Optimal Policies for Decarbonization via Carbon Capture: Tax, Subsidize, or Both?

Abstract

This study uses a two-stage game theoretic approach to derive and characterize optimal decarbonization policies, focusing on emission taxes and carbon capture and storage (CCS) subsidies. By maximizing a welfare function, the government first selects policy instruments, while carbon-intensive firms subsequently determine production levels and abatement efforts to maximize profit. The derived optimal policies are then analyzed through Monte Carlo simulations to assess their variability and sensitivity under different scenarios. Key findings are: (1) Emission tax and CCS subsidies are strategic substitutes where pollution damage governs this relationship, (2) The optimal policy mix could be a *tax-only regime* if carbon intensity exceeds a given threshold, otherwise the optimal policy mix either includes both instruments (if pollution damage is large enough) or is a *subsidy-only regime* (if pollution damage is not very large), (3) Optimal subsidies are relatively more variable than optimal emission taxes, and (4) Certainty in production and market parameters does not reduce optimal policy variability, but shifts the focus towards subsidies rather than taxes. These results highlight the need for flexible and adaptable decarbonization policies in dynamic markets with evolving technologies.

Keywords: CCS, emission tax, abatement subsidy, profits, game theory

JEL: C7, D21, D62, O33, Q4, Q5

1 Introduction

The study of optimal environmental policies, especially in carbon-intensive industries, is becoming increasingly crucial as governments aim to address the dual challenge of reducing carbon emissions while maintaining economic growth (Keohane and Olmstead, 2016). One of the key difficulties lies in designing policies that strike the right balance between environmental protection, profitability for businesses, and affordability for consumers (Lahiri and Symeonidis, 2017). A well-crafted policy should encourage firms to adopt pollution reduction and abatement technologies, without imposing excessive financial burdens that could either erode business profits or lead to increased energy prices for consumers.

Currently, several nations are increasingly focused on designing policies and incentive mechanisms to accelerate the adoption of carbon capture and storage (CCS) technologies (Waxman et al., 2021). With mounting pressure to meet climate targets and reduce carbon emissions, governments are exploring strategies such as offering subsidies, tax incentives, or grants to businesses that invest in CCS technologies (US Congressional Budget Office, 2023). These efforts aim to increase CCS adoption rates while ensuring that costs remain manageable for firms. For example, a recent study finds that countries like the US and the UK are leaders in the CCS technology space due to their generous financial incentives (Fikru et al., 2024b). There are over 130 carbon capture projects in the US and more than 50 in the UK, spanning pilot and demonstration, or operational phases. Many additional projects are expected to begin operations in the coming years. A majority of these projects are made possible due to financial grants and incentives provided by governments. A growing number of recent studies show that such financial incentives are instrumental in overcoming the initial capital cost expenditures, as well as reducing operational costs (e.g., through per capture subsidy or tax credits), hence ensuring the economic viability of CCS projects (Li et al., 2023, Yang et al., 2019, 2021, Fan et al., 2020).

While financial incentives have played a significant role in promoting CCS adoption, the formulation of cost-effective policies remains a complex challenge, in particular given that there are only few CCS projects worldwide (e.g., less than 350 projects according to Fikru et al. (2024b)) and hence more funding may be required until economies of scale are achieved. This stems from the often conflicting objectives that policymakers, firms, and consumers have. Governments aim to maximize social welfare by minimizing environmental harm, but firms are primarily driven by profit maximization motives (Kayalica and Lahiri, 2005). At the same time, consumers are sensitive to price increases, which could arise from the costs firms incur due to regulations such as carbon taxes or the adoption of capital intensive CCS technologies (Azure et al., 2023). Consumers may also be weary of additional tax burdens that could result from the incentivization of CCS technology among carbon-intensive industries. Thus, policy makers need to carefully consider trade-offs before designing new policies or amending existing ones. As an example, consider tax credits for carbon capture and management in the US which has been enhanced over the years (e.g., the Inflation Reduction Act enhanced the Section 45Q tax credit from \$50 to \$85 per ton of carbon captured for storage) and could face further changes (Congressional Research Service, 2023).

This study addresses the following questions: What are the welfare-maximizing combinations of emission taxes and carbon capture subsidies that incentivize firms to abate emissions through CCS, while accounting for industry profitability, consumer welfare, and the social cost of carbon?~~What are the optimal tax and subsidy policies that incentivize firms to manage carbon emissions via CCS while balancing industry profitability and fair consumer prices?~~ What factors cause variability in the optimal determination of such policies across different market conditions? Unlike previous studies that focused on the technical and economic performance of CCS under the assumption of exogenous environmental policies (Fikru, 2022, Fikru et al., 2024a), this research derives and characterizes welfare-enhancing policies and examines potential sources of variation in policy design. The results are expected to provide insights into how governments can craft effective and balanced mechanisms for the adoption of CCS technologies in a dynamic environment.

This research also contributes to the literature by providing a theoretical framework that incorporates the strategic behavior of carbon-intensive firms and the environmental regulator, and by using the energy sector as a case study to assess the impact of parameter variability on optimal policy outcomes. We consider a generic carbon-intensive product market with Cournot competition where firms that generate carbon emissions are penalized if they release carbon to the environment, and subsidized if they manage carbon using a CCS retrofit. Thus, the model considers two types of environmental policies to achieve decarbonization outcomes: a carbon emission tax and a CCS subsidy for carbon capture.

As in previous studies examining optimal environmental policies in a theoretical framework (Lahiri and Symeonidis, 2017, Kayalica and Lahiri, 2005), we use a two-stage game theory model to derive welfare-maximizing policies. In the first stage, the government sets environmental policies (both tax and subsidy), anticipating how firms will react. In the second stage, firms take policy as given and decide on their production and CCS-based abatement levels. The equilibrium is found by backward induction, where the second stage's optimal production decision informs the first stage's policy setting. This framework represents a Stackelberg game, where the government acts as the leader by setting environmental policies (tax and subsidy), anticipating the reaction of firms, which act as followers by optimizing their production and CCS-based abatement decisions accordingly. Once closed form optimal policies are derived, comparative statistics are used to characterize how input parameters influence optimal policy outcomes. The model's input parameters are categorized as follows: cost (production and carbon abatement), demand (market size, number of firms, slope of demand, disutility from emissions), and production (carbon intensity) parameters.

Next, using the energy industry as a case study, a range of data points for the exogenous parameters (cost, demand, and production parameters) are introduced into a Monte Carlo simulation to account for their variability. The simulation tracks how this variability in inputs propagates through the model and influences the determination of optimal policies. In this way, we determine the optimal policies (e.g., tax rates and subsidies) that maximize welfare in the energy industry, accounting for input variability.

Section 2 presents a brief summary of closely related studies. Section 3 presents the methodology for both the model framework and approaches used in the simulation. Section 4 presents results from solving the theoretical model while Section 5 presents the case study based on a Monte Carlo simulation of model solutions. Section 6 presents concluding remarks.

2 Literature Review

The adoption of carbon capture and storage (CCS) technologies by carbon-intensive industries, particularly power generators, has garnered significant academic attention. Yet based on a literature review of studies conducted between 2012 and 2023, Presty et al. (2024) identify a critical need for additional interdisciplinary research to advance the field of carbon dioxide management. While existing studies often evaluate the impact of specific policies on CCS adoption (Fikru, 2022) or analyze associated costs and environmental outcomes (Azure et al., 2023), determining the welfare-maximizing policy mix remains largely under explored (Colombe and Leibowicz, 2025). This study contributes to the literature by addressing this critical gap, offering insights into the optimal design of emission taxes and CCS subsidies.

Policy incentives and CCS: The role of policy in encouraging CCS adoption is well-documented, with several studies examining predefined policy frameworks. For example, Azure et al. (2023) explore the financial feasibility of CCS with tax credits, finding that these subsidies enhance CCS investment viability by increasing net present values. However, Colombe et al. (2024) highlight that uncertainties in the continuity of such incentives could undermine adoption rates. In the context of China, Yang et al. (2021) propose an alternative approach, recommending increased production quotas for coal-fired generators to offset the costs of CCS implementation.

European studies, such as Aune et al. (2022), suggest focusing subsidies on upstream CCS technology developers rather than downstream adopters, arguing that this strategy can better addresses market failures and fosters innovation. Krahé et al. (2013) advocate for an integrated policy architecture that combines multiple instruments—such as carbon pricing, CCS-specific incentives, and environmental benefit valuation—to transition CCS technologies from demonstration to deployment phases. These studies underscore the critical influence of policy incentives on CCS adoption but are primarily limited to assessing the impacts of predefined instruments rather than determining optimal policy configurations.

A more nuanced approach is observed in the study by Amiri-Pebdani et al. (2023) who use a game-theoretical framework to compare the effects of CCS investment subsidies and feed-in tariffs under cap-and-trade regulations. Their results indicate that investment subsidies are more effective at promoting CCS adoption and reducing emissions. However, their analysis does not extend to optimizing the policy mix for welfare maximization.

Other closely related studies include Colombe and Leibowicz (2025) and Duggan Jr et al. (2025) both of which used a game-theoretic model to examine policies to incentivize CCS adoption, highlighting the trade-offs between subsidies, emissions outcomes, and welfare. Duggan Jr et al. (2025) model a Cournot duopoly electricity market and Colombe and Leibowicz (2025) consider a Stackelberg framework with a monopoly firm under perfect and imperfect information. While Colombe and Leibowicz (2025) model optimal CCS subsidies, Duggan Jr et al. (2025) study the impact of both tax and subsidy on carbon emissions. Our study contributes to the former by modeling two policy instruments instead of one, and the latter by characterizing welfare-enhancing or optimal policies rather than exogenously given policy regimes.

Feasibility assessments: Beyond policy analysis, much of the CCS literature focuses on techno-economic feasibility and environmental outcomes. Studies such as Ng et al. (2013), Ye et al. (2019), Van der Spek et al. (2020), Sukor et al. (2020) assess CCS costs, including capital expenditures, operational expenses, and carbon management overheads, across various industrial applications. Huang et al. (2013) employ optimization models to minimize electricity generation costs under constraints like demand and generation capacity, providing insights into the financial implications of CCS adoption. However, previous studies typically treat policy incentives and demand as exogenous factors, limiting their applicability to policy design. Environmental studies, including those by Owebor et al. (2022) and Waxman et al. (2023), quantify the carbon reduction benefits of CCS deployment. On the contrary Furlanetto et al. (2024) show that the adoption of carbon capture can unintentionally worsen environmental outcomes by increasing co-pollutant emissions by creating the incentive for power generators to shift from natural gas to coal. Although these findings are valuable for understanding the contributions of CCS, they do not directly model policy optimization.

By focusing on the determination of welfare-maximizing policies, this study offers a contribution to the CCS literature, shifting the focus from evaluating given policies to systematically designing them for broader societal benefits. In addition, the study evaluates how variations in contextual factors, such as market conditions and cost structures, impact the optimal policy mix, providing a comprehensive understanding of how policy design may adapt to different economic and technological environments.

3 Theoretical Framework and Simulation Approaches

We consider an oligopolistic carbon-intensive industry where n number of firms compete in output production. We also consider an environmental regulator which sets an emission tax (τ) for any carbon emissions not managed (e.g., released to the environment) and a subsidy (s) to encourage carbon capture and storage (CCS) per unit of carbon captured. We model both policies following related studies (Gautier, 2013) to capture the case where the regulator uses both a carrot and stick approach to achieve decarbonization goals. This general approach also helps identify cases and scenarios where both versus only one policy is needed for welfare maximization.

Following previous studies on optimal environmental policies, we consider a two-stage Stackelberg game where the regulator is a leader and firms are followers (Elnaboulsi et al., 2018). The objective of the regulator is to maximize welfare whereas the objective of firms is profit maximization. In the first stage, the regulator, as the first mover, selects optimal policies by maximizing a welfare function to regulate carbon emissions. In the second stage, the n pollution-intensive firms (as followers) choose their production and abatement (i.e., carbon capture) efforts simultaneously to maximize profits.

The solution to this game is derived using backward induction, a method in game theory that begins by solving the final stage first (Lahiri and Symeonidis, 2017). In our case, the optimal production level and carbon abatement (carbon captured for storage) of the firms are derived based on the assumption that the two policies (τ, s) are fixed. By solving firms' reactions in Stage 2 as a Nash equilibrium, we can determine how the regulator anticipates these decisions when selecting the optimal policy in Stage 1. This means the government considers the firms' responses when formulating its policies, seeking an equilibrium that maximizes welfare. The game is a sequential game where players (i.e., the regulator and producers/firms) make decisions in turns across the two stages. The entire game leads to a subgame perfect equilibrium, ensuring that the strategy selected is optimal and consistent at every point of the game, across both stages.

A two-stage Stackelberg game framework is also employed in a recent model by Colombe and Leibowicz (2025), which analyzes optimal carbon capture subsidies. While their model offers valuable insights into CCS policy design, it focuses solely on a subsidy instrument and involves a single firm, without addressing the role of emissions taxation. In contrast, our study differs in several important ways: (1) we examine both an emissions tax and a carbon capture subsidy, offering a more comprehensive approach to environmental regulation; (2) we model an industry comprising multiple firms, capturing competitive behavior and aggregate emissions outcomes; and (3) we derive closed-form expressions for the welfare-maximizing tax and subsidy rates in terms of technological and economic parameters, allowing for comparative statics and sensitivity analysis.

3.1 Demand and cost function

The n number of firms produce a homogeneous good where $i = 1, 2, ..., n$. The assumption of homogeneous goods is appropriate in markets where consumers do not distinguish between producers and there are no product varieties (e.g, energy or electricity markets). The product market is assumed to be oligopoly with Cournot competition. Each firm i produces x_i units of the product where attributed emissions are measured as $e = \sigma x_i$ (e.g., metric tons of carbon dioxide) and σ is each firm's carbon-intensity (e.g., carbon tons generated per output). In addition to choosing output levels, firms choose the percent of carbon emissions to capture where $0 \leq k \leq 1$ is used to represent the percent of carbon captured by each firm where the total volume of carbon captured for storage is $k\sigma x$. Even though the case of $k = 1$ representing perfect carbon capture, is a theoretically ideal scenario that may be difficult to achieve in practice, we consider it in our model to establish an upper bound and mathematically feasible set. One limitation of modeling k as a decision variable where firms have control over is the operational constraint many existing CCS technologies, especially retrofit applications, have with limited short-term flexibility. Hence, the model is more appropriate for capturing scenarios where firms possess greater control over capture intensity, such as plants designed for flexible operation (e.g., carbon filters).

The inverse demand for the good is given as follows consistent with related studies (Kayalica and Lahiri, 2005, Lahiri and Symeonidis, 2017):

$$p = \alpha - \beta \sum_{i}^{n} x_i \tag{1}$$

The market size and slope parameters are strictly positive, $\alpha, \beta > 0$. The parameter β is the slope of the inverse demand function while α represents the reservation price of the good. The price of the good produced with a negative externality (i.e., carbon emissions) is represented by p.

The firm's total cost function is the sum of production cost and carbon abatement cost in the form of carbon capture and storage, $C(x, k) = cx + \theta k^2/2 + dk\sigma x + F$, given $c, \theta, d, F \geq 0$. The first term represents the production cost which is assumed to be linear. The second term represents the cost of carbon capture (abatement) which is assumed to be convex as in Fikru et al. (2024a). This means that capturing increasing shares of carbon emission for permanent storage imposes increasing levels of abatement cost. This is consistent with modeling approaches in the environmental economics literature (Lahiri and Symeonidis, 2017). Hence, assumption of convex abatement cost captures the notion that it becomes increasingly costly to capture additional units of carbon, reflecting diminishing returns to abatement technology. The third term is the cost of transporting and storing the captured carbon which is assumed to be linear (Smith et al., 2021). The last term, F, represents the firm's fixed costs. The inclusion of a fixed cost term captures capital or infrastructure investments that do not vary with output or abatement decisions, and is standard in firm-level modeling. We refer to c, θ, d as the cost parameters.

3.2 Second stage production and abatement decisions

The objective of the i^{th} firm is to simultaneously choose production level (x_i) and abatement rate (k) to maximize profits. The firm's profit function and the first-order profit maximization conditions are given as follows:

$$\pi_i(x_i, k) = px_i - C(x_i, k) + sk\sigma x_i - \tau(1-k)\sigma x_i \tag{2}$$

$$\frac{\partial \pi_i(x_i, k)}{\partial x_i} = p + x_i \frac{dp}{dx_i} - \frac{dC(.)}{dx_i} + sk\sigma - \tau(1-k)\sigma = 0 \tag{3}$$

$$\frac{\partial \pi(x_i, k)}{\partial k} = -\frac{dC(.)}{dk} + s\sigma x_i + \tau\sigma x_i = 0 \tag{4}$$

The first-order conditions imply that firms set production decision such that marginal revenue (price plus effect of production on prices) equals marginal production cost adjusted for the net policy incentive. The first-order condition with respect to k implies that firms choose the percent of carbon capture by equating marginal abatement cost with the sum of the subsidy benefit ($s\sigma x_i$) and the avoided tax penalty ($\tau\sigma x_i$) for emissions. These conditions illustrate the important role of policy incentives in shaping production and abatement decisions.

3.3 First stage policy decision

Consistent with previous studies (Lahiri and Symeonidis, 2017, Gautier, 2022, Elnaboulsi et al., 2023), we consider the following welfare function which the regulator optimizes to get solutions for optimal tax (τ) and CCS subsidy (s). This function incorporates consumer surplus, producer surplus, external costs, and government net revenue, reflecting a Pigovian approach to correcting market failures. As emphasized by Hébert and Ekelund (1984), standard optimality conditions break down in the presence of externalities, since marginal private costs diverge from marginal social costs. In such cases, welfare economics calls for corrective policy instruments—such as taxes and subsidies—to internalize externalities and restore allocative efficiency.

Anticipating firms' responses, the regulator maximizes W:

$$W(\tau, s) = CS(x) + n\pi + n\tau(1-k)\sigma x - nsk\sigma x - \gamma(1-k)n\sigma x \tag{5}$$

The first term represents the consumer surplus which is $CS(x) = 0.5\beta n^2 x^2$, which reflects the welfare accruing to consumers under linear demand and symmetric firm output. The second term is industry profit, the third term is tax revenue, and the fourth term represents the regulator's expenses in the form of subsidy disbursed for carbon capture. The last term represents disutility from carbon emissions where $\gamma > 0$ is a constant marginal damage cost (Gautier, 2022). Previous studies show that the parameter γ is exogenous and could represent the weight the government puts on environmental damages when designing environmental protection policies (Buccella et al., 2024). It could also represent the extent to which society is concerned over environmental issues (Gautier, 2015). The first-order welfare maximization conditions presented below are solved together to find optimal policies represented as τ^* and s^* (see Appendix A1 for a derivation):

$$\frac{\partial W(\tau, s)}{\partial \tau} = 0 \tag{6}$$

$$\frac{\partial W(\tau, s)}{\partial s} = 0 \tag{7}$$

The full Stackelberg equilibrium consists of firm-level equilibrium (x^*, k^*) and policy equilibrium (τ^*, s^*). The final optimal policy solutions are solved as functions of multiple model parameters, where $\tau^*(\alpha, \beta, n, \gamma, c, \theta, d, \sigma)$ and $s^*(\alpha, \beta, n, \gamma, c, \theta, d, \sigma)$. These expressions are nonlinear, involving interactions among several parameters, and hence standard comparative statics—where one parameter is varied at a time while holding others constant—becomes inefficient, particularly for certain parameters that have opposite effects on welfare depending on the level of other parameters, due to inter-dependencies and non-additive effects present in the system. To address this limitation, we employ Monte Carlo simulations, which provide a more comprehensive analysis of how different parameters influence optimal policies. This method allows us to better understand

and assess variability (generating the optimal policies under different parameter values) and identify dominant parameters (if any) while at the same time capturing the nonlinear interactions from multiple interactions.

3.4 Simulation approaches

For the Monte Carlo simulations, we consider input parameters from the US energy sector. These parameters are categorized as production cost (c) and emission intensity (σ), CCS or abatement cost (θ, d), and market demand parameters including disutility from emissions (α, β, n, γ). We measure energy production in megawatt hour (mwh) per year and costs are measured in US dollars after adjusting for inflation. Carbon emission is measured in metric tons per year (mt). Table 1 presents the initial and range of values used in the simulations. The range of values are the minimum and maximum possible, while the initial values are the modes or means depending on the assumed distributions. For the distribution functions, we adopt triangular distributions as in previous studies (Azure et al., 2023).

Production cost parameter: For the average cost of electricity production, c, we follow US EIA (2024b) which presents data on the cost of power plants that are investor-owned utilities. The cost for fossil-fuel-based power plants is given as 43.58 mills per kWh (mills means 1/1,000 dollars). This includes the cost of operation, maintenance, and fuel. Converting this to dollar per mwh gives \$48.58/mwh. We take this value as the initial cost and mode value and consider a range of values consistent with yielding feasible production volumes for all types of power generators recorded in US EIA (2024b).

Carbon-intensity parameter: Finally, the carbon intensity of energy production (σ) is based on data from the US EIA (2020) which ranges from 0.39 (natural gas) metric tons of carbon per mwh to 1.043 (coal-based production).

CCS cost parameters: We have two CCS related cost parameters, θ, d. For the average cost of carbon transportation and storage, d, we use a range of values from \$6 to \$62 per mt of carbon (Smith et al., 2021). According to Smith et al. (2021), the most typical value used in the literature is \$14 which we will use as the initial value. The cost of capturing a mt of carbon dioxide ranges from \$22 to \$172 according to US Congressional Budget Office (2023) after adjusting for inflation. This is a proxy for the average cost of carbon capture. Taking the total capture cost function in the model, that is $0.5\theta k^2$, the average cost is calculated from $0.5\theta k$ which is set equal to the range of values from US Congressional Budget Office (2023). This means that the θ ranges from $\$11/k$ to $\$86/k$. So, considering high ($k = 1$) and low ($k = 0.01$) feasible boundaries for k where $0 < k \leq 1$, the θ is estimated to range from \$11 to $\$8,600$, where we consider the average as the mode value.

Market demand parameters: For the slope of the demand line, β, we use the estimate of price elasticity of electricity given in Csereklyei (2020) which ranges from -0.53 to -0.56 for the residential sector. At the current price of electricity in the US ($\$127/mwh$), and considering total electricity sales (3.87 billion mwh) we calculate the corresponding β to range from 6.18 to 5.84 times 10^{-08} under the assumption that demand is linear (US EIA, 2024a). Given these values for β, we use the linear demand function along with the current price of electricity and total sales to proxy for α. This yields a range of values from \$239 to \$366 per mwh, which is above the market price ensuring $\alpha > p$. For the number of power generators, n, we consider it ranges from a monopoly market ($n = 1$) to an oligopoly market with $n = 200$. According to the US EIA (2019), there are 168 investor-owned utilities serving about 72% of electricity customers in the US where the two largest utilities are in California. Hence, we use 168 as the initial value.

Marginal damage from carbon emissions: The marginal disutility from carbon emissions is approximated by using the social cost of carbon estimate provided by the US EPA (2024) and this ranges from $\$19/mt$ (using 5% discount rate) to $\$187/mt$ (using top 95^{th} percentile high impact values) where the average value is estimated as $\$63/mt$ of carbon emissions. All values are adjusted for inflation using the US consumer price index.

Parameters	Units	Distribution	Data source
Cost parameters			
c	$\$/mwh$	$tri\ (1.64, 43.58, 85.52)$	US EIA (2024b)
θ	$\$/mt^2$	$tri\ (11, 4305.5, 8600)$	US Congressional Budget Office (2023)
d	$\$/mt$	$tri\ (6, 14, 62)$	Smith et al. (2021)
Demand parameters			
α	$\$/mwh$	$tri\ (239, 302.5, 366)$	US EIA (2024a)
β	$\$/mwh$	$tri\ (6.18e-08, 6.01e-08, 5.84e-8)$	Csereklyei (2020), US EIA (2024a)
n	Number	$tri\ (1, 168, 200)$	US EIA (2019)
Marginal damage parameter			
γ	$\$/mt$	$tri\ (19, 63, 187)$	US EPA (2024)
Carbon-intensity parameter			
σ	mt/mwh	$tri\ (0.39, 0.72, 1.043)$	US EIA (2020)

Table 1: Parameter values, distributions, and data sources.

4 Optimal Environmental Policy Design

4.1 Firms' best response to policy

The closed form solutions obtained from solving the firm's profit-maximization problem from Equations (3) and (4) are presented as follows (see Appendix A1 for how these are derived):

$$x^{**} = \frac{\theta(\alpha - c - \tau\sigma)}{\beta\theta(n+1) - \sigma^2(s+\tau-d)^2} \tag{8}$$

$$k^{**} = \frac{\sigma(s+\tau-d)(\alpha - c - \tau\sigma)}{\beta\theta(n+1) - \sigma^2(s+\tau-d)^2} \tag{9}$$

$$\tag{10}$$

These solutions represent the firm's reaction to each policy instrument where $x^{**}(\tau, s)$ and $k^{**}(\tau, s)$. These solutions suggest that both tax and subsidy affect the firm's production and abatement decisions in non-linear ways.

We find that for a positive output level, $x^{**} > 0$, the carbon-intensity of production should not exceed a given threshold. That is, we find that $x^{**} > 0$, when $\sigma < \hat{\sigma}$ where $\hat{\sigma} = \sqrt{\beta\theta(n+1)}/(s+\tau-d)$. In addition, the market size should be sufficiently large to allow non-negative levels of production where $\alpha - c - \tau\sigma > 0$. We also find that for $0 \leq k^{**} \leq 1$ to hold, the following two conditions must hold, (i) $s+\tau > d$, and (ii) $n > \bar{n}$, where $\bar{n} = [(\sigma(s+\tau-d)(\alpha-c+\sigma(s-d)/\beta\theta] - 1$. The first condition implies that the tax and subsidy rates should be higher than the cost of managing captured carbon, and the second condition implies that the number of firms must be large enough and above the given threshold. The closed form solutions also imply that profits decline with percent of carbon captured but increase with production levels which is generally consistent with previous studies (Daher et al., 2024).

Based on closed-form solutions, we derive the following comparative statics to examine the firm's best response to an exogenous change in each policy:

$$x_\tau = \frac{\partial x^{**}}{\partial \tau} = \frac{\sigma x(2k-1)}{\alpha - c - \tau\sigma} \tag{11}$$

$$x_s = \frac{\partial x^{**}}{\partial s} = \frac{2\sigma x k}{\alpha - c - \tau\sigma} > 0 \tag{12}$$

An increase in tax increases production if $k > 0.5$. This means that firms will be encouraged to produce more only if they invest to capture more than half of their carbon emissions, in which case they can benefit from tax savings. A higher tax rate, in this case, creates an abatement effect from which the firm benefits as long as $k > 0.5$ (Gautier, 2013). Alternatively if k is very low, say close to zero, then tax reduces production as shown in previous studies (Daher et al., 2024). Studies show that as long as the abatement is not too costly, firms can benefit from higher levels of abatement by reducing their tax burden (Requate, 2005). In addition, Equation 12 shows that an increase in the abatement subsidy increases production levels because with a higher subsidy firms are encouraged to produce more output and capture a higher percent of generated emissions.

Likewise, the firm's abatement response to both policies, given below, shows that:

$$k_t = \frac{\partial k^{**}}{\partial \tau} = \frac{\sigma x^{**}}{\theta} + \frac{x_\tau \sigma(s + \tau - d)}{\theta} > 0 \tag{13}$$

$$k_s = \frac{\partial k^{**}}{\partial s} = \frac{\sigma x^{**}}{\theta} + \frac{x_s \sigma(s + \tau - d)}{\theta} > 0 \tag{14}$$

The effect of both policy is to increase the percent of carbon captured in the feasible range of non-negative production and k bounded between zero and one. Equations (13) and (14) reflect the application of the chain rule to capture both the direct and indirect effects of policy changes on the firm's abatement decision. The chain rule allows us to decompose the total derivative of k with respect to each policy into: (i) a direct effect, holding output constant, and (ii) an indirect effect, operating through the policy's influence on production levels (that is via x_s and x_τ).

Lemma 4.1. *(i) An increase in carbon tax increases production if $k > 0.5$, and decreases production if $k < 0.5$. An increase in CCS subsidy always increases production. (ii) Firms increase the percent of carbon captured when carbon tax or CCS subsidy increases.*

4.2 Welfare maximizing policies

In this sub-section, we present the mathematical derivation of the two optimal policies and discuss findings. The closed form solutions, τ^*, s^*, are:

$$\tau^* = \frac{\beta\theta[\gamma\sigma(n+1) - (\alpha - c)] - (d-\gamma)^2\sigma^3\gamma}{n\beta\theta\sigma - (d-\gamma)^2\sigma^3} \tag{15}$$

$$s^* = \frac{\beta\theta(\alpha - c - \gamma\sigma)}{n\beta\theta\sigma - (d-\gamma)^2\sigma^3} \tag{16}$$

Using these optimal policies, we finalize solving the Stackelberg game by calculating the production and the carbon capture decisions as follows:

$$x^* = \frac{\theta(\alpha - c - \gamma\sigma)}{n\beta\theta - (d-\gamma)^2\sigma^2} \tag{17}$$

$$k^* = \frac{(d-\gamma)\sigma(\alpha - c - \gamma\sigma)}{n\beta\theta - (d-\gamma)^2\sigma^2} \tag{18}$$

The equilibrium production level x^* and abatement rate k^* depends on the net benefit of production $(\alpha - c - \gamma\sigma)$, where a higher cost of production or carbon penalty $(\gamma\sigma)$ reduces output and the carbon capture percent, while stronger market demand (α) for the product increases both.

In what follows, we highlight key results of the model consistent with the literature. First is the strategic substitutability between the two policies where γ has a role in determining the need for two versus one policy. Second is the role of σ is determining the need for a carbon capture subsidy. Finally, we illustrate the impact of other model parameters, such as market size and CCS costs, in affecting the characterization of optimal policies.

4.2.1 Factors governing policy substitutability

The closed form solutions for the optimal policies, as presented in Equations (15)-(16) suggest that disutility from marginal damages (γ) affects both policies in a non-linear way and contingent on the level of other parameters. Re-arranging the closed form solutions we find that the optimal emission tax and CCS subsidy are related, that is $\tau^* = \gamma - s^*$. This means as long as the disutility from carbon emissions is higher than the CCS subsidy rate, the optimal tax would be positive and serve the purpose of penalizing emissions. This means that the γ has to be sufficiently large enough to allow both policies to be feasible, taxing emissions on one hand with $\tau^* > 0$ and at the same time subsidizing abatement with $s^* > 0$. For example, if γ is close to zero, there would essentially be one policy, either a subsidy or a tax but not both. These results are consistent with the environmental economics literature which shows that a policy mix, such as using a combination of tax and subsidy, leads to a strategic substitutes relationship (Buccella et al., 2024).

For example, consistent with our findings, Buccella et al. (2024) find that the optimal emission tax is positive as long as the parameter measuring marginal pollution damages is sufficiently high. These results suggest that as one policy becomes stronger, the stringency of the other should decline. That is, if the regulator is already incentivizing abatement via a subsidy it may not need to increase the stringency of the carbon tax and hence the two policies are strategic substitutes to achieve the goal of reducing emissions. Furthermore, the results show that if subsidies are close to zero (e.g., when θ or β are close to zero), the optimal emission tax is equal to marginal damages from pollution, γ, that is referred to as the Pigouvian tax (Keohane and Olmstead, 2016, Lahiri and Symeonidis, 2017).

Consistent with our findings, Gautier and Fikru (2024) find that the optimal emission tax is positive only when marginal damages (γ) from pollution are above a given threshold as this is to allow higher pollution effects to justify taxing compared to exacerbating output distortion effects in oligopoly markets. Similarly, studies show that a higher environmental damage parameter (γ) lowers the optimal subsidy while increasing the optimal tax because of the need to raise tax revenues (Buccella et al., 2024). The main results of this sub-section are summarized as follows:

Proposition 4.2. *(a) Welfare maximizing carbon emission tax and carbon capture subsidy are strategic substitutes. (b) Disutility from emissions (γ) has to be sufficiently high to allow for both policies to co-exist where $\tau^*, s^* > 0$ in a policy-mix regime.*

4.2.2 Factors governing the need to subsidize carbon capture

The closed form solutions for τ^* and s^* show that σ affects both in non-linear ways potentially creating opposite effects. For example, the pressure to increase the optimal tax could occur when σ increases as long as $d = \gamma$ to penalize pollution. Similarly, we find that $ds^*/d\sigma < 0$ when $d = \gamma$. However, these effects could be moderated or grow weaker if $d > \gamma$ holds and large. The net effect of these opposing forces remains ambiguous while using comparative statics, and requires further analysis, such as simulations, to determine the prevailing influence.

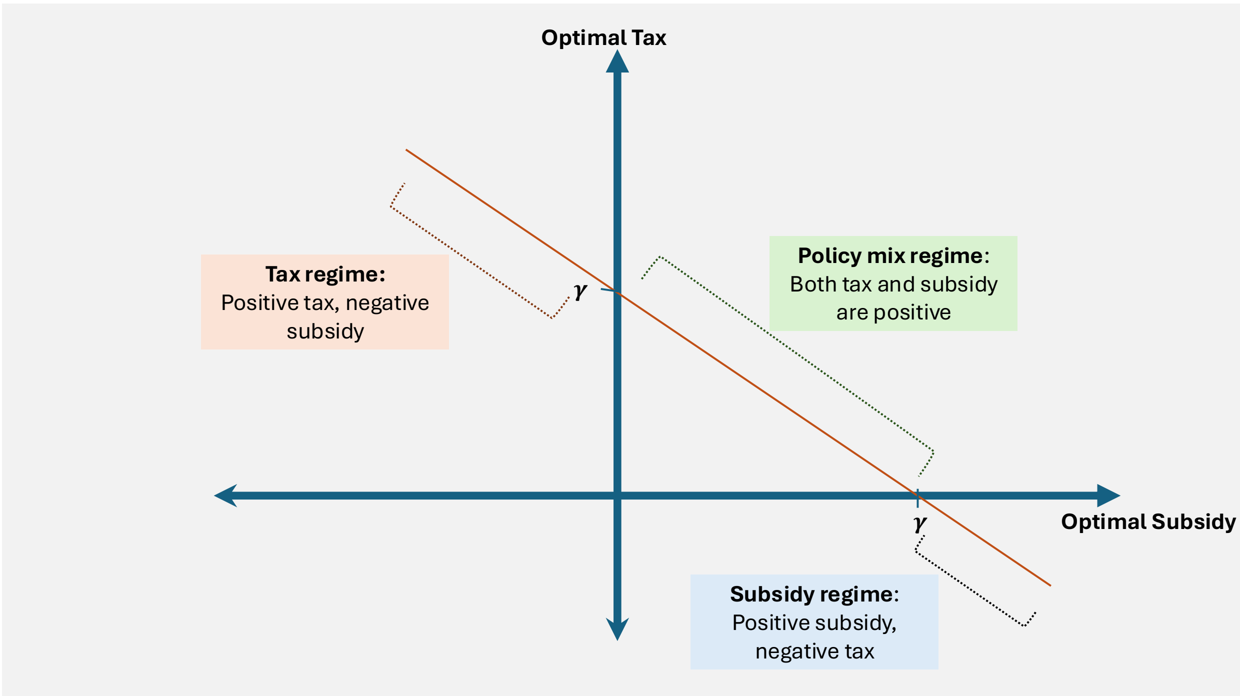
We find that $s^* > 0$ as long as $\sigma < \bar{\sigma}$, and otherwise negative ($\bar{\sigma} = \sqrt{n\beta\theta}/(d-\gamma)$). Since $\hat{\sigma} > \bar{\sigma}$, there are some feasible output levels where we get a negative subsidy, $s^* < 0$ in the (higher) range of carbon intensity between $\bar{\sigma}$ and $\hat{\sigma}$. When subsidy is negative, the optimal tax rate is always positive, $\tau^* > 0$ (we call this the *tax-only regime*, because a negative subsidy is essentially a tax as discussed in the literature) (Fujiwara, 2009). When subsidy is positive, the tax can either be positive (*policy mix regime*) or negative (*subsidy-only regime*). These results are summarized in Figure 1. The carbon intensity of production (σ) plays a role where subsidies are positive for lower ranges of carbon intensity (hence yielding either the policy mix or subsidy-only regimes), and negative subsidies which are effectively taxes for large enough σ.

Proposition 4.3. *(a) If carbon intensity of production is higher than a given threshold, $\sigma > \bar{\sigma}$, there is a single optimal policy, which is to tax emissions in a tax-only regime. (b) If this threshold is not reached ($\sigma < \bar{\sigma}$), it is welfare-enhancing to use subsidies $s^* > 0$ either alone on their own (if γ is not too large) or together with an emission tax (if γ is large enough).*

4.2.3 Other factors governing optimal policies

The solutions presented in Equations (15)-(16) also suggest that the optimal policies depend on the model's other key parameters such as costs (both production and abatement costs, c and θ, d, respectively) and market demand parameters (α, β, n). Depending on a combination of these model parameters, the optimal policies could either be both positive or one is positive while the other is negative as depicted in Figure 1. The impact of each parameter on the optimal policies depends on which regime we are (policy mix, tax-only, or subsidy-only regime).

Figure 1: Feasible optimal policy regimes.



For instance, in the policy mix regime ($\tau^* >, s^* > 0$), the impact of larger market size or increase in demand (via increases in $\alpha - c$) is to increase the optimal subsidy but reduce the optimal tax. This is generally consistent with previous studies (Gautier, 2015). This is because in larger markets, more of the good with a negative externality is produced generating more emissions, and hence increasing the need to use subsidies to control emissions via CCS. Furthermore, higher subsidy encourages more production of the good in the now expanded market, hence increasing consumer surplus and profits, while at the same time increasing carbon capture (welfare enhancing effect). Similarly, it would generally not be optimal to tax a good whose market size is increasing, unless marginal damages and/or pollution-intensities are large.

In a similar fashion, while higher slope of the marginal abatement cost due to θ or d affects the optimal policies in non-linear ways, higher marginal abatement cost is generally expected to increase the need to encourage abatement via CCS, as long as γ, σ are not too large. This is because when CCS is costly, abatement declines and emission increases, and additional subsidies are required to discourage emissions. With higher subsidies, the monetary benefit from carbon abatement increases increasing the percent of carbon captured (Buccella et al., 2024).

Overall, the impact of model parameters on the optimal policy design depends on the type of policy regime as presented in Figure 1. In addition, each parameter may have an opposing effect on optimal policy design where net effects depend on a combination of factors, the precise impacts of which will be examined in the next section.

5 Evaluating Variability in Optimal Policies

In this section, we present results from the Monte Carlo analysis. First, we present how variability in all input parameters propagates through the model, influencing the two model outcomes of interest, which are the two optimal policies (τ^*, s^*). This helps trace the economic mechanism and identify stronger channels through which optimal policies are impacted. Then, we relate the two model outcomes (optimal tax and subsidy) together to understand how input variability causes them to evolve in the same versus different directions, and assess the likelihood of one policy regime prevailing over the other. Finally, we present some robustness checks by considering the case where certain parameters are fixed rather than variable.

It is important to recognize that the analytical comparative statics results presented in Section 4 and the simulation findings discussed here capture distinct but complementary aspects of the model's behavior. The analytical results apply partial derivatives, which hold all other parameters fixed to isolate the effect of a single variable—such as abatement cost parameters—on the optimal subsidy and tax. Under these ceteris paribus conditions, higher abatement costs, for instance d, may lead to higher optimal subsidies and correspondingly lower emission taxes, yielding $\partial s^*/\partial d > 0, \partial \tau^*/\partial d < 0$. The simulation analysis, on the other hand, allows all model parameters to vary simultaneously based on their assumed distributions, thereby incorporating the joint interaction effects among all changing parameters. This explains why the simulation results are often non-monotonic. Together, the analytical and simulation approaches provide insights through isolated parameter changes and a broader perspective by examining the interplay of multiple factors simultaneously.

5.1 Impact of model parameters on variability of optimal policies

Appendix A2 presents distribution of values used for the input parameters. In this sub-section, we examine the impact of each input parameter on the two optimal policies when input parameters are as presented in Table 1. The results are summarized in Figures 2 and 3. These visualizations were generated using R's *geom-smooth* function, which employs Generalized Additive Models (GAMs) to capture relationships between exogenous parameters and endogenous variables. GAMs provide a flexible, data-driven approach to regression by fitting smooth, non-linear functions rather than imposing a strict linear structure. The graphs include a 95% confidence interval, visually illustrating the robustness of these trends. A wider confidence interval, shaded in gray, indicates greater uncertainty in the estimated trend, whereas narrower intervals suggest a more precise estimate.

First, we find that the optimal tax and subsidy are nonlinear functions of the input parameters, highlighting the complex nature of policy responses to changes in market conditions. This makes Monte Carlo simulation a suitable approach because it allows us to account for the variability in input parameters, providing a more efficient analysis of the distribution of optimal policy outcomes under changing environments. Second, these relationships indicate that optimal subsidies exhibit greater variability, as reflected in the wider confidence interval range and flatter lines compared to the optimal tax. This suggests that the estimated trend for subsidies is weak and less precise, whereas the relationship of input parameters with the optimal emission tax is relatively more robust (e.g., steeper slopes, narrower confidence interval for certain ranges, etc.).

Third, the illustrated trends, which depict the relationship between input parameters (exogenous variables) and endogenous variables (optimal tax and subsidy policies), generally align with findings in the existing literature (Gautier and Fikru, 2024, Gautier, 2013). For example, when abatement is expensive (e.g., due to higher $\cancel{\theta \text{ and }}\, d$), the need to subsidize abatement increases while the need to tax pollution declines. This is because with increasing marginal abatement costs, if optimal subsidy remains the same, firms will abate fewer quantities and hence to induce more abatement the regulator needs to increase subsidies. In this scenario, lowering the emission tax would be optimal because the two policies are strategic substitutes (Keohane and Olmstead, 2016). Similarly, higher carbon intensity generally reduces the need to subsidize abatement and increases the need to tax pollution after a certain threshold level. This is generally consistent with Proposition 4.3.

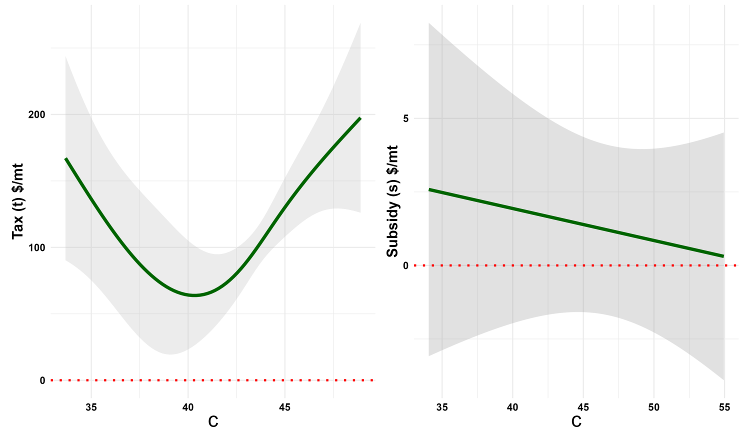
The impact of production cost on optimal subsidies, while showing a slight negative relationship, is weaker, flatter, and more variable. The impact of production cost on optimal tax is non-linear reducing it for ranges of values below the mode ($c > 43$) and increasing it thereafter. The portion of simulations yielding $dt/dc < 0$ is consistent with (Fujiwara, 2009) who showed that when optimal emission taxes are positive in oligopoly markets, the need to tax at a higher rate declines when output-reducing shocks, such as increase in cost, occur.

The impact of higher β is to increase the optimal subsidy and reduce the optimal tax up to a certain level. This is because higher β means consumers are less sensitive to prices and firms have more market power, and in such markets it is optimal for the regulator to encourage production via higher subsidies and lower taxes (due to output reducing effect of market power). The impact of α on the optimal subsidy is slightly positive but more uncertain, while the impact on tax is negative up to a certain level. These results highlight that even when the mathematically derived optimal policies are strategic substitutes ($\tau^* = \gamma - s^*$), this relationship does not hold uniformly across all simulated parameter values. This deviation likely arises due to non-linear interactions among parameter values in the model. Another possible explanation is that when the parameter in question reaches a certain threshold, the marginal benefit of increasing the subsidy diminishes, reducing its ability to fully offset the tax.

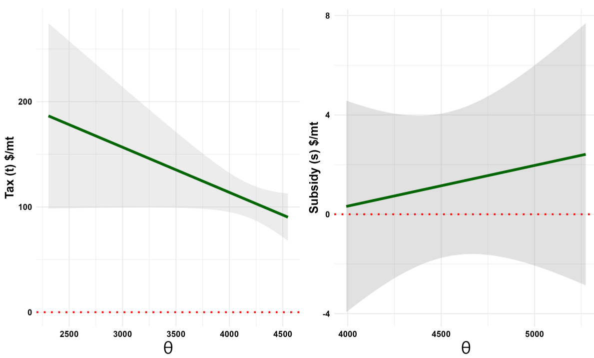
Consistent with Proposition 4.2, as the perceived disutility from carbon emissions increases, policymakers tend to implement stricter environmental policies by raising emission taxes as in (Gautier and Fikru, 2024) and (Fujiwara, 2009), while the effect on subsidies is negative (due to strategic substitutability) but less pronounced. The relationship between disutility (or marginal damages) and emission taxes is strong and consistent, whereas the impact on subsidies (while negative) is weaker and more variable, as indicated by the wider confidence interval and a less steep slope. This suggests that while higher disutility from emission reliably leads to higher emission taxes (e.g., such as the Pigouvian tax), its influence on subsidy reductions is less predictable.

Figure 3, Panel (c) illustrates that as the number of firms or energy producers rises facilitating competition, the optimal emission tax increases, whereas the effect on the optimal subsidy is weaker, as evidenced by the flatter line and wider confidence interval. The positive relationship between market competition and the stringency of environmental policies, particularly emission taxes, aligns with findings from previous studies such as (Gautier and Fikru, 2024) who show the need to tax more when market distortion effects are limited.

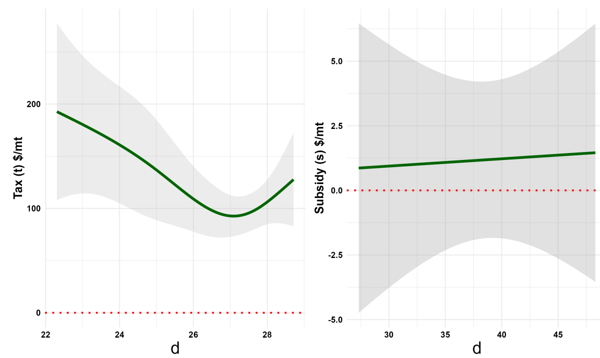
Figure 2: Impact of cost and production parameters on optimal policies.



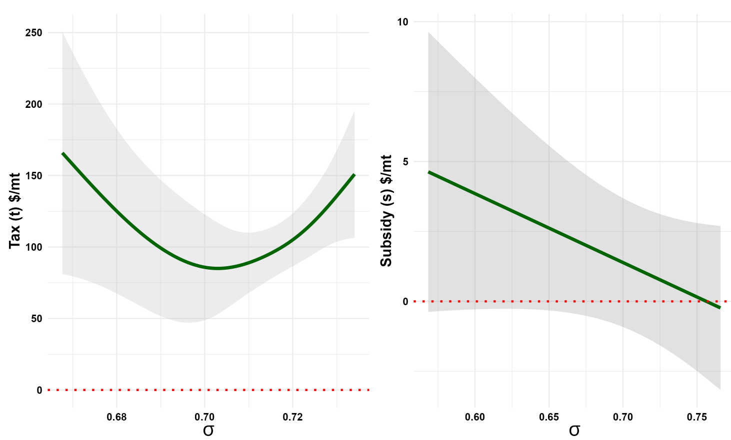
(a) Impact of production cost.



(b) Impact of θ on optimal policies.

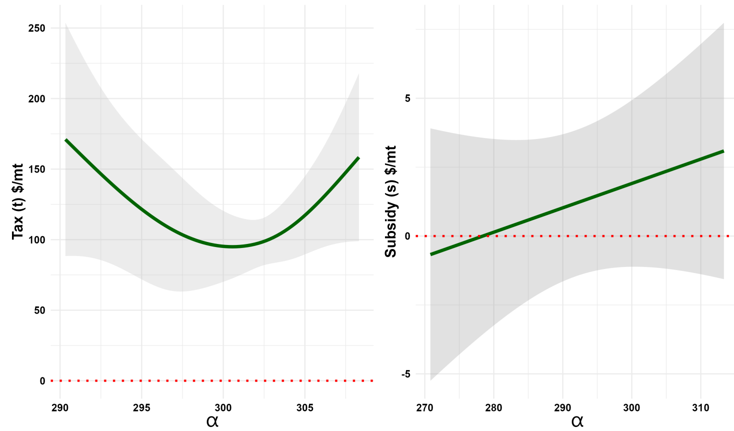


(c) Impact of d on optimal policies.

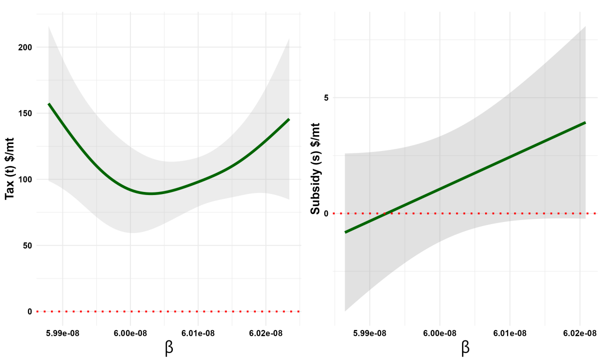


(d) Impact of σ on optimal policies.

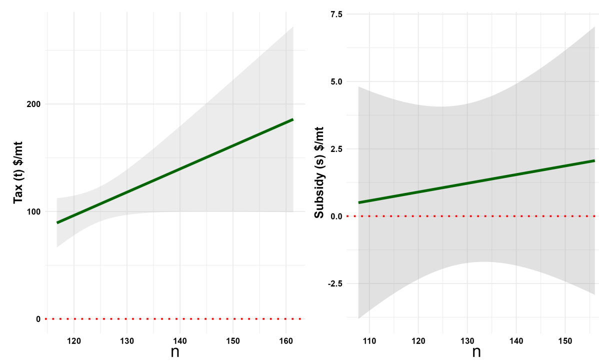
Figure 3: Impact of market and demand parameters on optimal policies.



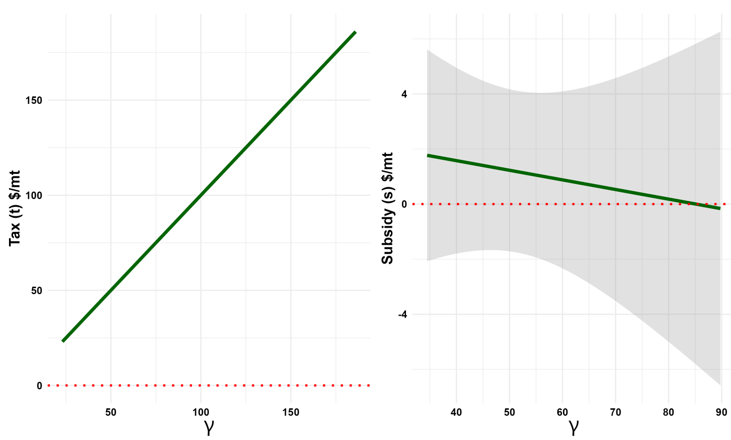
(a) Impact of α on optimal policies.



(b) Impact of β on optimal policies.



(c) Impact of n on optimal policies.



(d) Impact of γ on optimal policies.

5.2 Variable optimal policies under input variability

Figure 4 relates the evolution of the two optimal policies under three scenarios: (1) the case where none of the parameters are fixed, (2) the case where σ is fixed and (3) the case where σ, α, β, n. The two additional cases isolate specific sources of uncertainty to assess their impact on optimal policies. The second scenario fixes carbon intensity to focus on cost and market-related variability, while the second scenario fixes both carbon intensity and market parameters to highlight the influence of only cost-related uncertainties. These robustness checks help identify the key drivers of policy decisions in different uncertainty contexts.

Figure 4, Panel (a) presents the more general case where all model parameters are variable and there is full uncertainty regarding carbon intensity, market demand parameters, and cost parameters.

Panel (a) suggests that when policy makers face uncertainty across multiple dimensions there are two policy regimes consistent with Figure 1. Specifically, we observe the mixed policy regime $\tau^* > 0, s^* > 0$ (i.e., due to σ not so large yielding $s^* > 0$), and the tax regime where $\tau^* > 0, s^* < 0$ (i.e., due to large enough σ). In this scenario, where all parameters are variable, the confidence intervals are relatively wider at higher subsidy levels suggesting that small changes in assumptions could lead to significantly different policy recommendations, reinforcing the complexity of balancing taxes and subsidies in a dynamic market environment. In addition we find that, when optimal subsidy s^* is closer to zero (e.g., due to any combination of factors such as when θ or β are close to zero), the optimal tax is at its peak (τ^*) with relatively less variability. The wide confidence intervals in Panel (a) at the extreme ends highlight substantial uncertainty in the exact policy prescription, implying that the effectiveness of a given tax-subsidy mix is highly contingent on the underlying market conditions. The uncertainty surrounding the optimal policy levels reinforces the importance of adaptive regulatory frameworks that can adjust to evolving market and technological conditions rather than rigid, predetermined policy structures.

In Panel (b), when we remove uncertainty in carbon intensity and fix σ at its mode value (i.e., removing the probability of higher σ such as from coal plants), we observe that the simulations yield a majority of outcomes in the subsidy regime where $s^* > 0, \tau^* < 0$, but with higher variability. This outcome (subsidy regime) is likely due to eliminating simulations that produce higher carbon intensity ensuring σ is not too large to justify a positive CCS subsidy, while at the same time γ is not too large so there is less need for an emission tax.

Moving from scenario (a) to (b), where carbon intensity (σ) is fixed while other parameters remain variable, the policy framework shifts from one that includes carbon taxes for decarbonization to one that primarily relies on CCS subsidies. This suggests that when carbon intensity is uncertain (and likely to be large), an optimal policy mix includes taxation as a possible instrument to discourage emissions. However, once carbon intensity is fixed and more certain, the model identifies a policy regime that excludes carbon taxation, implying that in a more predictable emissions environment that potentially exclude high emission rates, subsidies alone may be sufficient to drive welfare-maximizing outcomes.

Despite this shift in the policy framework, there remains significant uncertainty regarding the exact optimal subsidy rate, as evidenced by the broad confidence intervals in Panel (b). The continued variability in subsidy levels suggests that other factors, such as fluctuations in energy demand, market competition, and the cost of carbon capture, still introduce uncertainty in determining the precise level of financial support required to achieve optimal abatement. The fact that taxation drops out of the optimal regime, while subsidies remain uncertain in Panel (b), underscores the sensitivity of policy recommendations to underlying market and technological conditions.

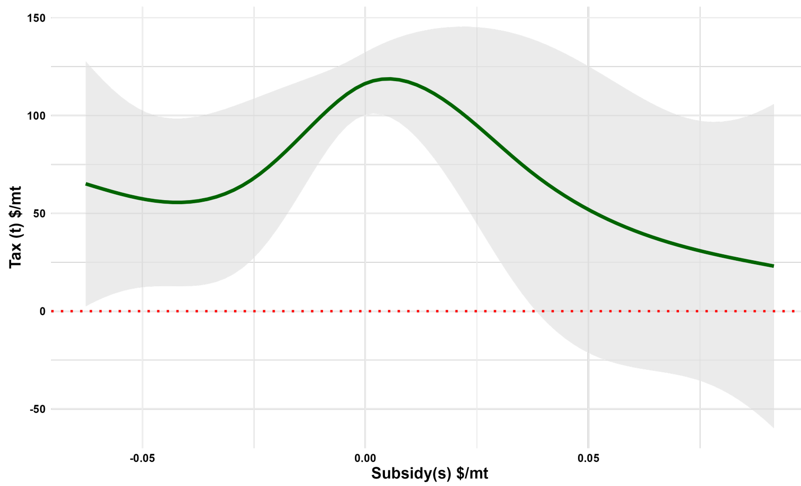
This result highlights the challenge policymakers face in setting stable and predictable subsidy rates. While removing taxation from the policy mix might simplify regulatory implementation, the persistent uncertainty around the optimal subsidy levels suggests that a one-size-fits-all approach may not be effective. Instead, a flexible subsidy mechanism, potentially tied to real-time market conditions or firm-level abatement costs, could provide a more adaptable and effective strategy for incentivizing carbon capture in the power sector.

Finally, in Panel (c) when we remove uncertainty due to carbon intensity and market demand parameters, we observe the mixed policy regime to some extent but also the subsidy regime. Comparing Panels (a), (b), and (c) suggests that when more variables are certain the policy regime is likely to exclude a tax only option. In addition, we still observe a wide range of confidence interval even after fixing the market demand parameters in Panel (c) which suggests that uncertainty in CCS and production costs by themselves create significant variation on the optimal policies.

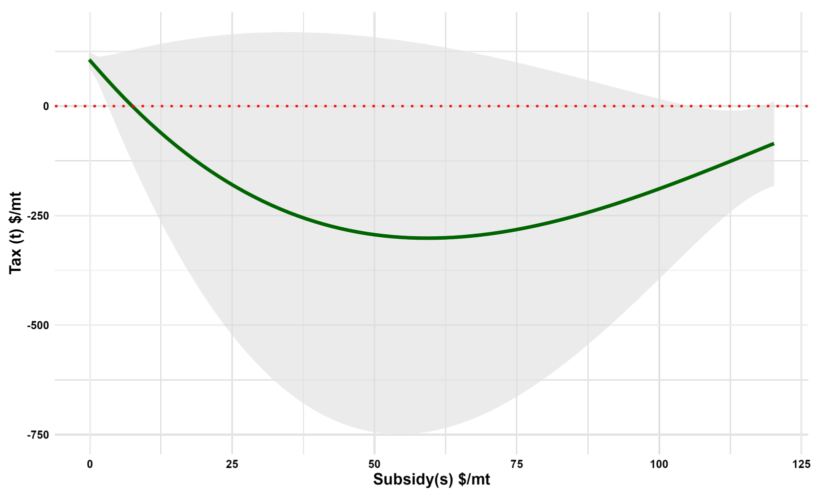
The persistence of large confidence intervals suggests that even when the broader market structure is well understood (that is, fixed α, β, n), the unpredictability of technology related parameters —such as the cost of carbon capture (θ), the cost of carbon management (d), and the marginal cost of energy production (c)— together with variability in marginal damages (γ) continue to drive uncertainty in policy outcomes. This implies that the feasibility and efficiency of carbon capture subsidies remain highly sensitive to the evolving cost structures of CCS technology and energy generation.

A key takeaway from Panel (c) is that fixing market-level parameters does not necessarily lead to greater policy precision if firm-level cost structures and marginal damages remain uncertain. For policymakers, this suggests that policies should account for potential cost volatility including the social cost of carbon, by incorporating flexible and heterogeneous subsidy mechanisms rather than fixed-rate support. Ultimately, the results highlight the need for continued technological advancements and cost reductions in CCS to improve the predictability and effectiveness of decarbonization policies.

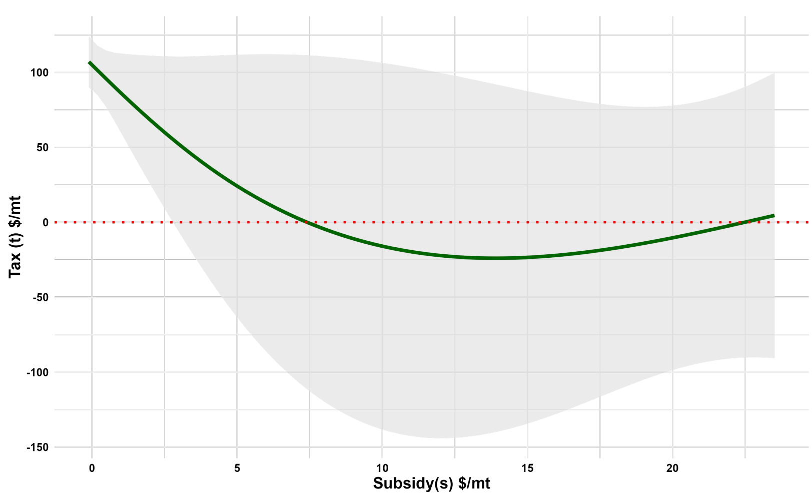
Figure 4: Feasible optimal policy regimes under three scenarios.



(a) Relating optimal tax and subsidy with no fixed parameters.



(b) Relating optimal tax and subsidy when σ is fixed.



(c) Relating optimal tax and subsidy when σ, α, β, n are fixed.

Our results in this section show that all parameters contribute more strongly to variation in the optimal subsidy than in the tax, indicating that subsidies are less precisely predicted and more sensitive to underlying conditions. Notably, even when we hold pollution intensity (carbon emissions per unit of output) and all demand-side parameters constant—including the slope and intercept of the demand curve and the number of firms—we still observe substantial variability in both policy instruments. This suggests that variability in optimal policy design is primarily driven by variation in cost and technology-related parameters, particularly production costs, carbon capture and management costs, and the marginal damages from pollution. These findings underscore the challenges in setting environmental policies in environments where technological and environmental parameters are evolving.

5.3 Lessons and implications

Our analysis yields additional several policy-relevant insights. First, from the analytical model, the emission tax and carbon capture subsidy function as strategic substitutes—when one instrument increases, the other should decrease. However, this relationship is conditional on the marginal damage from pollution: when damages are sufficiently high, a policy mix becomes optimal, justifying the simultaneous use of both instruments. Second, the pollution intensity of energy production plays a decisive role in policy selection. If pollution intensity exceeds a calculated threshold, taxes alone are optimal; below the threshold, subsidies or a combination of tax and subsidy may be warranted, depending again on the marginal damages.

Third, simulation results highlight that optimal subsidies are more sensitive to model input variability than optimal taxes, as evidenced by flatter estimated relationships and wider confidence intervals. Taxes, in contrast, are more stable and tightly linked to fundamentals. Fourth, when accounting for full variability in cost, technology, and damage parameters, we identify two dominant policy regimes: a tax-only regime and a mixed regime. The prevalence of the tax-only outcome under full variability underscores the robustness of taxes as a policy tool in uncertain environments. However, when variability is reduced—particularly in pollution intensity and demand factors—the subsidy-only regime emerges more frequently, suggesting that subsidies are more appropriate in predictable, well-characterized settings. Overall, policymakers should prioritize emission taxes as a baseline instrument in uncertain contexts, while designing flexible, performance-linked subsidies that can complement taxes where technological conditions or marginal damages justify a mixed approach. Table 2 maps the study's key findings with a summary of policy lessons.

Table 2: Summary of Key Results and Policy Implications

Result Type	**Key Finding**	**Policy Takeaway**
Analytical Result 1	Emission tax and carbon capture subsidy are strategic substitutes; the extent of substitution depends on the marginal damage from pollution.	Use a policy mix (tax + subsidy) only when marginal damages are high; otherwise, emphasize one instrument over the other.
Analytical Result 2	Pollution intensity determines the need for subsidy. If intensity exceeds a known threshold, tax-only policies are optimal; below the threshold, either subsidy or a mix may be optimal depending on marginal damages.	In high-pollution technologies, prioritize emission taxes; for cleaner technologies, consider subsidies or a policy mix.
Simulation Result 1	Optimal subsidies exhibit greater variability and weaker sensitivity to model parameters compared to taxes (flatter trends, wider confidence intervals).	Design subsidies with built-in flexibility (e.g., performance-based or linked to marginal abatement costs) to handle variability.
Simulation Result 2	Optimal taxes are more stable and more tightly aligned with model fundamentals (steeper slopes, narrower confidence intervals).	Emission taxes are a more robust policy tool under parameter uncertainty.
Simulation Result 3	Two regimes emerge under full parameter variability: (1) a mix regime and (2) a tax-only regime.	Expect policy mixes in complex or high-damage settings; taxes alone may be optimal in simpler, more uncertain contexts.
Simulation Result 4	Under reduced variability in pollution intensity and demand, subsidy-only regimes become more likely.	In predictable environments, subsidies can effectively serve as the primary policy instrument.
Robustness Finding	Even when demand-related parameters are fixed, cost and damage parameter variability alone lead to variable policy outcomes.	Uncertainty in cost and environmental impact remains a key source of policy variability. Accurate information on these is critical.

6 Conclusions

The motivation for this study stems from the urgent need to design optimal environmental policies that balance economic and environmental objectives, particularly in the context of carbon capture and storage (CCS). Governments face the dual challenge of reducing carbon emissions while maintaining economic growth and ensuring industry profitability. Existing research has explored various financial incentives and regulatory mechanisms, but a comprehensive understanding of the optimal policy mix—emission taxes and/or CCS subsidies—remains underdeveloped. This study employs a two-stage game-theoretic framework where the regulator set policy instruments in the first stage, anticipating firms' responses in the second stage. Using both closed-form solutions and Monte Carlo simulations, we characterize optimal policies and evaluate their variability under different market conditions.

Key findings highlight that optimal decarbonization policies are contingent on market characteristics, cost structures, and pollution damages. First, emission taxes and CCS subsidies function as strategic substitutes: when one is increased, the need for the other declines. The feasibility of using both policies simultaneously depends on the disutility from emissions. Second, the necessity of a CCS subsidy depends on the carbon intensity of production. If carbon intensity is above a critical threshold, taxing emissions alone becomes the optimal strategy, whereas lower-intensity industries benefit from a combination of subsidies and taxes. Third, the analysis reveals that both demand and cost parameters significantly influence the optimal policy mix. The Monte Carlo simulations confirm that variability in input parameters leads to significant fluctuations in optimal policies, reinforcing the importance of adaptable regulatory mechanisms.

The policy implications of these findings are multifaceted. Regulators should consider dynamic policy frameworks that adjust to evolving economic and technological conditions rather than implementing static tax or subsidy rates. Given that CCS subsidies are highly sensitive to cost and market fluctuations, governments may need to use flexible subsidy schemes linked to industry performance metrics or marginal abatement costs. Our simulation results underscore this point:

optimal subsidies exhibit substantially more variability than optimal taxes, with flatter trends and wider confidence intervals across parameter ranges. This suggests that fixed subsidy levels could be difficult to calibrate accurately in a dynamic environment and may result in over- or under-compensation. This finding reinforce the need for policy instruments, especially subsidies, to be designed with built-in flexibility that allows adjustment based on real-time market and technological signals. Such flexibility can help reduce policy uncertainty, improve cost-effectiveness, and ensure that incentives remain aligned with dynamic firm behavior and decarbonization goals.

Despite its contributions, this study has limitations that should be addressed in future research. First, we acknowledge that the assumption of homogeneous goods and Cournot competition is a simplification that enables analytical tractability but may limit generalizability. In practice, market structure plays a critical role in shaping optimal policy design. Under monopolistic competition or product differentiation (e.g., renewable versus non renewable), firms may have additional pricing power, which could alter both the incidence and effectiveness of policy instruments. For example, differentiated products may weaken the output-reducing effect of an emission tax, while subsidies may have stronger strategic effects in promoting cleaner production technologies to gain market share. Consequently, the optimal policy mix would likely differ in such settings. Future research could extend the model to incorporate differentiated goods or alternative competition frameworks to examine how these features affect environmental policy outcomes.

Second, another limitation of the model is the assumption that the government regulator has perfect information regarding firm-specific parameters such as costs, capture rates, and production decisions. While this assumption may be reasonable for regulated utilities subject to transparent reporting and oversight, it is less likely to hold for other carbon-intensive industries where private information and asymmetric knowledge can complicate the design and implementation of optimal tax and subsidy policies. Firms may have incentives to strategically misreport or withhold information to influence policy outcomes in their favor. Although explicitly modeling information asymmetry and strategic behavior under private information is beyond the scope of this study, our framework provides a foundation for future research to incorporate such complexities. Extending the model to analyze the effects of information asymmetry would offer valuable insights into policy robustness and enforcement mechanisms in less transparent sectors.

Third, since pollution-intensive firms may face technological and operational constraints that limit their ability to precisely adjust k, particularly in the case where ramping capture rates up or down may not be technically or economically feasible in the short run. While this modeling choice allows us to explore firm responses to policy incentives under idealized conditions, future research could relax this assumption by incorporating discrete technology choices, engineering constraints, or dynamic adjustment costs. Doing so would enhance the realism of the model and provide deeper insight into how CCS adoption responds to economic and technical frictions in real-world settings.

Additionally, the estimation of key parameters, such as the marginal cost of CCS and the social cost of carbon, is subject to uncertainty, which could influence the robustness of policy recommendations. Future studies could explore alternative regulatory frameworks, such as dynamic pricing models or sector-specific policies, to refine the characterization of optimal decarbonization policies. Moreover, empirical validation using real-world policy implementations would enhance the applicability of the findings. Addressing these limitations would provide a more comprehensive foundation for designing effective and resilient climate policies.

Acknowledgments: This study is based on work supported by the National Science Foundation (NSF) under Grant No. 2308737.

Conflict of interest statement: The authors have no conflict of interest to declare.

Financial disclosure statement: The authors have nothing to declare.

Data availability: The data and codes used in this study are publicly available on the Open Science Framework at `https://osf.io/u9bzy`.

References

Amiri-Pebdani, S., Alinaghian, M., and Khosroshahi, H. (2023). Pricing in competitive energy supply chains considering government interventions to support ccs under cap-and-trade regulations: A game-theoretic approach. *Energy Policy*, 179:113630.

Aune, F. R., Gaure, S., Golombek, R., Greaker, M., Kittelsen, S. A., and Md, L. (2022). Promoting ccs in europe: A case for green strategic trade policy? *The Energy Journal*, 43(6):71–102.

Azure, J. W., Frimpong, S., and Fikru, M. G. (2023). Stochastic modeling of decarbonizing strategy, policy, and market-induced incentives for the us electricity sector. *Journal of Cleaner Production*, 429:139324.

Buccella, D., Fanti, L., and Gori, L. (2024). Environmental policies in a polluting duopoly: a simple comparison. *Italian Economic Journal*, pages 1–26.

Colombe, C. and Leibowicz, B. D. (2025). Optimal subsidies for carbon capture: A stackelberg game analysis. https://ssrn.com/abstract=4854680. Available at SSRN.

Colombe, C., Leibowicz, B. D., and Mendoza, B. R. (2024). The effects of policy uncertainty and risk aversion on carbon capture, utilization, and storage investments. *Energy Policy*, 192:114212.

Congressional Research Service (2023). The section 45q tax credit for carbon sequestration. https://www.crs.gov. Accessed: 2024-02-11.

Csereklyei, Z. (2020). Price and income elasticities of residential and industrial electricity demand in the european union. *Energy Policy*, 137:111079.

Daher, W., Elnaboulsi, J. C., Fikru, M. G., and Gautier, L. (2024). An analysis of mergers in the presence of uncertainty in renewable energy integration costs. Available at SSRN 4911502.

Duggan Jr, J. E., Ogland-Hand, J. D., and Middleton, R. S. (2025). Modeling ccs policy support: Implications for market performance, net emissions, and welfare. *Applied Energy*, 389:125613.

Elnaboulsi, J. C., Daher, W., and Sağlam, Y. (2018). On the social value of publicly disclosed information and environmental regulation. *Resource and Energy Economics*, 54:1–22.

Elnaboulsi, J. C., Daher, W., and Sağlam, Y. (2023). Environmental taxation, information precision, and information sharing. *Journal of Public Economic Theory*, 25(2):301–341.

Fan, J. L., Wei, S., Zhang, X., and Yang, L. (2020). A comparison of the regional investment benefits of ccs retrofitting of coal-fired power plants and renewable power generation projects in china. *International Journal of Greenhouse Gas Control*, 92:102858.

Fikru, M. G. (2022). The impact of policies on profit-maximizing rates of reliance on carbon capture for storage versus cleaner production. *Journal of Cleaner Production*, 379:134659.

Fikru, M. G., Belaïd, F., and Ma, H. (2024a). Carbon capture and renewable energy policies: Could policy harmonization be a puzzle piece to solve the electricity crisis? *Energy Economics*, 136:107753.

Fikru, M. G., Shen, T., Brodmann, J., and Ma, H. (2024b). A strategic insight into the market for carbon management capacity. *Sustainable Futures*, 8:100374.

Fujiwara, K. (2009). Environmental policies in a differentiated oligopoly revisited. *Resource and Energy Economics*, 31(3):239–247.

Furlanetto, P. P., Ash, M., Baker, E., Diana, B., Donaghy, T., and Zakeri, G. (2024). Carbon capture and co-pollutants in a networked power system. *Environmental Research: Energy*, 1(3):035005.

Gautier, L. (2013). Multilateral and unilateral policy reform of emission taxes and abatement subsidies in a two-country model with oligopolistic interdependence. *Environmental Economics and Policy Studies*, 15:59–71.

Gautier, L. (2015). Horizontal product differentiation and policy adjustment in the presence of abatement subsidies and emission taxes. *Journal of Environmental Economics and Policy*, 4(1):64–81.

Gautier, L. (2022). The role of nonzero conjectural variation in pollution abatement and output in the design of emission taxes. *Environment and Development Economics*, 27(2):184–207.

Gautier, L. and Fikru, M. G. (2024). Mergers in cournot markets with environmental externality and product differentiation. In *Handbook of Merger Control and Environmental Policy: Theory and Applications*, pages 21–46. Springer International Publishing, Cham.

Huang, Y., Rebennack, S., and Zheng, Q. P. (2013). Techno-economic analysis and optimization models for carbon capture and storage: a survey. *Energy Systems*, 4(4):315–353.

Hébert, R. F. and Ekelund, R. B. (1984). Welfare economics. In *Economic Analysis in Historical Perspective*, pages 46–83. Butterworth-Heinemann.

Kayalica, M. and Lahiri, S. (2005). Strategic environmental policies in the presence of foreign direct investment. *Environmental and Resource Economics*, 30:1–21.

Keohane, N. O. and Olmstead, S. M. (2016). *Markets and the Environment*. Island Press.

Krahé, M., Heidug, W., Ward, J., and Smale, R. (2013). From demonstration to deployment: An economic analysis of support policies for carbon capture and storage. *Energy Policy*, 60:753–763.

Lahiri, S. and Symeonidis, G. (2017). Environmental protection without loss of international competitiveness. *Journal of Public Economic Theory*, 19(5):921–936.

Li, K., Yang, J., and Wei, Y. (2023). Impacts of carbon markets and subsidies on carbon capture and storage retrofitting of existing coal-fired units in china. *Journal of Environmental Management*, 326:116824.

Ng, K. S., Zhang, N., and Sadhukhan, J. (2013). Techno-economic analysis of polygeneration systems with carbon capture and storage and co2 reuse. *Chemical Engineering Journal*, 219:96–108.

Owebor, K., Diemuodeke, E. O., and Briggs, T. A. (2022). Thermo-economic and environmental analysis of integrated power plant with carbon capture and storage technology. *Energy*, 240:122748.

Presty, R., Massol, O., Jagu, E., and da Costa, P. (2024). Mapping the landscape of carbon dioxide removal research: a bibliometric analysis. *Environmental Research Letters*, 19(10):103004.

Requate, T. (2005). Environmental policy under imperfect competition: A survey. *Environmental and Resource Economics*, 32(1):219–239.

Smith, E., Morris, J., Kheshgi, H., Teletzke, G., Herzog, H., and Paltsev, S. (2021). The cost of co2 transport and storage in global integrated assessment modeling. *International Journal of Greenhouse Gas Control*, 109:103367.

Sukor, N. R., Shamsuddin, A. H., Mahlia, T. M. I., and Mat Isa, M. F. (2020). Techno-economic analysis of co2 capture technologies in offshore natural gas field: implications to carbon capture and storage in malaysia. *Processes*, 8(3):350.

US Congressional Budget Office (2023). Carbon capture and storage in the united states. Retrieved from https://www.cbo.gov/publication/59832#:~:text=As%20of%20September%202023%2C%2015,remaining%20oil%20to%20the%20surface.

US EIA (2019). Investor-owned utilities served 72% of u.s. electricity customers in 2017. Energy Information Administration. Accessed: 2025-02-13.

US EIA (2020). How much of u.s. carbon dioxide emissions are associated with electricity generation?

US EIA (2024a). Electric sales, revenue, and average price with data for 2023. Energy Information Administration. Accessed: 2025-02-13.

US EIA (2024b). How much does it cost to generate electricity with different types of power plants? Retrieved from https://www.eia.gov/tools/faqs/faq.php?id=19&t=3.

US EPA (2024). The social cost of carbon. US Environmental Protection Agency. Retrieved from https://www.epa.gov/environmental-economics/scghg.

Van der Spek, M., Fout, T., Garcia, M., Kuncheekanna, V. N., Matuszewski, M., McCoy, S., and Rubin, E. S. (2020). Uncertainty analysis in the techno-economic assessment of co2 capture and storage technologies. critical review and guidelines for use. *International Journal of Greenhouse Gas Control*, 100:103113.

Waxman, A., Huber-Rodriguez, H. R., and Olmstead, S. M. (2023). What are the likely air pollution impacts of carbon capture and storage? Available at SSRN.

Waxman, A. R., Corcoran, S., Robison, A., Leibowicz, B. D., and Olmstead, S. (2021). Leveraging scale economies and policy incentives: Carbon capture, utilization & storage in gulf clusters. *Energy Policy*, 156:112452.

Yang, L., Xu, M., Fan, J., Liang, X., Zhang, X., Lv, H., and Wang, D. (2021). Financing coal-fired power plant to demonstrate ccs (carbon capture and storage) through an innovative policy incentive in china. *Energy Policy*, 158:112562.

Yang, L., Xu, M., Yang, Y., Fan, J., and Zhang, X. (2019). Comparison of subsidy schemes for carbon capture utilization and storage (ccus) investment based on real option approach: Evidence from china. *Applied Energy*, 255:113828.

Ye, B., Jiang, J., Zhou, Y., Liu, J., and Wang, K. (2019). Technical and economic analysis of amine-based carbon capture and sequestration at coal-fired power plants. *Journal of Cleaner Production*, 222:476–487.

A Appendix

A1 Second and First Stage Solutions

Profit maximization: Solving the first order profit maximization conditions for each firm, we get the following equations which represent the firm's best response to policy:

$$x^{**} = \frac{\alpha - c - \tau\sigma + k^{**}\sigma(s + \tau - d)}{\beta(n+1)} \tag{A1}$$

$$k^{**} = \frac{(s + \tau - d)\sigma x^{**}}{\theta} \tag{A2}$$

These conditions suggest that as production level increases (e.g., caused by some external shock), the percent of carbon captured also increases. This indicates that the firm views production and carbon capture as strategic substitutes, increasing the percent of carbon captured when production volumes increase. The solutions also suggest that higher slope of the marginal carbon capture cost leads to lower percent of carbon captured while higher rates of both policies encourage abatement via carbon capture, for a given output level.

Consumer surplus: The consumer surplus (CS) is derived from the linear inverse demand function: $p = \alpha - \beta n x$, where n is the number of symmetric firms in the market, and x is the output produced by each firm. The total market quantity is therefore $Q = nx$. Consumer surplus is defined as the area under the demand curve and above the market price, up to the total quantity consumed.

$$CS = \frac{1}{2}Q(\alpha - p) = \frac{1}{2}\beta Q^2 = \frac{1}{2}\beta n^2 x^2. \tag{A3}$$

This formula represents the net benefit accruing to consumers from purchasing the good at price p, corresponding to the triangular area between the demand curve and the price line under linear demand with symmetric firms.

Welfare maximization: Further simplification of the welfare function gives the following expressions:

$$n^{-1}W = \frac{\beta x^{**2}(n+2)}{2} + (\tau - \gamma)\sigma x^{**} + \frac{\sigma^2 x^{**2}(s+\tau-d)(2\gamma - 3s - 3\tau + d)}{2\theta} \qquad \text{(A4)}$$

The first order conditions (drop the ** for simplicity):

$$n^{-1}\frac{\partial W}{\partial \tau} = x\beta(n+2)x_t + \sigma x + (\tau-\gamma)\sigma x_t + \frac{\sigma^2 x^2(\gamma - 3s - 3\tau + 2d)}{\theta} + \frac{\sigma^2 x x_t(s+\tau-d)(2\gamma - 3s - 3\tau + d)}{\theta} = 0($$

$$n^{-1}\frac{\partial W}{\partial s} = x\beta(n+2)x_s + (\tau-\gamma)\sigma x_s + \frac{\sigma^2 x^2(\gamma - 3s - 3\tau + 2d)}{\theta} + \frac{\sigma^2 x x_s(s+\tau-d)(2\gamma - 3s - 3\tau + d)}{\theta} = 0($$

Impact of k^* on gross emissions: A key concern raised in the literature is the possibility of perverse incentive effects stemming from large-scale CCS adoption and generous subsidies—namely, that such policies may unintentionally encourage greater carbon emissions (Furlanetto et al., 2024). Our analytical model provides a framework to examine this issue. Specifically, we derive the optimal gross emission level defined as $E = (1-k^*)n\sigma x^*$ by using Equations (17) and (18). Rearranging these expressions, we analyze E as a function of the optimal carbon capture rate k^*. The results indicate that when $k^* < 0.5$, an increase in the capture rate is associated with higher gross emissions, signaling a perverse incentive: more carbon capture at low levels of capture may lead to greater overall emissions. In contrast, when $k^* > 0.5$, higher levels of carbon capture reduce gross emissions, reflecting effective environmental policy design.

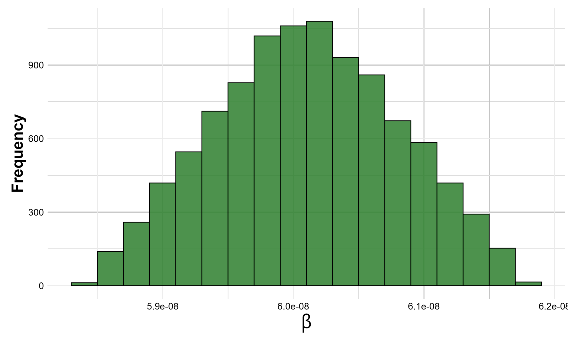
This non-monotonic relationship between k^* and E highlights a critical implication: CCS subsidies must be carefully structured to ensure that they incentivize sufficiently high capture rates. Otherwise, they risk undermining their environmental objective by enabling increased emissions under low capture efficiency. However, this creates a policy trade-off: achieving high capture rates often requires significantly greater financial support. Designing subsidies that are both environmentally effective and fiscally sustainable remains a key challenge for future CCS policy frameworks.

A2 Distribution of Input Parameters

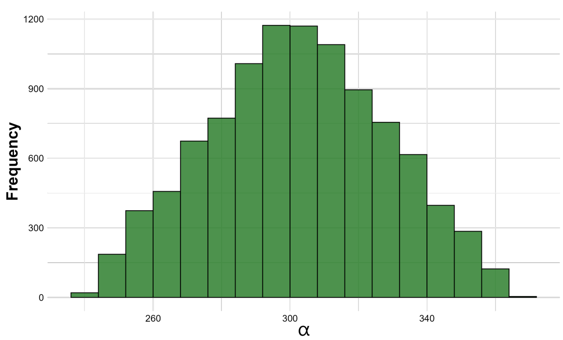
All input parameters are drawn from the triangular distribution. Figure A5 presents histograms for demand parameters α, β, n and the parameter used to measure disutility from carbon emissions

(γ). Figure A6 presents histograms for the three cost parameters (c, d, θ) as well as the carbon intensity of energy production, σ.

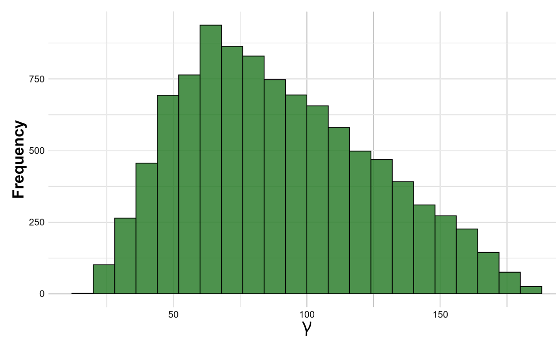
Figure A5: Demand parameters



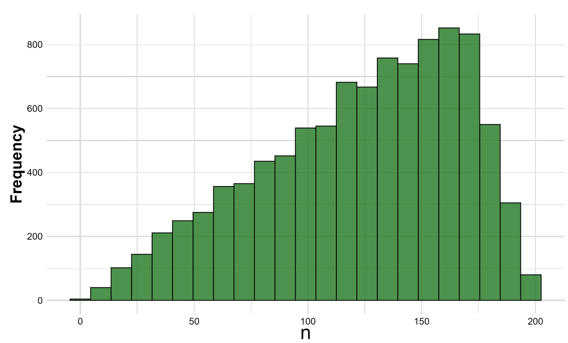
(a) Slope of demand is β



(b) Market size (α)

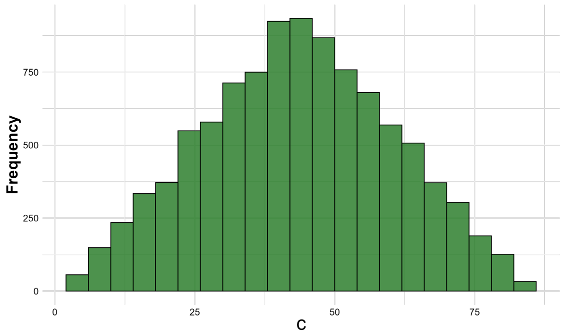


(c) Disutility from carbon emissions (γ)

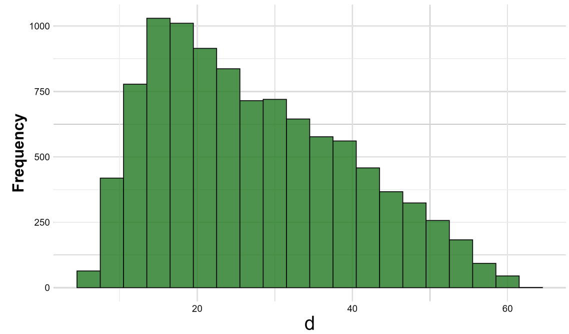


(d) Number of firms (n)

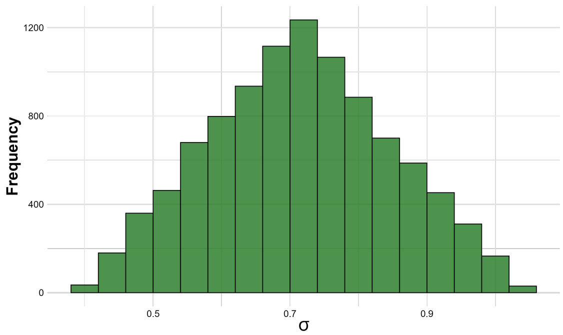
Figure A6: Cost parameters



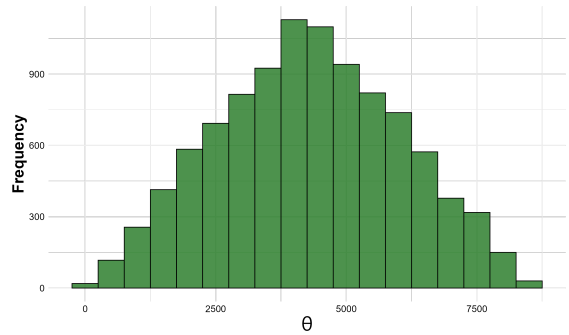
(a) Production cost (c)



(b) Cost of carbon transport and storage (d)



(c) Carbon intensity of production (σ)



(d) Slope of marginal cost of capture (θ)