_{m,j}}_{m,j,t}, \tag{20}$$

where $\zeta_{m,j}$ is the degree of nonlinearity in the carbon emissions function. This functional generalization allows for the possibility that the carbon emissions from production are not linear in output, which is a reasonable assumption given that the carbon emissions from production can be affected by the technology used and the scale of production. Moreover, it harbors the Golosov et al. (2014) model as a special case, where both $\theta_{m,j,t}$ and $\zeta_{m,j}$ are equal to unity for all m and j. Additionally, if $\theta_{m,j,t} = 0$, then the production process is a zero carbon emissions process, which is the case for renewable energy sources. Finally, I assume that the carbon intensity of the production process $\theta_{m,j,t}$ is time-varying, to reflect the fact that the carbon intensity of production processes can change over time due to technological progress or changes in the energy mix used in production.

The sector composite $X_{m,t}$ that enters the final goods production is a CES aggregate of the different types of products in sector m as outlined in Assumption 4, equation (11). The final-goods production function is of Cobb-Douglas specification:

$$Y_t = \exp\{-\gamma_t(S_t - \bar{S})\} A_{0,t} K^{\alpha}_t N^{1-\alpha-\sum_{m=1}^{M}\nu_m}_{0,t} \prod_{m=1}^{M} X^{\nu_m}_{m,t},$$

where $A_{0,t}$ is the exogenous total factor productivity (TFP) in the final-goods sector that grows at a constant rate g_0. The Cobb-Douglas production function is a special case of the CES production function with price elasticity of demand equal to unity. Labor employed by all producers has to sum up to the exogenous labor supply level N_t. Finally, I assume that there is full capital depreciation, given that each period is a decade.

The Cobb-Douglas production function and complete capital depreciation assumptions deliver a constant saving rate under optimality conditions, which was the assumption behind the OSCC expression derived in equation (12). Next, I characterize the solutions to the planning problem and three types of market equilibria.

3.1 The Planning Problem

Given the full capital depreciation assumption and the constant SCC-to-output ratio result, I can obtain a numerical solution to the planner's problem defined in Supplementary Appendix B.3, pinned down by the first-order condition with respect to the variable labor input used in sector m intermediate input j production, $N^{var}_{m,j,t}$, as formulated in equation (16). Unlike Golosov et al.'s (2014) solution method, there is no closed-form solution for the optimal paths when I generalize the carbon emissions function to be nonlinear in output. Given the functional assumptions made, the optimal paths for each sector $m = 1, \dots, M$ intermediate input $j = 1, \dots, J_m$ production simultaneously satisfy:

$$\chi_{m,j,t}\left[\frac{\nu_m \kappa_{m,j}}{X_{m,t}^{\frac{\eta_m - 1}{\eta_m}} X_{m,j,t}^{\frac{1}{\eta_m}}} - \theta_{m,j,t}\zeta_{m,j}\frac{\text{SCC}_{m,j,t}}{Y_t}X_{m,j,t}^{\zeta_{m,j}-1}\right] = \frac{1-\alpha-\sum_{m=1}^{M}\nu_m}{N_{0,t}}, \tag{21}$$

where $\text{SCC}_{m,j,t}$ is the social cost of carbon in sector m and type j and the ratio $\hat{\Lambda}_{m,j,t} \equiv \frac{\text{SCC}_{m,j,t}}{Y_t}$ is the ratio is a constant function of the exogenous parameters, as shown in equation (12).

The generalization of the carbon emissions function to be potentially nonlinear in output does not allow for a closed-form solution for the optimal paths of intermediate input production $X_{m,j,t}$, as in Golosov et al.'s (2014). However, I can obtain a numerical solution for the optimal paths similar to the solution method used in Golosov et al.'s (2014). The optimal paths of each intermediate sector $m = 1, \dots, M$ good $j = 1, \dots, J_m$ production satisfies:

$$X_{m,j,t} = \xi^*_{m,j,t} X_{m,t}^{-(\eta_m - 1)}, \tag{22}$$

where $\xi^*_{m,j,t}$ for the efficient allocations are given by:

$$\xi^*_{m,j,t} \equiv \left(\frac{\nu_m \kappa_{m,j} \chi_{m,j,t} N_{0,t}}{1-\alpha-\sum_{m=1}^{M}\nu_m + \chi_{m,j,t}\hat{\Lambda}_{m,j,t}N_{0,t}\theta_{m,j,t}\zeta_{m,j}X_{m,j,t}^{\zeta_{m,j}-1}}\right)^{\eta_m},$$

where $\theta_{m,j,t}\zeta_m X_{m,j,t}^{\zeta_{m,j}-1}$ is the marginal carbon emissions from production of intermediate input j in sector m at time t. Even though $\xi^*_{m,j,t}$ is a function of the endogenous path of firm-specific output $X_{m,j,t}$, I can obtain a numerical solution for the optimal paths of intermediate input production $X_{m,j,t}$, as follows.

First, I guess the paths of total labor demand $N_{m,j,t}$ of each producer j in sector m and the labor demand $N_{0,t}$ of the final goods sector. Specifically, I guess a constant path of final goods sector labor demand $N_{0,t}$ at 70% of the exogenous aggregate labor supply level $\bar{N}$, and a constant path of total labor demand $N_{m,j,t}$ of each producer j in sector m at $(1-0.7)\cdot\bar{N}/(M\cdot\max\{J_1,\dots,J_M\})$, where M is the number of intermediate sectors and J_m is the number of producers in sector m. Then, I calculate the firm-specific $\xi^*_{m,j,t}$ as a function of the guessed $X_{m,j,t}$ for each producer j in sector m implied by the guessed values of $N_{m,j,t}$ and $N_{0,t}$, and the exogenous parameters at time t.

Next, I obtain sector-level output $X_{m,t}$ by aggregating the firm-specific outputs $X_{m,j,t}$ implied by equation (22) across all producers j in sector m and period t by using the firm-specific $\xi^*_{m,j,t}$ obtained in the last step. Using the sector-level output $X_{m,t}$, I obtain updated values of firm-specific outputs $X_{m,j,t}$ for each producer j in sector m by using equation (22) and further update the paths of variable labor input $N^{var}_{m,j,t}$ for each producer j in sector m using the updated firm-specific outputs $X_{m,j,t}$ and the exogenous fixed costs $\Omega_{m,j,t}$ and the labor used in the final goods sector $N_{0,t}$.

Once I obtain the updated paths of labor inputs for every producer-sector-time combination, I compare the updated paths of labor inputs $N_{m,j,t}$ and $N_{0,t}$ with the guessed paths. If the paths are not sufficiently close to each other, I update the guessed paths of $N_{m,j,t}$ and $N_{0,t}$ by taking a convex combination of the guessed and updated paths, and repeat the process until convergence.

3.2 Decentralized Equilibrium

In a decentralized equilibrium, the intermediate producer j in sector m chooses its path of variable labor input $N^{var}_{m,j,t}$ to maximize its profits, given the path of taxes $\{\tau_{m,j,t}\}_{t=0}^{\infty}$, which are set exogenously by the government. Notably, the intermediate producers do not internalize their influences over the final goods production possibilities through the effect of their accumulated emissions on climate change. First, I describe the competitive equilibrium, as implemented in Golosov et al. (2014), and then consider the case of equilibrium with an oligopolistic intermediate production sectors.

3.2.1 The Competitive Equilibrium

In a competitive equilibrium, each producer is a price taker. Specifically, intermediate good producers do not internalize the pricing power they have through their control over their own and sectoral outputs. Supplementary Appendix B.4.1 gives the complete competitive equilibrium definition.

The equilibrium paths of each intermediate sector $m = 1, \ldots, M$ good $j = 1, \ldots, J_m$ production again solves each producer's first order condition with respect to its variable labor input choice equation (23), but unlike the first order condition in equation (21), the SCC term is not present in the first order condition. The first order condition with respect to the variable labor input $N^{var}_{m,j,t}$ of producer j in sector m is given by:

$$\chi_{m,j,t}\left[\frac{\nu_m \kappa_{m,j}}{X_{m,t}^{\frac{\eta_m-1}{\eta_m}} X_{m,j,t}^{\frac{1}{\eta_m}}} - \frac{\tau_{m,j,t}}{Y_t}\right] = \frac{1-\alpha-\sum_{m=1}^{M}\nu_m}{N_{0,t}}, \tag{23}$$

where $\tau_{m,j,t}$ is the tax on carbon emissions from production of intermediate input j in sector m at time t.

There is a closed-form solution for the unregulated competitive equilibrium pinned down by the first-order condition with respect to variable labor input $N^{var}_{m,j,t}$ choice of each producer j in sector

m given by equation (23). The equilibrium paths of each intermediate sector $m = 1, \ldots, M$ good $j = 1, \ldots, J_m$ production satisfies:

$$X_{m,j,t} = \xi^{CE}_{m,j,t} X_{m,t}^{-(\eta_m - 1)},$$

where $\xi^{CE}_{m,j,t}$ for the competitive equilibrium allocations are given by:

$$\xi^{CE}_{m,j,t} \equiv \left(\frac{\nu_m \kappa_{m,j} \chi_{m,j,t} N_{0,t}}{1 - \alpha - \sum_{m=1}^{M} \nu_m + \chi_{m,j,t} N_{0,t} \hat{\tau}_{m,j,t}} \right)^{\eta_m},$$

where $\hat{\tau}_{m,j,t} = \tau_{m,j,t}/Y_t$ is the ratio of the tax on carbon emissions from production of intermediate input j in sector m to aggregate output at time t. For the unregulated competitive equilibrium, the tax on carbon emissions from production of intermediate input j in sector m is zero, i.e., $\hat{\tau}_{m,j,t} = 0$.

The $\xi^{CE}_{m,j,t}$ is a function of exogenous parameters. I obtain the solution by guessing the paths of total labor demand $N_{m,j,t}$ of each producer j in sector m and the labor demand $N_{0,t}$ of the final goods sector. Given these guesses, I solve for the paths of $\xi^{CE}_{m,j,t}$, $X_{m,t}$, $X_{m,j,t}$, and $N^{var}_{m,j,t}$ of each producer j. Using the solution for the path of $N_{m,j,t}$, I obtain update the paths of $N_{m,j,t}$ and $N_{0,t}$. I check the convergence of the solution by comparing the updated and guessed paths of $N_{m,j,t}$ and $N_{0,t}$. If the paths are not close enough, I update the guessed paths of $N_{m,j,t}$ and $N_{0,t}$ by taking a convex combination of the guessed and updated paths and repeat until convergence.

3.2.2 The Oligopoly Equilibrium

In an oligopoly equilibrium, each intermediate producer j in sector m internalizes its influence over the sectoral composite and composite price but not the final output and the general price level. The definition of the complete oligopoly equilibrium is available in Supplementary Appendix B.4.2.

Importantly, the oligopolistic firms perceive their influence over their individual good price, $p_{m,j,t}$ given by equation (13), and the sectoral composite price $p_{m,t}$, which is equal to sectoral output's marginal product in final output production, given by:

$$p_{m,t} = \nu_m \frac{Y_t}{X_{m,t}},$$

though their influence over the sectoral output $X_{m,t}$ level. The oligopolistic firms do not internalize their influence over the final output and price levels. Intermediate good producing firms choose their paths of variable labor input $N^{var}_{m,j,t}$ to maximize their profits, given the path of taxes $\{\tau_{m,j,t}\}_{t=0}^{\infty}$, which are set exogenously by the government. The oligopolistic producer j in sector m's first order condition with respect to its variable labor input $N^{var}_{m,j,t}$ is given by:

$$\chi_{m,j,t} \left[\frac{\nu_m \kappa_{m,j}}{X_{m,t}^{\frac{\eta_m - 1}{\eta_m}} X_{m,j,t}^{\frac{1}{\eta_m}}} \frac{\sigma_m(s_{m,j,t}) - 1}{\sigma_m(s_{m,j,t})} - \frac{\tau_{m,j,t}}{Y_t} \right] = \frac{1 - \alpha - \sum_{m=1}^{M} \nu_m}{N_{0,t}}, \tag{24}$$

where $\sigma_m(s_{m,j,t})$ is the price elasticity of demand for the intermediate input j in sector m given by equation (14), and $s_{m,j,t}$ is the sales share of producer j in sector m given by:

$$\begin{aligned} s_{m,j,t} &= \frac{p_{m,j,t} X_{m,j,t}}{\sum_{j=1}^{J_m} p_{m,j,t} X_{m,j,t}} \\ &= \frac{p_{m,j,t} X_{m,j,t}}{p_{m,t} X_{m,t}}. \end{aligned}$$

Unless the oligopolistic firms are symmetric, i.e., they have the same labor productivity $\chi_{m,j,t}$ and the share parameters $\kappa_{m,j}$, they will have different sales shares $s_{m,j,t}$. Unlike the competitive equilibrium, the oligopolistic firms' first order condition with respect to the variable labor input $N^{var}_{m,j,t}$ of producer j in sector m is given by equation (24), which includes an inverse markup term $\frac{\sigma_m(s_{m,j,t})-1}{\sigma_m(s_{m,j,t})}$ that prevents a simple closed-form solution for the oligopolistic equilibrium. However, I can obtain a numerical solution for the oligopoly equilibrium paths similar to the solution method I utilize to solve the planning problem in section 3.1. The oligopoly equilibrium paths of each intermediate sector $m = 1, \ldots, M$ good $j = 1, \ldots, J_m$ production satisfies:

$$X_{m,j,t} = \xi^O_{m,j,t} X_{m,t}^{-(\eta_m - 1)},$$

where $\xi^O_{m,j,t}$ for the oligopoly equilibrium allocations are given by:

$$\xi^O_{m,j,t} \equiv \left(\frac{\nu_m \kappa_{m,j} \chi_{m,j,t} N_{0,t}}{1 - \alpha - \sum_{m=1}^{M} \nu_m + \chi_{m,j,t} N_{0,t} \hat{\tau}_{m,j,t}} \frac{\sigma_m(s_{m,j,t}) - 1}{\sigma_m(s_{m,j,t})} \right)^{\eta_m},$$

where $\frac{\sigma_m(s_{m,j,t})-1}{\sigma_m(s_{m,j,t})}$ is the inverse markup term that depends on the endogenous sales share $s_{m,j,t}$ of producer j in sector m at time t.

I can obtain a numerical solution for the oligopolistic equilibrium similar to the optimal planning problem solution. In particular, I obtain a numerical solution for the oligopolistic equilibrium by guessing the paths of total labor demand $N_{m,j,t}$ of each producer j in sector m and the labor demand $N_{0,t}$ of the final goods sector. Using the guesses, I obtain sector-level output $X_{m,t}$ by aggregating the firm-specific outputs $X_{m,j,t}$ implied by the guesses and the sales shares $s_{m,j,t}$ for each producer j in sector m using the fact that:

$$s_{m,j,t} = \kappa_{m,j} \left(\frac{X_{m,j,t}}{X_{m,t}} \right)^{\frac{\eta_m - 1}{\eta_m}},$$

and the demand elasticities $\sigma_m(s_{m,j,t})$ and the firm-level markups implied by the demand elasticities. Then, I calculate the firm-specific $\xi^O_{m,j,t}$ as a function of the guessed $X_{m,j,t}$ and markup for each producer j in sector m implied by the guessed values of $N_{m,j,t}$ and $N_{0,t}$, and the exogenous parameters at time t. The remainder of the solution algorithm is similar to the one I use to solve the optimal planning problem in section 3.1.

3.3 Calibration

Given the model structure and the parametric assumptions presented, next I describe the calibration of the structural model parameters. I calibrate the model to match the US economy in 2017. One period in the model corresponds to a decade, so the model is calibrated to match the US economy in 2017, which is the earliest year for which I have the sectoral concentration data.

As the carbon-intensive sectors, I consider the top five carbon-intensive four digit NAICS sectors in the US economy with output shares greater than 0.1 percent and are not the utilities sector (i.e., NAICS codes that start with 22) in 2017, which are: Coal mining (2121), Cement manufacturing, Ready-mix concrete manufacturing, Concrete pipe, brick, and block manufacturing, Other concrete product manufacturing (3273), Fertilizer manufacturing, Pesticide and other agricultural chemical manufacturing (3253), Pulp mills, Paper mills, Paperboard mills (3221), Petroleum refineries, Asphalt paving mixture and block manufacturing, Asphalt shingle and coating materials manufacturing, Other petroleum and coal products manufacturing (3241). I exclude the utilities sector, which is the most carbon-intensive sector in the US economy, because of its regulated natural monopoly structure.

Table 1 describes key sectoral parameters used in the calibration of the model for the top five carbon-intensive sectors in the US economy.[1] In Table 1, the columns are labeled by NAICS codes and ordered by sectoral carbon emission intensities in 2017, with the most carbon-intensive sector (Coal mining, NAICS 2121) as the left-most column, followed by Cement manufacturing (3273), Fertilizer manufacturing (3253), Pulp and paper mills (3221), and Petroleum refineries (3241).

The top five sectors I consider in my model accounted for 37.2 percent of the aggregate carbon emissions from the US economy on average between 2010 and 2023. Moreover, the long-term average of GHG emissions from the US economy relative to the global GHG emissions is approximately 14.6 percent.[2] I present my calculations to obtain these fractions in detail in Supplementary Appendix C.4. I next describe the construction of the dataset containing the sectoral economic statistics I use and how I obtain the sectoral parameters used in the calibration of the model.

3.3.1 Sectoral Output Shares

In order to calculate the sectoral output shares ν_m for each sector $m = 1, \ldots, M$, I use the Bureau of Economic Analysis's (BEA) Input Output (IO) Use Table dataset for 2017, which provides the spending on intermediate commodities by each sector. However, the IO Table dataset follows the industry classification system of the BEA, which does not map one-to-one to the NAICS system.

[1] The next five carbon-intensive sectors in the US economy, which I do not consider in my model, are: Petrochemical manufacturing, Industrial gas manufacturing, Synthetic dye and pigment manufacturing, Other basic inorganic chemical manufacturing, Other basic organic chemical manufacturing (3251), Iron and steel mills and ferroalloy manufacturing (3311), Flour milling and malt manufacturing, Wet corn milling, Fats and oils refining and blending, Soybean and other oilseed processing, Breakfast cereal manufacturing (3112), Plastics material and resin manufacturing, Synthetic rubber and artificial and synthetic fibers and filaments manufacturing (3252), Copper, nickel, lead, and zinc mining, Iron, gold, silver, and other metal ore mining (2122).

[2] The long-term average of GHG emissions from the US economy relative to the global GHG emissions is calculated using the data from the OWID (2023) dataset, which provides the GHG emissions data for all countries in the world.

Table 1: Calibrated parameters by NAICS sector

Parameter	2121	3273	3253	3221	3241
ν_m	0.002	0.005	0.003	0.004	0.022
J_m	21	136	25	15	16
η_m	4.0	16.2	6.5	7.3	14.2
$\bar{\chi}_m$	7.0×10^5	5.4×10^5	1.6×10^6	8.2×10^5	4.0×10^6
$\sigma_{\log \chi_m}$	0.60	0.18	0.41	0.30	0.57
g_{χ_m}	0.09	0.06	0.77	0.84	1.07
θ_m	3.1×10^{-4}	2.0×10^{-4}	1.9×10^{-4}	1.4×10^{-4}	1.3×10^{-4}

Note: The calculations and data sources used to obtain the sectoral parameters are described in detail in the present sections. Each row reports a sector-specific calibrated parameter: The first row presents the sectoral output shares ν_m, the second row presents the effective number of firms J_m in each sector, the third row presents the sectoral elasticity of substitution parameters η_m, the fourth row presents the average sectoral labor productivity $\bar{\chi}_m$, the fifth row presents the standard deviation of the logged sectoral labor productivity $\sigma_{\log \chi_m}$, the sixth row presents the annual growth rate of sectoral labor productivity $g_{\bar{\chi}_m}$, and the seventh row presents the average sectoral carbon intensity θ_m.Each column corresponds to a different NAICS sector. The sectors are ordered by their carbon emission intensities in 2017, with the most carbon-intensive sector on the left.

To map the BEA industry classification to the NAICS system, I use the mapping provided by the BEA (2024a), which maps the BEA codes to the 2017 NAICS codes. I calculate the gross output of sector m used as intermediates by summing the spending of each sector on intermediate commodities, reported under variable name "T001," with NAICS codes that start with the four-digit NAICS code of sector m. I obtain aggregate value added, i.e., Gross Domestic Product (GDP), as the sum of value added across all sectors in the economy, which is reported in the IO Table dataset, which is reported under label "VAPRO" in the IO Table dataset. Finally to calculate the sectoral output shares ν_m, I divide the gross output of sector m used as intermediates by the GDP of the economy.

The sectoral output shares ν_m for each sector $m = 1, \ldots, M$ are presented in the first row of Table 1. There is a negative correlation between the sectoral output shares ν_m and the carbon intensity of the sector, i.e., the carbon emissions per dollar of output produced in the sector. Thus, top carbon-intensive sectors have larger sectoral output shares, indicating that they are the more important sectors in terms of their contribution to the overall output of the economy.

3.3.2 Effective Sector Size

The industry size parameter, J_m, is calibrated to match the Herfindahl-Hirschmann Index (HHI) the selected five selected intermediate sectors. HHI is calculated by squaring the market share of each competing firm in the industry and then summing the resulting numbers. The result can range from close to zero to 10,000. Increases in HHI indicate a decrease in competition and an increase in market power. If all firms have an equal share, the reciprocal of the index shows the number of firms in the industry. When firms have unequal shares, the reciprocal of the index indicates the "equivalent" number of firms in the industry.

The US Census Bureau (2023) has detailed data on HHI for each NAICS sector in the US economy for 2017. I use the 2017 HHI values for the five carbon-intensive sectors I consider in my model and calculate the effective number of firms in each sector J_m as the reciprocal of the HHI/10,000. The effective number of firms in each sector J_m is presented in the second row of Table 1. There is no clear correlation between the effective number of firms in a sector and the carbon intensity of that sector. In general, the effective number of firms in a sector is low for the most carbon-intensive sectors, indicating that these sectors are resemble oligopolistic markets with a few large firms dominating the market.

3.3.3 Average Sectoral Markups

In order to incorporate the oligopolistic structure of the intermediate sectors, I need to calibrate the average sectoral markups $\kappa_{m,j}$ for each sector $m = 1, \ldots, M$ and firm $j = 1, \ldots, J_m$, which describe the average degree of market power in the sector. I calculate the sales-weighted average markups for each sector m using the S&P Global Market Intelligence's (2023) Compustat dataset, which provides the financial data for publicly traded firms in the US. The details of the markup calculations are available in Supplementary Appendix A. Given the average sectoral markups, I obtain the sectoral elasticity of substitution parameter η_m using the following formula:

$$\eta_m = \frac{1}{1 - \frac{1}{\bar{\mu}_m}}, \tag{25}$$

where $\bar{\mu}_m$ is the average sectoral markup for sector m.

The average sectoral markups $\bar{\mu}_m$ are presented in the third row of Table 1. The lower the average sectoral markup, the more competitive the sector is, and higher the elasticity of substitution η_m is. The sectors with the highest average sectoral markups among the top ten carbon-intensive sectors are petrochemical manufacturing (3251), coal mining (2121), and stone mining and quarrying (2123). Again, there is no clear correlation between the average sectoral markups and the carbon intensity of the sector, but carbon intensive sectors have positive profit margins, i.e., markups greater than unity. I present the history of average sectoral markups $\bar{\mu}_m$ values used in the calibration of η_m in Supplementary Appendix C.1.

3.3.4 Average Sectoral Labor Productivity Distribution

I use the average sectoral labor productivity in 2017 as the calibration target for the sectoral labor productivity $\chi_{m,j,t}$ of each intermediate sector $m = 1, \ldots, M$ and firm $j = 1, \ldots, J_m$. I calculate the average sectoral labor productivity using the sectoral value added values from the IO Table dataset and the sectoral total employment data from the US Census Bureau (2023) dataset for 2017. In order to calculate the value added for each four-digit NAICS sector, I use the sectoral value added, the variable "VAPRO," values from the BEA (2024a) dataset. Once I obtain the value added for each four-digit NAICS sector, I merge the value added data with the total employment data from the US Census Bureau (2023) dataset, which provides the total employment for each four-digit NAICS sector in 2017.

I calculate the base year average sectoral labor productivity $\bar{\chi}_m$ for each four-digit NAICS sector in 2017 by dividing the total value added of the sector by the total employment of the sector in 2017. The average sectoral labor productivity $\bar{\chi}_m$ for each sector $m = 1, \dots, M$ is presented in the fourth row of Table 1. In order to calculate the dispersion of the logarithm of sectoral labor productivity $\sigma^2_{\log \chi_m}$, I use the Compustat dataset. I calculate firm-specific annual value added by subtracting the cost (COGS) of goods sold from the total revenue (REVT) of each firm in the Compustat dataset. Then, I calculate firm-specific annual labor productivity by dividing the firm-specific annual value added by the total employment (EMP) of the firm reported in the Compustat. Finally, I calculate the standard deviation of the logarithm of firm-specific annual labor productivity for each four-digit NAICS. The sectoral productivity dispersion $\sigma^2_{\log \chi_m}$ is presented in the fifth row of Table 1.

Given the effective number of firms in each sector J_m I obtained by inverting the sectoral HHI, I simulate initial labor productivity level $\chi_{m,j,t}$ for each firm $j = 1, \dots, J_m$ in a sector m by drawing from a log-normal distribution with mean equal to the average sectoral labor productivity $\bar{\chi}_m$ and standard deviation equal to $\sigma^2_{\log \chi_m}$, i.e., $\log \chi_{m,j,0} \sim \mathcal{N}(\log(\chi_m), \sigma^2_{\log \chi_m})$. Overall, average sectoral labor productivity $\bar{\chi}_m$ displays a low positive correlation with the carbon intensity of the sector, but theire is no clear correlation between the sectoral labor productivity dispersion $\sigma^2_{\log \chi_m}$ and the carbon intensity of the sector.

3.3.5 Average Sectoral Labor Productivity Growth Rate

I obtain the historical sectoral labor productivity indices from the BEA (2024b) dataset, which is published jointly by the BEA and the Bureau of Labor Statistics (BLS). The ILPA dataset provides annual labor productivity indices for Production Account sectors, which use the BEA sector codes. Moreover, the most disaggregated sector classification in the BEA (2024b) dataset is at the three-digit BEA code level.

I present the historical annual sectoral labor productivity growth rates for the three-digit Production Account (BEA) sectors that contain the five most carbon-intensive sectors in Supplementary Appendix C.2. The BEA industry descriptions and their Production Account codes of the five modeled sectors are: Mining, except for oil and gas (212), Nonmetallic mineral products (327), Chemical products (325), Paper products (322), Petroleum and coal products (324).

For calibration of the sectoral labor productivity growth rate, I use the average annual growth rate of each sector's labor productivity from 2000 to 2023. I present the average annual growth rates of the sectoral labor productivity in the sixth row of Table 1. There is a strong positive correlation between the sectoral labor productivity growth rate and the carbon intensity of the sector.

3.3.6 Carbon Intensity

In the baseline calibration, I assume that the carbon intensities of each intermediate sector $m = 1, \dots, M$ are constant over time and across firms, i.e., $\theta_{m,j,t} = \theta_m$ for all j, t. I set the carbon intensities of the five carbon-intensive sectors to match the average carbon intensity of the sector in

2017, which I calculate using emissions data from the US Environmental Protection Agency (2024) and value added data from the BEA (2024a) datasets. The units of the carbon intensity θ_m are metric tons of carbon (mtC) per dollar of value added produced in the sector.

Using the facility-level carbon emissions data from the US Environmental Protection Agency (2024) dataset, which assigns a six-digit 2007 NAICS code to each facility, I calculate the aggregate carbon emissions of every four-digit NAICS sector and year represented in the sample. As I explain further below, I normalize the sectoral carbon emissions - output elasticity parameter ζ_m to 1, which implies that the sectoral carbon intensity θ_m is equal to the average carbon emissions per dollar of output produced in the sector in 2017. The GHGRP dataset spans 129 four-digit 2007 NAICS sectors and 14 years from 2010 to 2023. Importantly, GHGRP reports metric tons of carbon dioxide (CO2) equivalent emissions, and I convert the reported emissions to metric tons of carbon (GtC) by multiplying the reported emissions by 12/44.[3] I use the value added data from the BEA (2024a) dataset, as I described earlier, which is mapped to the 2017 NAICS codes. I use the concordance provided between the 2007 and 2017 NAICS codes by the US Census Bureau (2017) to map the 2007 NAICS codes to the 2017 NAICS codes.

I merge the emissions data from the US Environmental Protection Agency (2024) dataset with the value added data from the BEA (2024a) dataset to obtain the average carbon intensity of each four-digit NAICS sector in 2012, 2017, and 2022. Finally, I calculate the average carbon intensity of every large enough carbon emission reporting intermediate sector in 2017 by dividing the total carbon emissions of the sector by the total value added of the sector in 2017. I sort the four-digit NAICS sectors by their average carbon intensity in 2017 and select the top five carbon-intensive sectors I listed above. The average carbon intensities of the top five carbon-intensive sectors in 2017 are presented in the seventh row of Table 1 in units of metric tons of CO2 per billion dollar of value added.

3.3.7 Other Structural Parameters

I summarize the calibration strategy for the remaining structural parameters of my model $\left\{\alpha, \beta, \delta, N, g_0, \bar{\gamma}, \psi_0, \psi_L, \psi, \left\{\zeta_m, \{\Omega_{m,j}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}$, the initial conditions $\{K_0, A_{0,0}, \bar{S}, S_{1,-1}, S_{2,-1}\}$, and other calibration targets in Table 2. I provide explanations for the calibration of each parameter in the following paragraphs.

I follow the calibration of Golosov et al. (2014) for the parameters α, β, and δ. Full depreciation of capital and logarithmic utility function assumptions result in the crucial constant optimal social cost of carbon result. Unlike Golosov et al. (2014), I calibrate the global average annual TFP growth rate from 2007 to 2017 to 0.0073. I calculate this growth rate as the GDP-weighted global average of the country-level annual TFP growth rates by combining real GDP from the World Bank's World Development Indicators, WDI (2024), reported as "GDP, PPP (constant 2021 international $)," and TFP from World Bank's (2021) Cross-Country Database of Productivity, reported as

[3] The conversion factor is the ratio of the molecular mass of carbon (12 atomic mass units, or amu) to the molecular weight of carbon dioxide (44 amu).

Table 2: Baseline calibration of aggregate parameters

Parameter	Description	Value	Source
α	Output share of capital	0.3	Golosov et al. (2014)
β	Discount factor	0.985^{10}	Golosov et al. (2014)
δ	Capital depreciation rate	1.0	Golosov et al. (2014)
g_0	Annual TFP growth rate	0.0073	World Bank (2021) & WDI (2024)
N^{pop}	Exogenous labor supply (billions)	7.61	WDI (2024)
π^{hours}	Fraction of hours worked	0.24	ILO (2025b)
π^{LF}	Labor force participation rate	0.61	ILO (2025a)
$\bar{\gamma}$	Climate change damage elasticity	5.3×10^{-5}	Golosov et al. (2014)
ψ_L	Permanent emission share	0.2	Golosov et al. (2014)
ψ_0	Decadal retained emission share	0.1988	NOAA (2025a) & OWID (2023)
ψ	Decadal geometric emission decay rate	0.9555	NOAA (2025a) & OWID (2023)
$\bar{S}$	Pre-industrial carbon concentration	596.4	NOAA (2025a)
$S_{1,0}$	Permanent carbon stock in 2017	174.876	OWID (2023)
$S_{2,0}$	Transitory carbon stock in 2017	95.122	NOAA (2025a) & OWID (2023)
ζ_m	Output elasticity of emissions	1.0	Golosov et al. (2014)
$\Omega_{m,j}$	Fixed cost share	0	Golosov et al. (2014)
K_{-1}	Initial capital stock ($2021 trillions)	268.755	WDI (2024)
$A_{0,0}$	Final goods sector initial TFP	2.2×10^4	WDI (2024) & OEWS (2017)
E/E^{USA}	Modeled emissions to US emissions ratio	0.376	EPA 2024 & OWID (2023)
E^{USA}/E^{World}	US emissions to world emissions ratio	0.146	OWID (2023)

"Total factor productivity (TFP) in log difference, percent," at yearly and cross-country levels. The precise choice of the decadal TFP growth rate is only relevant for the generation of specific paths of allocations and only relevant for the discussion of robustness of the benchmark results.

I normalize the labor supply N to the total labor hours worked in the world in 2017, which is 1.11 billion hours. I calculate the total labor hours worked in the world in 2017 as the product of the world population in 2017 N^{pop}, which I obtain from WDI (2024), the fraction of hours worked in the world π^{hours}, which I obtain from the International Labour Organization (ILO) dataset, ILO (2025b), and the labor force participation rate π^{LF}, which I obtain from the ILO dataset, ILO (2025a). Moreover, I assume that there is no population growth over time.

I follow Golosov et al. (2014) in the choice of the climate change damage elasticity $\bar{\gamma}$, setting it equal to 5.3×10^{-5}.On the other hand, I deviate from Golosov et al. (2014) in the choice of the parameters $\{\psi, \psi_L, \psi_0\}$ and initial conditions $\{S_{1,0}, S_{2,0}, \bar{S}\}$ of the carbon cycle block of the model. I provide a detailed description of the calibration of the carbon cycle block in Supplementary Appendix C.3.

Although my model and solution algorithm are generalized to allow for nonlinear emissions-output elasticity $\zeta_{m,j}$ and firm-specific fixed costs $\Omega_{m,j,t}$, in the baseline calibration, I assume that $\zeta_m = 1$ for all m, j, and $\Omega_{m,j,t} = \Omega_{m,j}$ for all t and $\Omega_{m,j} = 0$ for all m, j.

The initial capital stock K_{-1} is set to 268 trillion dollars, which is the 2007 capital stock implied by the 2017 global GDP of 125.35 trillions of dollars, the capital's share of output $\alpha = 0.3$, and the annual real interest rate of 4.19 percent. I obtain the 2007-2017 total global GDP from the World Bank's World Development Indicators dataset, WDI (2024), and calculate the average 2007-2017

Table 3: Employment shares of the five most carbon-intensive sectors in 2017

Sector	Employment Share $\pi_{m,0}$ (2017)
Coal mining (212)	0.0013
Cement manufacturing (327)	0.0029
Fertilizer manufacturing (325)	0.0057
Paper pulp mills (322)	0.0026
Petroleum refineries (324)	0.0007

Note: The employment shares are calculated using the employment data from the OEWS (2017) dataset, which provides the employment data for all sectors in the US economy in 2017. The employment shares are calculated as the ratio of the employment in the sector to the total employment in the US economy in 2017, which is 142.5 million.

global interest rate as the GDP-weighted-average of country-specific real interest rates, also from WDI (2024), reported as "Real interest rate (percent)."

I set the initial TFP of the final goods sector in 2017, $A_{0,0}$, to 22.0 trillion dollars, which is I obtain by the following calculation:

$$A_{0,0} = \frac{\text{GDP}_{2017}^{World}}{\exp[-\bar{\gamma}(S_{1,0} + S_{2,0})](K_{-1})^{\alpha}\left[(\pi_{0,0}N)^{1-\alpha-\sum_{m=1}^{M}\nu_m}\right]\left[\prod_{m=1}^{M}(10 \cdot \bar{\chi}_m \pi_{m,0} N)^{\nu_m}\right]}$$

where $\text{GDP}_{2017}^{World}$ is the 2017 global GDP in 2021 dollars, which I obtain from WDI (2024), and I proxy the labor share of output in intermediate sectors by obtaining these sector's employment data from the OEWS (2017) dataset, which provides the employment data for all sectors in the US economy in 2017. OEWS (2017) reports the employment data for each three-digit NAICS sector. The 2017 employment shares of the five carbon-intensive sectors and the residual final goods sector I consider in my model are reported in Table 3. The final goods sector employment share is calculated as the residual of the total employment in the US economy in 2017, which is 142.5 million, minus the employment in the five carbon-intensive sectors I consider in my model.

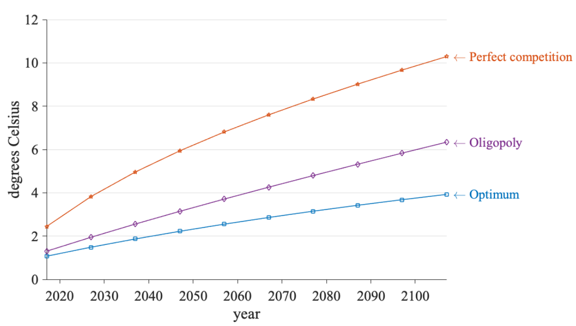
Finally, I introduce two new ratios, E/E^{USA} and E^{USA}/E^{World}, to account for the fact that the model is calibrated to the US economy, while the carbon cycle that governs the climate change block of the model is global. The ratio E/E^{USA} is the ratio of the modeled emissions to the US emissions, which is 37.65 percent. I calculate this ratio by first calculating the total emissions attributed to the five carbon-intensive sectors in the model by aggregating the facility-level emissions data from the US Environmental Protection Agency (2024) dataset for the five carbon-intensive sectors I consider in my model. Then, I divide the average total emissions attributed to the five carbon-intensive sectors by the total US emissions between 2010 and 2023, which I obtain from the Our World in Data, OWID (2023) dataset. The ratio E^{USA}/E^{World} is the ratio of the average ratio of US emissions to the world emissions calculated using OWID (2023) dataset between 2010 and 2023, which is approximately 14.6 percent. I include figures with the longest time series available for these two ratios in Supplementary Appendix C.4.

4 Quantitative Results

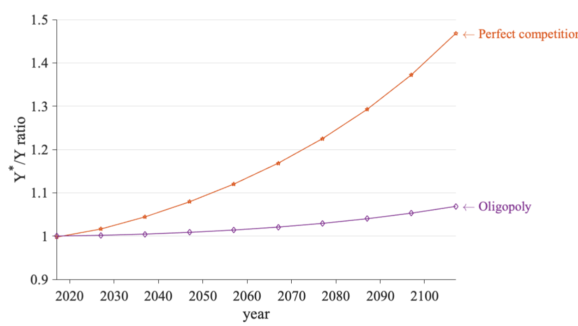
I quantitatively evaluate the model by simulating the optimal and equilibrium paths of allocations and prices using the baseline calibration described. In this section, I present the model's simulation results of mean global surface temperature change, sectoral and aggregate emissions, the ratio of optimal to equilibrium levels of output, and the optimal policy paths from 2017 to 2207. My baseline simulation results show that the net distortion of the oligopoly is lower than that of the competitive equilibrium, and accounting for sectoral and firm heterogeneity results in differing optimal policies across sectors and firms.

Figure 5 summarizes key simulation outcomes. Panel (a) shows global mean surface temperature change relative to pre-industrial levels. The temperature increase is highest under perfect competition, lower under oligopoly, and lowest under the optimal policy. The model predicts an optimal temperature rise of about 4 degrees Celsius by 2100, compared to 3 degrees Celsius in other studies (e.g., Nordhaus (2014), Golosov et al. (2014), Barrage (2019)). The oligopoly equilibrium path is closer to observed real-world temperature changes, which has reached about 1.63 degrees Celsius above pre-industrial levels in 2024 according to NOAA (2025b).

Figure 5: Model simulations



(a) Global mean surface temperature change relative to pre-industrial levels



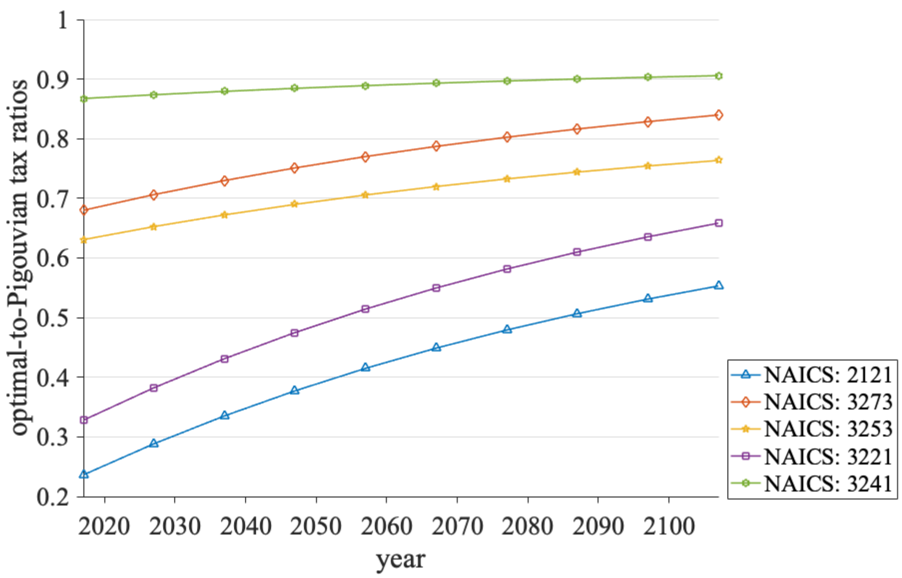
(b) Relative optimal output paths

Panel (b) shows the ratio of optimal to equilibrium aggregate output. The ratio is always above one, indicating that equilibrium output is suboptimal under both market structures. Oligopoly equilibrium output is closer to the optimum than perfect competition, suggesting that oligopoly leads to a smaller output distortion.

4.1 Market Structure and Optimal Policy

Optimal output taxes are consistently lower under oligopoly than perfect competition, with the ratio of oligopoly to competitive taxes always below one. Output taxes are measured in 2021 US dollars per dollar of value added. Figure 6 displays these ratios across sectors. The optimal output tax ratio varies by sector and firm, reflecting differences in market power. The ratio is highest for the most competitive sector, petroleum and coal products manufacturing (NAICS 3241), and lowest for the least competitive sector, coal mining (NAICS 2121). The levels of optimal output taxes are shown in Appendix C.5, Figure 15.

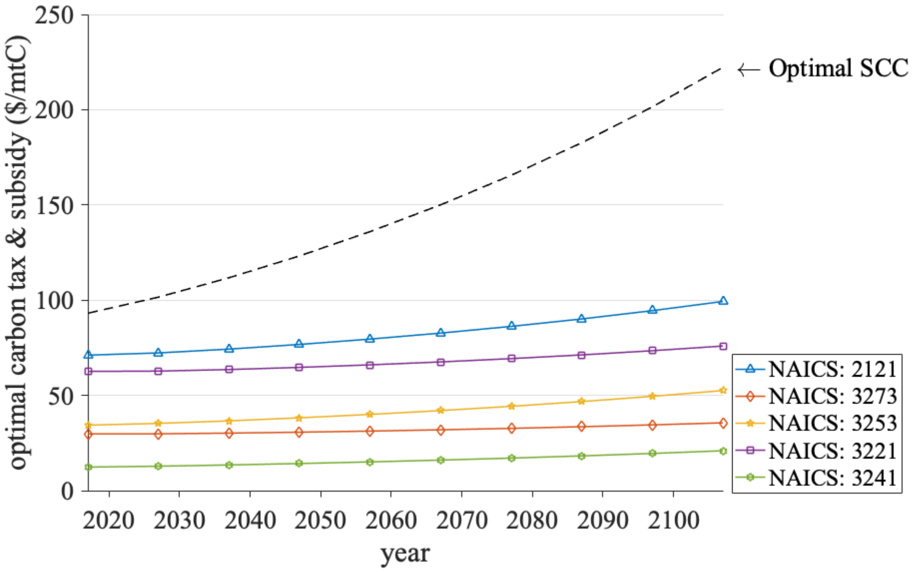
Figure 6: Optimal output taxes under perfect competition vs. oligopoly for the median productivity firm in five carbon-intensive NAICS sectors.



For interpretability, I convert the optimal output taxes in 2021 US dollars per metric ton of carbon emissions. To convert the output taxes to per-ton carbon taxes, I use the assumption that carbon emissions is a linear function of output (i.e., $\zeta_m = 1$, for all m). I divide the output tax by the firm's carbon emission intensity, which is the ratio of emissions to value added. Generally, within policy discussions, optimal carbon taxes are reported in dollars per ton of CO_2 equivalent emissions (see, e.g., EPA (2023)). For comparability, one can convert the per-ton carbon taxes reported above to per-ton CO_2 equivalent emissions by multiplying the carbon taxes by 44/12, which is the ratio of the molecular weight of CO_2 to that of carbon. Since the optimal carbon taxes are a combination of the Pigouvian tax, that is equal to the marginal external damages from the carbon emissions, and the output subsidy, that is equal to the marginal output distortion, I decompose the optimal carbon taxes into these two components. The marginal external damages from a unit of carbon emitted is uniform across all sectors and firms, and is equal to the OSCC.

Figure 7 shows the decomposition of the optimal output taxes into the Pigouvian tax and the output subsidy for the median productivity firm in five intermediate carbon-intensive sectors. The optimal carbon taxes equal to the Pigouvian tax minus the output subsidy, which is always positive, indicating that the climate change externality is always greater than the output distortion. The Pigouvian tax is equal to the optimal SCC, which is the marginal external damages from marginal carbon emissions, and is shown with the black dashed line in the figure. The output subsidy is equal to the marginal output distortion, which is the difference between the Pigouvian tax and the optimal output tax. In the figure, each sector's optimal output subsidy is shown with marked lines

Figure 7: Optimal carbon tax decomposition into Pigouvian tax and output subsidy for the median productivity firm in five carbon-intensive NAICS sectors.



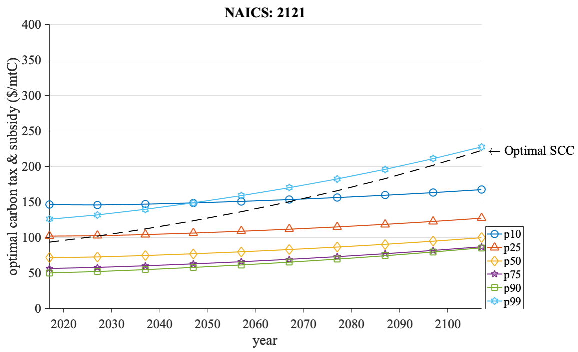
and mapped by the legend.

This decomposition also reflects the market structure differences across the carbon-intensive sectors. The marked distortion is greatest for the most carbon-intensive sector, coal mining (2121), and the least for the least carbon-intensive sector, petroleum and coal products manufacturing (3241). However, the size of the market distortion is not necessarily related to the carbon intensity of the sector, as the optimal output subsidy for the paper manufacturing (3221) sector is greater than that of the cement manufacturing (3273) and fertilizer manufacturing (3253) sectors, even though the latter two are more carbon-intensive. This relationship also holds when inspecting the optimal-to-Pigouvian tax ratios in Figure 6. The optimal output taxes are closer to the Pigouvian tax (i.e., the ratio is closer to one) when the market power is lower.

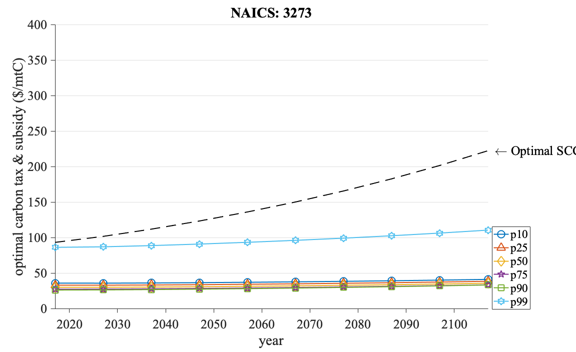
4.2 Optimal Policy and Firm Heterogeneity

Moreover, when firms within the same sector can have different levels of productivity they need different optimal policies. Figure 8 shows the optimal carbon taxes for the 10th, 25th, 50th, 75th, 90th, and 99th percentiles of the productivity distribution of firms in five intermediate carbon-intensive sectors. The black dashed line shows the OSCC. The other lines with markers show the optimal emissions subsidy for firms at different percentiles of the productivity distribution when market power is the only distortion and is firm- and sector-specific. The optimal firm-specific carbon taxes equal to the OSCC minus the firm-specific output subsidy. Thus, lower the subsidy, higher will be the optimal tax on emissions from the unregulated oligopolistic firm. When the output subsidy exceeds the OSCC, the optimal carbon tax becomes negative, indicating that the firm should be subsidized to increase its output.

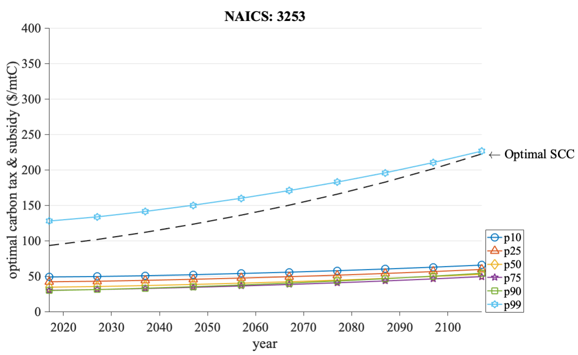
Figure 8: Optimal carbon taxes under perfect competition vs. oligopoly for lowest, median, and highest productivity firms in five carbon-intensive NAICS sectors.



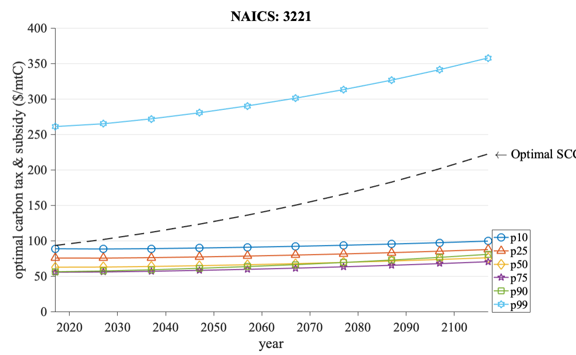
(a) Coal mining



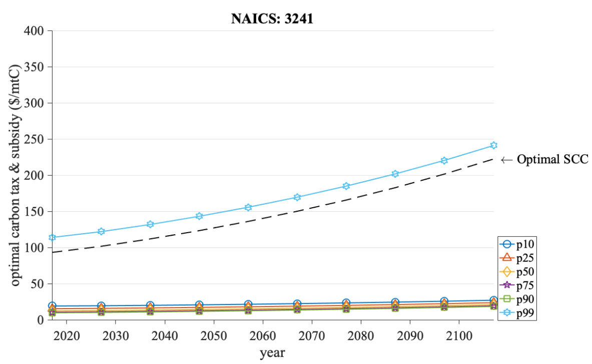
(b) Cement manufacturing



(c) Fertilizer manufacturing



(d) Paper manufacturing



(e) Petroleum and coal products manufacturing

In some cases, firms with higher productivity may face higher optimal carbon taxes, while in other cases, they may face lower taxes or even subsidies. This non-monotonic relationship highlights the importance of considering firm-specific characteristics when designing climate policies. Moreover, the dispersion of firm productivity distribution within a sector differs across sectors, as discussed in Section 3.3 Table 1. For example, the coal mining sector (NAICS 2121) and the petroleum and coal products manufacturing sector (NAICS 3241) have relatively high dispersion in firm productivity, while the cement manufacturing sector (NAICS 3273) has relatively low dispersion. Thus, the optimal carbon taxes for firms in the coal mining and petroleum and coal products manufacturing sectors vary more across firms than those in the cement manufacturing sector.

The non-monotonic relationship between firm productivity and optimal carbon taxes warrants further investigation. In a Cournot competition setting, firms with higher productivity produce more output since they have lower marginal costs. However, the more productive firms also have more market power and internalize a larger downward impact of their output on price, thus they withhold more output to increase their profits. The per-unit subsidy required to correct the output distortion is higher due to greater the market power of more productive firms, but also as productivity increases, the marginal cost of production decreases, leading to more output. Thus, in Cournot competition, the direction in which the optimal output subsidy changes with productivity depends on the relative rates of change of the firm's marginal cost, and the firm's markup distortion, which is linked to the firm's price elasticity of demand and to its strategic behavior.

5 Policy Experiments

I now evaluate the welfare consequences of alternative policies, focusing on cases where carbon-intensive sectors are either oligopolistic or perfectly competitive. As established in Section 2.5, the optimal output tax under oligopoly is firm-specific and depends on a firm's carbon intensity and elasticity of demand. However, much of the literature (e.g., Golosov et al. (2014) and Golosov et al. (2014)) assumes sector-wide uniform taxes, overlooking firm heterogeneity. I consider two policy settings.

In the first, the true market structure is Cournot oligopoly with heterogeneous firms. I compare three scenarios: (i) an economy-wide uniform carbon tax, equal to marginal external damages; (ii) a sector-wide uniform carbon tax, based on a representative firm's productivity and carbon intensity; and (iii) no policy intervention, serving as the benchmark decentralized equilibrium. To derive the carbon tax from an output tax, I divide by each firm's carbon intensity. The resulting tax per ton of emissions is constant across firms in scenario (i), but sector-specific in scenario (ii).

In the second setting, I assume the true market structure is perfect competition. I compare: (i) the firm-specific optimal output tax designed for oligopolistic sectors with heterogeneous firms from Section 2.5, and (ii) the sector-wide uniform tax described above. I also report welfare under no intervention.

Notably, the sector-wide tax appears in both sets of experiments, applied under different assumptions about market structure. For each case, I compute welfare losses relative to the planner's first-best allocation, using both consumption-equivalent losses and equivalent variation in trillions of 2021 USD. I present these results in Table 4.

The table reports welfare losses under various policy scenarios, relative to the first-best allocation. The top panel assumes carbon-intensive sectors are Cournot oligopolies with heterogeneous firms. Without intervention, the oligopoly equilibrium results in a 1.55% consumption-equivalent welfare loss (equivalent to 11.97 trillions of 2021 US dollars). Imposing an economy-wide uni-

Table 4: Welfare Losses Associated with Policy Experiments

Market Structure	Policy Scenario	CE Loss (%)	EV ($2021tril.)
Cournot Oligopoly	No Policy Intervention	1.55	$11.97
	Economy-Wide Uniform Carbon Tax	1.81	$14.03
	Output Tax for Homogeneous Oligopolistic Firms	5.35	$41.38
Perfect Competition	No Policy Intervention	11.22	$86.76
	Firm-Specific Output Tax for Oligopolistic Firms	121.25	$937.57
	Output Tax for Homogeneous Oligopolistic Firms	5.37	$41.52

Note: The first column reports the true market structure, which is either Cournot Oligopoly or Perfect Competition, of the carbon-intensive sectors. The second column reports the policy scenario, which is either no policy intervention, or the optimal tax for the incorrectly assumed market structure, or policy that ignores the heterogeneity of firms within the same sector. The third column reports the permanent percentage reduction in consumption that would make a representative agent indifferent between the policy scenario and the first-best allocation, i.e., the consumption-equivalent (CE) welfare loss. The fourth column reports the equivalent variation (EV) of the welfare loss in trillions of constant 2021 US dollars. EV represents the monetary value of the utility difference between the policy and the first-best scenario, calculated by applying the percentage loss to baseline aggregate consumption in 2017.

form carbon tax—optimal under perfect competition—yields a slightly higher loss of 1.81% (14.03 trillions of 2021 US dollars). A sector-wide uniform tax, based on a representative firm's characteristics, performs significantly worse, resulting in a 5.35% loss (41.38 trillions of 2021 US dollars). This policy undertaxes low-markup, high-emission firms, leading to greater environmental harm. These results show that both uniform taxes perform worse than no policy, underscoring the cost of ignoring heterogeneity in market power and emissions intensity.

The bottom panel considers the case where carbon-intensive sectors are perfectly competitive. Here, the unregulated equilibrium produces an 11.22% welfare loss (86.76 trillions of 2021 US dollars). Imposing the optimal tax derived for oligopolistic firms leads to a catastrophic 121.25% loss (937.57 trillions of 2021 US dollars), larger than global GDP in the base year. This reflects the danger of subsidizing output in competitive industries where the main distortion is excessive emissions. In contrast, applying the sector-wide uniform tax—originally designed for symmetric oligopolies—yields a smaller loss of 5.37% (41.52 trillions of 2021 US dollars), outperforming the laissez-faire case.

Together, these results highlight the importance of aligning policy design with market structure. Misclassifying a competitive industry as oligopolistic—and applying subsidy-heavy output taxes—can result in massive welfare losses. By contrast, applying imperfect but positive carbon pricing in competitive sectors is still preferable to inaction.

6 Conclusion

Economists going back to Buchanan (1969) have recognized that the two market failures associated with market power and negative environmental externalities work in opposite directions. While market power leads to monopolies restricting output in order to charge inefficiently high prices, negative environmental externalities mean that by failing to account for the damages they cause, polluters produce too much output and charge inefficiently low. A policy that corrects only one of these problems could be worse than not intervening at all.

Building on this insight, I argue that many of carbon-intensive industries have market power by showing the empirical correlation between markups and economic profit rates, two measures of market power, and greenhouse gas emission intensities of industries in the US. The most carbon-intensive industries have markups and economic profit rates that indicate that they are pricing power and operate in oligopolistic market structures. The higher carbon emissions per value added by these industries warrants a carbon tax to correct the negative externality associated with their production. However, their high markups and positive profit rates indicate that they restrict output to charge higher prices, which would warrant them to be subsidized to correct the market power externality. The ideal solution to correcting one of these market failures requires the other one to be corrected as well. However, in practice, it is difficult to implement two separate policies. Any policy to correct one of these market failures needs to take into account of the state of regulation of the other market failure.

Concerned with regulating carbon-intensive industries, I developed a neoclassical growth model with carbon-intensive goods produced by oligopolistically competitive firms with heterogeneous markups and productivity levels. I describe the centralized and decentralized solutions of the model and solve for the optimal firm-specific output taxes that decentralize the planner's solution. The optimal output tax is a combination of the optimal tax on perfectly competitive producers with negative environmental externalities and the optimal subsidy on oligopolistic producers without negative environmental externalities. When the market structure is fixed, the optimal output tax depends on a producer's carbon intensity and its firm- and industry- characteristics. Moreover, the optimal output tax that addresses both market failures for unregulated oligopolistic producers is lower than the optimal output tax for perfectly competitive producers with only negative environmental externalities.

Using data from the US, I calibrate the model to reflect the current carbon-intensity and market structure of the top five carbon-intensive industries in the US. The relative magnitudes of the optimal output tax for carbon-intensive perfectly competitive and carbon-intensive unregulated oligopolistic market structures are quite different. The difference between the optimal tax and the Pigouvian tax increases as the level of competition decreases. Given the current characteristics of US carbon-intensive industries, the output reduction from market power is less concerning that the output reduction needed to limit climate change.

Moreover, in a series of policy experiments, I compare the welfare losses associated with implementing the optimal output tax on firms in incorrectly assumed market structures. Implementing an optimal policy for an incorrectly assumed market structure may be worse than no policy intervention, regardless of whether the true market structure is oligopolistic or perfectly competitive. If the industries are oligopolistic, then no intervention is better than implementing the incorrectly designed output tax. If the industries are perfectly competitive, any positive tax is better than no intervention at all, even if the tax is not optimal for the true market structure, whereas subsidizing perfectly competitive and carbon-intensive industries could be catastrophic. This result is concerning and it highlights the importance of correctly identifying the market structure of industries when designing policies to correct the negative externalities arising from their carbon emissions.

The proposed policy has advantages over the standard distortion-specific policies, as it can still achieve the first-best allocation in the presence of two separate market failures. By regulating output rather than emissions directly, the regulator can employ a single policy instrument to both discourage high-emissions production and subsidize zero-emissions infant industries characterized by high market concentration and market power.

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous (2012). "The Environment and Directed Technical Change." *American Economic Review* 102.1, pp. 131–166.

Anthoff, David and Richard S. J. Tol (2013). "The Uncertainty About the Social Cost of Carbon: A Decomposition Analysis Using FUND." *Climatic Change* 117.3, pp. 515–530.

Atkeson, Andrew and Ariel Burstein (2008). "Pricing-to-Market, Trade Costs, and International Relative Prices." *American Economic Review* 98.5, pp. 1998–2031.

Barnett, A. H. (1980). "The Pigouvian Tax Rule Under Monopoly." *American Economic Review* 70.5, pp. 1037–1041.

Barrage, Lint (2019). "Optimal Dynamic Carbon Taxes in a Climate–Economy Model with Distortionary Fiscal Policy." *Review of Economic Studies*.

Baumol, William J. and Wallace E. Oates (1988). *The Theory of Environmental Policy*. 2nd ed. Cambridge University Press.

Buchanan, James M. (1969). "External Diseconomies, Corrective Taxes, and Market Structure." *American Economic Review* 59.1, pp. 174–177.

De Loecker, Jan and Jan Eeckhout (2017). *The Rise of Market Power and the Macroeconomic Implications*. Working Paper 23687. National Bureau of Economic Research.

Eeckhout, Jan (2025). "The Value and Profits of Firms." *Journal of the European Economic Association*.

Golosov, Mikhail, John Hassler, Per Krusell, and Aleh Tsyvinski (2014). "Optimal Taxes on Fossil Fuel in General Equilibrium." *Econometrica* 82.1, pp. 41–88.

Hassler, J., P. Krusell, and A.A. Smith (2016). "Chapter 24 - Environmental Macroeconomics". Ed. by John B. Taylor and Harald Uhlig. Vol. 2. Handbook of Macroeconomics. Elsevier, pp. 1893–2008.

International Labour Organization (2025a). *Labour Force Statistics (LFS)*. https://ilostat.ilo.org/data/. Accessed: 2025-06-24.

— (2025b). *Wages and Working Time Statistics (COND)*. https://ilostat.ilo.org/topics/working-time/. Accessed: 2025-06-24.

IPCC (2021). "Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change." Ed. by

V. Masson-Delmotte, Zhai P., Pirani A., S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Katsoulacos, Yiannis and Anastasios Xepapadeas (1996). “”Environmental Policy and Market Structure.””. Ed. by Carlo Carraro, Yiannis Katsoulacos, and Anastasios Xepapadeas. Springer Netherlands, pp. 3–22.

Lan, Xin and Ralph Keeling (2025a). *Trends in Atmospheric CO2, CH4, N2O, SF6.* https://gml.noaa.gov/ccgg/trends/data.html. Accessed: 202-06-01.

Lee, Sang-Ho (1999). “Optimal Taxation for Polluting Oligopolists with Endogenous Market Structure.” *Journal of Regulatory Economics* 15.3, pp. 293–308.

Levin, Dan (1985). “Taxation Within Cournot Oligopoly.” *Journal of Public Economics* 27.3, pp. 281–290.

Manne, Alan S. and Richard G. Richels (2005). “Energy and Environment.” Pp. 175–189.

National Research Council (2010). *Advancing the Science of Climate Change.* Washington, DC: The National Academies Press.

NOAA Global Monitoring Laboratory (2024). *Annual Greenhouse Gas Index (AGGI).* https://gml.noaa.gov/aggi/aggi.html. Accessed: 2025-06-01.

NOAA National Centers for Environmental Information (2025b). *Climate at a Glance: Global Time Series.* https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series. Accessed: 2025-06-30.

Nordhaus, William (2014). “Estimates of the Social Cost of Carbon: Concepts and Results from the DICE-2013R Model and Alternative Approaches.” *Journal of the Association of Environmental and Resource Economists* 1.1/2, pp. 273–312.

Nordhaus, William D (1994). *Managing the Global Commons: The Economics of Climate Change.* Vol. 31. MIT press Cambridge, MA.

Pigou, Arthur Cecil (1920). *The Economics of Welfare.* London, Macmillan and Co.

Requate, Till (2006). “Environmental Policy Under Imperfect Competition.” *International Yearbook of Environmental and Resource Economics 2006/2007.* Ed. by Tom Tietenberg and Henk Folmer.

Ritchie, Hannah, Pablo Rosado, and Max Roser (2023). “CO2 and Greenhouse Gas Emissions.” *Our World in Data.* https://ourworldindata.org/co2-and-greenhouse-gas-emissions.

S&P Global Market Intelligence (2023). *Compustat Daily Updates - Fundamentals Annual.* Tech. rep. Accessed: 2025-05-04.

Schneider, Stephen H. (1989). “The Greenhouse Effect: Science and Policy.” *Science* 243.4892, p. 771.

Shaffer, Sherrill (1995). “Optimal Linear Taxation of Polluting Oligopolists.” *Journal of Regulatory Economics* 7.1, pp. 85–100.

Simpson, R. David (1995). "Optimal Pollution Taxation in a Cournot Duopoly." *Environmental and Resource Economics* 6.4, pp. 359–369.

Tinbergen, Jan (1952). *On the Theory of Economic Policy.*

Traina, James (2018). *Is Aggregate Market Power Increasing? Production Trends using Financial Statements.* Tech. rep. SSRN.

US Bureau of Economic Analysis (2024a). *Input-Output Accounts Data, Use Tables.* Tech. rep. Accessed: 2024-04-10.

— (2024b). *Integrated Industry-Level Production Accounts (KLEMS).* Tech. rep. Accessed: 2024-02-24.

US Bureau of Labor Statistics (2017). *Occupational Employment and Wage Statistics (OEWS) Tables.* https://www.bls.gov/oes/. Accessed: 2025-06-24.

US Census Bureau (2017). *North American Industry Classification System (NAICS) Concordance Tables.* https://www.census.gov/naics/. Accessed: 2025-06-10.

— (2023). *Selected Sectors: Concentration of Largest Firms for the US: 2017.* Tech. rep. Accessed: 2024-02-14.

US Energy Information Administration (2017). *Coal Production Declines in 2016, with Average Coal Prices Below Their 2015 Level.* Tech. rep. Accessed: 2025-06-24. US Department of Energy.

US Environmental Protection Agency (2023). *EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances.* Tech. rep. Accessed: 2025-06-30. US Environmental Protection Agency (EPA).

— (2024). *Greenhouse Gas Reporting Program (GHGRP).* Tech. rep. Accessed: 2024-02-24.

US Geological Survey (2016). *Cement Statistics and Information.* https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information. Accessed: 2025-06-24.

World Bank (2021). *Global Productivity: A Cross-Country Database of Productivity.* Ed. by Alistair Dieppe. Accessed: 2025-06-30.

— (2024). *World Development Indicators (WDI).* https://databank.worldbank.org/. Accessed: 2025-06-01.

Supplementary Appendix

Appendix A Data

For the motivational evidence presented in Section 1 and data used in the model calibration in Section 3, I use two primary data sources: (i) US Environmental Protection Agency's (2024) Greenhouse Gas Reporting Program (GHGRP) data, for annual facility-level GHG emissions, and (ii) the S&P Global Market Intelligence's (2023) Compustat for financial statements of private sector. GHGRP data is available from 2010 to 2023, and has detailed information on the emissions of individual facilities in the US. Compustat data is available from 1950 to 2024, and contains information on the financial statements of publicly traded private sector firms in the United States with public equity or debt.

GHGRP reports emissions data in units of metric tons of carbon dioxide equivalent (CO_2e) for each facility that is subject to the reporting requirements of the program. Each facility has a unique facility identification number that is used to track emissions over time even if the facility's name or address changes. GHGRP requires reporting of GHG emissions and other relevant information from large emissions sources and suppliers of certain products in the US. GHGRP divides emissions based on the type of facility, such as direct emitter, onshore oil and gas production, gathering and boosting, transmission pipelines, local distribution companies (LDC) direct emissions, sulfur hexafluoride (SF6) from electrical equipment, and suppliers of products such as coal, oil, and natural gas.

Moreover, EPA also publishes data on the parent company ownership structure of facilities. I designate emissions attributable to each parent company by assigning a fraction of emissions of each facility based on the parent company's ownership share. Matching these facility-level emissions to parent company's that own them allows me to aggregate facility-level emissions to the parent company-level.

On the other hand, Compustat data contain firm-level balance sheet and income statement data. I use Compustat to construct three variables of interest: firm-level value added, economic profit rates, and markups. I restrict the sample to domestic firms, which have standard industry format in USD with Foreign Incorporation Codes (FIC) in the USA. I exclude utilities (NAICS codes starting with 22) because they are regulated and have different pricing structures than other industries. I also exclude firms with negative or missing assets, sales, cost of goods sold, operating expenses, or gross plants, property, and equipment (PPE). Finally, I also exclude observations in which acquisitions are larger than 5 percent of the value of total assets.

I also download price deflators from NIPA Table 1.1.9 to convert nominal Compustat variables to real variables. I use the GDP deflator from line 1 to deflate all nominal variables, except for deflating capital expenditures, which I deflate using the nonresidential fixed investment deflator from line 9.

I construct firm-level measure of capital using the perpetual inventory method. First, I initialize the capital stock using the first PPE observations for each firm. Then iterate forward on capital using the accumulation equation $K_{i,t} = K_{i,t-1} + I_{i,t} - \delta K_{i,t-1}$, where I compute net investment using changes to net PPE. I assume the depreciation rate δ is 0.07. Finally, to obtain a measure of the real capital stock, I deflate the net investment by the investment goods deflator. Moving forward, I use only real variables when I construct firm-level measures.

First, I construct a measure of firm-level value added by subtracting the cost of goods sold (COGS) from revenue (REVT) for each observation. Next, I calculate firm-level economic profit rates by following Eeckhout (2025). For profits (earnings) of the firm, I use the accounting profits $\pi_{i,t}$, also known as "net income":

$$\pi_{i,t} = \text{REVT}_{i,t} - \text{COGS}_{i,t} - \text{XSGA}_{i,t} - \text{XINT}_{i,t} - \text{DP}_{i,t} + \text{NOPI}_{i,t} + \text{SPI}_{i,t} - \text{TXPD}_{i,t},$$

where REVT is the revenue, COGS is the cost of goods sold, XSGA is the selling, general and administrative expenses, XINT is the interest expense, DP is the sum of depreciation tangible fixed assets and amortization of intangibles, NOPI is the net operating income before interest and taxes, SPI is the special items, and TXPD is the tax liability paid by the firm. Since some shareholders maintain some assets in the firm, Eeckhout (2025) argues that the accounting profits do not adequately measure the opportunity cost of those funds the shareholders expect to obtain, and which should be deduced to obtain the economic profits. He constructs economic profits as the difference between the accounting profits and the opportunity cost of capital, which is the product of the firm's shareholder equity and the cost of debt. I define a firm's shareholder equity E as equal to the the bookvalue of the firm, which is equal to its retained earnings RE plus the value of its common stock CEQ, minus its goodwill GDWL,

$$E_{i,t} = \text{RE}_{i,t} + \text{CEQ}_{i,t} - \text{GDWL}_{i,t}.$$

I calculate the firm-level cost of debt as the ratio of the firm's interest expense (XINT) to the firm's total debt, equivalent to Total Liabilities (LT) in Compustat:

$$\text{cost of debt}_{i,t} = \frac{\text{XINT}_{i,t}}{\text{LT}_{i,t}}.$$

After I construct the firm-level shareholder equity and cost of debt, I can calculate its economic profits as:

$$\pi^e_{i,t} = \pi_{i,t} - \text{cost of debt}_{i,t} \cdot E_{i,t-1}.$$

A firm's economic profit rate is calculated as profits as a share of the firm's revenue: $\pi^e_{i,t}/\text{REVT}_{i,t}$. I merge firm-level economic profit rates constructed from Compustat with the firm-level GHG emissions data constructed from the GHGRP data by matching the parent company names and years across the two datasets before I proceed to construct the markup measure.

Finally, I construct a measure of firm-level markups by following the production function approach framework proposed by De Loecker and Eeckhout (2017). De Loecker and Eeckhout (2017) derive a firm-level markup, $\mu_{i,t}$, formula as:

$$\mu_{i,t} = \theta^V_{i,t} \frac{P^Q_{i,t} Q_{i,t}}{P^V_{i,t} V_{i,t}}, \tag{26}$$

where $\theta^V_{i,t}$ is the output elasticity of a variable input, $P^Q_{i,t} Q_{i,t}$ is the output (sales), and $P^V_{i,t} V_{i,t}$ is the variable input cost (operating expenses). Following Traina (2018), I use operating expenses, OPEX, as a measure of variable input costs, which is the sum of COGS and XSGA. Whereas De Loecker and Eeckhout (2017) use only COGS as a measure of variable input costs, but Traina (2018) argues that OPEX is a better measure of variable input costs because it includes all the costs associated with producing and selling a product, including marketing and management. While, sales and input costs are measurable, the output elasticity is estimated in three stages. First, I estimate industry-level Cobb-Douglas production functions with variable inputs and capital using the following equation:

$$q_{i,t} = \theta_v v_{i,t} + \theta_k k_{i,t-1} + \omega_{i,t} + \varepsilon_{i,t}, \tag{27}$$

where $q_{i,t}$ is the log of sales, $v_{i,t}$ is the log of variable inputs, $k_{i,t-1}$ is the log of capital stock, $\omega_{i,t}$ is the log of productivity, and $\varepsilon_{i,t}$ is the error term. The productivity process is assumed to follow an AR(1) process:

$$\omega_{i,t} = \rho \omega_{i,t-1} + \zeta_{i,t},$$

where $\zeta_{i,t}$ is the innovation to productivity.

In the first stage, I remove the idiosyncratic measurement error from the production process by calculating predicted sales from the following sales-weighted regression with firm and year fixed effects:

$$q_{i,t} = \theta_v v_{i,t} + \theta_k k_{i,t-1} + \xi_i + \xi_t + \epsilon_{i,t}.$$

In the second stage, I use the predicted sales from the first stage to derive the implied productivity process from equation (27). I regress this productivity process on its lagged value to recover the persistence parameter ρ and to obtain innovation to productivity $\zeta_{i,t}$.

In the third stage, I use a Generalized Method of Moments (GMM) estimator to estimate the output elasticities, $\theta \equiv [\theta_v, \theta_k]$, by assuming the following moment conditions hold:

$$\mathbb{E}\left[\hat{\zeta}_{i,t}(\theta) \begin{pmatrix} v_{i,t} \\ k_{i,t-1} \end{pmatrix}\right] = 0.$$

The GMM estimator of θ_v is used to construct the firm-level markups following equation (26).

Appendix B Theoretical Derivations & Proofs

B.1 Derivation of the Constant Social Cost of Carbon

The social cost of carbon emitted at time t by firm j in sector m, in consumption units at this point is given by:

$$\text{SCC}_{m,j,t} = \sum_{s=0}^{\infty} \beta^s \frac{U'(C_{t+s})}{U'(C_t)} \frac{\partial Y_{t+s}}{\partial S_{t+s}} \frac{\partial S_{t+s}}{\partial E_t} \frac{\partial E_t}{\partial E_{m,t}} \frac{\partial E_{m,t}}{\partial E_{m,j,t}}.$$

The $\text{SCC}_{m,j,t}$ captures the externality of carbon emission from production of producer j in sector m. It depends on structural parameters in complicated ways. When Assumptions 1, 2, and 3 are satisfied, the expression for the SCC simplifies dramatically:

$$\begin{aligned} \text{SCC}_{m,j,t} &= \frac{\partial E_t}{\partial E_{m,t}} \frac{\partial E_{m,t}}{\partial E_{m,j,t}} \sum_{s=0}^{\infty} \beta^s C_t \frac{Y_{t+s}}{C_{t+s}} \gamma_{t+s}(1-d_s), \\ &= \sum_{s=0}^{\infty} \beta^s C_t \frac{Y_{t+s}}{C_{t+s}} \gamma_{t+s}(1-d_s), \end{aligned}$$

which expresses the costs of the externality only in terms of exogenous parameters and the endogenous aggregate saving rate, along with the contemporaneous level of aggregate consumption. If furthermore Assumption 6 holds, then the SCC expression simplifies significantly.

The baseline model parameterization implies that as long as the saving rates are constant across time in both the planner's solution and the representative consumer's solution, the saving rates are equal across these solutions. As long as the saving rate is constant and equal across the planner's solution and the representative consumer's solution, both the optimal and decentralized allocations will yield comparable dynamic structures. Assumption 6 follows Golosov et al. (2014) and simplifies the optimal SCC expression to:

$$\text{SCC}_{m,j,t} = Y_t \left[\sum_{s=0}^{\infty} \beta^s \gamma_{t+s}(1-d_s) \right],$$

which expresses the firm-specific SCC as a proportion of GDP and a function of exogenous parameters. This result is identical to Proposition 1 of Golosov et al. (2014). A final expression for their SCC is obtained by assuming that the expected time path for the damage parameter is constant, i.e., $\gamma_{t+j} = \bar{\gamma}_t$ for all j and d_j defined as in equation (10):

$$\frac{\text{SCC}_{m,j,t}}{Y_t} = \bar{\gamma}_t \left(\frac{\psi_L}{1-\beta} + \frac{(1-\psi_L)\psi_0}{1-(1-\psi)\beta} \right). \tag{28}$$

B.2 The General Model: Intermediate Sector m Producer j's Problem

I derive the first-order condition of sector m producer j's problem with respect to the choice of variable labor input $N^{var}_{m,j,t}$. First, rewrite the per-period profit maximization problem for sector m

producer j by substituting its price function from equation (13):

$$\max_{N_{m,j,t},N^{var}_{m,j,t}} \kappa_{m,j} p_{m,t} X_{m,j,t}^{1-\frac{1}{\eta_m}} X_{m,t}^{\frac{1}{\eta_m}} - w_t N_{m,j,t} \quad \text{s.t. } p_{m,t} = \nu_m \frac{Y_t}{X_{m,t}},$$
$$N_{m,j,t} = N^{var}_{m,j,t} + \Omega_{m,j,t}, \text{ and}$$
$$X_{m,j,t} = F_{m,j,t}(N^{var}_{m,j,t}).$$

As outlined in Assumption 4, the sector m producer j internalizes its influence over the intermediate sector m composite and price but not the final output and the general price level. Thus, the sector m producer j's first-order condition with respect to the choice of variable labor input $N^{var}_{m,j,t}$ is:

$$\max_{N_{m,j,t},N^{var}_{m,j,t}} \kappa_{m,j} p_{m,t} X_{m,j,t}^{1-\frac{1}{\eta_m}} X_{m,t}^{\frac{1}{\eta_m}} - w_t N_{m,j,t} \quad \text{s.t. } p_{m,t} = \nu_m \frac{Y_t}{X_{m,t}},$$
$$N_{m,j,t} = N^{var}_{m,j,t} + \Omega_{m,j,t}, \text{ and}$$
$$X_{m,j,t} = F_{m,j,t}(N^{var}_{m,j,t}).$$

As outlined in Assumption 4, the sector m producer j internalizes its influence over the intermediate sector m composite and price but not the final output and the general price level. Thus, the sector m producer j's first-order condition with respect to the choice of variable labor input $N^{var}_{m,j,t}$ is:

$$\kappa_{m,j} \frac{dX_{m,j,t}}{dN^{\text{var}}_{m,j,t}} \left[\frac{\partial p_{m,t}}{\partial X_{m,t}} \frac{\partial X_{m,t}}{\partial X_{m,j,t}} X_{m,j,t}^{1-\frac{1}{\eta_m}} X_{m,t}^{\frac{1}{\eta_m}} + \frac{1}{\eta_m} p_{m,t} X_{m,t}^{\frac{1}{\eta_m}-1} \frac{\partial X_{m,t}}{\partial X_{m,j,t}} X_{m,j,t}^{1-\frac{1}{\eta_m}} + \left(\frac{\eta_m - 1}{\eta_m}\right) p_{m,t} X_{m,t}^{\frac{1}{\eta_m}} X_{m,j,t}^{-\frac{1}{\eta_m}} \right] = w_t$$
$$\kappa_{m,j} p_{m,t} X_{m,t}^{\frac{1}{\eta_m}} X_{m,j,t}^{-\frac{1}{\eta_m}} \cdot \frac{dX_{m,j,t}}{dN^{\text{var}}_{m,j,t}} \left[\frac{\partial p_{m,t}}{\partial X_{m,t}} \frac{p_{m,j,t} X_{m,j,t}}{p^2_{m,t}} + \frac{1}{\eta_m} \frac{p_{m,j,t} X_{m,j,t}}{p_{m,t} X_{m,t}} + \left(\frac{\eta_m - 1}{\eta_m}\right) \right] = w_t$$
$$p_{m,j,t} F'_{m,j,t}(N^{\text{var}}_{m,j,t}) \left[\frac{\partial p_{m,t}}{\partial X_{m,t}} \frac{s_{m,j,t} X_{m,t}}{p_{m,t}} + \frac{1}{\eta_m} s_{m,j,t} + \left(\frac{\eta_m - 1}{\eta_m}\right) \right] = w_t$$
$$\left[\frac{\partial p_{m,t}}{\partial X_{m,t}} \frac{X_{m,t}}{p_{m,t}} s_{m,j,t} + \frac{1}{\eta_m} s_{m,j,t} + \left(\frac{\eta_m - 1}{\eta_m}\right) \right]^{-1} = \frac{p_{m,j,t}}{w_t / F'_{m,j,t}(N^{\text{var}}_{m,j,t})}$$

The right-hand side of the last equation line is price over marginal cost for sector m producer j, which is the producer j's markup. The markup expression can be rewritten as $\frac{\sigma(s_{m,j,t})-1}{\sigma(s_{m,j,t})}$, where $\sigma(s_{m,j,t})$ is the price elasticity of sector m producer j's demand. Thus,

$$\frac{\sigma(s_{m,j,t})}{\sigma(s_{m,j,t}) - 1} = \left[\frac{\partial p_{m,t}}{\partial X_{m,t}} \frac{X_{m,t}}{p_{m,t}} s_{m,j,t} + \frac{1}{\eta_m} s_{m,j,t} + \left(\frac{\eta_m - 1}{\eta_m}\right) \right]^{-1},$$

which implies that:

$$\sigma(s_{m,j,t}) = \left[\frac{1}{\eta_m}(1 - s_{m,j,t}) + \frac{X_{m,t}/p_{m,t}}{|\partial X_{m,t}/\partial p_{m,t}|} s_{m,j,t} \right]^{-1},$$

where $\frac{X_{m,t}/p_{m,t}}{|\partial X_{m,t}/\partial p_{m,t}|}$ is the absolute value of the inverse price elasticity of sector m composite demand.

B.3 Planning Problem

Building upon the multi-sector neoclassical growth model with multiple intermediate production sectors, I consider the case that the accumulated emissions from carbon-intensive intermediate input production result in external damages, which affect the final good production possibilities. The social planner will choose allocations taking this negative externality into account when maximizing aggregate welfare subject to technology, feasibility, and carbon cycle conditions:

$$\max_{\left\{C_t,K_{t+1},N_t,N_{0,t},\left\{X_{m,t},E_{m,t},\left\{N_{m,j,t},N^{\text{var}}_{m,j,t},X_{m,j,t},E^f_{m,j,t}\right\}_{j=1}^{J_m}\right\}_{m=1}^{M},E^f_t,S_t,Y_t\right\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \log(C_t)$$

$$\begin{aligned}
\text{subject to } \forall t, \quad C_t &= Y_t + (1-\delta)K_t - K_{t+1}, \\
Y_t &= \exp[-\gamma_t(S_t - \bar{S})]K_t^{\alpha}(A_{0,t}N_{0,t})^{1-\alpha-\sum_{m=1}^{M}\nu_m} \prod_{m=1}^{M} X_{m,t}^{\nu_m}, \\
X_{m,t} &= \left[\sum_{j=1}^{J_m} \kappa_{m,j} X_{m,j,t}^{\frac{\eta_m-1}{\eta_m}}\right]^{\frac{\eta_m}{\eta_m-1}}, \quad \forall m, \\
X_{m,j,t} &= \chi_{m,j,t} N^{\text{var}}_{m,j,t}, \quad \forall m, j, \\
N_{m,j,t} &= N^{\text{var}}_{m,j,t} + \Omega_{m,j,t}, \quad \forall m, j, \\
E_{m,j,t} &= \theta_{m,j,t} X_{m,j,t}^{\zeta_{m,j}}, \quad \forall m, j, \\
E_{m,t} &= \sum_{j=1}^{J_m} E_{m,j,t}, \quad \forall m, \\
E_t &= \sum_{m=1}^{M} E_{m,t}, \\
A_{0,t+1} &= (1+g_A)A_{0,t}, \\
\chi_{m,j,t+1} &= (1+g_{\chi_{m,j}})\chi_{m,j,t}, \quad \forall m, j, \\
C_t, K_{t+1}, X_t, X_{j,t}, X_{m,j,t} &\geq 0, \quad \forall m, j, \\
N_t &= N_{0,t} + \sum_{m=1}^{M} \sum_{j=1}^{J_m} N_{m,j,t}, \\
S_t &= \sum_{s=0}^{t+T} (1-d_s) E_{t-s},
\end{aligned}$$

Definition. The optimal allocations

$$\left\{C_t, K_{t+1}, N_{0,t}, \left\{X_{m,t}, E_{m,t}, \{N_{m,j,t}, N^{\text{var}}_{m,j,t}, X_{m,j,t}, E_{m,j,t}, \text{SCC}_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}, E_t, S_t, S_{1,t}, S_{2,t}, Y_t\right\}_{t=0}^{\infty}$$
that solve the planning problem satisfy the following equations for every period t:

$$\frac{1}{C_t} = \beta \frac{1}{C_{t+1}} \left(\alpha \frac{Y_{t+1}}{K_{t+1}} \right), \tag{29}$$

$$\chi_{m,j,t} \left[\frac{\nu_m \kappa_{m,j}}{X_{m,t}^{\frac{\eta_m - 1}{\eta_m}} X_{m,j,t}^{\frac{1}{\eta_m}}} - \theta_{m,j,t} \zeta_{m,j} \frac{\text{SCC}_{m,j,t}}{Y_t} X_{m,j,t}^{\zeta_{m,j}-1} \right] = \frac{1 - \alpha - \sum_{m=1}^{M} \nu_m}{N_{0,t}}, \tag{30}$$

$$C_t = Y_t + K_{t+1}, \tag{31}$$

$$Y_t = \exp[-\gamma_t (S_t - \bar{S})] K_t^{\alpha} (A_{0,t} N_{0,t})^{1-\alpha-\sum_{m=1}^{M} \nu_m} \prod_{m=1}^{M} X_{m,t}^{\nu_m},$$

$$X_{m,j,t} = \chi_{m,j,t} N^{var}_{m,j,t}, \ \forall m, j$$

$$N_{m,j,t} = N^{var}_{m,j,t} + \Omega_{m,j,t}, \ \forall m, j$$

$$X_{m,t} = \left[\sum_{j=1}^{J_m} \kappa_{m,j} X_{m,j,t}^{\frac{\eta_m - 1}{\eta_m}} \right]^{\frac{\eta_m}{\eta_m - 1}}, \ \forall m$$

$$N_t = N_{0,t} + \sum_{m=1}^{M} \sum_{j=1}^{J_m} N_{m,j,t},$$

$$E_{m,j,t} = \theta_{m,j,t} X_{m,j,t}^{\zeta_{m,j}}, \ \forall m, j$$

$$E_{m,t} = \sum_{j=1}^{J_m} E_{m,j,t}, \ \forall m$$

$$E_t = \sum_{m=1}^{M} E_{m,t},$$

$$S_t = S_{1,t} + S_{2,t},$$

$$S_{1,t} = S_{1,t-1} + \psi_L E_t,$$

$$S_{2,t} = \psi S_{2,t-1} + \psi_0 (1 - \psi_L) E_t,$$

$$\text{SCC}_{m,j,t} = \frac{\partial E_t}{\partial E_{m,t}} \frac{\partial E_{m,t}}{\partial E_{m,j,t}} \sum_{s=0}^{\infty} \beta^s C_t \frac{Y_{t+s}}{C_{t+s}} \gamma_{t+s} (1 - d_s), \tag{32}$$

Conditions (29) and (31) are satisfied if and only if the saving rate is constant at $\alpha\beta$. Then by Proposition 1 from Golosov et al. (2014), the optimal SCC_t expression in equation (32) simplifies to $\Lambda_{m,j,t}$. Moreover, the ratio $\text{SCC}_{m,j,t}/Y_t$ that appears in equation (30) is constant at level $\hat{\Lambda}_{m,j,t}$ as shown in equation (12).

B.4 Decentralized Equilibrium

B.4.1 Competitive Equilibrium

Definition. In a competitive equilibrium, given the exogenous paths of aggregate labor supply $\{N_t\}_{t=0}^{\infty}$, taxes $\left\{\left\{\{\tau_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}_{t=0}^{\infty}$, and fixed costs $\left\{\left\{\{\Omega_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}_{t=0}^{\infty}$, the allocations $\left\{C_t, K_{t+1}, Y_t, N_{0,t}, \left\{X_{m,t}, E_{m,t}, \{N_{m,j,t}, N_{m,j,t}^{\text{var}}, X_{m,j,t}, E_{m,j,t}, \text{SCC}_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}, E_t, S_t, S_{1,t}, S_{2,t}\right\}_{t=0}^{\infty}$, prices $\left\{q_t, w_t, r_t, \left\{p_{m,t}, \{p_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}_{t=0}^{\infty}$, transfers $\{T_t\}_{t=0}^{\infty}$, and profits $\{\Pi_0, \Pi_{m,j}, \Pi\}$ that satisfy the set of conditions for every period t:

$$\chi_{m,j,t}\left[\frac{\nu_m \kappa_{m,j}}{X_{m,t}^{\frac{\eta_m-1}{\eta_m}} X_{m,j,t}^{\frac{1}{\eta_m}}} - \frac{\tau_{m,j,t}}{Y_t}\right] = \frac{1-\alpha-\sum_{m=1}^{M}\nu_m}{N_{0,t}}, \forall m, j,$$

$$X_{m,t} = \left[\sum_{j=1}^{J_m} \kappa_{m,j} X_{m,j,t}^{\frac{\eta_m-1}{\eta_m}}\right]^{\frac{\eta_m}{\eta_m-1}}, \forall m,$$

$$p_{m,j,t} = \kappa_{m,j} p_{m,t} X_{m,t}^{\frac{1}{\eta_m}} X_{m,j,t}^{-\frac{1}{\eta_m}}, \forall m, j,$$

$$\frac{1}{C_t} = \beta \frac{1}{C_{t+1}} r_{t+1},$$

$$C_t = Y_t + K_{t+1},$$

$$Y_t = \exp[-\gamma_t(S_t - \bar{S})] K_t^{\alpha} (A_{0,t} N_{0,t})^{1-\alpha-\sum_{m=1}^{M}\nu_m} \prod_{m=1}^{M} X_{m,t}^{\nu_m},$$

$$X_{m,j,t} = \chi_{m,j,t} N_{m,j,t}^{var}, \forall m, j,$$

$$N_{m,j,t} = N_{m,j,t}^{var} + \Omega_{m,j,t}, \forall m, j,$$

$$E_{m,j,t} = \theta_{m,j,t} X_{m,j,t}^{\zeta_{m,j}}, \forall m, j,$$

$$N_t = N_{0,t} + \sum_{m=1}^{M}\sum_{j=1}^{J_m} N_{m,j,t},$$

$$E_{m,t} = \sum_{j=1}^{J_m} E_{m,j,t}, \forall m,$$

$$E_t = \sum_{m=1}^{M} E_{m,t},$$

$$S_t = S_{1,t} + S_{2,t},$$

$$S_{1,t} = S_{1,t-1} + \psi_L E_t,$$

$$S_{2,t} = \psi S_{2,t-1} + \psi_0(1-\psi_L)E_t,$$

$$q_t = \beta^t \left(C_t/C_0\right)^{-1},$$

$$r_t = \alpha Y_t/K_t,$$

$$w_t = \left(1 - \alpha - \sum_{m=1}^{M} \nu_m\right) Y_t/N_{0,t},$$

$$p_{m,t} = \nu_m Y_t/X_{m,t},$$

$$\sum_{t=0}^{\infty} q_t T_t = \sum_{t=0}^{\infty} q_t \sum_{m=1}^{M} \sum_{j=1}^{J_m} \tau_{m,j,t} X_{m,j,t},$$

$$\Pi_0 = \sum_{t=0}^{\infty} q_t \left[Y_t - r_t K_t - w_t N_{0,t} - \sum_{m=1}^{M} p_{m,t} X_{m,t}\right],$$

$$\Pi_{m,j} = \sum_{t=0}^{\infty} q_t \left[(p_{m,j,t} - \tau_{m,j,t})X_{m,j,t} - w_t N_{m,j,t}\right],$$

$$\Pi = \Pi_0 + \sum_{m=1}^{M} \sum_{j=1}^{J_m} \Pi_{m,j}.$$

B.4.2 Equilibrium with Oligopolistic Intermediate Sectors

Definition. In an equilibrium with oligopolistically competitive intermediate good producers, given the exogenous paths of labor supply $\{N_t\}_{t=0}^{\infty}$, taxes $\left\{\left\{\{\tau_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}_{t=0}^{\infty}$, and fixed costs $\left\{\left\{\{\Omega_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}_{t=0}^{\infty}$ the allocations $\left\{C_t, K_{t+1}, Y_t, N_{0,t}, \left\{X_{m,t}, E_{m,t}, \{N_{m,j,t}, N_{m,j,t}^{\text{var}}, X_{m,j,t}, E_{m,j,t}, s_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}, E_t, S_t, S_{1,t}, S_{2,t}\right\}_{t=0}^{\infty}$, prices $\left\{q_t, w_t, r_t, \left\{p_{m,t}, \{p_{m,j,t}\}_{j=1}^{J_m}\right\}_{m=1}^{M}\right\}_{t=0}^{\infty}$, transfers $\{T_t\}_{t=0}^{\infty}$, and profits $\{\Pi_0, \Pi_{m,j}, \Pi\}$ that satisfy the set of conditions for every period t:

$$\chi_{m,j,t}\left[\frac{\nu_m \kappa_{m,j}}{X_{m,t}^{\frac{\eta_m-1}{\eta_m}} X_{m,j,t}^{\frac{1}{\eta_m}}} \frac{\sigma(s_{m,j,t})-1}{\sigma(s_{m,j,t})} - \frac{\tau_{m,j,t}}{Y_t}\right] = \frac{1-\alpha-\sum_{m=1}^{M}\nu_m}{N_{0,t}}, \ \forall m, j,$$

$$X_{m,t} = \left[\sum_{j=1}^{J_m} \kappa_{m,j} X_{m,j,t}^{\frac{\eta_m-1}{\eta_m}}\right]^{\frac{\eta_m}{\eta_m-1}}, \ \forall m,$$

$$p_{m,j,t} = \kappa_{m,j} p_{m,t} X_{m,t}^{\frac{1}{\eta_m}} X_{m,j,t}^{-\frac{1}{\eta_m}}, \ \forall m, j,$$

$$s_{m,j,t} = \frac{p_{m,j,t} X_{m,j,t}}{p_{m,t} X_{m,t}}, \ \forall m, j,$$

$$\frac{1}{C_t} = \beta \frac{1}{C_{t+1}} r_{t+1},$$

$$C_t = Y_t + K_{t+1},$$

$$Y_t = \exp[-\gamma_t(S_t - \bar{S})] K_t^{\alpha} (A_{0,t} N_{0,t})^{1-\alpha-\sum_{m=1}^{M} \nu_m} \prod_{m=1}^{M} X_{m,t}^{\nu_m},$$

$$X_{m,j,t} = \chi_{m,j,t} N_{m,j,t}^{var}, \; \forall m, j,$$

$$N_{m,j,t} = N_{m,j,t}^{var} + \Omega_{m,j,t}, \; \forall m, j,$$

$$E_{m,j,t} = \theta_{m,j,t} X_{m,j,t}^{\zeta_{m,j}}, \; \forall m, j,$$

$$N_t = N_{0,t} + \sum_{m=1}^{M} \sum_{j=1}^{J_m} N_{m,j,t},$$

$$E_{m,t} = \sum_{j=1}^{J_m} E_{m,j,t}, \; \forall m,$$

$$E_t = \sum_{m=1}^{M} E_{m,t},$$

$$S_t = S_{1,t} + S_{2,t},$$

$$S_{1,t} = S_{1,t-1} + \psi_L E_t,$$

$$S_{2,t} = \psi S_{2,t-1} + \psi_0 (1 - \psi_L) E_t,$$

$$q_t = \beta^t \left(C_t / C_0 \right)^{-1},$$

$$r_t = \alpha Y_t / K_t,$$

$$w_t = \left(1 - \alpha - \sum_{m=1}^{M} \nu_m \right) Y_t / N_{0,t},$$

$$p_{m,t} = \nu_m Y_t / X_{m,t}, \; \forall m,$$

$$\sum_{t=0}^{\infty} q_t T_t = \sum_{t=0}^{\infty} q_t \sum_{m=1}^{M} \sum_{j=1}^{J_m} \tau_{m,j,t} X_{m,j,t},$$

$$\Pi_0 = \sum_{t=0}^{\infty} q_t \left[Y_t - r_t K_t - w_t N_{0,t} - \sum_{m=1}^{N} p_{m,t} X_{m,t} \right],$$

$$\Pi_{m,j} = \sum_{t=0}^{\infty} q_t \left[(p_{m,j,t} - \tau_{m,j,t}) X_{m,j,t} - w_t N_{m,j,t} \right], \; \forall m,$$

$$\Pi = \Pi_0 + \sum_{m=1}^{M} \sum_{j=1}^{J_m} \Pi_{m,j}.$$

Appendix C Calibration Details

C.1 Sectoral Markups & Economic Profit Rates

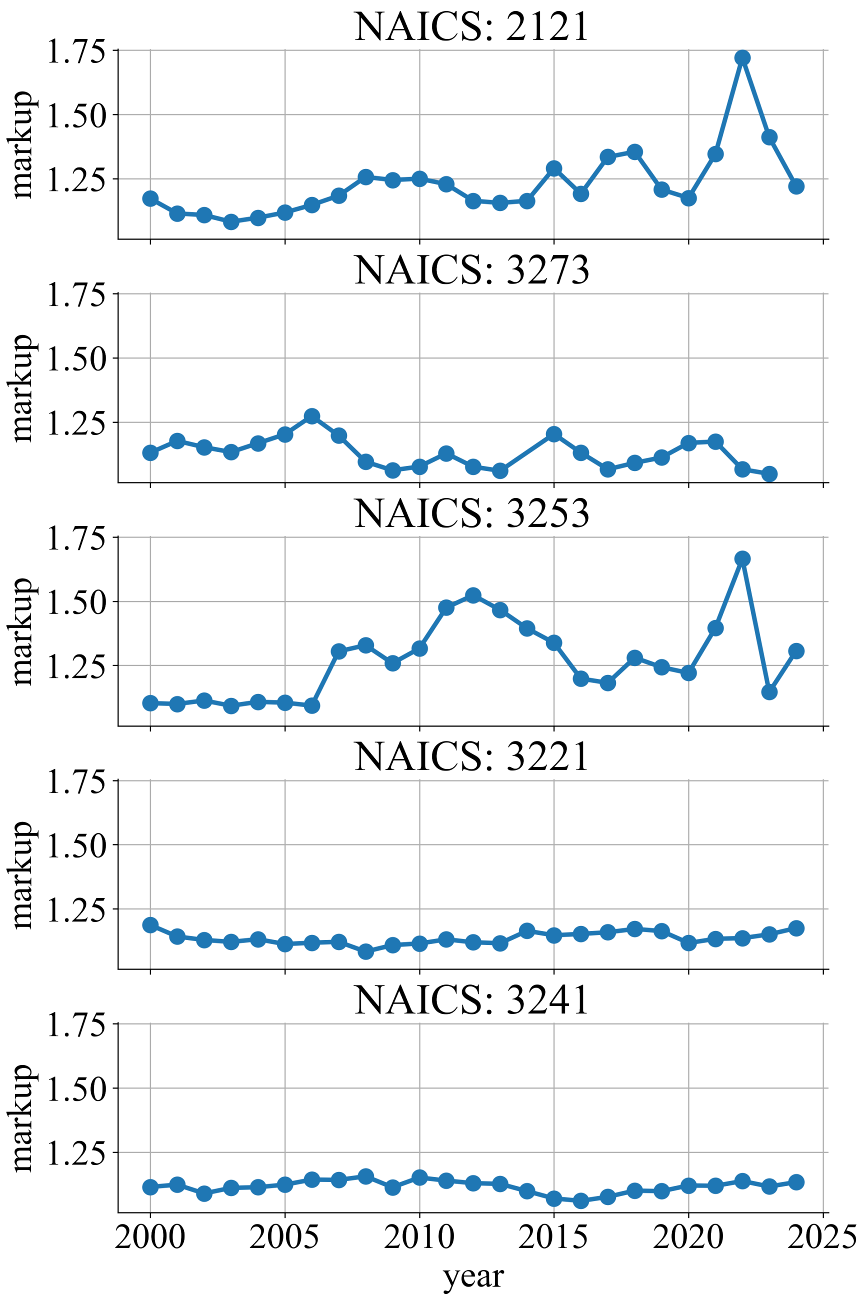
I estimate the sectoral markups and calculate economic profit rates as described in Appendix A. I present the sales-weighted average markups for the top five most carbon-intensive sectors in Figure 9. I use the 2017 average sectoral markups as the base year for the calibration of the model. The average markups for the top five most carbon-intensive sectors consistently exceed one, indicating that these sectors have pricing power and can set prices above their marginal costs.

Moreover, although not directly used in calibration, I also present the sales-weighted average economic profit rates for the top five most carbon-intensive sectors in Figure 10.

Although majority of the sectors historially have positive economic profit rates, the sectoral economic profit rates for some sectors are negative in some years. Notably, the coal mining sector (2121) experienced negative economic profit rates between 2013 and 2016 due to a sharp decline in coal demand from the electric power sector amid the shale gas boom driven fall in natural gas prices, which led to a significant reduction in coal production and prices, unusually warm weather, which drove coal production to its lowest level since 1978, US Energy Information Administration (2017) Moreover, the cement manufacturing sector (3273) experienced negative economic profit rates following the 2008 financial crisis, which could be attributed to slowing housing construction and infrastructure projects. The dip in US cement industry economic profit rates around 2016 was likely due to a combination of slowing construction demand, overcapacity-driven price pressures, rising maintenance and input costs, and consolidation-related disruptions, US Geological Survey (2016).

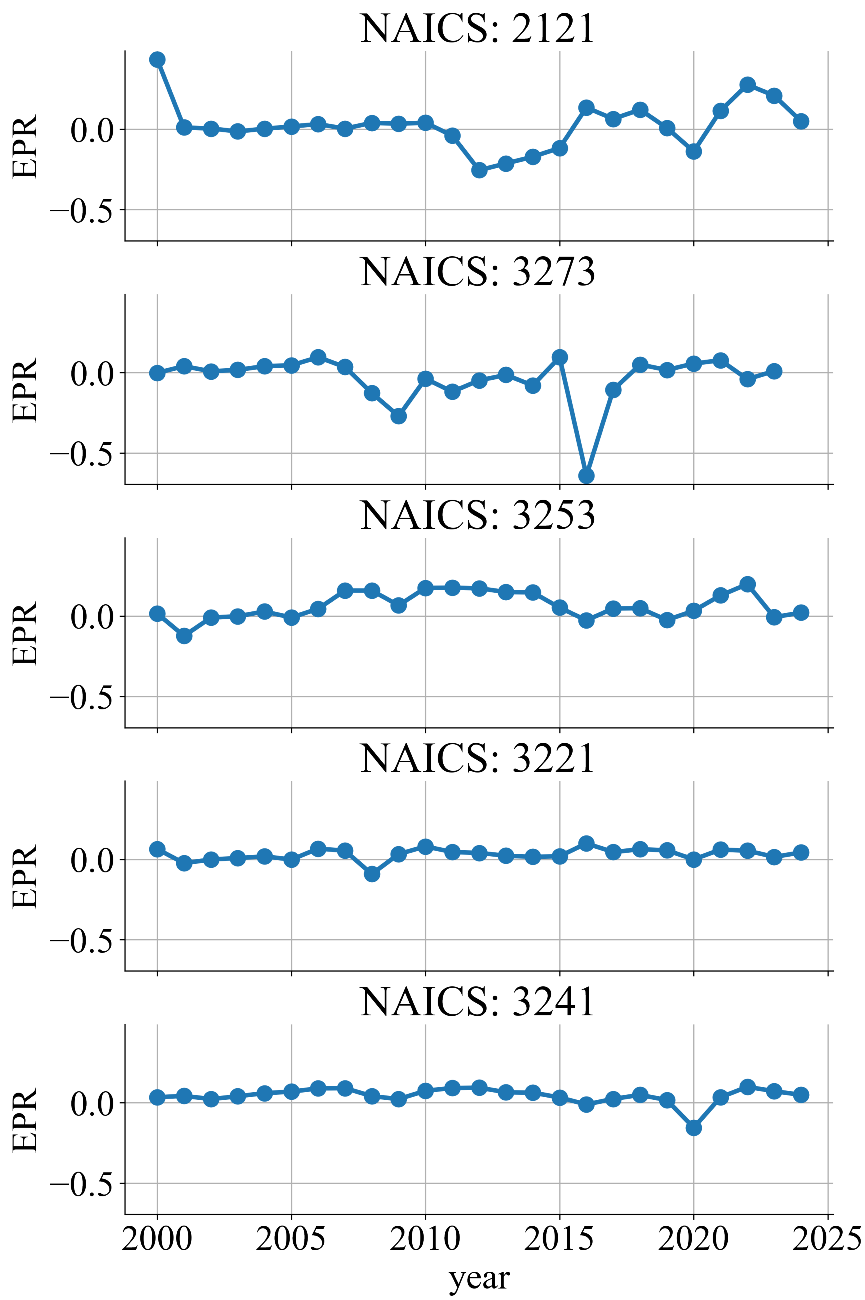
Except the few outliers, the average economic profit rates for the top five most carbon-intensive sectors are positive, indicating that these sectors have been able to generate excess returns above their cost of capital and lack of competition in these sectors product markets.

Figure 9: History of sectoral sales-weighted average markups of the top five most carbon-intensive sectors



Note: The sectors are ordered by their carbon intensity in 2017, descending from left to right. The sectors are: 1. Coal mining (2121), 2. Cement manufacturing, Ready-mix concrete manufacturing, Concrete pipe, brick, and block manufacturing, Other concrete product manufacturing(3273), 3. Fertilizer manufacturing, Pesticide and other agricultural chemical manufacturing (3253), 4. Pulp mills, Paper mills, Paperboard mills (3221), 5. Petroleum refineries, Asphalt paving mixture and block manufacturing, Asphalt shingle and coating materials manufacturing, Other petroleum and coal products manufacturing (3241).

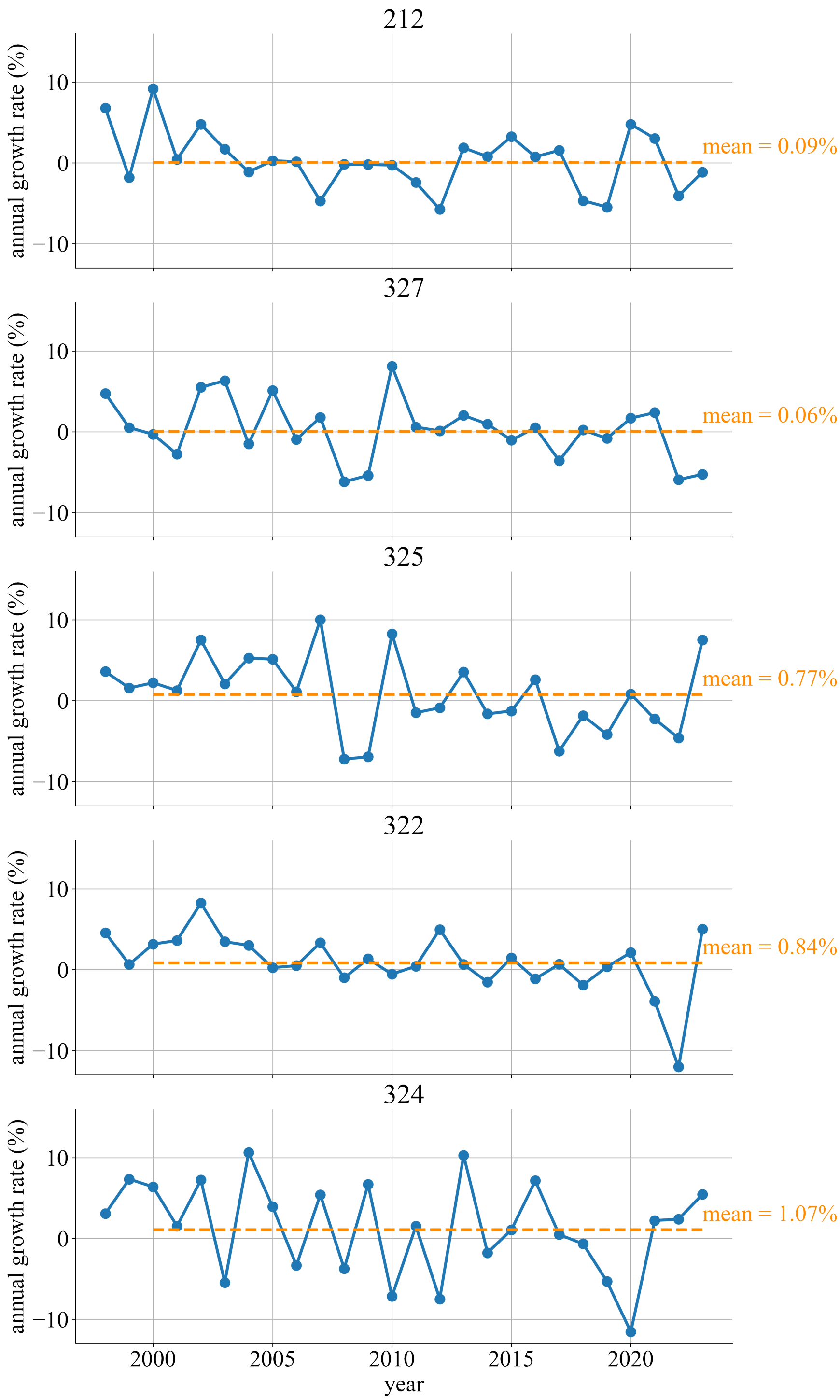
Figure 10: History of sectoral sales-weighted average economic profit rates of the top five most carbon-intensive sectors



C.2 Sectoral Labor Productivity Growth

The blue dotted line in Figure 11 represents the annual labor productivity growth rate for each sector, while the orange dashed line represents the average annual sectoral labor productivity growth rate for years 2000-2023, which is used for the calibration of the model. Additionally the average annual sectoral labor productivity growth rates are printed in orange on the right side of each sector's subplot.

Figure 11: Historical sectoral labor productivity growth rates of the the three-digit Production Account (BEA) sectors that contain the five most carbon-intensive sectors



Note: The mapping between the four-digit NAICS codes of the top five most carbon-intensive sectors and the three-digit BEA codes and their industry descriptions is as follows: 1. 2121: 212, Coal extraction; 2. 3273: 327, Nonmetallic mineral products; 3. 3253: 325, Chemical products; 4. 3221: 3221, Paper products; 5. 3241: 3241, Petroleum and coal products.

C.3 Carbon Cycle and Climate Module

Given my model's different base year, I adjust the parameters of the carbon cycle and climate module to match the observed atmospheric carbon concentration and annual carbon emissions data from 1960 until 2020. First, I adjust the initial pre-industrial carbon concentration $\bar{S}$ to match the NOAA (2024) estimate of 280 parts per million before the start of the industrial revolution and convert it to gigatons of carbon (GtC) using the conversion factor of 2.13 GtC per ppm, which results in $\bar{S} = 596.4$ GtC. Second, I keep the share of permanent emissions ψ_L at 0.2 as reported by IPCC (2021), which is the same as in Golosov et al. (2014). However, I deviate from Golosov et al. (2014) when I estimate the decadal retained emission share ψ_0 and the decadal geometric emission decay rate ψ to match the path of atmospheric carbon concentration implied by linear equation system for the carbon cycle restated below in equation (33) and the path of observed atmospheric carbon concentration and the annual carbon emissions given the initial pre-industrial carbon concentration $\bar{S}$, using the following linear system of equations:

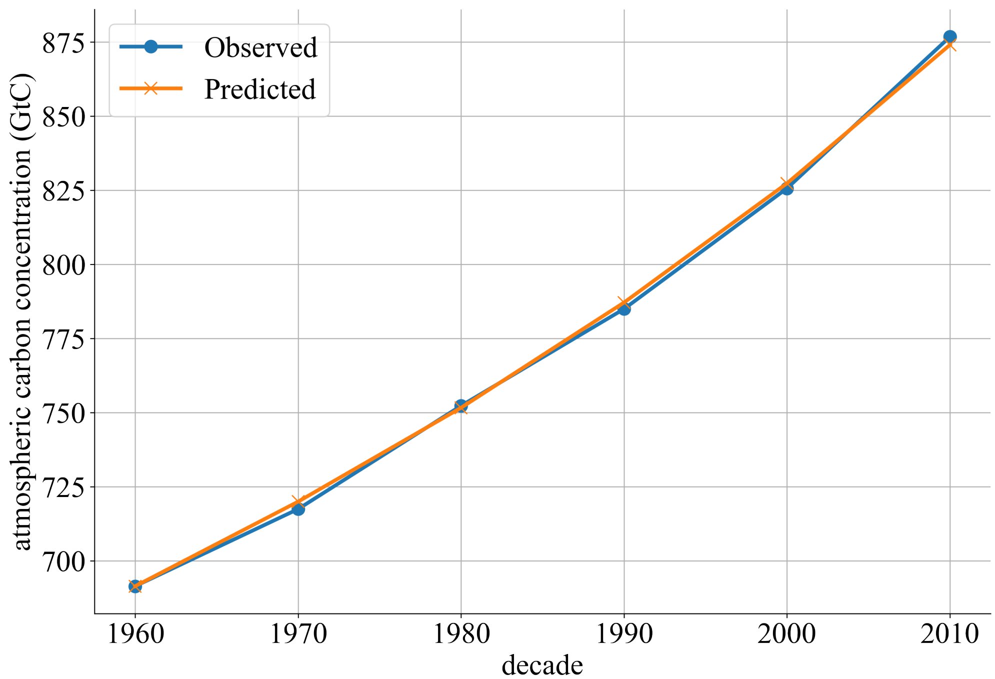
$$\begin{aligned} S_{1,t} &= S_{1,t-1} + \psi_L E_t, \\ S_{2,t} &= \psi S_{2,t-1} + \psi_0(1-\psi_L)E_t, \\ S_t &= \bar{S} + S_{1,t} + S_{2,t}. \end{aligned} \tag{33}$$

I obtain the historical atmospheric carbon concentration data from the NOAA (2025a) dataset, which provides the annual atmospheric carbon concentration data from 1960 until 2020 in units of parts per million (ppm). I convert the atmospheric carbon concentration data from ppm to GtC using the conversion factor of 2.13 GtC per ppm. I obtain the annual carbon emissions data from the OWID (2023) dataset, which provides the annual carbon emissions data for all countries in the world from 1850 until 2020 in units of metric tons of C_2 equivalent emissions. I convert the annual carbon emissions data from metric tons of CO_2 equivalent emissions to GtC by multiplying the reported emissions by $12/44/10^{-9}$.

I estimate the decadal retained emission share ψ_0 to be 0.1988 and the decadal geometric emission decay rate ψ to be 0.9555, which are the values that match the observed atmospheric carbon concentration from 1960 until 2020 given the initial pre-industrial carbon concentration $\bar{S}$ and the annual carbon emissions data from the OWID (2023) dataset. I calibrate the initial permanent carbon stock $S_{1,0}$ by summing up annual emissions from 1850 to 2017 and multiplying this sum by ψ_L, which equals 174.876 GtC. I calculate the initial transitory carbon stock $S_{2,0}$ by subtracting the initial permanent carbon stock $S_{1,-1}$ from the atmospheric carbon concentration in 2017, which is 866.399 GtC as reported by the NOAA (2025a) dataset, resulting in the initial transitory carbon stock to be 95.122 GtC. Figure 12 shows the calibration of the carbon cycle and climate module, where the blue line represents the observed atmospheric carbon concentration from 1960 until 2020, and the orange line represents the model-implied atmospheric carbon concentration given the calibrated parameters from 1960 until 2020.

I deviate from Golosov et al. (2014) when I calibrate the carbon cycle because my model has

Figure 12: Calibration of the carbon cycle and climate module



a different base year, and I aim to match the observed atmospheric carbon concentration and annual carbon emissions data rather than using reports from the IPCC. As Figure 12 shows, the model-implied atmospheric carbon concentration closely follows the observed atmospheric carbon concentration from 1960 until 2020, indicating that the calibrated parameters of the carbon cycle and climate module are consistent with the observed data.

C.4 Carbon Shares

Figure 13 shows the historical global share of US carbon emissions from 1960 until 2020, which is calculated as the ratio of US carbon emissions to the total global carbon emissions using data from OWID (2023). The red dashed horizontal line represents the average of this ratio from 2010 until 2023, which is 14.6% and is used for the calibration of the model.

Figure 14 shows the historical share of carbon emissions from the five carbon-intensive sectors considered in the model using data from the US Environmental Protection Agency (2024), to the total US carbon emissions data from OWID (2023). These five most carbon-intensive sectors are coal mining (NAICS 2121), cement manufacturing (NAICS 3273), fertilizer manufacturing (NAICS 3253), pulp and paper mills (NAICS 3221), and petroleum refineries (NAICS 3241). The red dashed horizontal line represents the average of this ratio from 2010 until 2023, which is 37.6% and is used for the calibration of the model.

Over time, both the share of US carbon emissions and the share of these top five most carbon-intensive sectors in the US have been declining.

Figure 13: Historical global share of US carbon emissions

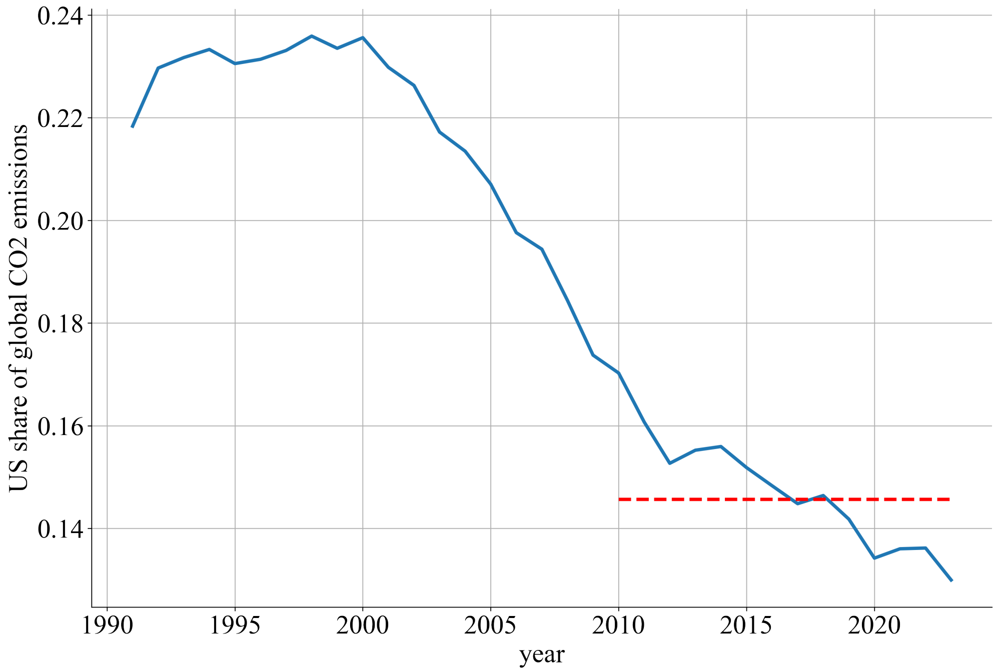
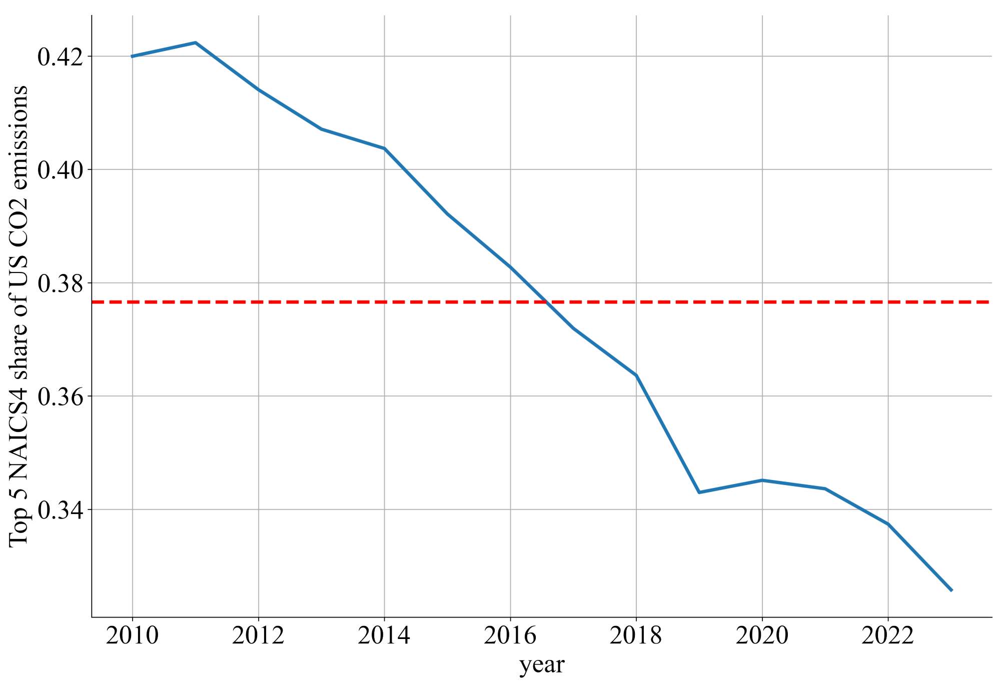


Figure 14: Historical US carbon emissions share of the top five most carbon-intensive sectors in 2017

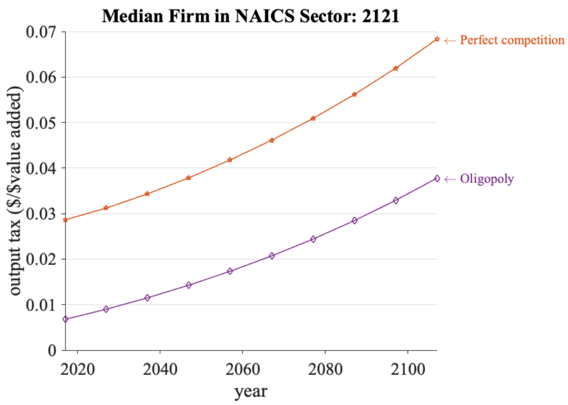


C.5 Additional Results

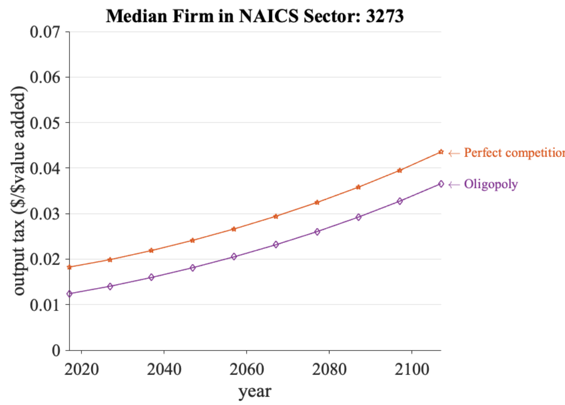
Figure 15 displays optimal output taxes for the median productivity firm in five carbon-intensive sectors under perfect competition and oligopoly. Under perfect competition, the optimal tax equals the Pigouvian tax (marginal external damages per unit of output). Under oligopoly, optimal taxes are generally lower, reflecting firms' market power. Optimal policy varies by sector and firm. Output taxes are measured in 2021 US dollars per dollar of value added, where one equals a 100% tax rate.

The optimal output taxes under perfect competition only reflect the climate-externality correction. Thus, the optimal output taxes under perfect competition decrease as the carbon intensity of the sector decreases, reflecting the greater emissions and damages from a unit of value added in more carbon-intensive sectors. On the other hand, the optimal output taxes under oligopoly reflect both the climate-externality correction and the output distortion correction. Thus there is no clear relationship between the optimal output taxes under oligopoly and the carbon intensity of the sector. The optimal output taxes under oligopoly are lower than those under perfect competition, reflecting the market power of firms. However, the difference between the oligopoly and perfect competition output taxes depends on the scale of the output distortion, which is not necessarily related to the carbon intensity of the sector.

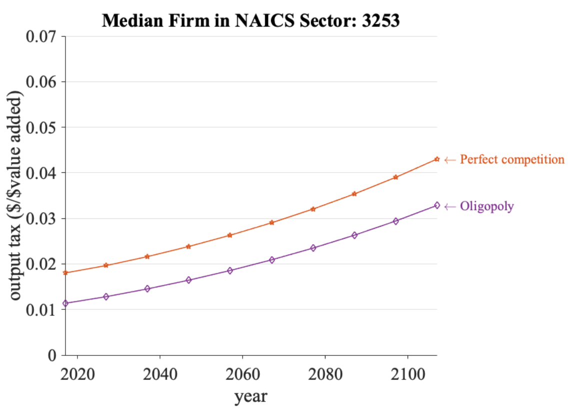
Figure 15: Output taxes under perfect competition vs. oligopoly for the median productivity firm in five carbon-intensive NAICS sectors.



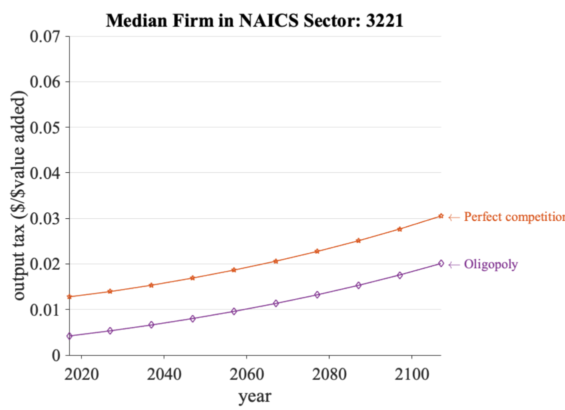
(a) Coal mining



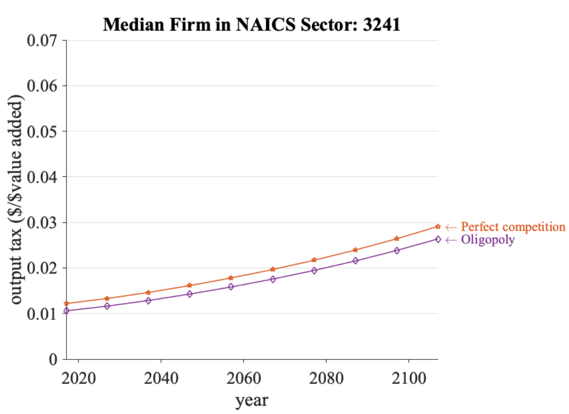
(b) Cement manufacturing



(c) Fertilizer manufacturing



(d) Paper manufacturing



(e) Petroleum and coal products manufacturing