Theory and Analysis of Taxation and Regulation Design in Energy Markets

by

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ABSTRACT

Energy markets are central for sustaining modern day productive activities. They are also essential contributors to climate change due to their generalized reliance on fossil fuels. How does power demand uncertainty matter for welfare of different approaches to market-based regulation of emissions? Do institutional design features of energy markets matter for cost-effectiveness of subsidies to wind investments? Should the government subsidize production or investment goods in order to incentivize wind investments at the least welfare cost? I address these questions by using plant-level survey data and high frequency variation in power consumption to estimate a dynamic model of industry equilibrium in the context of the U.S. electricity sector. I show that the choice between policy instruments depends on how firms and consumers balance unpredictable output volatility (higher with carbon taxes) vs. price volatility (higher with cap-and-trade regulation). Over a wide range of policy-relevant abatement targets, I find carbon taxes outperform cap-and-trade in terms of welfare. I also find that structuring subsidies based on key features of the type of procurement contracts associated to wind projects leads to major reductions in public expenditures in terms of subsidy payments to wind developers without undermining investment incentives. Last, I find that subsidizing production can increase average yearly investment rates in wind capacity up to 2.5 percentage points over mean investment rates under alternative subsidies to capital.

DEDICATION

To God, my family, Diana, academic mentors, and friends who made it possible for me to have the privilege of achieving this milestone.

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PREFACE

The welfare consequences of price versus quantity-based regulation are known to differ when information about marginal benefits or costs of abatement is imperfect. Does uncertainty about demand for the polluting good also matter for welfare of these two approaches to regulation? In chapter 1, I use plant-level survey data and high frequency variation in power consumption to assess the dynamic implications of uncertainty about future demand for the relative welfare consequences of carbon taxes and cap-and-trade regulation. I address this question in the context of the electricity sector where demand risk is particularly salient. I show that the choice between policy instruments depends on how firms and consumers balance unpredictable output volatility (higher with carbon taxes) vs. price volatility (higher with cap-and-trade regulation). Over a wide range of policy-relevant abatement targets, I find carbon taxes outperform cap-and-trade in terms of welfare.

Financial incentives like the Production Tax Credit are central initiatives behind wind power as the leading renewable energy source in the U.S. But do institutional design features of energy markets matter for cost-effectiveness of subsidies to wind investments? In chapter 2, I answer this question by investigating how the design of procurement contracts that are typically used by wind developers affects their investment incentives. Using unit-level data from wind farm production and installed capacity, I find that structuring subsidies based on key features of the type of procurement contracts associated to wind projects leads to major reductions in public expenditures in terms of subsidy payments to wind developers without undermining their investment incentives.

The U.S. federal government is known to have a history of heavily subsidizing the wind power industry. Subsidies either to output (Production Tax Credit) or investment goods (Investment Tax Credit) have been critical to replace emissions-intensive technologies with wind power. Which type of subsidy is best to incentivize wind investments at the least cost? In chapter 3, I use plant-level data of wind facilities from the Texas electricity market to develop and estimate a model of investment decisions that accounts for productivity shocks at the wind farm level and prudent behavior of developers. I find that subsidizing production can increase average yearly investment rates in wind capacity up to 2.5 percentage points over mean investment rates under alternative subsidies to capital. This is driven by precautionary savings that developers accumulate to smooth out potential future shocks to investment income when adverse weather conditions lead to low subsidy payments.

Chapter 1

CAP-AND-TRADE VS. CARBON TAXES: INDUSTRY DYNAMICS AND THE ROLE OF DEMAND RISK

1.1 Introduction

The U.S. has traditionally relied on permit systems as the market-based policy of choice for mitigating emissions[1]. However, there is ongoing debate about the welfare advantages of quantity versus price-based regulation dating back to seminal work from Weitzman (1974). Literature has focused on understanding how information gaps and genuine uncertainty about marginal benefits and marginal costs of abatement matter for the choice of the policy instrument(e.g. Aldy and Armitage (2022) Pizer and Prest (2020), Laffont (1977), Yohe (1978)). Still, the role of uncertainty about demand for the polluting good in regulation design remains an unstudied question. This paper brings a new dimension to the debate by analyzing how risk from shocks to demand matter for the choice of the regulation mode. I show that, with cap-and-trade, demand uncertainty creates permit price volatility which affects welfare because it distorts production decisions by exposing the firm to uncertain permit prices. Therefore, the welfare-maximizing control mode depends on how firms and consumers balance output volatility vs. price volatility of the polluting good.

[1] California runs a joint permit program with Quebec that regulates emissions from electric generators and stationary sources (e.g. refineries, cement production facilities, oil and natural gas drilling entities, glass manufacturing firms, and food-processing plants). Alternatively, the Regional Greenhouse Gas Initiative (RGGI) in the Northeast section of the U.S. exclusively regulates carbon emissions from power generators with nameplate capacity above 25MW.

Demand risk is particularly salient in the electricity sector because demand is closely tied to unpredictable weather conditions (Bushnell and Novan (2021), Borenstein et al. (2019), and Schaeffer et al. (2012)). This dependence maps exogenous weather uncertainty into demand for AC and heating services. Additionally, it also makes net consumption from entities with access to distributed generation (e.g. rooftop solar and wind turbines) more dependant on uncertain weather shocks. A feature of the electricity sector that reinforces demand risk is the fact that these markets clear on extremely high frequency basis when feasible options for large-scale battery storage are especially limited. With access to large-scale battery storage, firms would be able to carry over production surpluses for consumption during periods of high demand shocks. The lack of large scale storage capabilities implies that supply must commit to accommodate all unpredictable variation in demand. Given that electricity is the second largest industry in terms of U.S. carbon emissions (approximately 25% as of 2019), understanding the role of demand risk for the choice of the policy instrument should be at the heart of emissions regulation design.

To understand how demand uncertainty matters for relative welfare consequences between price and quantity-based regulation, I develop a dynamic equilibrium model of the electricity sector with aggregate shocks to power demand. The economy is inhabited by heterogeneous electricity producers. Firms own multiple power plants which differ based on fuel type (e.g. coal, natural gas, nuclear, etc), costs, and capacity limits. Capacity limits act as upper bounds for production and are central to model the mix of fuel inputs that firms use to meet demand. The composition of the fuel mix matters for aggregate emissions because the emissions intensity of electricity production depends on how fuel inputs are mixed in the production process[2]. Additionally, firms incur in cycling costs at the power plant level which constitute adjustment costs in production. These result from the additional mechanical effort that is exerted by generators to modify the rate of production. This additional mechanical effort is costly because it consumes in the process electricity or fuel inputs. Accounting for unit-level cycling costs is important because it makes production decisions inherently dynamic. Furthermore, I model electricity as a non-storable good. As previously discussed, this is important because it precludes firms from carrying over production surpluses that would otherwise smooth out adjustments in production (which are costly due to cycling costs) in response to demand shocks.

I use this framework to separately analyze dynamic equilibrium effects of counterfactual carbon taxes and cap-and-trade. My approach to modeling permit systems accounts for several features of how cap-and-trade regulation operates. First, the government sets an emissions cap to the aggregate level of emissions within a compliance cycle. It then auctions permits to firms in the first period of the compliance cycle, but allows firms to trade their initial endowments of permits on a period-by-period basis as they learn the realized history of demand shocks. Second, firms trade permits as financial assets that have value to them because they can be used either to: i) avoid abatement costs when such costs are high relative to permit prices, and ii) minimize expected present value of emissions costs to the firm through banking and borrowing of allowances. Third, I model permit trading under uncertain allowance prices due to demand risk in the electricity sector. Firms are forward-looking and have rational expectations of permit prices in equilibrium. Hence, my model allows me to keep

[2]e.g. coal generates on average 1 ton of emissions per MWh while natural gas just .44 tons per MWh

track of how demand shocks in the electricity market drive permit price dynamics and subsequent supply adjustments in response to changes in permit prices.

The model captures the key tension between carbon taxes and cap-and-trade. On one hand, output prices in equilibrium are more volatile with cap-and-trade regulation. A positive demand shock increases electricity prices which incentivizes firms to increase the usage of emissions-intensive power plants. However, the unexpected rise in emissions increases permit prices which reinforces the initial increase in electricity prices. This unpredictable volatility in electricity prices induces costly production adjustments in generation *at the unit level* due to the existence of cycling costs. In contrast, with a carbon tax the emissions price is fixed. Therefore, a carbon tax leads to lower electricity price volatility which is beneficial to firms.

On the other hand, unpredictable volatility in *aggregate* output is lower with cap-and-trade. This is because a positive demand shock increases permit prices which increase the marginal cost of using fossil fuel plants. The unexpected increase in demand is partially offset with a contraction in supply. Differences in aggregate output volatility matter to firms and consumers because fuel mixes in equilibrium differ across control modes. First, larger output volatility that comes with carbon taxes translates into more usage of high marginal cost plants. Second, different fuel mixes translate into differences in emissions and climate benefits. Determination of the right policy instrument becomes a quantitative question and depends on how firms and consumers balance *aggregate output volatility* vs. *output price volatility* after accounting for equilibrium effects. This generalizes results from traditional Weitzman-style frameworks where the choice of the policy instrument depends exclusively on the relative slopes of marginal costs and marginal benefits of abatement.

I estimate the model to compare welfare effects of permit systems and carbon taxes for the case of ERCOT[3]. I design a Simulated Method of Moments strategy to estimate structural parameters which relies on three data sources. For supply side parameters, I use data on the universe of ERCOT firms (271 firms) from the EIA-860 and EIA-930 surveys which provide granular unit-level data on plant ownership, generation, fuel type and input consumption, fuel costs, and capacity limits. To identify unit-level cost parameters, I exploit time variation in generation data at the power plant level across all plants owned by the same firm along with variation in engineering estimates of cycling costs across fuel types. My estimation results show that, on average, natural gas plants are costlier to operate at the margin than coal-fired plants (these are the two main fossil fuel energy sources). However, dispersion around the mean is larger in marginal costs of natural gas units relative to coal-fired plants. For demand side parameters, I exploit time variation in hourly electricity consumption from load time series to identify key parameters that regulate average hourly consumption and demand shock size.

I use the estimated model to design a policy experiment that allows me to quantify the difference in welfare between price and quantity-based regulation. In the policy experiment, I simulate the history of power demand shocks for an entire year in hourly time blocks. This is to account for the high frequency nature of equilibrium realization in electricity markets. Then, I separately solve the model under both regulatory regimes to examine how welfare effects quantitatively differ. In my framework, the welfare measure encapsulates four key components: aggregate firms' profits, consumer surplus,

[3]ERCOT (Electric Reliability Council of Texas) is the Regional Transmission Organization supplying ∼90% of Texas electricity demand and second largest U.S. market in generating capacity per consumer.

climate benefits, and policy revenues. The simulation procedure allows addressing a wide variety of interesting counterfactual scenarios that include a quantitative assessment of the key primitives of the model driving welfare differences between control modes.

I find that for a wide range of abatement targets consistent with policy goals from active U.S. permit systems, carbon taxes outperform cap-and-trade in terms of welfare. Conditional on the emissions target, the difference in welfare oscillates between 9% and 16% of business-as-usual industry profits. This finding underscores the importance of rethinking the leading role that has been assigned to permit systems over carbon taxes in key U.S. energy markets. I also show that the distribution of plant-level costs across units of different energy types is the key primitive determining the welfare-maximizing policy instrument. In particular, I show that this result can be reverted with a sufficiently large increase in natural gas prices (i.e. a rightward shift in the distribution of marginal costs of natural gas plants). Last, I discuss how the qualitative prediction of the policy experiment is robust to other extensions of the model including market power and endogenous investments in capacity.

This paper contributes to three different strands of economic literature. First, it is tightly connected to research on price versus quantity based regulation. Previous efforts focus on the role of: i) information asymmetries between regulators and firms (e.g. Laffont (1977) and Weitzman (1974)), ii) aggregate uncertainty about marginal costs and marginal benefits of abatement or firm-level productivity (e.g. Stranlund and Ben-Haim (2008) and Kelly (2005)), and iii) uncertainty from updating policy or hybrid regulation design on the choice of policy instruments (e.g. Weitzman

(2020) and Fell et al. (2012))[4]. Two recent developments that address sources of aggregate uncertainty have been studies from Aldy and Armitage (2022) and Pizer and Prest (2020). Aldy and Armitage (2022) consider uncertainty in permit prices due to abatement cost shocks that undermines efficiency of cap-and-trade regulation because firms err on their forecasts of permit prices and fail to achieve cost-effective abatement. Alternatively, Pizer and Prest (2020) account for uncertainty arising from unpredictable policy updating as firms and government learn the true marginal benefits and costs of abatement. They show that the welfare advantage depends on how firms formulate expectations of policy updates instead of relative slopes between marginal costs and benefits of abatement. However, none of these papers addresses the key role of uncertainty in output demand.

A distinctive feature of my paper is to consider an environment where a private good (i.e. electricity) is bundled together with a public good (i.e. abatement) so that the source of uncertainty is about future market demand of the private good. Therefore, demand uncertainty in the market of the private good matters for the choice of the policy instrument because it translates into permit price uncertainty under cap-and-trade regulation given that future cumulative emissions are unknown. Under price-based regulation, demand risk in the market of the private good is irrelevant for the emissions price given that the carbon tax is exogenously fixed by the government and publicly announced. Kelly (2005) considered a similar equilibrium setting with productivity shocks in the output market. However, unlike Kelly (2005), in my

[4]See Heutel (2020), Weitzman (2020), Karp (2019), Mideksa and Weitzman (2019), Requate et al. (2019), Weitzman (2017), Kollenberg and Taschini (2016), Boleslavsky and Kelly (2014), Fell et al. (2012), Montero (2008), Karp and Zhang (2005), Kelly (2005), Newell et al. (2005), Moledina et al. (2003), Newell and Pizer (2003), Kaplow and Shavell (2002), Montero (2002), Pizer (2002), Williams (2002), Yates (2002), Hoel and Karp (2001), Yates and Cronshaw (2001), Yohe (1978), Laffont (1977), Weitzman (1974).

model unpredictable volatility in cap-and-trade permit prices matters for welfare differences across control modes because it is costly to firms due to the existence of adjustment costs in production (i.e. cycling costs). This also means that genuine demand randomness is relevant for the choice of policy instruments even when firms have the same expectation about such randomness – something that is impossible in Weitzman (1974) and Laffont (1977). My simulation results provide first estimates of welfare differences between price and quantity-based regulation of emissions from electricity markets.

Additionally, I contribute to research on permit trading in cap-and-trade markets that: i) examines the role of market design features on price dynamics (e.g. Burtraw et al. (2022), Dardati (2016), Wood and Jotzo (2011), Murray et al. (2009), Ellerman and Buchner (2008), Jacoby and Ellerman (2004)), ii) analyzes the implications of uncertainty in emissions and permit prices (e.g. Borenstein et al. (2019) and Cantillon and Slechten (2018)), and iii) empirically assesses the welfare and distributional consequences of cap-and-trade regulation (e.g. Fowlie et al. (2016), Fowlie (2010), and Carlson et al. (2000)). The closest article to my paper in this section of economic literature is that of Toyama (2019) where he develops an equilibrium model of dynamic trading with banking and transaction costs for regulating electric utilities. Although I do not account for transaction costs, I differentiate from Toyama (2019) by incorporating aggregate uncertainty and equilibrium dynamics in both permit and electricity markets. More generally, I depart from previously cited work by developing and estimating an asset pricing model for carbon allowances that allows an integrated assessment of welfare effects from cap-and-trade by accounting for: i) dynamic equilibrium interactions between the electricity and allowance markets, ii) uncertainty in permit prices, iii) rational expectations from forward-looking firms, and iv) banking/borrowing of allowances *within* compliance cycles.

Last, I advance literature on the effects of regulation on energy markets, particularly for wholesale electricity. Previous work has examined the role of regulation on competition (e.g. Cicala (2022)), investment on clean energy technology (e.g. Bushnell et al. (2008)), distributional effects of environmental policy and welfare (e.g. Linn and McCormack (2019), Cicala (2015), Holland and Mansur (2008), Mansur (2008), and Carlson et al. (2000)). Previous empirical work from Cullen and Mansur (2017), Fabra and Reguant (2014), and Fowlie (2010) specifically examines effects of market-based regulation of emissions. However, these papers do not explore the role of demand uncertainty on the choice of the policy instrument. A distinctive feature of my paper is that it investigates how the interaction between demand uncertainty with key supply-side frictions as output non-storability, capacity limits, and dynamic cycling costs matters for welfare consequences of emissions regulation.

I structure the paper as follows. Section 1.2 describes from a conceptual perspective the key mechanism. I lay down the analytical model in Section 1.3. Section 1.4 describes the policy experiment and estimation strategy. I analyze results in Section 1.5. Section 1.6 extends the main analysis from this paper along other dimensions that have been previously studied in literature. Finally, I draw concluding remarks in Section 1.7.

1.2 The Role of Demand Risk

1.2.1 A Simple Two-period Model

I discuss a stylized two-period model that elaborates on the role of demand uncertainty. With demand risk, output price volatility is lower with carbon taxes, but aggregate output volatility is lower with cap-and-trade regulation. The choice of the policy instrument depends on how firms and consumers balance *aggregate output volatility* vs. *output price volatility.*

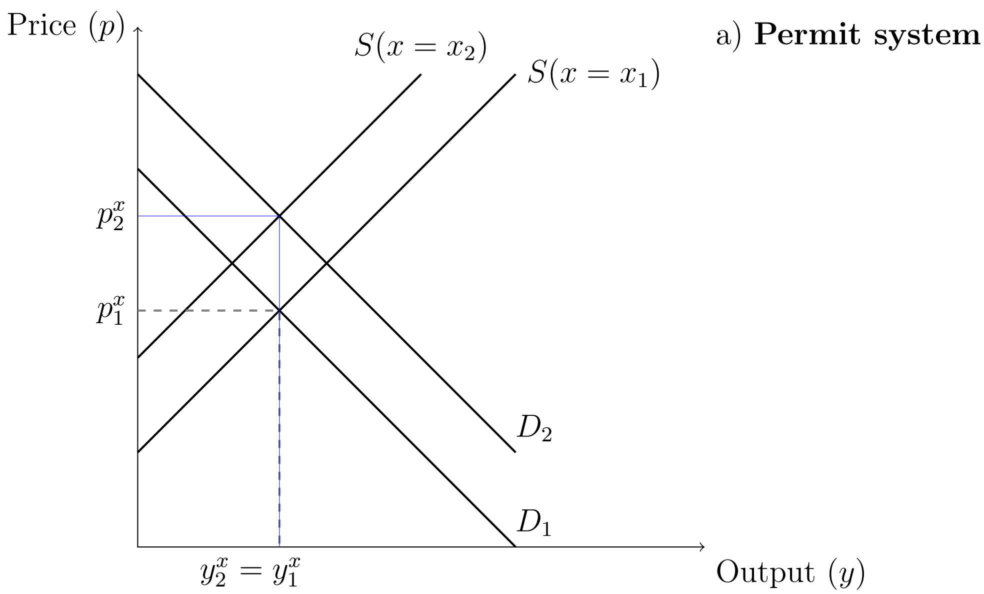
Consider good y with upward sloping supply curve S. Associated to good y is a negative externality in the form of emissions that arise as a byproduct of production. Producers sell each unit of y at a price p to consumers with downward-sloping market demand. Consider two periods in this setup and suppose that demand unexpectedly increases from D_1 in period 1 to D_2 in period 2.

Panel a) in Figure 1 shows equilibrium effects in the output market with quantity-based regulation of emissions. The government caps the level of emissions at $\bar{M}$ and requires firms to purchase a permit at the unit price of x for each unit of emissions generated. Firms are legally bounded to fully cover their total emissions by the end of period 2. Therefore, the supply curve in period 1 is $S(x = x_1)$ to account for the fact that firms purchase allowances at a price of x_1 to cover a portion of their current emissions. Equilibrium output and price levels are denoted by y_1^x and p_1^x, respectively. Since demand unexpectedly increases in period 2, permit prices must increase from x_1 to x_2 for the permit market to clear given that the emissions cap is fixed at $\bar{M}$ and firms are generating more emissions to meet higher output demand.

The increase in permit prices shifts supply upwards to $S(x = x_2)$ because firms need to buy allowances at price x_2 to have all emissions covered by the end of period 2. Therefore, the adjustment on permit prices cancels out the effect of the unexpected increase in demand on output [5]. Production in period 2, denoted by y_2^x, is equal to output in period 1 and the increase in permit prices reinforces the effect of the demand shock on the output price which increases to p_2^x.

To understand how output allocations are systematically different between regulatory regimes, panel b) shows the equilibrium effects of the same demand shock with price-based regulation. With an emissions tax, the government exogenously sets a per unit price of emissions that must be payed by firms. To enable a consistent comparison between control modes, suppose the government levies a tax $\tau = \mathbb{E}(x)$ so that the comparison takes place between regulation modes that are 'price-equivalent' in expectation. This means that $x_1 < \tau = \mathbb{E}(x) < x_2$. The supply curve is $S(\tau = \mathbb{E}(x))$ with output in period 1 denoted by y_1^τ. Moreover, since $\tau > x_1$, then output allocations and prices across control modes differ because $y_1^\tau < y_1^x$ and $p_1^\tau > p_1^x$. In period 2, demand unexpectedly rises to D_2 so output and price increase to y_2^τ and p_2^τ, respectively. In this case, supply does not adjust in response to the demand shock because the emissions price τ is exogenous. This implies that output allocations and prices between regulatory regimes also differ in period 2 because $y_2^\tau > y_2^x$ and $p_2^\tau < p_2^x$.

[5] The increase in permit prices need not fully offset the increase on output of unexpectedly higher demand.



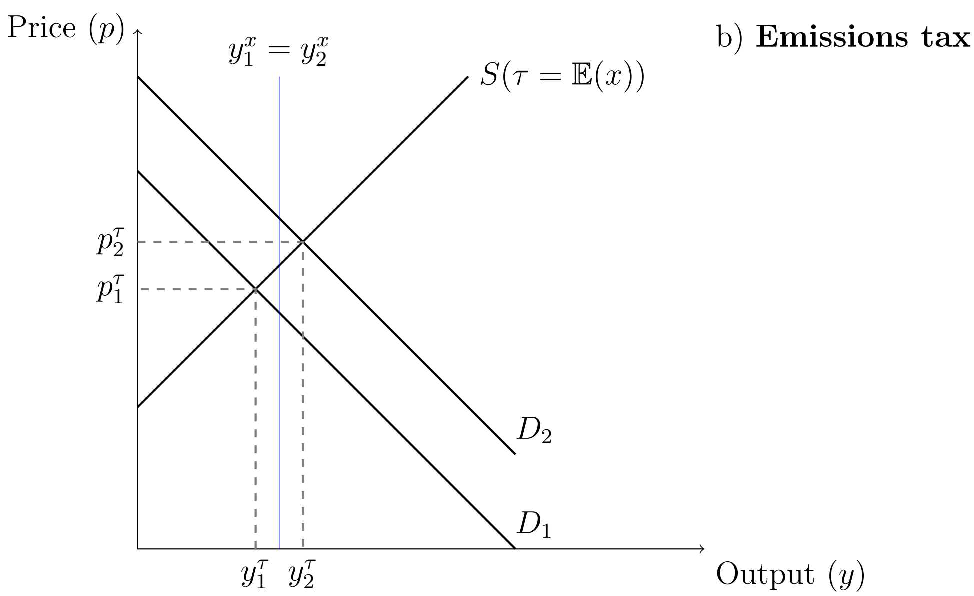


Figure 1. Different output allocations and prices across control modes

Note: D_1 and D_2 represent demand in periods 1 and 2, respectively. Lines $S(x = x_1)$ and $S(x = x_2)$ correspond to supply when the price of permits is x_1 in period 1 and x_2 in period 2, respectively. Line $S(\tau = \mathbb{E}(x))$ represents supply under a hypothetical carbon tax $\tau = \mathbb{E}(x)$ equal to the expected price of permits. The changes in prices and quantities correspond to the equilibrium effects of an unexpected increase in demand from D_1 and D_2.

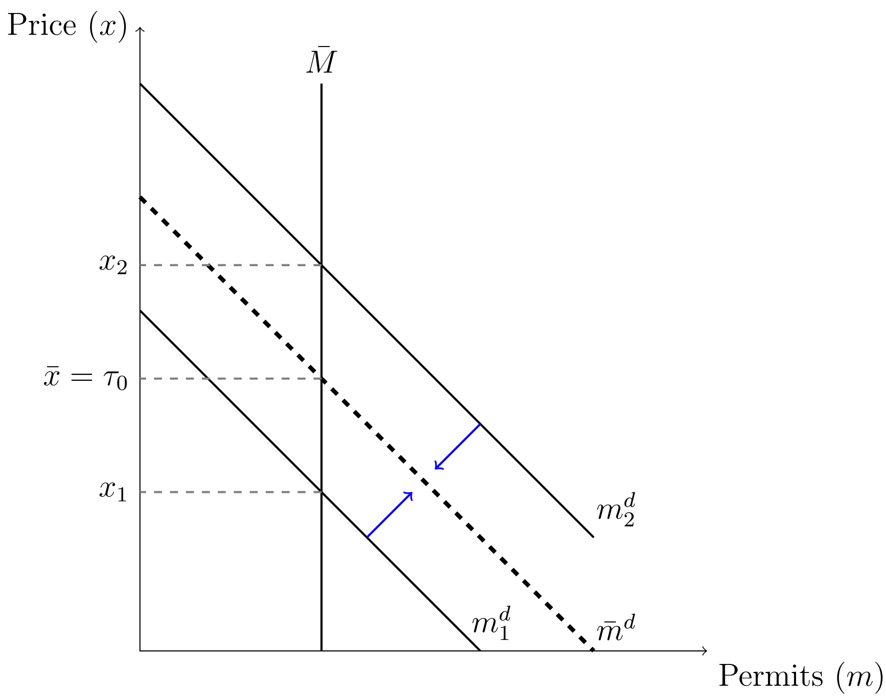


Figure 2. Permit prices are constant in the absence of demand risk

Note: m_1^d and m_2^d represent permit demand in periods 1 and 2 at prices x_1 and x_2, respectively. Line $\bar{m}^d$ corresponds to demand in both periods after arbitrage has eliminated price differences in time. Line $\bar{M}$ represents the fixed supply of permits. A carbon tax τ_0 is equivalent to a permit system with allowance prices constant at $\bar{x}$.

I show in Figure 2 what would happen if consumers and firms had perfect foresight – i.e. no demand risk – and intertemporal trade of allowances is possible. The x-axis measures the stock of permits m available on a period-by-period basis. Demand for allowances in period 1 and 2 is represented by m_1^d and m_2^d, respectively. Supply of allowances is perfectly inelastic at $\bar{M}$ to capture the fact that permits exist in a fixed amount. Moreover, demand for permits in period 2 is higher to rationalize the fact that the price of permits increases in period 2 from x_1 to x_2 due to the positive demand shock in the output sector.

With perfect foresight, such situation cannot be sustained as an equilibrium outcome. This is because firms would realize there are arbitrage opportunities in the permit market: they can make profits at zero risk by purchasing permits in period 1 and selling them in period 2 at a higher price. This increases permit demand in period 1 and decrease it in period 2 until the price of allowances is constant at $\bar{x}$ throughout both periods. An alternative price-equivalent emissions tax would set the Pigouvian tax τ_0 equal to $\bar{x}$ so output allocations and prices are invariant with respect to the regulatory regime. This means that policy instruments are equivalent and the welfare would is zero without demand risk.

The previous exercise explains why with demand risk, output price volatility is lower with carbon taxes, but aggregate output volatility is lower with cap-and-trade regulation. The difference in welfare effects across control modes will depend on how firms and consumers balance *aggregate output volatility* vs. *output price volatility* in equilibrium. My model in Section 1.3 formalizes the policy trade-off. This contrasts with Weitzman (1974) and subsequent literature where the welfare meximizing regulation mode depends on relative slopes of marginal costs and benefits of abatement. This is because in my framework, uncertainty is about future demand of the private good (electricity) with which the public good (abatement) is bundled with rather than uncertainty or information deficits about the marginal value and marginal costs of abatement.

1.3 Model

Consider a model with S heterogeneous firms. Each energy provider $s \in \{1, ..., S\}$ has access to n_s power plants. Moreover, each unit $i \in \{1, ..., n_s\}$ produces with a different energy type, so plant-wise marginal costs within firms are heterogeneous across units. Time is discrete and indexed by $t \in \{1, ..., T\}$. The electricity market is competitive which means that power producers take electricity prices as given when making production decisions[6].

Firm s earns profits at the power plant level from producing electricity and consequently selling it in the wholesale market. Specifically, it receives a price p_t per unit of output y_{its} that is produced and sold with unit i in period t. Moreover, power producer s incurs in a cost of c_{is} per unit of output produced with energy type i.

I model three key supply-side frictions that are important technological features of firms in electricity markets. First, plant-level cycling costs are adjustment costs in production that result from the additional mechanical effort exerted on a turbine to change how much power it generates. This process consumes additional fuel or electricity to change the operating rate of rotors within the turbines. Also, cycling dynamics cause additional tear and wear of equipment which translates into higher maintenance costs at the unit level. I incorporate quadratic cycling costs at the plant level by modeling operating profits of firm s at period t from unit i as follows,

$$p_t y_{its} - c_{is} y_{its} - \alpha_{is} (y_{its} - y_{i,t-1,s})^2, \ \alpha_{is} > 0.$$

Dynamic cycling costs allow interior solutions at the unit level by introducing convexity in production costs. Otherwise, plant-level generation decisions would be band-bang solutions. If $p_t > c_{is}$, the power plant produces at full capacity. Else,

[6]See Section 1.6 for a discussion about the implications of allowing oligopolistic competition in this environment

it shuts down. Second, capacity limits are upper bounds to production at the unit level. These hard limits y_{is}^{max} result from the physical properties of generators (e.g. maximum rate of rotor rotation, length of blades, energy type, etc.) and act as a constraint on technological feasibility, i.e.

$$0 \leq y_{its} \leq y_{is}^{max}, \ \forall i = 1, ..., n_s, \ t = 1, ..., T, \ s = 1, ..., S.$$

Capacity limits determine what capacity is available in the grid per energy type. This affects the energy mix used to meet electricity demand. The resulting energy mix is important for determining the total level of emissions because different energy types have different levels of carbon-intensity (e.g. generation with coal produces more emissions per MWh than with natural gas). Last, to model output non-storability, I require that the market clears on each period so that all output is consumed. Hence, supply continuously accommodates demand and electricity prices adjust accordingly so that the system is always balanced[7].

To model demand risk, I specify a constant price-elasticity market demand[8],

$$\ln(D_t) = \ln(z_t) - \beta \ln(p_t), \ \forall t = 1, ..., T \tag{1.1}$$

where D_t represents demanded quantity at t and β is the absolute value of price-elasticity. Realizations of z_t capture exogenous period-by-period shocks to demand

[7]This will be explicitly specified in the definition of equilibrium.

[8]This structural specification is consistent with empirical literature on electricity demand estimation. For instance, see Ito (2014).

and are drawn from a finite state space Z. I assume realizations of the demand shock follow a Markov process $\pi(z_t|z_{t-1})$ of degree 1. This feature introduces persistence in the endogenous stochastic dynamics of prices and quantities along the equilibrium time path.

In a business-as-usual (BAU) environment with no carbon policy intervention, firm s makes production decisions to maximize the expected discounted present value of unit-level profits across all power plants owned by the firm subject to capacity limits. Formally, let δ be the discount factor, z^t denote the history of demand shocks until period t, $Q(z^t)$ the probability of observing history z^t, Z^t the set of histories for the demand shock until t, and n_s the number of energy units available to firm s[9]. Firm s chooses contingent production plans $\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}$ while taking as given electricity prices and the Markov process for the demand shock to solve the following profit-maximization problem[10],

[9]Observe that since Z is finite, then Q is a measure defined over a finite set of outcomes. Additionally, $Q(z^t)$ can be directly calculated for any given history z^t using the Markov process $\pi(z_t|z_{t-1})$.

[10]The decision timeline within periods is as follows. First, period t begins and the demand shock z_t is realized. Secondly, firms observe the realization z_t and proceed to make production decisions from period t. This means that prices from period t are available to firms for making optimal decisions at t. Finally, period t ends and firms enter period $t+1$.

$$
\begin{cases}
\max\limits_{\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}} & \sum\limits_{z^T \in Z^T} Q(z^T) \sum\limits_{t=1}^{T} \delta^{t-1} \sum\limits_{i=1}^{n_s} \Big[p_t(z^t) y_{its}(z^t) - c_{is} y_{its}(z^t) - \alpha_{is}(y_{its}(z^t) \\
& \quad - y_{i,t-1,s}(z^{t-1}))^2 \Big] \\
\text{s.t.} & 0 \leq y_{its}(z^t) \leq y_{is}^{max}, \ \forall i = 1, ..., n_s, \forall t = 1, ..., T, \ \forall z^t \in Z^t \\
& z_0, \{y_{i0s}\}_{i=1}^{n_s} \text{ — given.}
\end{cases}
\tag{1.2}
$$

The model accommodates heterogeneity in production costs and capacity limits across units and firms through problem (1.2). The realization of endogenous variables at t depends on the history of shocks due to the existence of dynamic cycling costs at the unit level. This makes contingent production plans and equilibrium prices dependant on all past history.

Carbon emissions of power producer s are a linear combination of its plant-wise generation levels from period 1 through T,

$$
\sum_{t=1}^{T} \sum_{i=1}^{n_s} \psi_i y_{its}(z^t). \tag{1.3}
$$

Each emissions rate ψ_i regulates how much metric tons of emissions are generated with one unit of output produced at unit of energy type i. For instance, this means that emission rates of wind or solar energy units are 0. Additionally, it also implies that emissions rates for coal-fired and natural gas-fired plants are positive.

1.3.1 Equilibrium

In a competitive equilibrium, production plans $\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}$ across firms $s = 1, ..., S$, electricity consumption $\{D_t(z^t)\}_{t=1}^{T}$, and prices $\{p_t(z^t)\}_{t=1}^{T}$ satisfy the following two conditions for a given set of initial values $z_0, \{y_{i0s}\}_{s,i=1}^{S,n_s}$:

1. Taking prices $\{p_t(z^t)\}_{t=1}^{T}$ and the Markov process $\pi(z_t|z_{t-1})$ for the demand shock as given, each power producer s solves problem (1.2).
2. At each $z^t \in Z^t$, the electricity market clears: $\sum_{s=1}^{S} \sum_{i=1}^{n_s} y_{its}(z^t) = D_t(z^t)$ for all $t = 1, ..., T$.

1.3.2 Carbon Policy

Carbon tax — In a carbon tax regime, each emitter s pays a per unit tax τ per metric ton of carbon emissions. The carbon tax increases plant-wise marginal costs at fossil fuel units consistently with their specific degree of emissions intensity ψ_i. Since there is heterogeneity in costs across fuel types and firms, firms will adjust production levels and energy mixes in response to the emissions tax τ.

Taking prices and the Markov process of demand shocks z_t as given, the competitive firm solves the following profit-maximization problem,

$$
\begin{cases}
\max\limits_{\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}} \quad \sum\limits_{z^T \in Z^T} Q(z^T) \sum\limits_{t=1}^{T} \delta^{t-1} \sum\limits_{i=1}^{n_s} \Big[p_t(z^t) y_{its}(z^t) - (c_{is} + \tau\psi_i) y_{its}(z^t) - \\
\qquad \qquad \alpha_{is} (y_{its}(z^t) - y_{i,t-1,s}(z^{t-1}))^2 \Big] \\
\text{s.t.} \;\; 0 \leq y_{its}(z^t) \leq y_{is}^{max}, \;\forall i = 1, ..., n_s, \forall t = 1, ..., T, \;\forall z^t \in Z^t \\
\quad z_0, \{y_{i0s}\}_{i=1}^{n_s} \text{ — given.}
\end{cases}
\tag{1.4}
$$

Cap-and-trade — With a permit system, I model allowance holdings as an additional decision in the firm's profit maximization problem. The firm must purchase an allowance for each unit of emissions generated. The permit price is an equilibrium object that fluctuates stochastically on a period-by-period basis depending on the history of shocks to power demand. This introduces an additional layer of uncertainty in the firm's decision making problem (relative to a carbon tax regime) because future permit prices are unknown to the power producer. I assume the permit market is competitive.

A regulator exogenously sets the emissions cap M for a full compliance cycle that runs from $t = 1$ through T. Allowances are auctioned off to firms at price x_1 at the beginning of period 1. Subsequently, firms are allowed to trade their allowances in a permit market at any period $t \leq T$[11]. In period T, producers must validate all emissions generated throughout the compliance period by surrendering an amount of permits equal to the volume of emissions produced during the compliance cycle. This means they must hold enough permits by the end of the expiration date T to cover the complete amount of individual emissions generated from $t = 1$ through T.

[11] The share of M which producer s receives at the permit auction is exogenous.

The timing of allowance holdings decisions is as follows. Let m_{ts} denote the stock of permits with which firm s enters period t. The firm observes the realization of z_t and proceeds afterwards to choose the amount of permits $m_{t+1,s}$ for period $t+1$. Any engagement in trade at t is conducted by firms at the competitive price x_t. This implies that net expenses of acquiring allowances by firm s at t is,

$$x_t(z^t)(m_{t+1,s}(z^t) - m_{ts}(z^{t-1})).$$

At any time t, the firm can either be a net buyer or net seller of allowances (or not engage in trade at all). Intertemporal trade through banking and borrowing of allowances is also possible since firms can buy permits at t to resell them in the future or accumulate negative stocks of permits for as long as $t < T$.

The fact that power producers must surrender allowances at the expiration date T means that each firm s faces the following environmental compliance constraint which must hold independently of whatever history of demand shocks is realized,

$$\sum_{t=1}^{T} \sum_{i=1}^{n_s} \psi_i y_{its}(z^t) = m_{Ts}(z^{T-1}), \ \forall z^T \in Z^T. \tag{1.5}$$

Firms make production and allowance holdings decisions to: i) maximize expected present value of unit-level profits across all owned units, and ii) minimize the expected cost of permit transactions. This means that each firm s chooses contingent production plans $\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}$ and allowance holdings decisions $\{m_{t+1,s}(z^t)\}_{t=1}^{T}$ while taking as given prices $\{p_t(z^t), x_t(z^t)\}_{t=1}^{T}$ and the Markov process of the demand shock $\pi(z_t|z_{t-1})$ to solve,

$$
\begin{cases}
\max\limits_{\{y_{its}(z^t), m_{t+1,s}(z^t)\}_{i,t=1}^{n_S,T}} \sum\limits_{z^T \in Z^T} Q(z^T) \sum\limits_{t=1}^{T} \delta^{t-1} \left\{ \sum\limits_{i=1}^{n_s} \Big[p_t(z^t) y_{its}(z^t) - c_{is} y_{its}(z^t) - \right. \\
\left. \alpha_{is} (y_{its}(z^t) - y_{i,t-1,s}(z^{t-1}))^2 \Big] - x_t(z^t) \left(m_{t+1,s}(z^t) - m_{ts}(z^{t-1}) \right) \right\} \\
\\
\text{s.t. } \ 0 \le y_{its}(z^t) \le y_{is}^{max}, \ \forall i = 1, ..., n_s, \forall t = 1, ..., T, \ \forall z^t \in Z^t \\
\qquad \sum\limits_{t=1}^{T} \sum\limits_{i=1}^{n_s} \psi_i y_{its}(z^t) = m_{Ts}(z^{T-1}), \ \forall z^T \in Z^T \\
\qquad z_0, m_{1s}, \{y_{i0s}\}_{i=1}^{n_s} \text{ — given.}
\end{cases}
\tag{1.6}
$$

1.3.3 Equilibrium with Carbon Policy

Carbon tax — In competitive equilibrium, production plans $\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}$ across firms $s = 1, ..., S$, electricity consumption $\{D_t(z^t)\}_{t=1}^{T}$, and prices $\{p_t(z^t)\}_{t=1}^{T}$ satisfy the following two conditions for a given per-unit carbon tax τ and set of initial values z_0 and $\{y_{i0s}\}_{s,i=1}^{S,n_s}$:

1. Taking prices $\{p_t(z^t)\}_{t=1}^{T}$ and the Markov process $\pi(z_t|z_{t-1})$ for the demand shock as given, each power producer s solves problem (1.4).
2. At each $z^t \in Z^t$, the electricity market clears, i.e. $\sum_{s=1}^{S} \sum_{i=1}^{n_s} y_{its}(z^t) = D_t(z^t)$ for all $t = 1, ..., T$.

Cap-and-trade — In competitive equilibrium, production plans $\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}$ and allowance holdings $\{m_{t+1,s}(z^t)\}_{t=1}^{T}$ across firms $s = 1, ..., S$, electricity consumption

$\{D_t(z^t)\}_{t=1}^T$, and prices $\{p_t(z^t), x_t(z^t)\}_{t=1}^T$ satisfy the following two conditions for a given emissions cap M and set of initial values z_0 and $\{m_{1s}, y_{i0s}\}_{s,i=1}^{S,n_s}$:

1. Taking prices $\{p_t(z^t), x_t(z^t)\}_{t=1}^T$ and the Markov process $\pi(z_t|z_{t-1})$ for the demand shock as given, each power producer s solves problem (1.6).
2. Power and allowance markets clear, i.e. $\sum_{s=1}^S \sum_{i=1}^{n_s} y_{its}(z^t) = D_t(z^t)$ for all $z^t \in Z^t$ and $t = 1, ..., T$; and $\sum_{s=1}^S m_{Ts}(z^{T-1}) = M$ for all $z^T \in Z^T$, respectively.

1.3.4 Characterization of Competitive Equilibrium

Carbon tax — Competitive equilibrium is characterized by the following set of equations describing electricity price dynamics and firms' optimal production decisions at the extensive (i.e. which power units operate at a given moment) and intensive (how much to produce at each operating unit) margins[12].

Firm's production decision. For all $t = 1, ..., T, s = 1, ..., S, i = 1, ..., n_s$ and $z^t \in Z^t$:

$$\begin{aligned} & p_t(z^t) - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \\ & 2\alpha_{is}\delta \cdot \mathbb{E}\left[y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)|z^t\right] \begin{cases} > \psi_i\tau, \text{ iff } y_{its} = y_{is}^{max} \\ < \psi_i\tau, \text{ iff } y_{its} = 0 \\ = \psi_i\tau, \text{ iff } 0 < y_{its}(z^t) < y_{is}^{max}. \end{cases} \end{aligned} \tag{1.7}$$

Market-clearing (output). For all $t = 1, ..., T$ and $z^t \in Z^t$:

[12] Details on a step-by-step derivation of the equilibrium characterization are provided in Section A.1.1 of the Appendix.

$$\frac{z_t}{p_t(z^t)^\beta} = \sum_{s=1}^{S}\sum_{i=1}^{n_s} y_{its}(z^t). \tag{1.8}$$

Expression (1.7) characterizes the firm's optimal production decision for a given electricity price $p_t(z^t)$. In the case of an interior solution, it states that firm s should choose output $y_{its}(z^t)$ at plant i and period t so that the expected marginal profits of an additional unit of output equals the associated costs of emissions. Equation (1.8) states that in equilibrium aggregate demand must equal electricity output across firms and power units. The characterization is complete with the set of initial conditions z_0 and $\{y_{i0s}\}_{i=1}^{n_s}$ for all $s = 1, ..., S$. An analogous equilibrium characterization of the BAU setup can be obtained simply by setting the carbon tax τ to zero in (1.7).

Cap-and-trade — Let $\mu_s(z^T)$ denote the Lagrange multiplier associated to the environmental compliance constraint (1.5) from firm s. The corresponding characterization of competitive equilibrium under cap-and-trade is described as follows.

Allowance price dynamics. For all $t = 1, ..., T$ and $z^t \in Z^t$:

$$\begin{cases} x_t(z^t) = \delta \cdot \mathbb{E}\left[x_{t+1}(z^{t+1})|z^t\right], \ \forall\ t = 1, ..., T-2 \\ x_{T-1}(z^{T-1}) = \delta \cdot \mathbb{E}[x_T(z^T)|z^{T-1}] + \mathbb{E}\left[\dfrac{\mu_s(z^T)}{\delta^{T-2}}|z^{T-1}\right] \\ x_T(z^T) = \mu_s(z^T), \ \forall s = 1, ..., S. \end{cases} \tag{1.9}$$

Firm's production decision. For all $t = 1, ..., T, s = 1, ..., S, i = 1, ..., n_s, z^t \in Z^t$:

$$p_t(z^t) - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) +$$

$$2\alpha_{is}\delta \cdot \mathbb{E}\left[y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)|z^t\right] \begin{cases} > \psi_i \mathbb{E}\left[\dfrac{\mu_s(z^T)}{\delta^{t-1}}|z^t\right], \text{ iff } y_{its} = y_{is}^{max} \\ < \psi_i \mathbb{E}\left[\dfrac{\mu_s(z^T)}{\delta^{t-1}}|z^t\right], \text{ iff } y_{its} = 0 \\ = \psi_i \mathbb{E}\left[\dfrac{\mu_s(z^T)}{\delta^{t-1}}|z^t\right], \text{ iff } 0 < y_{its}(z^t) < y_{is}^{max}. \end{cases} \tag{1.10}$$

Market-clearing (output). For all $t = 1, ..., T$ and $z^t \in Z^t$:

$$\frac{z_t}{p_t(z^t)^\beta} = \sum_{s=1}^{S}\sum_{i=1}^{n_s} y_{its}(z^t).$$

Market-clearing (permits). For all $t = 1, ..., T$ and $z^t \in Z^t$:

$$\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{n_s} \psi_i y_{its}(z^t) = M. \tag{1.11}$$

Equations (1.10) and (1.8) describe equilibrium dynamics for output and electricity prices. Condition (1.11) requires market-clearing in the permit sector. Equation (1.9) dictates the dynamics of permit prices. These conditions along with the set of initial values z_0 and $m_{1s}, \{y_{i0s}\}_{i=1}^{n_s}$ for all $s = 1, ..., S$ complete the equilibrium characterization. The last equation in (1.9) states that in equilibrium, the value to the firm of an additional permit must be equated across power producers to the competitive permit price at the expiration date T. Otherwise, incentives to trade would persist as firms with low permit valuations would be willing to sell allowances to firms with higher permit valuations.

1.3.5 Plant-level Output Decisions at the Margin

The equilibrium characterization is key for understanding *how* output allocations are systematically different between control modes. Specifically, it implies the following relationship between permit price at the expiration date and information available at period t[13],

$$\mathbb{E}\left[x_T(z^T)|z^t\right] = \frac{\delta^{T-t-1}}{\delta^{2(T-t)-1}+1} x_t(z^t),\ \forall t = 1, ..., T-2. \tag{1.12}$$

Using the fact that $x_T(z^T) = \mu_s(z^T)$ and substituting equation (1.12) into condition (1.10) allows us to connect unit-level output decisions at t with contemporaneous allowance prices $x_t(z^t)$. Hence, output decisions at the margin with C&T are characterized as follows[14],

$$\begin{aligned} &p_t(z^t) - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \\ &\underbrace{2\alpha_{is}\delta \cdot \mathbb{E}\left[y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)|z^t\right]}_{\text{Unit-level expected marginal profits}} = \underbrace{\frac{\delta^{T-2t}}{1+\delta^{2(T-t)-1}}}_{\text{Uncertainty wedge}} \cdot \underbrace{\psi_i x_t(z^t)}_{\text{Emissions cost}},\ \forall t = 1, ..., T-2. \end{aligned} \tag{1.13}$$

The analogous condition with a carbon tax (see equation (1.7)) is,

[13] See derivation of equation (1.12) in Section A.1.1 of the Appendix.

[14] For ease of explanation, I restrict attention to the case of interior solution, but the same logic applies directly to the cases with corner solutions at the unit level.

$$
\begin{aligned}
&p_t(z^t) - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \\
&\underbrace{2\alpha_{is}\delta \cdot \mathbb{E}\left[y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)|z^t\right]}_{\text{Unit-level expected marginal profits}} = \underbrace{\psi_i\tau}_{\text{Emissions cost}}, \ \forall t = 1, ..., T.
\end{aligned}
\tag{1.14}
$$

Equation (1.14) indicates that with a carbon tax, firms make unit-level production decisions that equate expected marginal profits to the associated emissions costs. However, in a permit system the effect of such emissions costs is weighted by an additional uncertainty wedge that *dampens* the impact of contemporaneous emissions prices on output decisions at carbon-intensive units. This is because with price-based regulation, all relevant abatement incentives to firms are encapsulated in the exogenously fixed and publicly known carbon tax. However, with quantity-based regulation, firms consider both contemporaneous and future (unknown) allowance prices to make current abatement decisions due to the fact that firms are legally bounded to fully cover emissions only at the expiration date T of the compliance cycle. Therefore, the current permit price will not be as relevant for current abatement decisions with cap-and-trade regulation as a carbon tax is with price-based regulation. The fact that abatement decisions are fundamentally different across control modes means that expected emissions prices can also differ between price and quantity-based regulation even if we compare policies that in expectation implement the same level of cumulative emissions.

1.3.6 Permit Price Dynamics and Hotelling's Rule

A property of this model is that the equilibrium time path of allowance prices is consistent *in expectation* with Hotelling's Rule. According to Hotelling (1931), an exhaustible known commodity with no substitutes would experience a price growth rate equal to the inverse of the discount factor δ. Carbon allowances satisfy this set of characteristics given that their publicly known supply M is fixed throughout the compliance cycle by the environmental regulator. These permits become more scarce as power producers generate emissions that need to be eventually covered with a fixed endowment of allowances. This is a consequence of efficient trading in the permit market. Additionally, this result is independent of the initial allocation of permits.

To obtain a version of Hotelling's Rule in expectation for allowances prices, recall from the equilibrium characterization that[15],

$$x_t(z^t) = \delta \cdot \mathbb{E}\left[x_{t+1}(z^{t+1})|z^t\right], \ \forall t = 1, ..., T-2$$

or, equivalently,

$$\mathbb{E}\left[\frac{x_{t+1}(z^{t+1}) - x_t(z^t)}{x_t(z^t)} + 1 \mid z^t\right] = \frac{1}{\delta}. \tag{1.15}$$

The existence of shocks to aggregate demand implies that a smooth Hotelling time path for prices is not possible. Still, (1.15) shows it will hold for the expected growth rate of allowance prices in equilibrium. Because of rational expectations, Hotelling's Rule operates as a non-arbitrage condition implying that in equilibrium firms exploit all possible gains from intertemporal trade of permits given the information available. Without demand uncertainty, the analogous equation for allowance price dynamics in equilibrium would be,

[15] See Section A.1.1 of the Appendix for details on the derivation.

$$x_t = \delta \cdot x_{t+1}, \ \forall t = 1, ..., T-2$$

which is equivalent to the original deterministic version of Hotelling's Rule,

$$\frac{x_{t+1} - x_t}{x_t} + 1 = \frac{1}{\delta}.$$

1.3.7 Welfare Measure

I consider a welfare measure that accounts for total value of firms, expected present value of consumer surplus, expected climate change benefits, and expected policy revenues. I define such measure of ex-ante welfare as follows,

$$\begin{aligned} &\underbrace{\sum_{s=1}^{S} V_s}_{\text{Value of firms}} + \underbrace{\sum_{z^T \in Z^T} Q(z^T) \sum_{t=1}^{T} \delta^{t-1} \int_0^{Y_t^*(z^t)} \left[\left(\frac{z_t}{Y_t(z^t)} \right)^{1/\beta} - p_t^*(z^t) \right] dY_t(z^t)}_{\text{Expected consumer's surplus}} \\ &+ \underbrace{\sum_{z^T \in Z^T} Q(z^T) \sum_{t=1}^{T} \delta^{t-1} \mathrm{SCC} \sum_{s=1}^{S} \sum_{i=1}^{n_s} \psi_i (y_{its}^{\mathrm{bau}}(z^t) - y_{its}(z^t))}_{\text{Expected climate change benefits}} + \underbrace{\sum_{z^T \in Z^T} Q(z^T) \mathscr{R}(z^T)}_{\text{Expected policy revenues}}. \end{aligned} \tag{1.16}$$

Let V_s represent the value of firm s – i.e. the expected discounted present value of profits from firm s in competitive equilibrium. Parameter SCC represents the social cost of carbon, $y_{its}^{bau}(z^t)$ stands for output at unit i and time t from firm s in BAU, and $(p_t^*(z^t), Y_t^*(z^t))$ denotes the equilibrium electricity price and quantity at period t, respectively. Term $\mathscr{R}(z^T)$ represents policy revenues conditional on history z^T. In the case of a carbon tax, this has the following functional form,

$$\mathscr{R}(z^T) = \sum_{t=1}^{T} \delta^{t-1} \tau \sum_{s=1}^{S} \sum_{i=1}^{n_s} \psi_i (y_{its}^{\text{bau}}(z^t) - y_{its}(z^t))$$

while under a permit system, policy revenues emanate from permits being auctioned off to firms at price x_1[16],

$$\mathscr{R}(z^T) = x_1 \sum_{s=1}^{S} m_{1s}.$$

This welfare measure highlights a key trade-off in carbon policy design that explains why welfare effects from any given regulation mode are ambiguous. On one hand, higher carbon taxes or tighter emissions caps increase climate change benefits by reducing emissions at fossil fuel units through higher emissions prices. However, either policy also reduces firm profits and consumer surplus through lower generation in equilibrium at higher electricity prices (through increases in marginal costs at fossil fuel units). The sign of welfare effects from carbon pricing (either price or quantity instruments) depends on which one of the previous two forces is dominant.

Most importantly, the welfare measure captures how firms and consumers balance *aggregate output volatility* vs. *output price volatility* when choosing between price and quantity-based instruments. Specifically, it is possible to choose the per unit tax τ and the emissions cap M such that in expectation total cumulative emissions are the same across control modes. This fixes the value of expected climate benefits. With carbon

[16]Although x_1 is a predetermined initial value for the sequence of realized permit prices, it but must be consistent with the exogenous emissions cap M.

taxes, lower output price volatility benefits firms (due to unit-level cycling costs) but higher output volatility is detrimental to consumers that are averse to consumption risk. With cap-and-trade it is the opposite situation: higher output price volatility is detrimental for firms, but lower aggregate output volatility is benefitial for consumers. These two opposing forces will drive differences in welfare across control modes. Any difference in average emissions prices between control modes translates into a transfer of wealth from firms and consumers to the government but is irrelevant for aggregate welfare differences.

1.4 Simulation

1.4.1 Experiment Design

The goal of the policy experiment is to enable a quantitative comparison of welfare effects between control modes. I simulate the sequence of shocks to power demand $\{z_t\}_{t=1}^{T}$ and solve the model under BAU. Then, I fix the simulated history of demand shocks $\{z_t\}_{t=1}^{T}$ and separately solve the model for each of the two policy counterfacturals – i.e. a carbon tax and a cap-and-trade. I benchmark outcomes under each policy scenario against BAU in order to isolate the causal welfare effects of carbon regulation under each alternative regulatory mode.

To enable a consistent comparison between regulatory regimes, I consider carbon taxes and permit systems that are price-equivalent *in expectation*. The natural way to implement this principle is by adequately choosing the per unit carbon tax τ and emissions cap M such that average emissions prices are the same across counterfactual control modes – i.e. choosing the policy variables to compare welfare outcomes between control modes to satisfy $\tau = \mathbb{E}(x_t(z^t))$.

The basic steps for implementing the simulation procedure are as follows:

1. Simulate 1,000 different sequences for the history of demand shocks.
2. At each simulated history j, solve the model for the BAU setup. Compute average welfare w_0.
3. Define a set of values $\{\tau_k\}_{k=1}^{K}$ for the carbon tax. At each τ_k, solve the model for all J histories of the demand shock and compute average welfare $w_k(\tau_k)$.
4. At each $k = 1, ..., K$, for each j history choose the emissions cap M_{jk} such that the average price of allowances matches τ_k. Calculate average welfare $w_k(M_k)$ across all j.
5. Compare $w_k(\tau_k) - w_0$ to $w_k(M_k) - w_0$ for all $k = 1, ..., K$.

I solve the model for a full compliance cycle spanning an entire year in hourly time blocks. Additionally, I model electricity *residual demand* – i.e. total demand minus generation from wind and solar capacity – because power production from wind and solar is determined by exogenous weather conditions – e.g. speed of wind or availability of sunlight – rather than equilibrium electricity prices. Hence, subtracting generation from wind and solar to total demand allows to explicitly account for residual demand uncertainty that emanates from limited capacity to predict future output from solar stations and wind farms.

1.4.2 Data

ERCOT is the grographic market where 90% of Texas electricity consumption takes place. It is also the second largest U.S. power grid in terms of generating capacity per consumer. I use three main data sources from the universe of ERCOT firms in the quantitative analysis[17]. First, I use EIA-860 and EIA-923 2017 surveys to collect plant-level data on technological attributes from ERCOT firms. These are mandatory reports US power producers submitted on a monthly basis to the Energy Information Administration (EIA). The reports include data at the power plant level on unit identifier, electricity production, fuel costs (per energy source), fuel consumption and stocks, regulation status, energy-type emissions rates, and generation capacity limits, among other information. Approximately, 97% of 2017 ERCOT residual demand was met from power generated either from coal (∼39%), natural gas (∼45%), or nuclear (∼13%) sources. As such, I abstract in the quantitative exercise from any other inputs different from these three – e.g. diesel or biomass.

Second, I use 2017 ERCOT data on hourly load (in MWh) and average hourly prices at the system level. This dataset includes information about hourly power consumption at the aggregate and zonal level – i.e. North, North Central, South, South Central, and West zones. Data on aggregate load combined with EIA-860 information about solar and wind shares in total generation are used for computing the relevant residual electricity demand moments.

[17] See EIA (2017) and ERCOT (2017).

1.4.3 Estimation and Identification

I implement a two-step procedure to estimate structural parameters. First, I calibrate emissions rates ψ_i, price-elasticity of demand β, social cost of carbon SCC, and capacity limits y_{is}^{max} using available engineering or reduced-form estimates. Second, I design a SMM approach to estimate unit-level marginal cost and cycling cost parameters (c_{is}, α_{is}). On the demand side, I adopt the following parametrization of equation (1.1) in the SMM strategy to estimate the demand intercept ρ_0 and shock size ζ[18].

$$\begin{cases} \ln(D_t) = \underbrace{(\rho_0 + \varepsilon_t)}_{=\ln(z_t)} - \beta \ln(p_t) \\ \mathbb{E}(\varepsilon_t) = 0 \text{ and } \varepsilon_t \in \{-\zeta, 0, \zeta\}, \ \forall t. \end{cases} \tag{1.17}$$

1.4.3.1 Step 1: Calibration

I report calibrated parameters in Table 1 and Table 2. Data on average emission rates are available only at the energy type level but not at the unit level. Hence, I assume emissions rates at units using the same fuel type to be equal across firms. To compute average emissions rates, I use estimates from EIA data that correspond to 2.21 lbs/kWh for coal and 0.98 lbs/kWh for natural gas units. I convert these estimates to units in tons/MWh. This implies average emissions rates of 1 ton/MWh for coal and .44 tons/MWh for natural gas (see Table 1). I annualize the hourly discount factor to be consistent with a yearly discount of .98 by setting δ consistently

[18] By definition, $\rho_0 + \varepsilon_t = \ln(z_t)$. Therefore, ε_t follows a zero-mean Markov process of degree 1 since it inherits the stochastic properties of z_t.

with $\delta^{365 \cdot 24} = .98$. Additionally, I use the upper bound reduced-form estimate for price-elasticity of electricity demand in Ito (2014).

Values for parameters y_{is}^{max} in Table 2 correspond to the maximum capacity limit of unit of type i from firm s. I calibrate these values using unit level engineering estimates of nameplate capacity for all ERCOT firms in the EIA surveys. Additionally, I map energy portfolios at the firm level into the economic environment by consolidating the firm's total installed capacity per energy type into one power. For instance, a firm with two natural gas units of 100 MW capacity and three coal units of 50 MW capacity in the data would have one natural gas unit of 200 MW capacity and one coal unit of 150 MW capacity in this simulation setup.

Table 1. Emissions and preferences parameters

Parameter	Definition	Value	Source
(ψ_1, ψ_2, ψ_3)	**Emission rates**	(1, .44, 0)	EIA (2018)
β	**Price-elasticity of demand**	.034	Ito (2014)
δ	**Discount factor**	$\sim$1	Assumption
SCC	**Social Cost of Carbon**	51	EPA (2021)

Note: This table reports externally calibrated values I take from existing estimates. Emissions rates are expressed as CO^2ton/MWh. Parameters ψ_1, ψ_2, ψ_3 correspond to average emissions rates at coal, natural gas, and nuclear power units, respectively.

I consolidate total capacity of firms that own only one energy type (natural gas or coal-fired units) into two separate atomistic firms: one that owns a single coal unit and a second one with a single natural gas unit. Since firms that own a single type of fossil fuel technology can only abate emissions by cutting down production, this is without loss of generality in terms of how the model captures firm responses to carbon prices. I model individually all other power producers that own installed capacity in two or more energy types.

Table 2. GW capacity limits (EIA, 2017)

Parameter	Power producer	Value
$(y_{11}^{max}, y_{21}^{max}, y_{31}^{max})$	**Luminant Generation Company, LLC.**	(8.594, 3.846, 2.430)
$(y_{12}^{max}, y_{22}^{max})$	**NRG Texas Power, LLC.**	(4.587, 6.424)
$(y_{13}^{max}, y_{23}^{max})$	**Southwestern Public Service Co**	(1.773,1.681)
$(y_{14}^{max}, y_{24}^{max})$	**City of San Antonio - (TX)**	(2.376, 3.775)
$(y_{15}^{max}, y_{25}^{max})$	**Lower Colorado River Authority**	(1.690, 2.049)
$(y_{16}^{max}, y_{26}^{max})$	**Southwestern Electric Power Co**	(1.837, 1.423)
$(y_{17}^{max}, y_{27}^{max})$	**Single-plant firm – coal**	(5.210, 0)
$(y_{18}^{max}, y_{28}^{max})$	**Single-plant firm – natural gas**	(0, 26.131)

Note: This table reports externally calibrated values I take from engineering estimates of nameplate capacity from the EIA 860 and EIA 930 surveys. All numbers are in Gigawatt units (GW).

1.4.3.2 Step 2: Estimation and Identification

I use a Simulated Method of Moments (SMM) strategy to estimate the rest of structural parameters. To implement the SMM, I define a set of key moments for estimating each parameter of interest and use a number of moments equal to the number of parameters to be estimated. Then, I simulate the exogenous variation within the model – i.e. the history of demand shocks $\{\varepsilon_t\}_{t=1}^{T}$ – to compute the simulated moments obtained from solving the economic model by using the equilibrium characterization in Section 1.3.4. Subsequently, I find the parameters that allow matching each of these model-dependent moments to those calculated from the data.

Table 3. Target moments for SMM estimation

Parameter	Target	Moment	
		Model	*Data*
Unit-level marginal costs (c_{is})			
Luminant Generation Company	Energy mix	(72.5, .8, 26.7)	(72.8, .5, 26.7)
	Avg. coal power production	5,869	5,869
NRG Texas Power	Energy mix	(85.3, 14.7)	(85.3, 14.7)
	Avg. coal power production	2,774	2,774
Southwestern Public Servico Co.	Energy mix	(83.8, 16.2)	(83.9, 16.1)
	Avg. coal power production	1,113	1,113
City of San Antonio - (TX)	Energy mix	(61.9, 38.1)	(61.9, 38.1)
	Avg. coal power production	1,086	1,086
Lower Colorado River Authority	Energy mix	(60.1, 39.9)	(60.1, 39.9)
	Avg. coal power production	1,032	1,032
Southwestern Electric Power Co.	Energy mix	(95.7, 4.3)	(95.4, 4.6)
	Avg. coal power production	1,125	1,123
Single-plant firm – coal	Avg. coal power production	3,647	3,647
Single-plant firm – natural gas	Avg. natgas power production	13,834	13,834
Unit-level cycling costs (α_{is})			
Luminant Generation Company	Avg. cycling cost/MW cap.	(141, 101, 339)	(142, 100, 339)
NRG Texas Power	Avg. cycling cost/MW cap.	(141, 100)	(142, 100)
Southwestern Public Servico Co.	Avg. cycling cost/MW cap.	(142, 99)	(142, 100)
City of San Antonio - (TX)	Avg. cycling cost/MW cap.	(142, 100)	(142, 100)
Lower Colorado River Authority	Avg. cycling cost/MW cap.	(141, 101)	(142, 100)
Southwestern Electric Power Co.	Avg. cycling cost/MW cap.	(142, 100)	(142, 100)
Single-plant firm – coal	Avg. cycling cost/MW cap.	142	142
Single-plant firm – natural gas	Avg. cycling cost/MW cap.	100	100
Power demand			
Demand Intercept, ρ_0	Avg. hourly consumption	33,442	33,442
Demand shock size, ζ	S.D. hourly consumption	7,482	7,481

Note: This table reports targets used for estimating each of the firm-level and demand parameters. Column 'Parameter' defines the parameter group in italic and the firm's name to which the specific parameter is associated to in standard font. Column 'Target' defines the moments to match in the data. Energy mixes (in % points) are at the firm level. Avg. coal/natgas power production (in MWh) and avg. cycling costs per MW capacity are at the hourly level. For vectors with energy mix and cycling cost data, first slots are for coal units, second slots are for natural gas units, and third slots (if any) are for nuclear units. Mean and standard deviation (S.D.) of hourly (residual) electricity consumption are at the system level. Column 'Moment' compares model-dependent moments to those calculated from the data.

I rely on a SMM approach given that it is not possible to compute closed form analytical solutions of the key moments directly from the economic model. Instead, I compute the model-dependent moments with a simulation technique that exploits demand shocks as the key source of exogenous variation behind equilibrium dynamics.

I report estimation results in Table 3 and Table 4. In Table 3, I define moments used to estimate each parameter and report the goodness-of-fit[19]. In Table 4, I report estimated values and bootstrapped standard errors. For supply side parameters, I exploit time variation in plant-level generation across power units owned by the same firm along with variation in cycling costs across energy types to estimate unit-level marginal cost parameter c_{is} and cycling cost parameter α_{is}. I do this by jointly estimating unit level cost parameters $(c_{is}, \alpha_{is})_{i=1}^{n_s}$ at the firm level to match the following set of key moments: i) annual share of coal and natural gas power at the firm level ($n_s - 1$ moments), ii) average hourly production of coal power at the firm level (1 moment), and iii) average cycling costs per MW capacity at the fuel type level (n_s moments). I use the same empirical moment to estimate cycling cost parameters of units with the same fuel type because data is available at the energy type level but not at the firm level. For demand side parameters, I exploit time variation in hourly electricity consumption at the system level to identify ρ_0 and ζ. I do this by jointly estimating (ρ_0, ζ) to match the mean and variance of hourly electricity consumption at the system level.

I use firm-level energy mix as a key moment for estimating marginal costs c_{is} given that shares of coal and natural gas electricity within firms are determined by

[19]See Section A.1.2 of the Appendix for a sensitivity analysis of how each model-dependent moment changes with a 1% change in estimated parameters.

relative production costs between power plants. Since the same energy mix can be consistent with multiple combinations of unit-level production levels, I also use average generation at the coal-fired plant to complete the set of moments that allow estimating plant-level marginal costs c_{is}.

Table 4. SMM estimation results

Parameter	Notation	Estimate	S.E.
Unit-level marginal costs			
Luminant Generation Company, LLC	(c_{11}, c_{21}, c_{31})	(22.14, 27.51, .01)	(5.269, 11.191, 4.652)
NRG Texas Power, LLC	(c_{12}, c_{22})	(23.30, 41.13)	(1.428, .607)
Southwestern Public Servico Co.	(c_{13}, c_{23})	(24.39, 30.93)	(1.455, 8.341)
City of San Antonio - (TX)	(c_{14}, c_{24})	(24.44, 80.55)	(.403, 25.647)
Lower Colorado River Authority	(c_{15}, c_{25})	(24.39, 47.23)	(1.413, 16.405)
Southwestern Electric Power Co	(c_{16}, c_{26})	(24.39, 38.89)	(1.064, 4.965)
Single-plant firm – coal	c_{17}	23.84	1.2×10^{-15}
Single-plant firm – natural gas	c_{28}	44.37	1.0×10^{-17}
Unit-level cycling costs			
Luminant Generation Company, LLC	$(\alpha_{11}, \alpha_{21}, \alpha_{31})$	(1.12, .01, .94)	(.496, .355, .001)
NRG Texas Power, LLC	$(\alpha_{12}, \alpha_{22})$	(1.35, .01)	(.328, .001)
Southwestern Public Servico Co.	$(\alpha_{13}, \alpha_{23})$	(.05, .02)	(.003, .001)
City of San Antonio-(TX)	$(\alpha_{14}, \alpha_{24})$	(.03, .01)	(.001, .004)
Lower Colorado River Authority	$(\alpha_{15}, \alpha_{25})$	(.05, .02)	(.002, .003)
Southwestern Electric Power Co	$(\alpha_{16}, \alpha_{26})$	(.05, .02)	(.002, .002)
Single-plant firm – coal	α_{17}	.44	1.0×10^{-13}
Single-plant firm – natural gas	α_{28}	.01	1.4×10^{-13}
Power demand			
Demand Intercept	ρ_0	10.53	.001
Demand shock size	ζ	.27	.050

Note: This table reports estimation results for each firm-level and demand parameter. Column 'Parameter' defines the parameter group and the firm's name to which the specific parameter is associated to. Column 'Notation' reports parameters as defined in the model. Column 'S.E.' reports bootstrapped standard errors clustered at the unit level for supply-side parameters. For vectors with cost parameters, first slots are for coal units, second slots are for natural gas units, and third slots (if any) are for nuclear units.

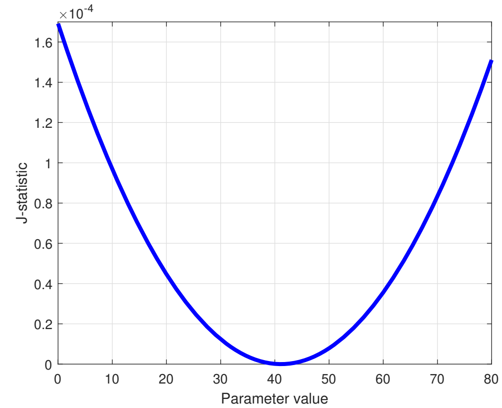
On the demand side, I use the hourly average in electricity consumption as the moment to estimate ρ_0 given that the demand shock ε_t has zero mean. Additionally, I estimate ζ using the variance of hourly power consumption as key moment because larger demand shocks increase volatility of power consumption in equilibrium, and vice versa.

I show in Figure 3 how the value of the J-statistic (i.e. the estimated value of the distance between the model-dependent moments and their empirical values in the data) changes with perturbations to estimated parameter values in all four categories of parameters. To keep the reporting of sensitivity analysis results succinct, for cost parameters I only show results for the case of NRG Texas Power Co. The J-statistic is zero at the estimated parameter values from Table 4 because the model is exactly identified (i.e. same number of moments as parameters to estimate) so that each moment is exactly matched (see Table 3). For purposes of model identification, these results indicate that the value of the J-statistic indeed achieves a global minimum at the vector of estimated parameters over the relevant parametric space. Moreover, Table 5 shows that the model performs well matching other key moments that were not directly targeted in the estimation procedure given that their empirical values fall within the 95% confidence intervals generated by the model.

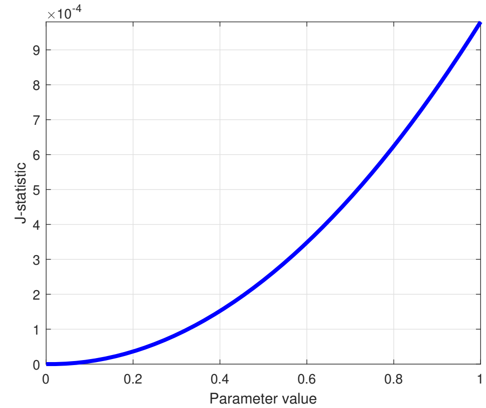
Table 5. Key untargeted moments

Definition	**Model**	**95% CI**	**Data** (2017)
Avg. hourly price ($/MWh)	31.2	28.1 – 34.3	28.3
Avg. emissions (tons)	207,050,000	202,899,770 – 211,200,230	210,151,200

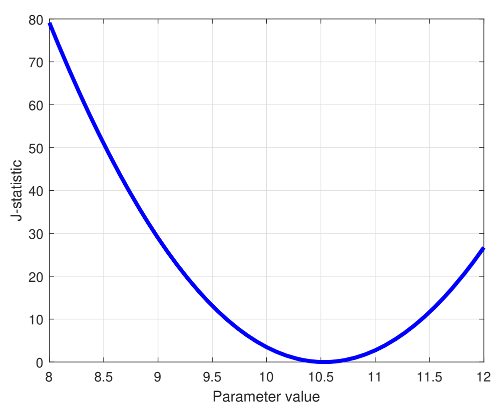
Note: This table reports key untargeted moments from solving the economic model parametrized with the vector of estimated parameters. Empirical moments in the data fall within the 95% confidence intervals.



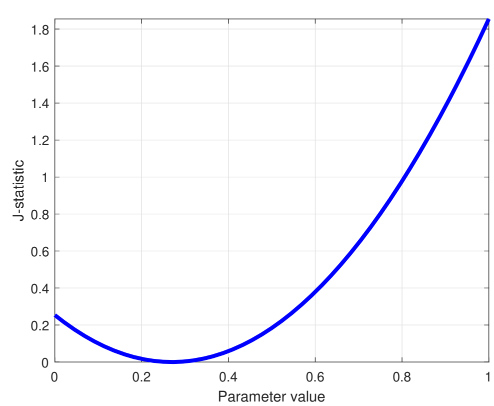
(a) Marginal cost at natural gas plant (c_{22})



(b) Cycling cost parameter at natural gas plant (α_{22})



(c) Demand intercept ρ_0



(d) Shock size ζ

Figure 3. J-statistic Sensitivity Analysis

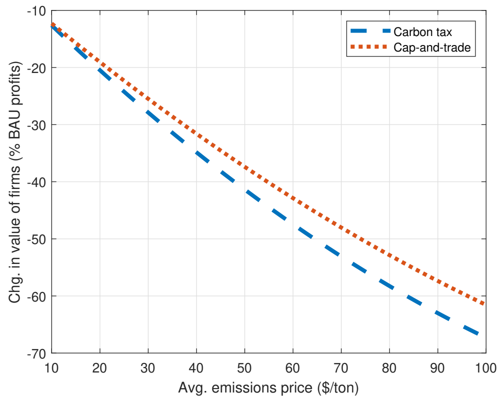
Note: This figure shows how the value of the J-statistic changes with perturbations to estimated parameter values in all four categories of estimated parameters. The J-statistic is zero at the estimated parameter values from Table 4 because the model is exactly identified (i.e. same number of moments as parameters to estimate). Cost parameters correspond to estimation results for NRG Texas Power Co.

1.5 Simulation Results

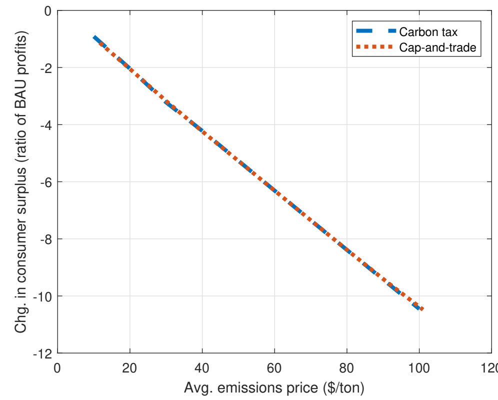
In this section I quantitatively assess the performance of carbon taxes and cap-and-trade regulation on welfare grounds. To do this, I compare price and quantity-based regulation using two alternative criteria. First, I present results that compare regulation modes with the same price of emissions *in expectation* (i.e. $\tau = \mathbb{E}_0(x_t(z^t))$. Then, I present and focus on results that compare policy instruments that implement, *in expectation*, the same level of cumulative emissions. These are the key results from the policy experiment as real-world regulation is designed based on emissions targets rather than price targets.

Over a wide range of policy relevant emissions targets or prices, carbon taxes have higher welfare. Still, the distributional consequences between consumers and firms are sensible with respect to the point of comparison. This is because by comparing emissions-equivalent policies, climate benefits are (by construction) equalized across control modes. However, climate benefits are also allowed to vary across control modes when comparing price-equivalent policies.

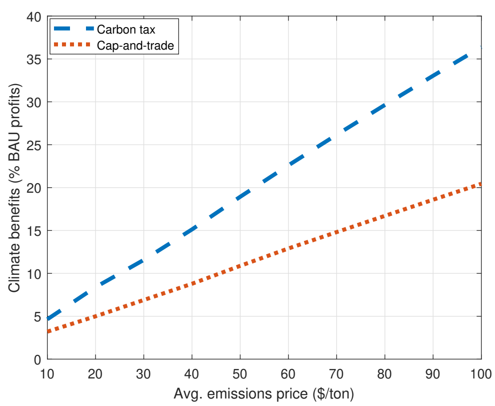
Figure 4 decomposes welfare effects from Figure 6 into the key components of the welfare measure defined by (1.16) in Section 1.3.7. Implications for equilibrium prices, allocations and energy mix are reported in Figure 7 and Figure 8.



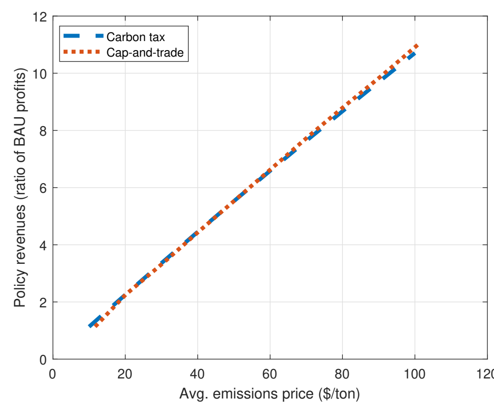
(a) Policy Effect on Value of Firms



(b) Policy Effect on Consumer Surplus



(c) Climate Change Benefits



(d) Policy Revenues

Figure 4. Comparative Welfare Analysis

Note: This figure shows the policy effects across alternative control modes on each of the components of the welfare measure from equation (1.16), i.e. firms' profits (a), consumer surplus (b), climate benefits (c), and policy revenues (d). The dashed line represents policy effects from a carbon tax while the dotted line corresponds to effects from a permit system.

Panel (a) in Figure 4 measures the change on firms' profits in equilibrium – i.e. relative to BAU – in response to different levels of average emissions prices (which is τ in the case of a carbon tax). Carbon taxes are more costly to firms than price-equivalent permit systems. This is because of the uncertainty wedge that affects firms under cap-and-trade regulation (see equation (1.13)). Intertemporal trade of permits dampens the effect of allowance prices on contemporaneous output decisions at the plant level because firms consider both current and future permit prices for making contemporaneous abatement decisions. Hence, with cap-and-trade emissions prices are less distortive to firms relative to a price-equivalent carbon tax which lacks this intertemporal link.

Panel (b) measures the change in expected present value of consumer surplus in response to average emissions prices. Carbon prices have detrimental effects on consumer welfare because of lower consumption at higher post-policy electricity prices (see Figure 7). However, quantitative differences in expected consumer surplus between regulation modes are negligible. This is consistent with the fact that production (on a yearly basis) and hourly electricity prices are, on average, similar between regulatory regimes (see Figure 7).

Panel (c) shows expected climate benefits from carbon pricing as a function of average emissions prices. Climate benefits have been quantified as total carbon reductions (relative to BAU emissions) valued at a social cost of carbon of \$51. From equations (1.13) and (1.14), higher emissions prices generate larger abatement at the unit level (via decreases in production) which translate into more benefits from emissions avoided due to the policy. Moreover, climate benefits are non-trivially higher under carbon taxes because firms abate more aggressively in the carbon tax case (see

Figure 8) by replacing generation from coal-fired units towards natural gas (see Figure 7) which is a less emissions intensive fuel.

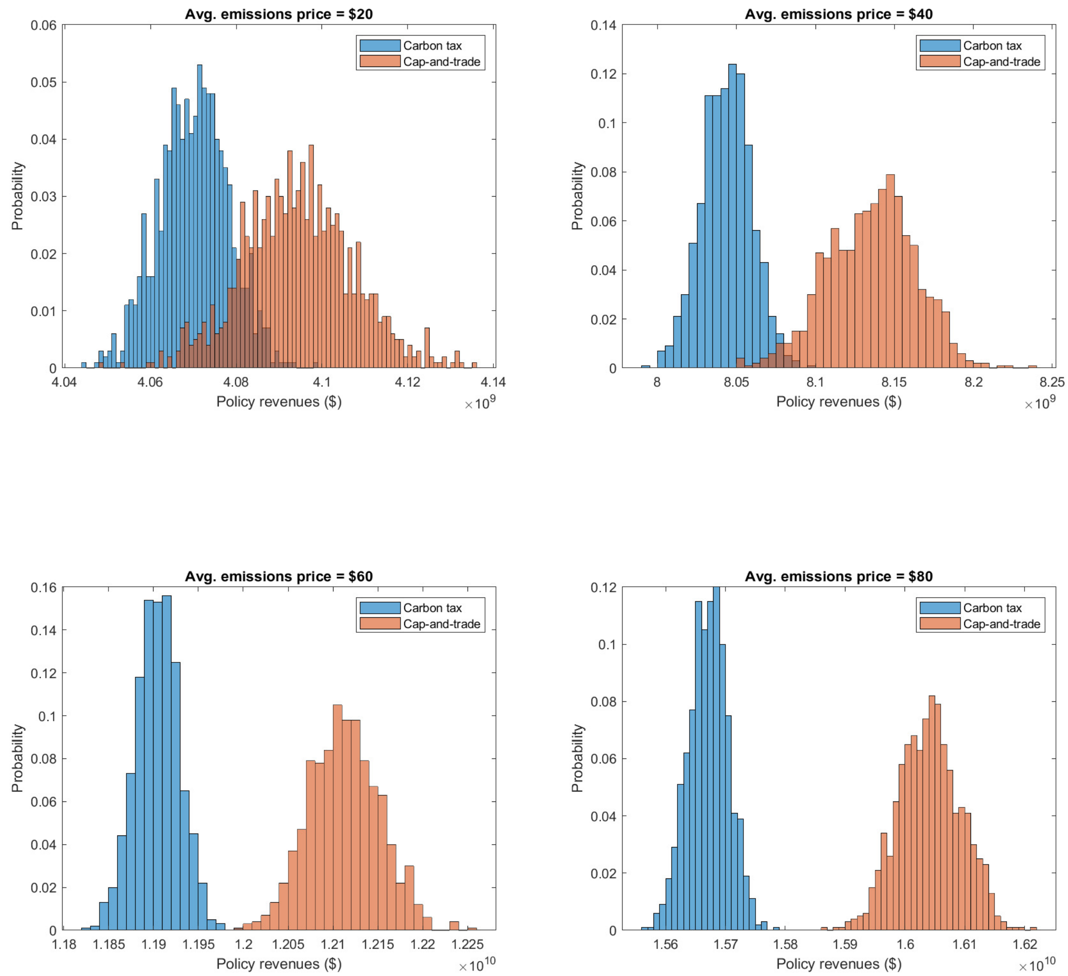


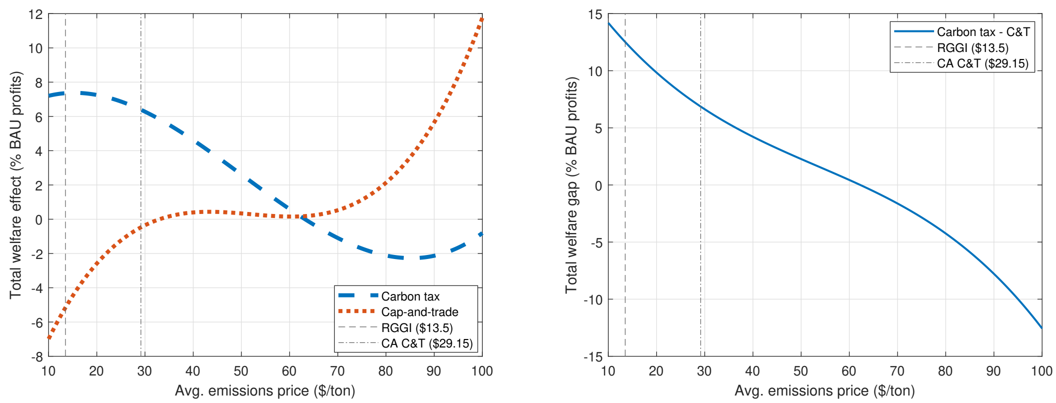
Figure 5. Probability Density Functions of Policy Revenues

Note: This figure shows the estimated probability density functions of policy revenues between alternative regulatory regimes for different levels of expected carbon prices. Blue histograms are for pdfs under carbon taxes while orange histograms are for pdfs under cap-and-trade systems. The Figure shows that the distance in means across control modes grows larger as the expected carbon price increases.

Panel (d) reports expected policy revenues between regulatory regimes as a function of average carbon prices. Quantitative findings show expected revenues *in equilibrium* are strictly increasing on average carbon prices. Regime-wise probability density functions of policy revenues in Figure 5 indicate these are higher, *on average*, with permit systems. This is because of higher expected emissions in the C&T case at any given expected carbon price.

Figure 6 aggregates distributional impacts of market-based carbon regulation from Figure 4. Carbon taxes have higher welfare at expected emissions prices below $63, while permit systems dominate for average prices above the cutoff. Under cap-and-trade, welfare effects are smaller at expected carbon prices below the cutoff because of lower climate benefits and policy revenues relative to carbon taxes. Welfare effects at the low end of average emissions prices are negative with permit systems because climate benefits and policy revenues are offset by the detrimental effects of regulation on consumer surplus and firms' profits. However, above the cutoff these become larger relative to welfare effects from a carbon tax because of the increasing difference in firms' profits and policy revenues across control modes.

Results from Figure 6 can be used to derive policy implications from regulatory design that draws upon policy parameters consistent with allowance prices from active U.S. cap-and-trade systems. For instance, the settlement price for CA cap-and-trade allowances for Feb. 2022 auction closed at $29.15. Alternatively, the clearing price of RGGI permits for Mar. 2022 auction settled at $13.5. Results show that from a Utilitarian planner's perspective, a carbon tax is preferred for a wide range of expected carbon prices that is consistent with permit prices observed in RGGI and CA cap-and-trade markets. The dominance of carbon taxes over price-equivalent permit systems is more pronounced at average emissions prices closer to RGGI prices given that the welfare gap increases from 6.7% at \$29.5/CO_2ton to 13.6% of BAU industry profits at \$13.5/CO_2ton[20].

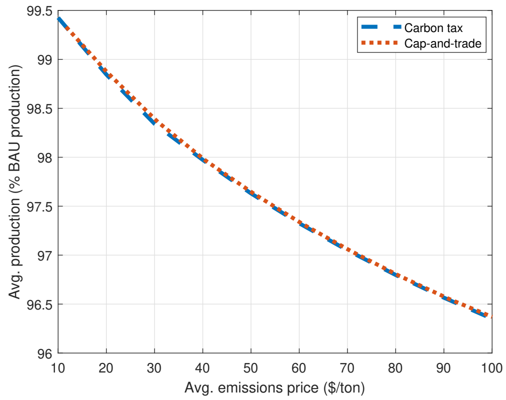


(a) Total Welfare Effect (b) Welfare Gap

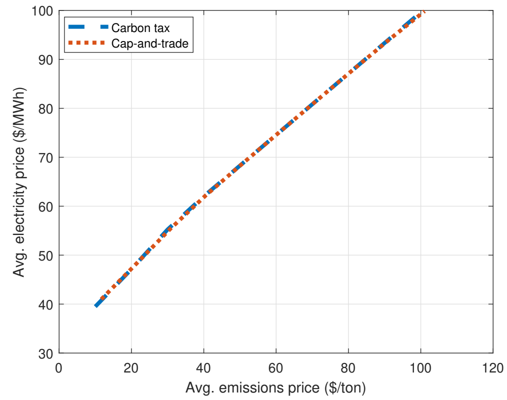
Figure 6. Aggregate Welfare Effects

Note: This figure aggregates in panel (a) the policy effects on each of the components of the welfare measure from equation (1.16) across alternative control modes. The dashed line represents welfare effects from a carbon tax while the dotted line corresponds to effects from a permit system. Panel (b) plots the difference in welfare effects between regulatory regimes. Positive differences mean that a carbon tax has higher welfare effects, and vice versa..

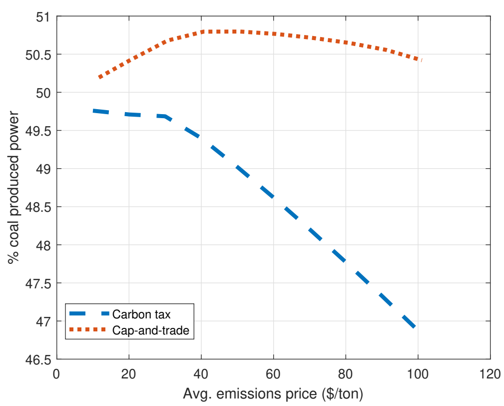
[20] See Section A.1.4 of the Appendix for additional results on the estimated density functions of endogenous outcomes.



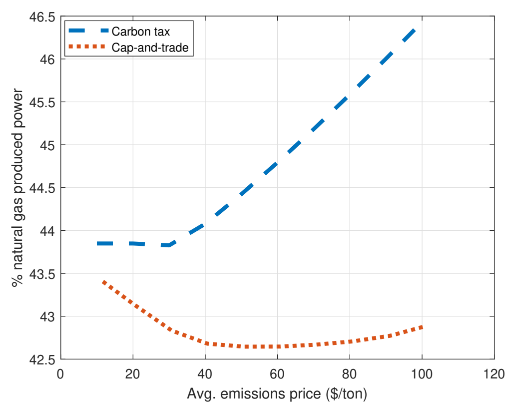
(a) Output



(b) Prices



(c) % Output Produced with Coal



(d) % Output Produced with Natural Gas

Figure 7. Effects on the Electricity Market across Regulatory Regimes

Note: This figure compares policy effects on the electricity market across alternative control modes. Panel (a) plots policy effects on avg. hourly output, panel (b) shows effects on avg. hourly electricity prices, panel (c) plots the response in the share of coal-produced electricity and panel (d) shows the effect on the share of natural gas-produced power. The dashed line represents policy effects from a carbon tax while the dotted line corresponds to effects from a permit system.

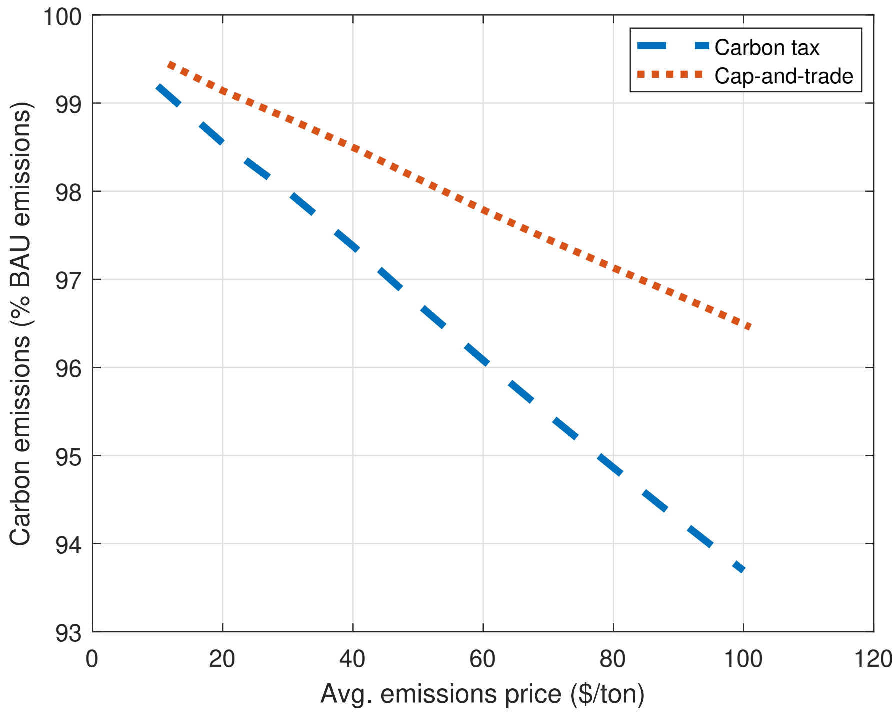
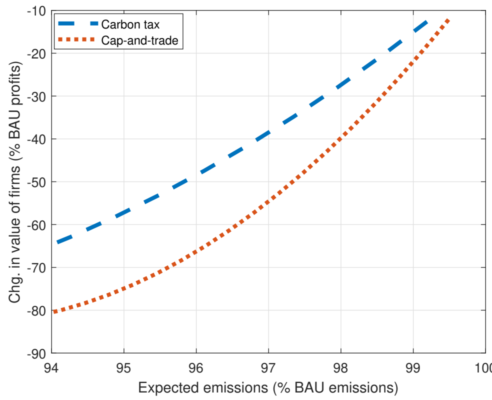
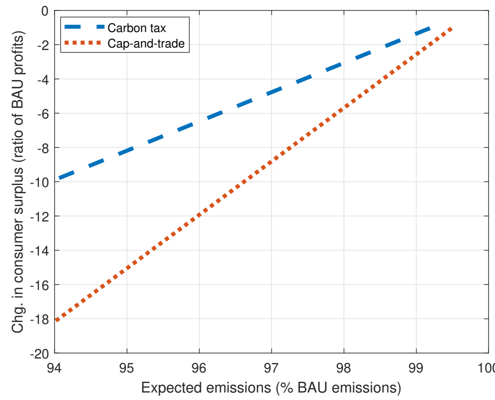


Figure 8. Emissions across Regulatory Regimes

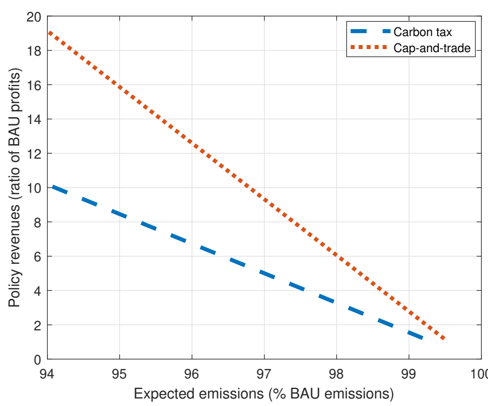
Note: This figure compares total expected emissions between alternative control modes. The dashed line represents policy effects from a carbon tax while the dotted line corresponds to effects from a permit system. In both cases, expected emissions decrease as a result of higher average carbon prices (either from higher carbon taxes or lower emissions caps).



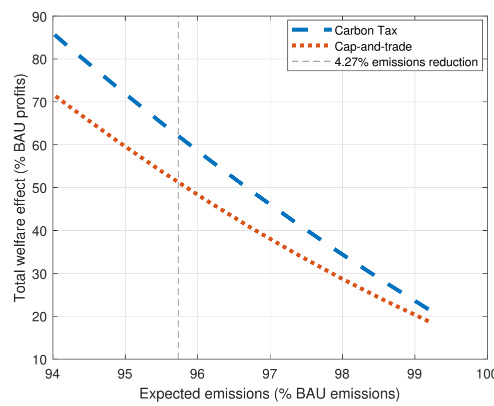
(a) Policy effect on value of firms



(b) Policy effect on consumer surplus



(c) Policy Revenues



(d) Total welfare effect

Figure 9. Welfare Effects of Different Abatement Targets across Control Modes

Note. This figure shows the policy effects across alternative control modes on the following components of welfare in equation (1.16): firms' profits (a), consumer surplus (b), policy revenues (c), and total welfare (d). The dashed line represents policy effects from a carbon tax while the dotted line corresponds to effects from a permit system. The 1.05% abatement level corresponds to the target consistent with avg. year-over-year reductions in total U.S. emissions. The 4.27% abatement level corresponds to the target consistent with a 60% of 1990 emissions by 2030.

In Figure 9, I construct the equilibrium relationships between welfare and market outcomes as functions of expected emissions. This is consistent with comparing regulation modes that are emissions-equivalent – i.e. total emissions from the compliance cycle are the same *in expectation*. These are the key quantitative results from the experiment. From a policy perspective, focus on these findings is of key importance given that in practice policy goals from emissions regulation are set as abatement targets rather than price targets. Panel (d) aggregates the distributional implications of alternative regulation modes in panels (a), (b), and (c) into total welfare effects (relative to BAU).

Results in Figure 9 capture the welfare implications of how firms and consumers balance aggregate output volatility vs. output price volatility. Panel (a) shows that firms' profits are significantly higher with a carbon tax. This is because with alternative cap-and-trade regulation, electricity price volatility is higher and this induces costly adjustments in production due to the existence of cycling costs. Additionally, panel (b) shows that consumer surplus is higher with carbon taxes even if aggregate output volatility is larger with price-based regulation. This is because, in equilibrium, the difference in average emissions prices also matters for consumer surplus. As Figure 8 shows, average emissions prices are significantly higher with cap-and-trade regulation. This offsets the welfare gain from lower unpredictable volatility in consumption with permit systems. At the aggregate level, this difference if average emissions prices is irrelevant for welfare effects because it constitutes a transfer of wealth from consumers to the government. Therefore, the fact that firms favor carbon taxes due to lower output price volatility becomes the quantitatively key channel that drives differences in welfare across regulation modes.

I draw upon policy goals from the California cap-and-trade market to benchmark this analysis with emissions targets from active U.S. permit systems. California set an emissions target of 40% below 1990 levels by 2030. This requires a year-over-year 4.27% emissions reduction from 2019 through 2030[21]. Results in Figure 9 imply that implementing a 4.27% abatement target with a carbon tax delivers a welfare gain of 16.4% of BAU industry profits relative to using a permit system. An abatement target consistent with the 2005-2019 historical average of year-over-year changes in state emissions sets the policy goal at a 1.05% abatement rate. The welfare gain of using carbon taxes falls to 7.6% of BAU profits. At this abatement target, a price instrument is welfare-enhancing while a quantity instrument would be welfare-deteriorating. These results indicate that for a wide range of abatement targets consistent with current policy goals, carbon taxes outperform cap-and-trade in terms of welfare. Last, these results vary in their degree of sensibility to different parameters of the model. In particular, the welfare ranking crucially depends on the joint distribution of unit-level marginal costs across fuel types (see Section A.1.3 of the Appendix for a sensitivity analysis).

1.6 Discussion

Market power and endogenous capital investments are two important avenues that have been studied in related literature. I analyze how the model in section 1.3 can be extended to account for both of these dimensions. I also assess the robustness

[21] According to estimates from the California ARB, 1990 carbon emissions were 427 MMT while 2019 emissions were 418.2 MMT. Conservative calculations using 414.2 MMT for 2019 yields a 4.27% abatement rate.

of the key analytical and quantitative implications from the main analysis to the incorporation of these extensions.

1.6.1 Market Power

Several research efforts have studied the role of market power in energy markets. Some of these studies go back to the early years of restructured electricity markets[22]. Others have focused on how market power can interact with the bidding mechanism that regulates the design of restructured markets, generation costs, vertical arrangements or other features of the industry[23].

In this section, I extend the model from Section 1.3.2 to account for strategic behavior of firms in their production decisions. I show that even in such augmented model, market power does not interact with the uncertainty wedge in permit systems. This implies that the mechanism driving discrepancies in welfare between price and quantity based regulation operates exactly as in the competitive case.

Assume there exist S oligopolistic firms that play a dynamic Cournot game. Moreover, consider the existence of a competitive fringe with a continuum of price-taking firms. Total demand $\bar{D}_t$ is perfectly inelastic from period to period and is jointly met by strategic and competitive firms. However, oligopolistic firms face a downward-sloping *residual demand* curve (i.e. the difference between total demand less supply from producers in the competitive fringe) since price-taking firms in the

[22] E.g. Borenstein et al. (2002).

[23] E.g. Cicala (2022), Ito and Reguant (2016), Reguant (2014), Bushnell et al. (2008), and Hortaçsu and Puller (2008).

competitive fringe optimally adjust their production plans to price changes. I specify the following reduced-form inverse residual demand that is faced by oligopolistic firms,

$$p_t = \frac{\bar{D}_t - \sum_{s=1}^{S}\sum_{j=1}^{n_s} y_{jts}}{Y_t^c} \tag{1.18}$$

where $Y_t^c = \int_0^1 \sum_{j=1}^{n_s} y_{jts}^c ds$ represents total output from firms in the competitive fringe. Equation (1.18) indicates that prices fall either if oligopolistic firms unilaterally increase output or total production in the competitive fringe increases, and viceversa.

With a carbon tax, competitive firms maximize expected profits according to (1.4). However, an oligopolistic firm s solves the following problem for a given strategy profile of the production decisions from the other firms,

$$\begin{cases} \max\limits_{\{y_{its}(z^t)\}_{i,t=1}^{n_s,T}} \quad \sum\limits_{z^T \in Z^T} Q(z^T) \sum\limits_{t=1}^{T} \delta^{t-1} \sum\limits_{i=1}^{n_s} \Bigg[\underbrace{\left(\frac{\bar{D}_t - \sum_{s=1}^{S}\sum_{j=1}^{n_s} y_{jts}(z^t)}{Y_t^c(z^t)} \right)}_{=p_t(z^t)} y_{its}(z^t) - \\ \qquad\qquad (c_{is} + \tau\psi_{is}) y_{its}(z^t) - \alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1}))^2 \Bigg] \\ \text{s.t.} \quad 0 \le y_{its}(z^t) \le y_{is}^{max}, \ \forall i = 1, ..., n_s, \forall t = 1, ..., T, \ \forall z^t \in Z^t \\ \qquad z_0, \{y_{i0s}\}_{i=1}^{n_s} \text{ — given.} \end{cases} \tag{1.19}$$

The key difference with a competitive firm is that the strategic producer considers in its profit function the effect on prices from individual output decisions. This is captured by the residual demand equation. However, competitive firms take prices as given which means that prices in their profit maximization problems are independent of any individual decision-making process.

With a permit system, competitive firms maximize expected profits according to (1.6). Alternatively, an oligopolistic firm solves the following problem while taking as given the strategy profile of other firms,

$$\begin{cases} \max_{\{y_{its}(z^t), m_{t+1,s}(z^t)\}_{i,t=1}^{n_S,T}} \sum_{z^T \in Z^T} Q(z^T) \sum_{t=1}^{T} \delta^{t-1} \Bigg\{ \sum_{i=1}^{n_s} \Bigg[\underbrace{\left(\frac{\bar{D}_t - \sum_s^S \sum_j^{n_s} y_{jts}(z^t)}{Y_t^c(z^t)} \right)}_{=p_t(z^t)} y_{its}(z^t) \\ \quad - c_{is} y_{its}(z^t) - \alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1}))^2 \Bigg] - x_t(z^t) \left(m_{t+1,s}(z^t) - m_{ts}(z^{t-1}) \right) \Bigg\} \\ \text{s.t.} \;\; 0 \le y_{its}(z^t) \le y_{is}^{max}, \;\forall i = 1, ..., n_s, \forall t = 1, ..., T, \;\forall z^t \in Z^t \\ \qquad \sum_{t=1}^{T} \sum_{i=1}^{n_s} \psi_i y_{its}(z^t) = m_{Ts}(z^{T-1}), \;\forall z^T \in Z^T \\ \qquad z_0, m_{1s}, \{y_{i0s}\}_{i=1}^{n_s} \text{ — given.} \end{cases} \tag{1.20}$$

An equilibrium in this augmented environment is a set of contingent quantities and prices such that the following holds. First, best responses from oligopolistic firms constitute a Subgame Perfect Nash Equilibrium. Second, contingent plans from firms in the competitive fringe maximize expected profits while taking prices as given. Last, for the carbon tax case the electricity market clears on a period-by-period basis[24]. Alternatively, in a cap-and-trade setup the permit market clears as well at the expiration date T.

[24] Observe this means that firms in the competitive fringe meet whatever portion of demand that is not met by oligopolistic firms.

Optimization problems in (1.19) and (1.20) both show oligopolistic firms realize that their optimal production decisions have influence on electricity prices. For the C&T case, unit-level production decisions at the intensive margin from oligopolistic firm s are characterized by the following Euler condition,

$$
\begin{aligned}
&\underbrace{\frac{\bar{D}_t - \sum_{s=1}^{S}\sum_{j\neq i}^{n_s} y_{jts}(z^t)}{Y_t^c(z^t)} - \frac{2y_{its}(z^t)}{Y_t^c(z^t)}}_{\text{Output-price interaction}} - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \\
&2\alpha_{is}\delta \cdot \mathbb{E}\left[y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)|z^t\right] = \underbrace{\frac{\delta^{T-2t}}{1+\delta^{2(T-t)-1}}}_{\text{Uncertainty wedge}} \cdot \underbrace{\psi_{is}x_t(z^t)}_{\text{Emissions cost}}\ ,\ \forall t = 1, ..., T-2.
\end{aligned}
\tag{1.21}
$$

However, the analogous Euler equation in a carbon tax environment with per unit tax τ is instead given by,

$$
\begin{aligned}
&\underbrace{\frac{\bar{D}_t - \sum_{s=1}^{S}\sum_{j\neq i}^{n_s} y_{jts}(z^t)}{Y_t^c(z^t)} - \frac{2y_{its}(z^t)}{Y_t^c(z^t)}}_{\text{Output-price interaction}} - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \\
&2\alpha_{is}\delta \cdot \mathbb{E}\left[y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)|z^t\right] = \underbrace{\psi_{is}\tau}_{\text{Emissions cost}}\ ,\ \forall t = 1, ..., T-2.
\end{aligned}
\tag{1.22}
$$

The analogous expressions for firms in the competitive fringe are the same as (1.13) and (1.14) from the benchmark framework. Direct comparison of equations (1.13) with (1.21) and (1.14) with (1.22) proves an important fact: the size of the uncertainty wedge in output allocations between regulatory regimes is independent of the degree of market competition. This implies that the mechanism driving differences in welfare between control modes is immune to the possibility of strategic behavior in production decisions from ERCOT firms.

With oligopolistic firms, output is lower and electricity prices are higher in equilibrium relative to the competitive benchmark from Section 1.3. However, electricity demand is considerably price-inelastic at high frequency intervals[25] For quantitative results in this paper, a price-elasticity of demand of $\beta = 0.034$ implies that a percentage point increase in prices leads to a decrease in electricity consumption of just .034 percentage points. Hence, we would need non-trivial electricity price increases relative to competitive prices from Section 1.5 in order to observe quantitatively relevant differences in equilibrium output and welfare from accomodating strategic firm behavior. Such prices would not align with observed hourly electricity prices in ERCOT data.

1.6.2 Endogenous Capital Investment, Entry, and Exit

There is a large body of literature that studies long-term effects of carbon policy on emissions abatement via adjustments on the investment margin of firms and entrepreneurs[26]. In this section, I augment the benchmark model from Section 1.3.2 to endogenize capital investment decisions. The natural way is by endogeneizing investment decisions in capacity per energy type. This will also allow me to accomodate firm-level entry and exit dynamics. I prove that endogenizing firms' investment decisions does not affect the size of the wedge in output allocations between regulatory regimes. This implies that the mechanism driving differences in welfare between control modes is independent of capital dynamics.

[25]The policy experiment uses hourly realizations of electricity demand for the quantitative results.

[26]E.g. Barrage (2020), Fried (2018), Fowlie et al. (2016), Golosov et al. (2014).

Let n be the number of energy types (or technologies) available in the economy with which to produce electricity. At the beginning of period t, firms observe the demand shock z_t. Knowing history z^t, producers choose unit-level capacity per plant of energy type i for period $t+1$. I represent this dynamic decision with $\bar{y}_{i,t+1,s}(z^t)$. Moreover, firms face adjustment costs on capital investments besides the regular costs of acquiring necessary machinery and equipment[27]. These adjustment costs of capital increase with the size of investment relative to the existent capital stock at the unit level. I model this feature by assuming that total investment costs are given by a strictly increasing, strictly convex C^1 function $G(\bar{y}_{i,t+1,s} - \bar{y}_{its})$.

In this augmented environment, a competitive firm that operates under a carbon tax solves the following problem while taking prices as given,

$$\begin{cases} \max\limits_{\{y_{its}(z^t), \bar{y}_{i,t+1,s}(z^t)\}_{i,t=1}^{n,T}} \sum\limits_{z^T \in Z^T} Q(z^T) \sum\limits_{t=1}^{T} \delta^{t-1} \sum\limits_{i=1}^{n} \Big[p_t(z^t) y_{its}(z^t) - (c_{is} + \tau \psi_{is}) y_{its}(z^t) \\ \qquad - \alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1}))^2 - G(\bar{y}_{i,t+1,s}(z^t) - \bar{y}_{its}(z^{t-1})) \Big] \\ \text{s.t. } \; 0 \leq y_{its}(z^t) \leq \bar{y}_{its}(z^{t-1}), \; \forall i = 1, ..., n, \forall t = 1, ..., T, \; \forall z^t \in Z^t \\ \qquad z_0, \{y_{i0s}, \bar{y}_{i1s}\}_{i=1}^{n} \text{ — given.} \end{cases} \tag{1.23}$$

Alternatively, a price-taking firm under a C&T system solves the following problem,

[27]These adjustment costs are necessary for having positive bounded levels of capacity per energy type at the unit level. See Hayashi (1982b).

$$
\begin{cases}
\max_{\{y_{its}(z^t),\bar{y}_{i,t+1,s}(z^t),m_{t+1,s}(z^t)\}_{i,t=1}^{n,T}} \sum_{z^T \in Z^T} Q(z^T) \sum_{t=1}^{T} \delta^{t-1} \Bigg\{ \sum_{i=1}^{n} \Big[p_t(z^t) y_{its}(z^t) - c_{is} y_{its}(z^t) \\
\quad - \alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1}))^2 - G(\bar{y}_{i,t+1,s}(z^t) - \bar{y}_{its}(z^{t-1})) \Big] - x_t(z^t)(m_{t+1,s}(z^t) \\
\quad - m_{ts}(z^{t-1})) \Bigg\} \\
\\
\text{s.t.} \quad 0 \leq y_{its}(z^t) \leq \bar{y}_{its}(z^{t-1}), \ \forall i = 1, ..., n, \forall t = 1, ..., T, \ \forall z^t \in Z^t \\
\qquad \sum_{t=1}^{T} \sum_{i=1}^{n} \psi_{is} y_{its}(z^t) = m_{Ts}(z^{T-1}), \ \forall z^T \in Z^T \\
\qquad z_0, m_{1s}, \{y_{i0s}, \bar{y}_{i1s}\}_{i=1}^{n} \ \text{— given.}
\end{cases}
\tag{1.24}
$$

In this augmented environment, competitive equilibrium dynamics imply that the equations regulating how differences in output allocations translate into welfare discrepancies between carbon taxes and permit systems are still described by (1.14) and (1.13), respectively. The only difference is that contingent production plans at the unit level are now technologically constrained by endogenous capacity limits. This implies that the size of the wedge in output allocations between regulatory regimes is independent of endogenous capital dynamics.

Quantitative results on welfare *differences* between control modes are robust to whether investment dynamics are endogenous or exogenous[28]. This is because quantitative results from comparing relative welfare across price-equivalent control modes tacitly account for such investment responses. Since emissions prices across regulation modes are the same on average, adjustments on the investment margin are

[28]This is not the case with welfare levels because with endogenous investment decisions firms can adjust their mix of energy units to further minimize the policy costs.

also in line with each other. This implies that quantitatively relevant discrepancies in welfare would still generate from demand risk driving differences in output allocations between regulatory regimes rather than differences on investment decisions.

1.7 Concluding Remarks

Traditional thinking in economic literature has predominantly been to consider imperfect information about marginal benefits and marginal costs of abatement as the leading source of differences in welfare between policy instruments. Weitzman-style analyses determine the welfare-maximizing regulatory regime by comparing relative slopes between marginal costs and marginal benefits of abatement given the existence of idiosyncratic shocks at the firm-level. I analyzed the dynamic implications of demand uncertainty about the polluting goods as a fundamentally and empirically relevant source of uncertainty that matters for the choice of the policy instrument. With uncertainty about future output demand, demand risk distorts production decisions through unpredictably volatile permit prices in the case of quantity-based regulation. Therefore, the choice of the policy instrument depends on how firms and consumers balance aggregate output volatility vs. output price volatility, not on the relative slopes of marginal benefits and marginal costs of abatement.

I implemented a policy experiment with plant-level data from the Texas electricity market. For a wide range of abatement targets consistent with policy goals from active U.S. permit systems, I find that carbon taxes outperform cap-and-trade in terms of welfare. Similar qualitative results could be expected for other power markets with quantitatively similar demand uncertainty, energy composition of installed capacity and plant-wise marginal costs per fuel type. This finding underscores the importance of rethinking the leading role that has been assigned to permit systems over carbon taxes in key U.S. energy markets.

Chapter 2

DO VERTICAL ARRANGEMENTS MATTER FOR COST-EFFECTIVENESS OF OUTPUT SUBSIDIES?

2.1 Introduction

The relevance of wind power as a key energy source for the economy has significantly increased during the last two decades. As of 2000, generation from wind as a percentage of total U.S. power production barely reached 0.1%. By 2020, that share had increased to 8.4%. The growing reliance on wind power as an alternative to thermal generation has been reinforced by a wide variety of state and federal-level initiatives that subsidize investments in wind capacity. The Production Tax Credit (PTC), a subsidy program for non fossil fuel facilities extended until 2025 under the $386B climate package of the Inflation Reduction Act, is a leading example of such initiatives.

This expansive trend has motivated the necessity to develop bilateral procurement contracts that wind developers use as a channel to access financing. This is because wholesale electricity prices are volatile and uncertain. Therefore, debt investors are generally reluctant to finance wind projects without some guarantee that the stream of revenues can predictably cover financing costs. Developers achieve this by locking a price for electricity that will be eventually produced by the wind project through the use of procurement contracts with a future buyer. In this paper, I investigate how the structure of procurement contracts matters for cost-effectiveness of policies that subsidize wind investments (e.g. the PTC).

Developers typically rely on two central types of contract structures for providing proof of creditworthiness[29]. First, pay-as-produced contracts are negotiated directly with a utility offtaker, who commits to buy electricity from the project at a fixed price per MWh whenever the unit is available for production[30]. Alternatively, in fixed-volume contracts the developer agrees to deliver a specific quantity of output on a period-by-period basis. These contracts are negotiated by her either with a utility offtaker or a financial institution. In the case of financial institutions, the bank acts as a hedging party that swaps the stream of floating payments received by the developer in the wholesale market for a stream of fixed payments.

These features of market institutional design imply that a fixed-volume contract represents a commitment on a deliverable quantity and a price from both parties, while a pay-as-produced agreement requires just a commitment to a price. Hence, contract types interact differently with investment incentives because fixed-volume contracts expose the developer to a non-linear pricing schedule: i) a predetermined contract price for production within the volume limit, and ii) an uncertain market price for generation beyond that threshold. This implies that output subsidies have different impacts in investment incentives depending on the type of contract held by the developer.

To understand how these features of procurement contracts matter for cost-effectiveness of subsidies to wind investments, I develop an analytical framework to model the extensive and intensive margins of investment decisions in intermittent

[29]As of 2018, more than 90% of existing wind projects had been developed either under a Power Purchase Agreement (either physical or syntethic) or a bank hedge. See Bartlett (2019)

[30]Production at wind farms depends on exogenous weather conditions (e.g. consistent availability and speed of wind).

renewable sources (e.g. solar and wind). I use this model to investigate the differentiated effects of contract type on investment incentives of the developer. This allows to study how output subsidies (e.g. the PTC) have different effects on investment decisions that depend on the type of contract associated to the project. Subsequently, I exploit variation in unit-level production and installed capacity data from the universe of ERCOT firms to estimate structural parameters of the model[31]. ERCOT is the U.S. power market with the most wind turbine generation and installed capacity. I use the estimated model to quantify the decrease in expected payments to wind developers, given an investment rate target, from using an alternative subsidy scheme where payments are conditional on contract types relative to a standard subsidy structure with a fixed output subsidy that is independent of contract types.

This paper delivers two key findings. First, the subsidy scheme that minimizes total public expenditures for a given investment target conditions transfers to developers on contract type. Specifically, for projects under fixed-volume contracts, a subsidy per unit of output is allotted only to production units beyond the volume limit. However, all output units from projects associated to pay-as-produced agreements receive the same fixed subsidy. The per unit subsidy to projects with fixed-volume contracts is larger than for pay-as-produced agreements to account for endogenous selection into contract types. Second, I find for the Texas wind power industry that implementing this alternative subsidy structure leads to major reductions in expected transfers to developers without undermining investment incentives. For instance, a 10% investment rate is consistent with a decrease in expected subsidy payments of ∼50% relative to standard subsidy policies with fixed payments per unit of output that are independent

[31]Electric Reliability Council of Texas (ERCOT) is the regional market that supplies ∼90% of Texas electricity demand.

of contract types. This is important because in practice such subsidy payments are typically funded with distorting taxes on consumers or firms.

This paper is closely related to studies from several strands of literature. First, this paper advances environmental literature on the effects of financial incentives on wind investments[32]. Second, I contribute to research that assesses the role of institutional design features of energy markets (e.g. procurement contracts) on investment outcomes[33]. Last, this study contributes to work on optimal capital accumulation theory in presence of risk and capital adjustment costs[34]. This paper departs from existing literature by investigating how the link between procurement contract design and investment incentives at the extensive (i.e. energy type decision) and intensive margins (i.e. plant size) matters for cost-effectiveness of output subsidies like the PTC.

I structure the paper as follows. Section 2.2 develops the baseline analytical model. Section 2.3 extends the baseline framework to model the effect of alternative contract design on investment incentives. Section 2.4 describes the data, simulation, and estimation procedure. I report quantitative findings in Section 2.5. Last, I draw concluding remarks in Section 2.6.

[32]See Aldy et al. (2018), Schmalensee (2016), Fell and Linn (2013), Hitaj (2013), Schmalensee (2012), Yin and Powers (2010), Bird et al. (2005)

[33]See Joskow (1987) and more recently Cicala (2015)

[34]See Dixit et al. (1999), Dixit et al. (1999), Abel et al. (1996), Dixit (1995); Kaslow and Pindyck (1994); Pindyck (1993); He and Pindyck (1992), Pindyck (1991), and Hayashi (1982a)

2.2 Baseline Model

Consider an infinite horizon setup with discrete time where a power producer engages in an investment project. The project consists in building a new power plant and requires the firm to make decisions along the following two dimensions: energy type of the plant and size of the investment – i.e. its capacity limit m. Specifically, the firm can decide between a fossil fuel unit (e.g. a natural gas plant) or a "green energy" unit (e.g. a wind farm).

There are two key differences between both energy types. Firstly, fossil fuel units have positive marginal costs of production while green energy units have zero[35]. Marginal costs $c(q)$ for fossil fuel units are positive because the plant needs to meet fuel input requirements per unit of output at a price of q in order to produce electricity. The firm is competitive in both electricity and fuel input markets, and the price of fuel inputs q follows a first order Markov process $\pi(\cdot|q)$. The electricity price p is given to the competitive firm and follows an i.i.d. process J with constant mean. Second, production at fossil fuel unit is endogenous and takes place whenever $p \geq c(q)$ – in which case the power unit produces at maximum capacity m. However, production at the green energy unit is exogenous as it depends on local weather conditions[36]. Particularly, assume that the capacity factor $\theta \in [0, 1]$ associated to the green energy unit follows a first order Markov process $H(\cdot|\theta)$ with constant mean[37].

[35] This is consistent with the fact that electricity produced at wind turbines or solar panels bears negligible costs at the intensive margin.

[36] Generation at solar stations and wind farms depends on availability of sunlight and wind speed, respectively.

[37] Capacity factor is defined as the proportion of a unit's capacity m that is used for production

Let $i \in \{f, g\}$ where $i = f$ indexes the fossil fuel unit and $i = g$ represents the green energy plant. Here, F_i represents the dollar cost of acquiring investment goods for adding an extra capacity unit at plant of energy type i. Following Hayashi (1982a), the developer also incurs in installation costs for increasing plant-level capacity. Thus, total capital costs of increasing current installed capacity from m to m' in the following period at plant i are given by,

$$\underbrace{F_i \cdot (m' - m)}_{\text{Cost of investment goods}} + \underbrace{G_i \left(\frac{m' - m}{m} \right)}_{\text{Installation costs}}, \ G_i' > 0, G_i'' > 0. \tag{2.1}$$

Convex costs in capital accumulation capture how investment costs depend on the size of the investment relative to current capacity. These adjustment costs play a key role in determining the dynamics of power plant size. A higher degree of convexity implies smaller investments and lower capacity m' that becomes available the period after investments are realized.

The firm's investment decision encompasses two mutually exclusive choices. First, after observing contemporaneous prices p and q, the firm can decide to: i) build the fossil fuel unit, or ii) build the green energy plant. Conditional on the energy type decision, the firm makes subsequent period-by-period investments in capacity. If the firm decides to build the fossil fuel unit, it earns the expected payoff $V_f(0, q)$ described by the following Bellman equation[38],

at a given period. For instance, a 1 MW capacity wind turbine running at a 50% capacity factor for a given hourly period means that the turbine generated .5 MWh during that time frame. Put differently, θ indicates how fully a unit's capacity is used.

[38] $\mathbb{I}_{\{p \geq c(q)\}}$ is an indicator variable that takes the value of 1 whenever $p \geq c(q)$ and 0 otherwise.

$$
\begin{aligned}
V_f(m,q) = \max_{m' \geq 0} \Big\{ & \mathbb{I}_{\{p \geq c(q)\}} \cdot (p - c(q))m - F_f \cdot (m' - m) \\
& - G_f \left(\frac{m' - m}{m} \right) + \beta \int_{p' \in \mathscr{P}} \int_{q' \in \mathscr{Q}} V_f(m', q') \pi(dq'|q) J(dp') \Big\}
\end{aligned} \tag{2.2}
$$

with (m, q) as state variables and where $\beta \in (0, 1)$ represents the discount factor. Alternatively, the firm can choose to build the green energy unit. Choosing this action makes the firm earn the expected payoff $V_g(0, \theta)$ given by the following equation with state (m, θ),

$$
\begin{aligned}
V_g(m,\theta) = \max_{m' \geq 0} \Big\{ & \theta m p - F_g \cdot (m' - m) - G_g \left(\frac{m' - m}{m} \right) + \\
& \beta \int_{\theta \in \Theta} \int_{p' \in \mathscr{P}} V_g(m', \theta') H(d\theta'|\theta) J(dp') \Big\}
\end{aligned} \tag{2.3}
$$

Hence, a profit-maximizing firm chooses the alternative that maximizes expected payoff given current electricity and fossil fuel prices. Using (2.2), (2.3), the investment problem of a competitive developer can be defined with the following Bellman equation,

$$
V(q, \theta) = \max \{ V_f(0, q)), V_g(0, \theta) \} . \tag{2.4}
$$

Equation (2.4) captures the fact that the firm's investment decision is multidimensional. This is because a developer chooses the unit's energy type upon observing current period fossil fuel prices. Then, it makes subsequent plant capacity decisions on a period-by-period basis to maximize the expected discounted value of a project.

2.2.1 Characterization of the Optimal Investment Rule

The optimal investment rule encompasses both dimensions of the firm's investment decision. I provide and discuss a characterization of such solution while leaving all corresponding proofs to the Appendix in Section B.1.

When building a new power plant, the firm chooses between a fossil fuel unit or an intermittent one. Therefore, conditional on building the fossil fuel unit, plant capacity dynamics are given by the following Euler equation,

$$\begin{aligned} & - F_f - \frac{1}{m} G_f^{'} \left(\Delta'\right) + \beta \mathbb{E}_q \left[\mathbb{I}_{\{p' \geq c(q')\}} \cdot (p' - c(q')) \right] \\ & \qquad + \beta F_f - \frac{\beta}{(1+\Delta')m} \mathbb{E}_q \left[G_f^{'}(\Delta'')(1+\Delta'') \right] = 0 \end{aligned} \tag{2.5}$$

where $\Delta' = (m' - m)/m$ denotes the investment rate. Alternatively, building an intermittent unit means that plant capacity dynamics are characterized as follows[39],

$$- F_g - \frac{1}{m} G_g^{'}(\Delta') + \beta \mathbb{E}_\theta \left[\theta' p'\right] + \beta F_g - \frac{\beta}{(1+\Delta')m} \mathbb{E}_\theta \left[G_g^{'}(\Delta'')(1+\Delta'') \right] = 0. \tag{2.6}$$

Equations (2.5) and (2.6) plus the corresponding initial values fully determine plant capacity dynamics conditional on a particular energy type chosen by the developer.

[39] See Section B.1 for a derivation of Euler conditions (2.5) and (2.6).

The next step is to characterize the energy type decision. To do so, it is useful to notice that $V_f(0,q)$ is continuous and decreasing in the fossil fuel price q. If $V_f(0,0) \geq V_g(0,\theta)$, there exists a reservation price $q^*(\theta)$ defined as [40],

$$q^*(\theta) = inf \left\{ q \mid V_f(0,q) = V_g(0,\theta) \right\}. \tag{2.7}$$

The reservation price is key for determining the firm's energy type decision. A firm builds the fossil fuel unit if $q \leq q^*(\theta)$. Otherwise, $q > q^*(\theta)$ and the developer builds the intermittent green energy unit instead. Intuitively, if fossil fuel prices are above a threshold given by the reservation price $q^*(\theta)$, the cost of acquiring fuel inputs for producing output is so high that it renders the investment project less profitable relative to building a zero marginal cost intermittent unit. Moreover, since fossil fuel prices are time-persistent, it is likely that they remain high in the future as well. I summarize this optimal investment rule characterization in Theorem 1.

Theorem 1. *The following rule characterizes optimal firm investment decisions:*

1. *If $q \leq q^*(\theta)$, the developer chooses to build a fossil fuel unit and subsequent period-by-period capacity investments are chosen accordingly to (2.5).*
2. *Else, $q > q^*(\theta)$ and the developer chooses to build the intermittent green energy plant. Subsequent period-by-period capacity investments are determined in accordance to (2.6).*

Figure 10 provides a graphical interpretation of the result of Theorem 1. For a given capacity factor θ that captures the current state of weather conditions, if fossil

[40] See Section B.1 for a proof on these claims.

fuel prices are such that the firm's marginal costs from the fossil fuel unit are higher than the threshold $c(q^*)$, the power producer builds the renewable intermittent unit. Otherwise, it would be more profitable to build the fossil fuel unit. This baseline model provides the ideal starting point for examining how the commercial structure in contracting will interact with the investment decisions of the developer.

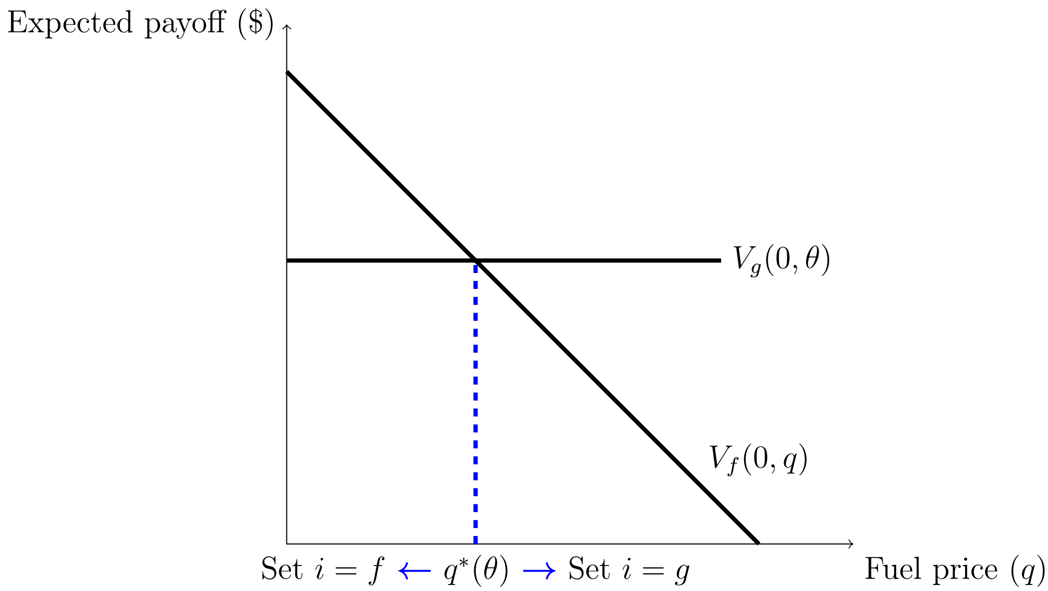


Figure 10. Graphical Interpretation of Energy Type Decision Rule

Note: This figure illustrates the energy type decisions rule. Upon knowing current weather conditions summarized by θ, is fossil fuel prices are above the reservation price $q^*(\theta)$, the developer builds a green energy unit (i.e. sets $i = g$). Otherwise, it builds a fossil fuel unit (i.e. sets $i = f$).

2.2.2 Relation with Tobin's Marginal Q

This theory can be connected to the strand of literature related to Tobin's marginal q in Tobin (1969) and its neoclassical interpretation. Following Hayashi (1982a), the existence of capital adjustment costs is fundamental to establish this connection since

Tobin's idea that investment rate depends on the ratio of the market value of new additional investment commodities to their replacement cost – i.e. the q-ratio – is conceptually equivalent to optimal capital accumulation with adjustment costs.

Consider the plant-level optimal capacity problem conditional on the developer choosing to invest in a green energy unit. Tobin's marginal q – which I represent with Q – is equal to the marginal value of one unit of capital installed at the intermittent unit. Therefore, define Q as,

$$Q = -F_g + \beta \mathbb{E}\left[\frac{\partial V_f(m'; \theta', p')}{\partial m'}\right]. \tag{2.8}$$

Inserting definition (2.8) in the FOC of problem (2.2) with respect to capital level m' yields,

$$Q = \frac{1}{m} G_g^{'} \left(\frac{m' - m}{m}\right) \tag{2.9}$$

or, equivalently,

$$\underbrace{m' - m}_{\text{Investment}} = m \left(G_g^{'}\right)^{-1} (mQ) \tag{2.10}$$

which means that period-by-period investment is a function of Tobin's marginal q. Additionally, the Envelope Condition of problem (2.3) with respect to capital m can be combined with (2.9), (2.10) and substituted into the definition of Q to obtain the following law of motion[41],

[41] I provide a proof on this derivation in Section B.1.

$$Q = \beta\mathbb{E}_\theta\left(\theta' p'\right) - (1-\beta)F_g + \mathbb{E}_\theta\left\{\left[1 + \left(G_g'\right)^{-1}(m'Q')\right]m'Q'\right\} \tag{2.11}$$

which captures the time persistence of Tobin's marginal q used to determine the investment rate. A similar procedure can be used to obtain the analogous expression for the case of the fossil fuel unit from problem (2.2).

2.3 Subsidies and the Role of Contract Design

2.3.1 Fixed-volume vs. Pay-as-produced Contracts

The analysis so far assumes developers sell production at floating prices directly into wholesale markets. However, developers typically lock their output price through procurement contracts so that debt investors who provide financing can use this as a guarantee that they can predictably recover financing costs from project revenues. In this section, I model how the contract structure (fixed-volume or pay-as-produced) matters for investment incentives of wind developers at the extensive and intensive margins. This is important for understanding how output subsidies – e.g. the PTC – can have heterogeneous effects on such margins depending on the contract type associated to the project.

Consider a fixed per unit output subsidy $s > 0$. A wind developer entering a fixed-volume contract with deliverable quantity y and price p_y earns the payoff $V_g^y(0, \theta)$ specified by the Bellman equation,

$$
\begin{aligned}
V_g^y(m,\theta) = \max_{m' \geq 0} \Bigg\{ & \mathbb{I}_{\{m>0\}} \cdot \Bigg[(p_y + s)y \quad + \underbrace{(p+s)(\theta m - y)}_{\text{Fixed-volume effect}} \Bigg] - F_g \cdot (m' - m) \\
& -G_g \left(\frac{m' - m}{m} \right) + \beta \int_{\theta \in \Theta} \int_{p' \in \mathscr{P}} V_g^y(m', \theta') H(d\theta'|\theta) J(dp') \Bigg\}
\end{aligned}
\tag{2.12}
$$

Equation (2.12) incorporates the effect on the firm's stream of revenues of the fixed-volume feature. The developer commits to deliver a volume of electricity y per period at a price p_y. Any output shortfall relative to delivery obligations is covered with electricity from the wholesale market bought at the spot price p. This means that the developer is exposed to volume risk – i.e. the probability of falling below delivery obligation y and having to cover the shortfall at a spot price higher than p_y. The decision m' optimally balances between insufficient generation (relative to y) and likelihood of significant unhedged production.

Alternatively, a wind developer entering a pay-as-produced contract that pays p_0 per unit of output instead earns a payoff $V_g^0(0,\theta)$ according to the Bellman equation,

$$
\begin{aligned}
V_g^0(m,\theta) = \max_{m' \geq 0} \{ & (p_0 + s)\theta m - F_g \cdot (m' - m) \\
& -G_g \left(\frac{m' - m}{m} \right) + \beta \int_{\theta \in \Theta} V_g^0(m', \theta') H(d\theta'|\theta) \Bigg\}
\end{aligned}
\tag{2.13}
$$

Equation (2.13) indicates that the firm under a pay-as-produced arrangement earns the per unit price p_0 whenever the wind plant is available for production. Moreover, since the utility offtaker buys whatever output is generated by the project, the contract removes all volume risk from the developer's side. This is because a pay-as-produced arrangement represents a commitment to a price p_0 per MWh. However, with a fixed-volume contract the commitment is both on a price p_y and a quantity y to trade.

Theorem 2 draws upon (2.12) and (2.13) to derive the key analytical predictions of the model. This result highlights the importance of the commercial structure of contracts. Both insights have been summarized in Corollary 2.3.1.

Theorem 2. *Optimal dynamics of wind capacity investments are dictated by the following equations,*

1. *Fixed-volume contract:*

$$\begin{aligned} &- F_g - \frac{1}{m} G_g^{'}(\Delta') + \beta \mathbb{E}_\theta \left[(p' + s)\theta' \right] + \\ &\quad \beta F_g + \frac{\beta}{(1+\Delta')m} \mathbb{E}_\theta \left[G_g^{'}(\Delta'')(1+\Delta'') \right] = 0 \end{aligned} \tag{2.14}$$

2. *'Pay-as-produced' contract:*

$$\begin{aligned} &- F_g - \frac{1}{m} G_g^{'}(\Delta') + \beta (p_0 + s) \mathbb{E}_\theta (\theta') + \\ &\quad \beta F_g + \frac{\beta}{(1+\Delta')m} \mathbb{E}_\theta \left[G_g^{'}(\Delta'')(1+\Delta'') \right] = 0 \end{aligned} \tag{2.15}$$

Proof. To obtain the Euler condition for the case of a fixed-volume contract, take the FOC with respect to m' in (2.12) to verify that,

$$- F_g - \frac{1}{m} G_g^{'} \left(\frac{m' - m}{m} \right) + \beta \mathbb{E}_\theta \left[\frac{\partial V_g^y(m'; \theta', p')}{\partial m'} \right] = 0. \tag{2.16}$$

Moreover, by the Envelope Theorem,

$$\frac{\partial V_g^y(m;\theta,p)}{\partial m} = \mathbb{I}_{\{m>0\}}(p+s)\theta + F_g + G_g^{'}\left(\frac{m'-m}{m}\right)\cdot\frac{m'}{m^2}. \tag{2.17}$$

Iterate (2.17) one period ahead and substitute into (2.16) to obtain (2.14). The procedure for the case of a 'pay-as-produced' contract is analogous: the resulting FOC has the same functional form as (2.16), but the Envelope condition is instead given by,

$$\mathbb{I}_{\{m>0\}}(p_0+s)\theta + F_g + G_g^{'}\left(\frac{m'-m}{m}\right)\cdot\frac{m'}{m^2} = \frac{\partial V_g^0(m;\theta)}{\partial m}. \tag{2.18}$$

Iterate (2.18) one period ahead and substitute into the corresponding FOC to obtain (2.15).

□

Corollary 1. *Output subsidies to production units that receive price p_y under the fixed-volume contract have no effect on optimal capacity decisions at the intensive margin. Moreover, if $\mathbb{E}(p') > p_0$, the optimal rate of investment Δ' is larger in projects with a fixed-volume contract. Otherwise, it is larger at projects under a pay-as-produced agreement.*

Proof. The first claim is immediate from equation (2.14). The second claim is a consequence of using $\mathbb{E}_\theta(p'\theta') = \mathbb{E}(p')\mathbb{E}_\theta(\theta')$ in (2.14) and comparing to (2.15). Notice that $\mathbb{E}_\theta(p'\theta') = \mathbb{E}(p')\mathbb{E}_\theta(\theta')$ follows from the fact that p' and θ' are independently drawn. □

Even though contract prices are parameters of the model, not any configuration is consistent with selection of developers into contract types. Selection exists because given a state θ, the expected payoff of the project is different across contract types. This implies that wind developers will choose the contract type that maximizes the expected payoff given the state. Hence, a combination of contract prices that is consistent with selection is one under which developers are indifferent across contract types, i.e. $V_g^y(0,\theta) = V_g^0(0,\theta)$. Otherwise, developers would only accept the profit-maximizing contract type. In that case, the buying side in the transaction would have incentives to offer a lower contract price as long as the wedge in expected payoffs across contract types remains.

2.4 Policy Experiment

2.4.1 Experiment Design

The goal of the policy experiment is to understand how subsidy payments change depending on the type of contract held by the developer. This will allow to determine payments conditional on contract type that can be designed to subsidize wind investments at the least possible cost. Since contract design affects how output subsidies impact investment incentives, this implies that for an arbitrary investment target there exists a cost-minimizing subsidy scheme of payments that is conditional on contract type.

The basic steps for implementing the policy experiment are as follows:

1. Simulate 1,000 different histories for capacity factor and wholesale price realizations.
2. Set deliverable quantity y and pay-as-produced contract price p_0. Define a set of values $\{s_k\}_{k=1}^{K}$ for the per-unit subsidy. At each s_k, solve the developer's problem under a pay-as-produced contract (i.e. problem (2.13)).
3. At each s_k, find the contract price p_y at which the project's expected payoff for the developer is independent of the contract type, i.e. $V_g^y(0;\theta,p) = V_g^0(0;\theta)$.
4. For an arbitrary investment rate, compare expected subsidy payments between contracts types.

I use equations (2.14) and (2.15) to compute numerical solutions for the policy functions of investment. Then, I use these policy functions to evaluate (2.12) and (2.13) to calculate the numerical solution of $V_g^y(0,\theta)$ and $V_g^0(0,\theta)$ in steps 2. and 3. Given the policy functions and $V_g^0(0,\theta)$ from step 2, I implement in step 3 an iterative approach for computing the contract price p_y by starting from an arbitrary initial value so that $V_g^y(0,\theta)$ equals $V_g^0(0,\theta)$.

2.4.2 Data

ERCOT, which manages $\sim 90\%$ of Texas electricity generation, is the U.S. power market that has experienced the largest increase in wind power capacity. This makes it an ideal empirical study case for this paper. I use three main data sources from the universe of ERCOT firms in the quantitative analysis. First, I use the 2019 EIA-860 and EIA-923 surveys to collect plant-level data on technological attributes from ERCOT wind firms. These are mandatory reports US power producers submit on a monthly and annual basis to the Energy Information Administration (EIA). The reports include data at the power plant level on unit identifier, electricity production, fuel costs (per energy source), fuel consumption and stocks, regulation status, energy-type emissions rates, and generation capacity limits, among other information. Second, I use ERCOT 2019 data on hourly load (in MWh) and balancing prices at the system level. This dataset includes information about hourly prices and power consumption at the aggregate and zonal level – i.e. North, North Central, South, South Central, and West zones.

2.4.3 Identification and Estimation

To estimate structural parameters, I define the necessary parametrizations for model primitives. First, I consider the following functional form of installation costs,

$$G_g\left(\frac{m'-m}{m}\right) = \alpha_g \left(\frac{m'-m}{m}\right)^2, \ m > 0. \tag{2.19}$$

Additionally, I define the following AR(1) structure and i.i.d. process to parametrize the stochastic processes for the capacity factor and wholesale prices, respectively,

$$\theta' = \rho_0 + \rho_1 \theta + \varepsilon', \ \varepsilon' \sim \text{unif}\left[-b, b\right]. \tag{2.20}$$

$$p' \sim \text{gamma}[k, \gamma] \tag{2.21}$$

I implement the estimation strategy in two steps. First, I calibrate the discount factor β, contract price p_0, and deliverable quantity y. Then, I use a Simulated Method of Moments (SMM) approach to estimate the unit cost of capacity F_g, installation costs parameter α_g, autoregression intercept ρ_0, autocorrelation parameter ρ_1, and white noise parameter b.

2.4.3.1 Step 1: Calibration

I report calibrated parameters in Table 8. I set the annual discount factor at $\beta = .98$. Additionally, I consider a contract price for pay-as-produced arrangements at a 10% discount relative to prevailing average wholesale prices. Last, I consider a deliverable quantity y parameter in line with average production from per MW of capacity available at wind farms in ERCOT.

Table 6. Calibrated parameters

Parameter	Definition	Value	Source
β	**Discount factor**	.98	Assumption
p_0	**Contract price**	34.2	Assumption
y	**Deliverable quantity**	843	EIA (2021)

Note: This table reports values of externally calibrated parameters. Units of deliverable quantity y are in MWh per month. The contract price is expressed in dollars per MWh.

2.4.3.2 Step 2: Estimation

I report estimation results and goodness-of-fit in Table 7. I use a SMM strategy to estimate the rest of structural parameters. To implement the SMM, I define a set of key moments for estimating each parameter of interest and use a number of moments equal to the number of parameters to be estimated. Then, I simulate the exogenous variation within the model – i.e. the history of shocks to electricity prices and capacity factor – to compute the simulated moments obtained from solving the economic model. Subsequently, I find the parameters that allow matching each of these model-dependent moments to those calculated from the data. I rely on a SMM approach given that it is not possible to compute analytical solutions of the key moments used to estimate cost parameters (F_g, α_g).

For technological parameters, I exploit cross-sectional variation in installed capacity across wind power firms to identify unit cost of capacity F_g. In addition, I use time variation in installed capacity within firms to identify installation cost parameter α_g. I do this by jointly estimating (F_g, α_g) to match average installed capacity across firms and average within-firm investment rate in wind capacity, respectively.

I estimate structural parameters of the stochastic processes for the capacity factor and wholesale prices using the following procedure. First, I exploit cross-sectional variation across wind power firms and time variation within firms in capacity factor data to identify parameters of the Markov process (2.20). I do this by jointly estimating (ρ_0, ρ_1, b) to match the following set of moments: i) average capacity factor across wind power firms, average within-firm (first order) autocorrelation of capacity factor realizations across firms, and iii) average variance of within-firm capacity factor realizations across producers. Then, I exploit time variation in 2019 day-ahead ERCOT electricity prices to identify parameters of the i.i.d. process (2.21) by jointly estimating (k, γ) to match the mean and variance of hourly day-ahead market prices.

Table 7. SMM estimation results

Parameter	Definition	Estimate	Target	Moment	
				Model	*Data*
F_g	**Unit cost of capacity**	1.76 (.52)	Avg. installed capacity (MW)	200	200
α_g	**Installation cost parameter**	.43 (.05)	Avg. investment rate (%)	3.7	3.7
ρ_0	**Autoregression intercept**	.20 (.01)	Avg. capacity factor (%)	35	35
ρ_1	**Autocorrelation parameter**	.42 (.11)	First-order autocorrelation	.42	.42
b	**White noise parameter**	.24 (.07)	Variance capacity factor	.03	.03
k	**Shape parameter**	1.76 (.2)	Avg. day-ahead electricity price	38	38
γ	**Scale parameter**	21.54 (3.4)	Std. dev. day-ahead electricity price	28.6	28.6

Note: This table reports SMM estimation results for structural parameters that were not calibrated in Step 1. Empirical moments are calculated from installed capacity data from ERCOT wind power producers in the EIA-860 and EIA-923 surveys. Values in parenthesis from column 'Estimate' correspond to bootstrapped standard errors.

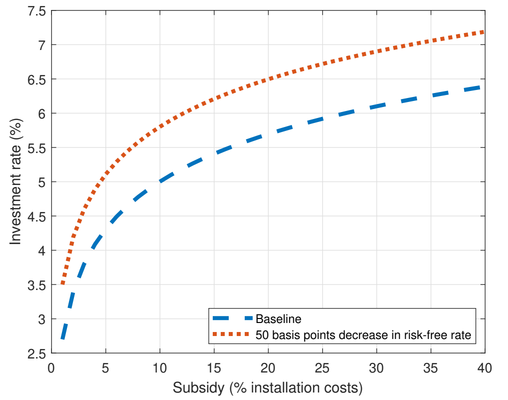
2.5 Results

I report main results in Figure 11 and Figure 12. Panel (a) in Figure 11 shows the set of contract price configurations that account for selection intro contracts types. This is because at any pair of prices in the blue dashed line, wind developers earn the same expected payoff independently of the contract type. An increase in contract prices of pay-as-produced agreements p_0 requires higher prices of fixed-volume contracts in order for expected payoffs to remain equivalent across contract types.

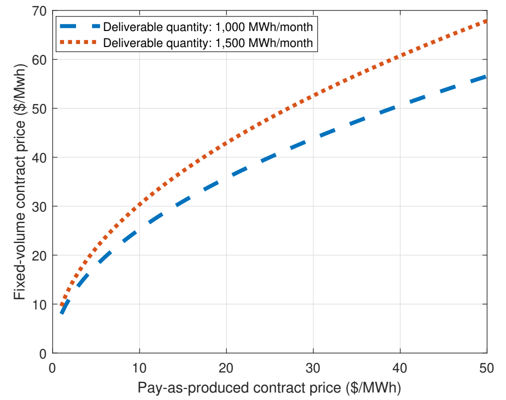
Panel (b) shows how the set of contract price configurations that account for selection into contract types changes with different deliverable quantities specified in the fixed-volume agreement. Given a contract price p_0 for pay-as-produced agreements, higher deliverable quantities imply that developers incur in more costs to develop larger wind farms to meet contract obligations. This requires a higher fixed-volume contract price p_y for developers to remain indifferent across contract types.

Panel (c) reports how the investment rate of a project under a pay-as-produced contract changes with an increase of the contract price p_0. A higher contract price p_0 increases the profitability of adding more capacity units and incentivizes larger investment rates. However, the investment rate of projects under a fixed volume contract is independent of contract prices as the profitability of adding an extra unit of capacity depends only on average wholesale prices – see equation (2.14).

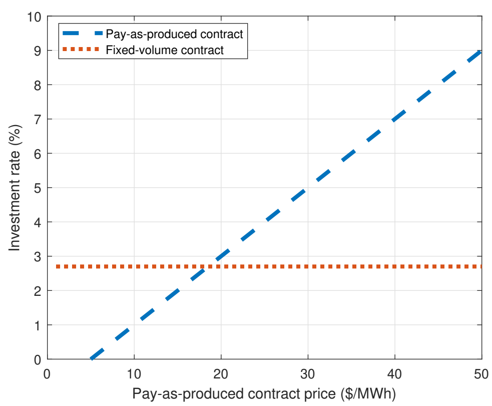
Panel (d) considers the case in which subsidy payments are conditional on contract types. Subsidies to capacity investments do not affect incentives at the extensive margin for projects under fixed-volume contracts (see Corollary 2.3.1). Therefore, an alternative design to output-based subsidization policies with fixed per-unit transfers (e.g. the PTC) is to only subsidize output units beyond the volume limit in the case of projects under fixed volume contracts. Panel (d) shows that the contract-wise subsidy payment per MWh needed for developers to be indifferent across contract types would be significantly larger for fixed-volume contracts to account for selection into contracts.



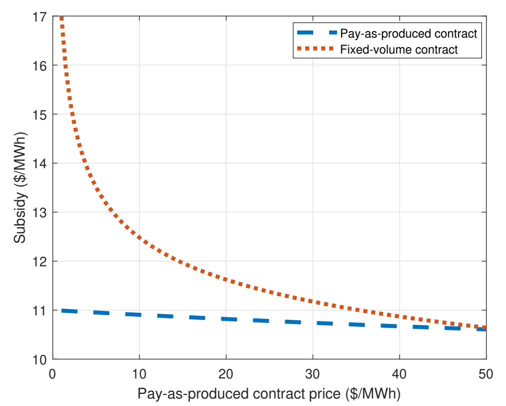
(a) Contract Prices & Avg. Wholesale Price



(b) Contract Prices & Deliverable Quantities



(c) Investment Rates



(d) Production Tax Credit

Figure 11. Contract Prices, Investment Rates and Subsidy Payments

Note: This figure shows simulation results on contract prices, investment rates in wind capacity, and per unit subsidies across contract types. The blue dashed represents results for wind developers on pay-as-produced agreements while the red dotted line reports results for the case of fixed-volume contracts.

Figure 12 delivers the key policy implication. It shows that if subsidy payments were structured accordingly with results from panel (d) in Figure 11, it is possible to design a subsidy scheme that implements a given investment target at a significantly lower cost in terms of payments issued to wind developers. This is because under this alternative subsidization design, wind developers under fixed volume contracts receive the output subsidy only for production beyond the volume limit. Therefore, total payments are lower at any given investment rate even if subsidies per MWh are higher than the payments issued to developers with pay-as-produced contracts.

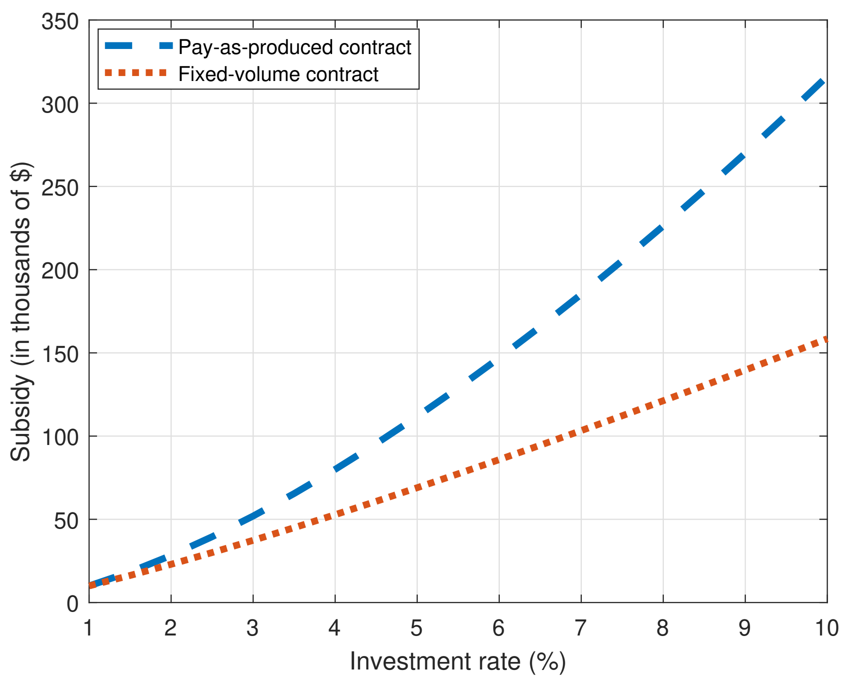


Figure 12. Total Subsidy Payments across Contract Types

Note: This figure shows simulation results on total subsidy payments to developers across contract types under the proposed alternative subsidization scheme. The blue dashed represents results for wind developers on pay-as-produced agreements while the red dotted line reports results for the case of fixed-volume contracts.

Business-as-usual subsidization policy under initiatives like the PTC provide the same fixed subsidy per MWh independently of the contract type under which the wind farm is developed. However, from a point of view of policy cost-effectiveness, these results imply that conditioning subsidy payments based on contract types can translate into major savings in terms of tax revenues allotted to wind developers that hold fixed-volume contracts. This is important as such reductions in policy costs do not undermine investment incentives in capacity at the intensive margin for developers holding fixed-volume contracts.

2.6 Concluding Remarks

For more than three decades, the Production Tax Credit has constituted a primary channel through which the federal government allocates subsidies to wind investments. In this paper, I have shown that conditioning such subsidy payments based on contract types can significantly reduce the amount of tax revenues needed to implement any given investment target in wind generating capacity. This is because in the case of of wind projects associated to fixed-volume contracts, output subsidies to production within the volume limits have no effect on investment incentives in capacity at the intensive margin. Therefore, significant reductions in transfers to wind developers can be achieved through an alternative incentives scheme that only subsidizes production beyond the volume limit in the case of wind developers holding fixed-volume contracts – without undermining investment incentives from wind project developments.

Future iterations of this project will extend the analytical framework in this paper to an equilibrium model that incorporates electricity demand and generation from thermal power plants. The purpose of extending the analysis along this dimension will be to account for the effect of output subsidies from the Production Tax Credit on equilibrium electricity prices. This is important as the downward adjustment on equilibrium prices will partially offset the effect of output subsidies on investment incentives at the intensive margin of wind developers holding fixed-volume contracts. Additionally, it will allow to derive policy implications about the advantages of subsidy schemes that condition payments on contract type from the viewpoint of an equilibrium welfare analysis.

Chapter 3

SHOULD WE SUBSIDIZE PRODUCTION OR INVESTMENT GOODS?

3.1 Introduction

The U.S. federal government has an established history of heavily subsidizing the wind power industry. Just in 2019, it allocated \$4.7B worth of subsidies. Moreover, its commitment went a step further when it allocated a major proportion of the \$386B climate package of the recently passed Inflation Reduction Act (henceforth, the 'Act') to incentivize investments in clean energy like wind power. Two key components of this climate package are the extensions of the Production Tax Credit (PTC) and the Investment Tax Credit (ITC) in Section 45 and Section 48 of the Act, respectively. Under the PTC, wind developers are eligible for \$26/MWh of output for 10 years after completion of the wind facility (in 2022 dollars). Alternatively, under the ITC taxpayers qualify for a subsidy equal to 30% of their total investment costs. Which subsidy is more cost-effective? In this paper, I investigate which subsidy type minimizes the required public expenditures to meet a given investment target.

A primary distinction between both subsidy types consists in the fact that payments under the PTC throughout that 10-year period are stochastic because production at wind farms critically depends on uncertain weather conditions (e.g. local availability and speed of wind). However, the one-time payment under the ITC is known with absolute certainty by the time the developer decides to build the wind project. This distinction is central from the point of view of economic behavior. There is important empirical evidence that agents exhibit *prudent* behavior (i.e. convex marginal utility of consumption) when considering investment decisions[42]. Moreover, prudent wind developers will save a larger share of their investment income with a PTC when the expected present value of subsidy payments is equal to the one-time certain payment they would receive under an alternative ITC. This is because prudent developers accumulate wealth as a channel to self-insure against adverse income variations in the future by saving to even out periods with low (or null) PTC payments. Consequently, a part of these precautionary savings translates into larger investments than with an alternative ITC.

I study this mechanism by developing a dynamic framework that models the entrepreneur's consumption and investment decisions in wind capacity and a risk-free asset. The availability of a risk-free asset captures the fact that in practice entrepreneurs face a variety of investment alternatives that compete with wind investments. I incorporate risk aversion and prudence as critical features of the entrepreneur's preferences over intertemporal consumption choices. Next, I estimate the structural parameters of the model by using a SMM strategy that exploits variation in unit-level production and capacity data from ERCOT wind facilities[43]. ERCOT constitutes the U.S. power market with the largest stock of wind generation capacity. This makes it an ideal empirical setup for studying the interaction of subsidy type with wind investment outcomes. Last, I use this model to quantify the difference in investment rates across subsidy types for a given expected present value of subsidy payments.

[42]See Carroll and Samwick (1998), Carroll and Samwick (1998), Carroll et al. (2003), and Hurst et al. (2010).

[43]Electric Reliability Council of Texas (ERCOT) is the regional transmission organization that supplies ∼90% of Texas electricity demand.

The policy experiment delivers two key findings. First, I find that within a reasonable range of subsidy payments, the PTC can increase average yearly investment rates in wind capacity up to 2.5 percentage points over mean investment rates under an alternative ITC. This is explained by precautionary savings from developers with prudent behavior aiming to smooth out adverse shocks to investment income under the PTC. Therefore, a portion of these precautionary savings is allocated to additional wind investments. This implies that output subsidies are more cost-effective at achieving a given investment target than alternative investment subsidies. Second, I also find that average yearly investment rates in wind capacity significantly increase due to: i) decreases in the risk-free rate of return, ii) increases in relative prudence (e.g. due to higher relative risk aversion), and iii) increases in the variance of plant-level productivity at wind facilities (which primarily depends on weather conditions).

This paper contributes to two different strands of economic literature. First, it advances research efforts aiming to understand the relative welfare consequences of subsidies to consumption and investment goods[44]. Second, it also contributes to literature on prudent investment behavior and precautionary savings[45]. This paper extends previous work by providing a theory and first estimates of how prudent behavior matters for cost-effectiveness in the context of alternative subsidies (i.e. the PTC and ITC) to the wind industry.

The rest of the paper is structured as follows. Section 3.2 lays down the analytical model. Section 3.3 describes the policy experiment and estimation procedure. Section

[44] See Goolsbee (2004), House and Shapiro (2008), Groote and Verboven (2019), Schmalensee (2012), and Johnston (2019).

[45] See Courbage and Rey (2019), Crainich et al. (2013), Dionne and Li (2011), Ebert and Wiesen (2011), Eeckhoudt and Gollier (2011), Kimball (1990), and Mayrhofer (2017).

3.4 reports the key quantitative findings. Section 3.5 discusses key connections of results to literature and research agenda for future iterations. Last, Section 3.6 concludes.

3.2 Model

Consider an infinite horizon environment with discrete time and a set of identical risk-averse entrepreneurs that maximize lifetime utility of consumption. Preferences over intertemporal consumption are described by the additively separable utility function,

$$\sum_{t=0}^{+\infty} \beta^t u(c_t) \tag{3.1}$$

with discount factor $\beta \in (0,1)$ and instant utility given by a C^3 function $u : \mathbb{R}_+ \to \mathbb{R}$ that satisfies $u' > 0$ and $u'' < 0$. Additionally, I assume $u''' > 0$ to account for prudent behavior.

At each period t, the stand-in entrepreneur earns labor income for inelastically supplying all of her time endowment in the labor market in exchange for a wage w. If income is not consumed, she can save by investing a portion of her income on a wind project or on an alternative one-period risk-free asset. Investing a_{t+1} consumption units on the asset at t pays Ra_{t+1} units of consumption in period $t+1$ where $R > 1$.

Wind investments require that the entrepreneur chooses capacity levels m_{t+1} for the wind farm which become available at the beginning of the subsequent period given current capacity m_t. There are two types of costs associated to investing in wind capacity. First, the entrepreneur faces a fixed cost F per unit of capacity added. This represents the cost of acquiring machines and equipment necessary to increase installed capacity. Second, there are installation costs $G\left(\frac{m_{t+1}}{m_t}-1\right)$ that are strictly increasing on the investment size relative to existing capacity. There is no depreciation.

Marginal costs at the wind farm are zero and production is exogenous as it depends on availability and speed of wind. Namely, output is determined by an exogenous capacity factor $\theta_t \in [0,1]$ whose dynamics are dictated by the stochastic process $J(\theta_{t+1}|\theta_t)$ with state space Θ and constant mean. This capacity factor refers to the proportion of a unit's capacity that is used for production at a given period[46]. Each unit produced at the wind farm is sold in a wholesale market at the price p_t. The entrepreneur behaves competitively in the wholesale market and the competitive price p_t evolves according to the stochastic process $H(p_{t+1}|p_t)$ with state space P and constant mean. Once built, a wind farm remains active forever – although capacity units may be sold back in the market at the per unit installation cost F.

The environment structure implies that the entrepreneur faces the following sequential budget constraint at each period t,

$$c_t + \underbrace{F(m_{t+1}-m_t)}_{\text{Installation costs}} + a_{t+1} \leq w + \underbrace{p_t\theta_t m_t - G\left(\frac{m_{t+1}}{m_t}-1\right)}_{\text{Wind farm profits}} + Ra_t. \tag{3.2}$$

Period by period consumption spending, installation costs, and asset acquisitions must be covered with labor income, profits from selling wind electricity in the wholesale

[46]For instance, a 2MW capacity wind turbine running at a 50% capacity factor for a given hourly period means that the turbine generated 1 MWh during that time frame. Therefore, θ indicates how fully a unit's capacity is used given weather conditions

market, and proceeds from last period investments in the financial asset. Upon observing prices w_t, p_t and the gross rate of return R, the entrepreneur chooses consumption c_t, wind capacity m_{t+1}, and asset holdings a_{t+1} to maximize the expected discounted value of her lifetime utility flow, i.e.

$$\begin{cases} \max\limits_{\{c_t, m_{t+1}, a_{t+1}\}_{t=0}^{\infty}} & \mathbb{E}_0 \sum\limits_{t=0}^{+\infty} \beta^t u(c_t) \\ \text{s.t.} & c_t + F(m_{t+1} - m_t) + a_{t+1} \leq \\ & \quad w + p_t \theta_t m_t - G\left(\dfrac{m_{t+1}}{m_t} - 1\right) + Ra_t, \ \forall t \\ & c_t, m_{t+1} \geq 0, \ \forall t \\ & m_0, a_0 \text{ — given.} \end{cases} \tag{3.3}$$

3.2.1 Production Tax Credit vs. Investment Tax Credit

Production Tax Credit — The entrepreneur pays a lump-sum tax T_t and receives an ad-quantum subsidy $S > 0$ per unit of electricity produced at the wind farm. This sequence of tax payments is exogenously determined by the government and publicly announced at period 0. Therefore, her new sequential budget constraint is given by,

$$c_t + \underbrace{F(m_{t+1} - m_t)}_{\text{Installation costs}} + a_{t+1} \leq w + \underbrace{(p_t + S)\theta_t m_t - G\left(\frac{m_{t+1}}{m_t} - 1\right)}_{\text{Wind farm profits}} + Ra_t - T_t. \tag{3.4}$$

Revenues to the entrepreneur from the PTC are inherently stochastic. This is because payments depend on the level of electricity output which in random – i.e. depends on the realization of the period-specific capacity factor θ_t.

Investment Tax Credit — The government issues to developers a one-time payment at $t = 0$ that represents a fixed proportion $s \in [0, 1]$ of the entrepreneur's installation costs. This means that her sequential budget constraint for $t = 0$ must account for net installation costs as follows,

$$c_0 + \underbrace{(1-s)F(m_1 - m_0)}_{\text{Installation costs}} + a_1 \leq w + \underbrace{p_0\theta_0 m_0 - G\left(\frac{m_1}{m_0} - 1\right)}_{\text{Wind farm profits}} + Ra_0 - T_0. \tag{3.5}$$

In this case, the level of additional resources to the developer is certain. This is because conditional on receiving the subsidy, such payment does not depend on any decision beyond period 0 that could require observing the realization of θ_t. The sequential budget constraint for periods after 0 preserves the same form as in (3.2).

3.2.2 Characterization of the Optimal Investment Rule

Production Tax Credit — Using (3.4) to solve the entrepreneur's utility maximization problem (3.3) delivers the following Euler equations that jointly characterize optimal dynamics of consumption, capacity investments, and asset holdings,

$$c_t = w + (p_t + S)\theta_t m_t - G\left(\frac{m_{t+1}}{m_t} - 1\right) + Ra_t - T_t - F(m_{t+1} - m_t) - a_{t+1} \tag{3.6}$$

$$\underbrace{u'(c_t)\left[G'\left(\frac{m_{t+1}}{m_t}-1\right)\frac{1}{m_t}+F\right]=}_{\text{Utility value of consumption forgone in } t \text{ to increase capacity in 1 MW}}$$
$$\underbrace{\beta\cdot\mathbb{E}_t\left\{u'(c_{t+1})\left[\theta_{t+1}(p_{t+1}+S)+G'\left(\frac{m_{t+2}}{m_{t+1}}-1\right)\frac{m_{t+2}}{m_{t+1}^2}+F\right]\right\}}_{\text{Expected utility value of extra consumption in } t+1 \text{ due to marginal increase in capacity}} \tag{3.7}$$

$$u'(c_t)=\beta R\cdot\mathbb{E}_t\{u'(c_{t+1})\}. \tag{3.8}$$

Investment Tax Credit — Analogously, one can solve the utility maximization problem (3.3) while using budget constraint (3.5) for period $t=0$ to jointly characterize optimal dynamics of consumption, wind farm capacity investments, and asset holdings,

For period $t=0$:

$$c_t=w+p_t\theta_t m_t-G\left(\frac{m_{t+1}}{m_t}-1\right)+Ra_t-T_t-(1-s)F(m_{t+1}-m_t)-a_{t+1} \tag{3.9}$$

$$\underbrace{u'(c_t)\left[G'\left(\frac{m_{t+1}}{m_t}-1\right)\frac{1}{m_t}+(1-s)F\right]=}_{\text{Utility value of consumption forgone in } t \text{ to increase capacity in 1 MW}}$$
$$\underbrace{\beta\cdot\mathbb{E}_t\left\{u'(c_{t+1})\left[\theta_{t+1}p_{t+1}+G'\left(\frac{m_{t+2}}{m_{t+1}}-1\right)\frac{m_{t+2}}{m_{t+1}^2}+F\right]\right\}}_{\text{Expected utility value of extra consumption in } t+1 \text{ due to marginal increase in capacity}} \tag{3.10}$$

For periods $t>0$:

$$c_t=w+p_t\theta_t m_t-G\left(\frac{m_{t+1}}{m_t}-1\right)+Ra_t-T_t-F(m_{t+1}-m_t)-a_{t+1} \tag{3.11}$$

$$
\begin{aligned}
u'(c_t)\left[G'\left(\frac{m_{t+1}}{m_t}-1\right)\frac{1}{m_t}+F\right] &= \\
\beta\cdot\mathbb{E}_t\left\{u'(c_{t+1})\left[\theta_{t+1}p_{t+1}+G'\left(\frac{m_{t+2}}{m_{t+1}}-1\right)\frac{m_{t+2}}{m_{t+1}^2}+F\right]\right\}
\end{aligned}
\tag{3.12}
$$

For periods $t \geq 0$:

$$
u'(c_t) = \beta R\cdot\mathbb{E}_t\{u'(c_{t+1})\} \tag{3.13}
$$

Equations (3.7) and (3.10) formalize the key difference between subsidy types. The PTC increases the return (in consumption units) of a marginal investment in wind capacity while leaving its cost unchanged. This return is uncertain as it depends on future realizations of the capacity factor (e.g. due to unknown future weather conditions). Alternatively, the ITC is a direct reduction to contemporaneous marginal investment costs (in consumption units) and it is always known by the entrepreneur at the time capacity investment decisions take place. Therefore, when facing equivalent subsidy types, i.e.

$$
\underbrace{sF(m_1-m_0)}_{\text{Subsidy under ITC}} \quad = \quad \underbrace{\mathbb{E}_0\sum_{t=0}^{+\infty}\beta^t(S\cdot\theta_t m_t)}_{\text{Expected subsidy under PTC}} \quad = \quad \underbrace{\sum_{t=0}^{+\infty}\beta^t T_t}_{\text{Tax collections}}\ , \tag{3.14}
$$

the risk averse entrepreneur will strictly prefer the ITC given that the payment under PTC is a mean-preserving spread of the subsidy under ITC. However, prudent behavior induced by $u''' > 0$ implies that investments in wind capacity are *weakly larger* with the PTC. This is because the entrepreneur uses *precautionary savings* as a channel to self-insure against possible low capacity factor realizations in the future. Since

PTC payments are a mean-preserving spread of the ITC subsidy, they increase the variance in consumption growth and incentivize the entrepreneur to further reduce current consumption through precautionary investments either in more wind capacity or acquisitions of the risk-free asset. From the point of view of policy that subsidizes wind industry growth, this is important because it implies that the PTC delivers (weakly) larger investments in capacity at the same expected cost relative to ITC.

To show that the entrepreneur uses precautionary savings to self-insure against higher variance in consumption growth, consider the second-order Taylor approximation of u' centered at c_t and write (3.8) and (3.13) as follows,

$$u'(c_t) \approx \beta R \cdot \mathbb{E}_t \left[u'(c_t) + u''(c_t)(c_{t+1} - c_t) + \frac{1}{2} u'''(c_t)(c_{t+1} - c_t)^2 \right]$$

$$\implies 1 \approx \beta R \cdot \mathbb{E}_t \left[1 + c_t \frac{u''(c_t)}{u'(c_t)} \frac{(c_{t+1} - c_t)}{c_t} + \frac{1}{2} \cdot c_t \frac{u'''(c_t)}{u''(c_t)} c_t \cdot \frac{u''(c_t)}{u'(c_t)} \cdot \left(\frac{c_{t+1} - c_t}{c_t} \right)^2 \right].$$

Such second-order Taylor expansion of u' at c_t exists given that $u''' > 0$. Define $\gamma_t = -c_t \frac{u''(c_t)}{u'(c_t)}$ and $\psi_t = -c_t \frac{u'''(c_t)}{u''(c_t)}$ as the coefficients of relative risk aversion and relative prudence, respectively. These time-dependant parameters are well-defined because $u' > 0$ and $u'' < 0$. Using these definitions and rearranging terms in the previous expression yields,

$$\mathbb{E}_t \left[\frac{c_{t+1} - c_t}{c_t} \right] \approx \underbrace{\frac{1}{\gamma_t} \frac{\beta R - 1}{\beta R}}_{\text{Impatience vs. return to savings}} + \underbrace{\frac{1}{2} \psi_t \mathbb{V}_t \left[\frac{c_{t+1} - c_t}{c_t} \right]}_{\text{Precautionary savings motive}} \tag{3.15}$$

where I have used the fact that $\mathbb{E}_t\left[c_{t+1}\right] \approx c_t$ in an open ball at c_t where $c_{t+1} \approx c_t$. Therefore, higher variance in consumption growth due to the PTC increases expected consumption growth. This implies lower current consumption at t which is driven by precautionary savings to smooth out possible low subsidy payments in the case of adverse capacity factor realizations in the future. Since the entrepreneur saves by allocating income to investments in wind capacity or the risk-free asset, higher precautionary savings with the PTC translate into weakly larger capacity investments relative to the ITC. The key policy implication is that cost-effective subsidization would only provide the PTC because it incentivizes (weakly) larger wind investments at the same fiscal cost relative to the ITC.

3.3 Policy Experiment

3.3.1 Experiment Design

The aim of the policy experiment is to understand how wind investments change depending on the subsidy type (i.e. PTC and ITC). Conditional on a fixed level of expected subsidy payments, this will allow to determine the quantitative relevance of prudent behavior as a key driver of differences in policy effects from subsidizing output or investment goods. Prudent behavior from developers matters for policy design in the wind industry because subsidies to output are inherently stochastic but payments to investment efforts are not.

The basic steps for implementing the policy experiment are as follows:

1. Simulate 1,000 different histories for capacity factor realizations for a 10-year period in monthly time blocks.
2. Define a set of values $\{s_k\}_{k=1}^{K}$ for the proportional subsidy under the ITC. At each s_k, solve the entrepreneur's problem (i.e. problem (3.3) using budget constraint (3.5)) for all histories of capacity factor realizations and compute average investment rate.
3. For each s_k, find the per unit subsidy S by solving the model under the PTC (i.e. problem (3.3) using budget constraint (3.4)) for all histories such that subsidy payments are equivalent on average across subsidy types. Compute the average investment rate across histories.
4. For each level of expected subsidy payments, compare average investment rates between PTC and ITC.

3.3.2 Data

ERCOT, which manages $\sim 90\%$ of Texas electricity generation, is the U.S. power market that has experienced the largest increase in wind power capacity. This makes it an ideal empirical study case for this paper. I use three main data sources from the universe of ERCOT firms in the quantitative analysis. First, I use the 2019 EIA-860 and EIA-923 surveys to collect plant-level data on technological attributes from ERCOT wind firms. These are mandatory reports US power producers submit on a monthly and annual basis to the Energy Information Administration (EIA). The reports include data at the power plant level on unit identifier, electricity production, fuel costs (per energy source), fuel consumption and stocks, regulation status, energy-type emissions rates, and generation capacity limits, among other information. Second, I use ERCOT 2019 data on hourly load (in MWh) and balancing prices at the system level. This dataset includes information about hourly prices and power consumption at the aggregate and zonal level – i.e. North, North Central, South, South Central, and West zones.

3.3.3 Identification and Estimation

I adopt the following parametrizations of key model primitives to estimate structural parameters. First, I consider the following functional form of installation costs,

$$G\left(\frac{m'-m}{m}\right) = \alpha\left(\frac{m'-m}{m}\right)^2, \ m > 0. \tag{3.16}$$

Additionally, I define the following AR(1) structure and i.i.d. process for the stochastic processes of capacity factors and wholesale prices, respectively,

$$\theta' = \rho_0 + \rho_1\theta + \varepsilon', \ \varepsilon' \sim \text{unif}\left[-b, b\right]. \tag{3.17}$$

$$p' \sim \text{gamma}[k, \gamma] \tag{3.18}$$

Last, I adopt the following CRRA utility function to parametrize the entrepreneur's preferences over consumption streams,

$$u(c_t) = \frac{c_t^{1-\sigma} - 1}{1-\sigma} \tag{3.19}$$

I implement the estimation strategy in two steps. First, I discipline the discount factor β, rate of return R, and wage w through direct calibration. Then, I use a Simulated Method of Moments (SMM) approach to estimate the unit cost of capacity F, installation costs parameter α, autoregression intercept ρ_0, autocorrelation parameter ρ_1, white noise parameter b, shape and scale parameters of the distribution of wholesale prices (k, γ), and CRRA coefficient σ.

3.3.3.1 Step 1: Calibration

I report calibrated parameters in Table 8. I set the annual discount factor at $\beta = .98$. Additionally, I consider a 3% yearly rate of return for the risk-free asset that is consistent with recent trends in the annual yield of the U.S. 1 Year Treasury Bills. Last, I consider a yearly wage income in line with the average annual net compensation per worker during 2020 as reported by the Social Security Administration (SSA).

Table 8. Calibrated parameters

Parameter	**Definition**	**Value**	**Source**
β	**Discount factor**	.98	Assumption
R	**Rate of return**	1.03	U.S. 1 Year Treasury Bill
w	**Wage income**	53,383.18	SSA (2020)

Note: This table reports values of externally calibrated parameters. The rate of return is consistent with the mean annual return of the S&P 500 during the period 2012-2021. Wage income is in line with average annual net compensation per worker during 2020.

3.3.3.2 Step 2: Estimation

I report estimation results and goodness-of-fit in Table 9. I use a SMM strategy to estimate the rest of structural parameters. To implement the SMM, I define a set of key moments for estimating each parameter of interest and use a number of moments equal to the number of parameters to be estimated. Then, I simulate the exogenous variation within the model – i.e. the history of shocks to capacity factor and electricity prices – to compute the simulated moments obtained from solving the economic model. Subsequently, I find the parameters that allow matching each of these model-dependent moments to those calculated from the data. I rely on a SMM approach given that it is not possible to compute analytical solutions of the key moments used to estimate cost and preference parameters (F, α, σ).

To estimate the entrepreneur's preferences and technology parameters, I exploit cross-sectional variation in installed capacity across wind power firms to identify unit cost of capacity F. In addition, I use time variation in installed capacity within firms to identify the installation cost parameter α and the CRRA coefficient σ. I do this by jointly estimating (F, α, σ) to match: i) average installed capacity across firms, ii) average within-firm investment rate in wind capacity, and iii) variance of within-firm investment rate in wind capacity, respectively.

Table 9. SMM estimation results

Parameter	**Definition**	**Estimate**	**Target**	**Moment**	
				Model	*Data*
F	**Unit cost of capacity**	1.67 (.44)	Avg. installed capacity (MW)	200	200
α	**Installation cost parameter**	.51 (.08)	Avg. investment rate (%)	3.7	3.7
ρ_0	**Autoregression intercept**	.20 (.01)	Avg. capacity factor (%)	35	35
ρ_1	**Autocorrelation parameter**	.42 (.11)	First-order autocorrelation	.42	.42
b	**White noise parameter**	.24 (.07)	Variance capacity factor	.03	.03
k	**Shape parameter**	1.76 (.2)	Avg. day-ahead electricity price	38	38
γ	**Scale parameter**	21.54 (3.4)	Std. dev. day-ahead electricity price	28.6	28.6
σ	**CRRA coefficient**	1.4 (.30)	Std. dev. investment rate (%)	2.3	2.3

Note: This table reports SMM estimation results for structural parameters that were not calibrated in Step 1. Empirical moments are calculated from installed capacity data from ERCOT wind power producers in the EIA-860 and EIA-923 surveys. Values in parenthesis from column 'Estimate' correspond to bootstrapped standard errors.

I estimate structural parameters of the stochastic processes for the capacity factor and wholesale prices using the following procedure. First, I exploit cross-sectional variation across wind power firms and time variation within firms in capacity factor data to identify parameters of the Markov process (3.17). I do this by jointly estimating (ρ_0, ρ_1, b) to match the following set of moments: i) average capacity factor across wind power firms, average within-firm (first order) autocorrelation of capacity factor realizations across firms, and iii) average variance of within-firm capacity factor realizations across producers. Then, I exploit time variation in 2019 day-ahead ERCOT electricity prices to identify parameters of the i.i.d. process (3.18) by jointly estimating (k, γ) to match the mean and variance of hourly prices.

3.4 Results

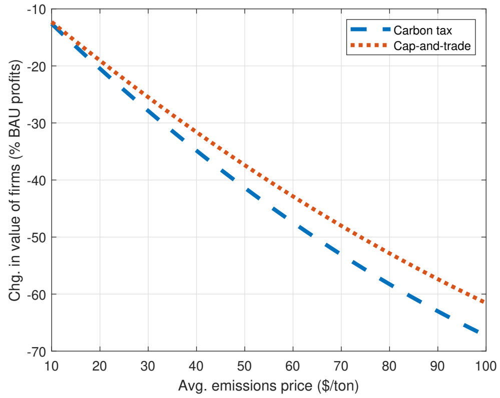
I present main results from the policy experiment in Figure 13. Panel (a) shows expected investment rates in wind capacity as a function of the proportional subsidy under the ITC. The investment rate function is concave due to the convexity of installation costs. As the proportional subsidy increases, installation costs of increasing wind capacity relative to initial capacity also increase. These two effects influence the entrepreneur's invesetment decisions in opposite directions. However, the net quantitative effect is primarily driven by the rate at which installation costs increase with larger levels of added capacity. Additionally, panel (a) shows that a decrease in the rate of return of the risk-free asset increases the expected investment rate for any given proportional subsidy under the ITC. This is because a lower rate of return lowers the threshold at which additions in wind capacity become the most profitable investment alternative.

In panel (b), I report expected investment rates as a function of the per unit subsidy under the PTC. Similar to the case in panel (a), concavity is due to convexity in installation costs. Moreover, results show that an increase in relative prudence – consistent with a larger CRRA coefficient σ – increases the expected investment rate for any given level of the per unit subsidy. This is because more prudent behavior reinforces the precautionary savings channel that drives the entrepreneur to increase savings through wind investments to self-insure against possible low capacity factor realizations in the future.

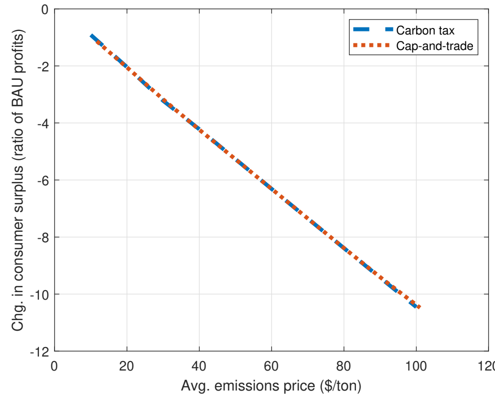
Panel (c) shows investment rates as a function of the total expected present value of subsidy payments for both alternative subsidy types. The key policy implication is that at any given level of expected subsidy payments, investment rates in wind capacity are larger under the PTC. Over such range of feasible subsidy payments, the PTC can increase average yearly investment rates in wind capacity up to 2.5 percentage points over mean investment rates under an alternative ITC.

As previously anticipated, this is a critical consequence of prudent behavior. Subsidy transfers under the PTC are directly linked to period-by-period output decisions that depend on (random) capacity factor realizations. Therefore, given that payments under the PTC constitute a mean-preserving spread of the subsidy transfer under the ITC in panel (c), this increases volatility in consumption growth under the PTC. The precautionary savings channel implies that the entrepreneur saves more to smooth out its expected consumption growth path. This leads to larger wind investments in the PTC case at the same expected cost in terms of subsidy payments to developers.

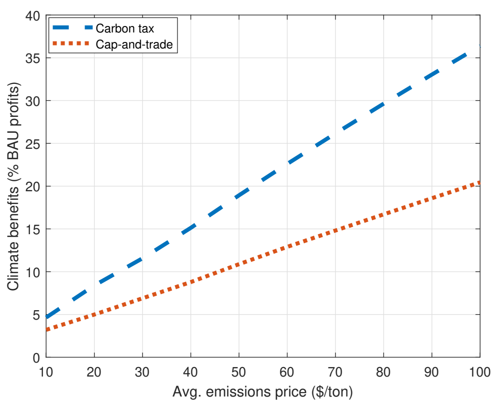
Last, in panel (d) I report expected investment rates under a PTC as the variance of capacity factor realizations increases. Higher variance capacity factor dynamics (i.e. because of largely volatile local weather and wind conditions) translates into larger volatility in consumption growth. Consistently with previous results, because of prudent behavior this incentivizes the entrepreneur to save more through wind investments in order to even out the adverse effects on consumption growth from plausible low capacity factor realizations.



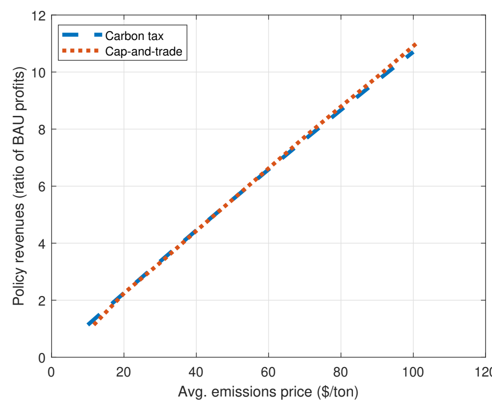
(a) Investment Tax Credit



(b) Production Tax Credit



(a) Investment vs. Production Tax Credit



(b) Effect of Larger Variance of Capacity Factor

Figure 13. Relative performance of Production vs. Investment Tax Credit

Note: This figure compares how the expected investment rate in wind capacity responds to policy across subsidy types. Panel (a) reports how investment rates responds as the percentage of subsidized installation costs under the ITC increases. Panel (b) shows how investment rates adjust to increasing per unit subsidies under the PTC. Panel (c) compares investment rates across alternative subsidy types for a given present value of expected subsidy payments. Last, panel (d) reports the effect on investment rates of higher variance in capacity factor realizations when receiving the PTC.

3.5 Discussion

There is a strand of literature that has previously assessed the relative cost-effectiveness of policies that subsidize output and investment goods. Aldy et al. (Forthcoming) is another example of recent research efforts that have addressed this question in the context of the wind power industry. This paper exploits data from a natural experiment where wind developers where temporarily able to choose between: i) claiming \$23/MWh for the first 10 years of output under the PTC, or ii) an upfront cash payment of 30% of total investment costs under the Section 1603 grant of the American Recovery and Reinvestment Act of 2009. After accounting for selection into subsidy types, their key findings suggest that developers who claim the investment subsidy are significantly less productive and, therefore, the PTC would be more cost-effective over a wide range of output targets.

A critical caveat that is acknowledged by Aldy et al. (Forthcoming) is the fact that the extremely limited lifespan of the 1603 grant program (2009–2012) importantly limits the scope for understanding how wind capacity would adjust in the long run to more prevalent policy changes. The results presented in Section 3.4 fill this gap in the literature by explicitly modeling the entrepreneur's investment response (at the extensive and intensive margin) to subsidies in way that is consistent with utility-maximizing behavior. This innovation allows to gain better understanding about capital accumulation dynamics in the long run where data availability could be severely limited. In this sense, key findings both in this paper as well as in Aldy et al. (Forthcoming) show that subsidizing output leads to more cost-effective policy than subsidizing investment goods. However, while Aldy et al. (Forthcoming) focus on understanding how plant-level technological features of wind farms matter for differences in cost-effectiveness across subsidy types, my findings contribute to current literature by showing that prudent behavior of wind developers is a primary driver of such differences in the long run.

There are two central innovations that will be incorporated in future iterations of this paper. First, I will extend the model to an equilibrium framework of wholesale power production that accounts for thermal and intermittent generation. This is of critical relevance for understanding how wholesale prices change after the policy intervention which then affects investment decisions in subsequent periods. Second, I will account for heterogeneity in technological characteristics at the wind farm level. This is important to allow for richer interactions between subsidy payments and responses in system-level investment rates.

3.6 Concluding Remarks

The U.S. federal government has a history of heavily subsidizing the wind power industry. Subsidies to output (PTC) and investment goods (ITC) have been critical approaches to incentivize replacement of emissions-intensive technologies for low emissions energy sources. In this paper, I have investigated which subsidy type incentivizes wind investments at the least cost in terms of necessary public expenditures. Results showed that over a reasonable range of total subsidy payments, the PTC can increase average yearly investment rates in wind capacity up to 2.5 percentage points over mean investment rates under an alternative ITC. This implies that output subsidies are more cost-effective at achieving a given investment target than alternative investment subsidies. This is primarily driven by precautionary savings from developers with prudent behavior seeking to smooth out potential adverse shocks to investment income under the PTC (given that the one-time payment under the ITC is certain). A proportion of such precautionary savings under the PTC is then allocated to additional wind investments. This means that prudent behavior of wind developers is a primary driver of differences in cost-effectiveness of in the long run between subsidies that target consumption or investment goods.

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APPENDIX A

CHAPTER 1: CAP-AND-TRADE VS. CARBON TAXES: INDUSTRY DYNAMICS AND THE ROLE OF DEMAND RISK

A.1 Appendix

A.1.1 Derivation of competitive equilibrium characterization

Solving the firm's problem (1.4) by setting up the associated Lagrangean and taking FOCs is standard so I omit the procedure from this Appendix. Obtaining from here the analogous characterization for the firm's problem (1.2) under BAU is simply a matter of setting $\tau = 0$ in the FOC. Solving for the firm's problem (1.6) under a permit system is different because the additional allowance holdings decision and environmental compliance constraint (1.5) undo a possible recursive formulation. Therefore, we first need to define the corresponding Lagrangean as a summation over all possible histories – given the existence of the time-aggregated constraint (1.5). Accordingly, let us define the following notation (some of which has already been defined in the main body of this paper):

- z: demand shock
- z_t: realization of shock z at time t
- Z: (finite) state space for random variable z
- $\pi(z_t|z_{t-1})$: Markov process for demand shock
- z^t: a history of shocks from period 1 to t
- Z^t: set of all histories from period 1 to t
- $z^t|z^j$: a history of shocks from period 1 to t conditional on observing history z^j $(t > j)$
- $Z^t|z_{t'}$: set of all histories from period 1 to t where $z_{t'}$ is observed at t'
- $Q(z^t)$: probability of observing history z^t

Making use of this additional notation, we can define the Lagrangian associated to problem (1.6) as follows ($\nu_{its}, \lambda_{its}, \mu_{ts}$ represent the corresponding Lagrange multipliers),

$$\mathscr{L} = \sum_{z^T \in Z^T} Q(z^T) \sum_{t=1}^{T} \delta^{t-1} \Bigg\{ \sum_{i=1}^{n_s} \Big[p_t(z^t) y_{its}(z^t) - c_{is} y_{its}(z^t) - \alpha_{is}(y_{its}(z^t) -$$

$$y_{i,t-1,s}(z^{t-1}))^2 + \nu_{its}(z^t) y_{its}(z^t) - \lambda_{its}(z^t)(y_{its}(z^t) - y_{is}^{max}) \Big] -$$

$$x_t(z^t) \left(m_{t+1,s}(z^t) - m_{ts}(z^{t-1}) \right) \Bigg\} + \sum_{z^T \in Z^T} Q(z^T) \mu_s(z^T) \Bigg(- \sum_{t=1}^{T} \sum_{i=1}^{n_s} \psi_i y_{its}(z^t)$$

$$+ m_{Ts}(z^{T-1}) \Big)$$

The **FOC** w.r.t. $m_{t+1,s}(z^t)$ for $t = 1, ..., T-2$ yields,

$$-Q(z^t)\delta^{t-1}x_t(z^t) + \sum_{z^{t+1}\in Z^{t+1}|z^t} Q(z^{t+1})\delta^t x_{t+1}(z^{t+1}) = 0$$

$$\implies x_t(z^t) = \delta \sum_{z^{t+1}\in Z^{t+1}|z^t} \frac{Q(z^{t+1})}{Q(z^t)} x_{t+1}(z^{t+1}) = \delta \cdot \mathbb{E}\left[x_{t+1}(z^{t+1})|z^t\right]. \tag{A.1}$$

Analogously, the **FOC** w.r.t. $m_{T,s}(z^{T-1})$ delivers,

$$-Q(z^{T-1})\delta^{T-2}x_{T-1}(z^{T-1}) + \sum_{z^T\in Z^T|z^{T-1}} Q(z^T)\delta^{T-1}x_T(z^T) + \sum_{z^T\in Z^T|z^{T-1}} Q(z^T)\mu_s(z^T) = 0$$

$$\implies x_{T-1}(z^{T-1}) = \delta \sum_{z^T\in Z^T|z^{T-1}} \frac{Q(z^T)}{Q(z^{T-1})} x_T(z^T) + \sum_{z^T\in Z^T|z^{T-1}} \frac{Q(z^T)}{Q(z^{T-1})} \frac{\mu_s(z^T)}{\delta^{T-2}}$$

$$\implies x_{T-1}(z^{T-1}) = \delta \cdot \mathbb{E}[x_T(z^T)|z^{T-1}] + \mathbb{E}\left[\frac{\mu_s(z^T)}{\delta^{T-2}}|z^{T-1}\right]. \tag{A.2}$$

The dynamics of allowance prices in equilibrium (i.e. the set of conditions in (1.9)) are determined by equations (A.1) and (A.2) along with the condition $x_T(z^T) = \mu_s(z^T)$.

Additionally, observe that combining equations (A.1) and (A.2), we can express allowance prices in $t = 1, ..., T-2$ as functions of expectations of $x_T(z^T)$ and $\mu_s(z^T)$ given the information available at period t,

$$x_t(z^t) = \delta^{T-t}\mathbb{E}\left[x_T(z^T)|z^t\right] + \mathbb{E}\left[\frac{\mu_s(z^T)}{\delta^{T-t-1}}|z^t\right], \quad t = 1, ..., T-2.$$

Using condition $x_T(z^T) = \mu_s(z^T)$ in the equation for allowance prices $x_t(z^t)$ and rearranging terms allows us to express the expectation of $x_T(z^T)$ as a function of the realized allowance price at t,

$$\mathbb{E}\left[x_T(z^T)|z^t\right] = \frac{\delta^{T-t-1}}{\delta^{2(T-t)-1}+1}x_t(z^t),\ \forall t = 1, ..., T-2$$

which proves equation (1.12) from Section 1.3.7.

Moving forward to analyze the production decision at the intensive and extensive margins, the **FOC** w.r.t. $y_{its}(z^t)$ yields,

$$\begin{aligned}
&Q(z^t)\delta^{t-1}\left\{p_t(z^t) - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \nu_{its}(z^t) - \lambda_{its}(z^t)\right\} \\
&+ \sum_{z^{t+1}\in Z^{t+1}|z^t} Q(z^{t+1})\delta^t \cdot 2\alpha_{is}(y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)) - \\
&\sum_{z^T\in Z^T|z^t} Q(z^T)\mu_s(z^T)\psi_i = 0
\end{aligned}$$

$$\begin{aligned}
&\implies p_t(z^t) - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \\
&2\alpha_{is}\delta \sum_{z^{t+1}\in Z^{t+1}|z^t} \frac{Q(z^{t+1})}{Q(z^t)}(y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)) = \\
&\lambda_{its}(z^t) - \nu_{its}(z^t) + \frac{\psi_i}{\delta^{t-1}} \sum_{z^T\in Z^T|z^t} \frac{Q(z^T)}{Q(z^t)}\mu_s(z^T)
\end{aligned}$$

where $\nu_{its}(z^t)$ and $\lambda_{its}(z^t)$ represent the Lagrange multipliers associated to the upper and lower bounds for production at the unit level. Since Lagrange multipliers are non-negative, we can write the previous FOC as follows to obtain equation (1.10),

$$\begin{aligned}
&p_t(z^t) - c_{is} - 2\alpha_{is}(y_{its}(z^t) - y_{i,t-1,s}(z^{t-1})) + \\
&2\alpha_{is}\delta \cdot \mathbb{E}\left[y_{i,t+1,s}(z^{t+1}) - y_{its}(z^t)|z^t\right]
\begin{cases}
> \psi_i \mathbb{E}\left[\dfrac{\mu_s(z^T)}{\delta^{t-1}}|z^t\right], & \text{iff } y_{its} = y_{is}^{max} \\
< \psi_i \mathbb{E}\left[\dfrac{\mu_s(z^T)}{\delta^{t-1}}|z^t\right], & \text{iff } y_{its} = 0 \\
= \psi_i \mathbb{E}\left[\dfrac{\mu_s(z^T)}{\delta^{t-1}}|z^t\right], & \text{else.}
\end{cases}
\end{aligned}$$

These equations plus the equilibrium conditions from the competitive equilibrium definition in Section 1.3 deliver the full characterization for the cap-and-trade case.

A.1.2 Sensitivity analysis for moments used in SMM

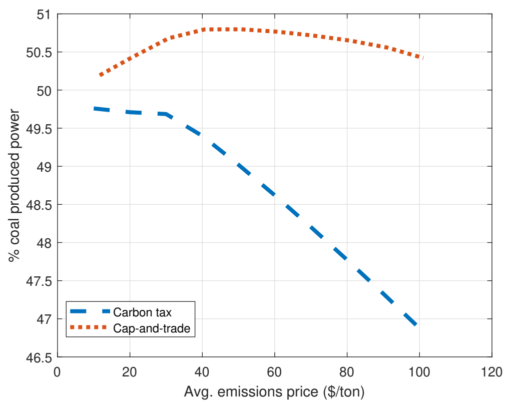
Table 10 reports results of the sensitivity analysis measuring the change in model-dependent moments as a consequence of a 1% increase in estimated parameters. Given the number of structural parameters and for ease of exposition, I report results in firm-level moments only for the case of NRG Texas Power. Similar qualitative results are observed for other multi-unit firms.

Table 10. Sensitivity analysis for model-dependent moments

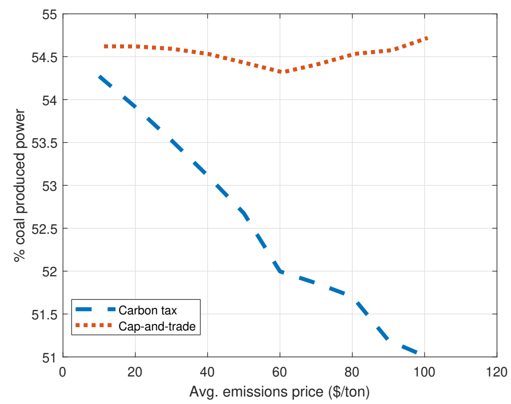
	Avg. coal	**% natgas power**	**Avg. cycling cost**	**Avg. load**	**S.D. load**
c_{12}	-.0026	.0971	1.6778	0	0
c_{22}	.0005	-.2506	-6.9749	0	0
α_{22}	.0005	.0788	.6234	0	0
ρ_0	.0451	4.8295	-5.9642	10.7864	12.2089
ζ	-.0005	-.0029	.6814	-.0672	1.3656

Note: This table reports the change in model-dependent moments (top row) as a consequence of a 1% increase in each of the parameters on the leftmost column. Column 'Avg. coal' reports changes in the average hourly production at the coal-fired unit of NRG Texas Power. Column '% natgas power' corresponds to the share of natural gas power at NRG Texas Power. Column 'Avg. cycling cost' reports the change in average cycling costs per MW at the natural gas unit of NRG Texas Power. Columns 'Avg. load' and 'S.D. load' report changes in average and standard deviation of hourly power consumption at the system level, respectively. Parameters $c_{12}, c_{22}, \alpha_{22}, \rho_0$ and ζ represent marginal costs at the coal and natural gas units (resp), cycling cost parameter at the natural gas unit, demand intercept, and shock size, respectively. Numbers in the '% natgas power' column are in percentage points; all others are in % changes.

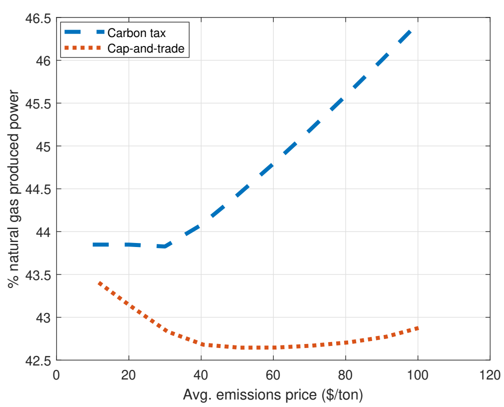
A.1.3 Sensitivity analysis for a 100% increase in natural gas prices



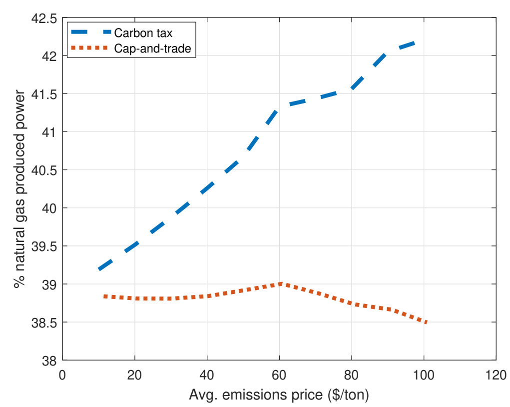
(a) Baseline parameters



(b) With 100% increase in natural gas prices



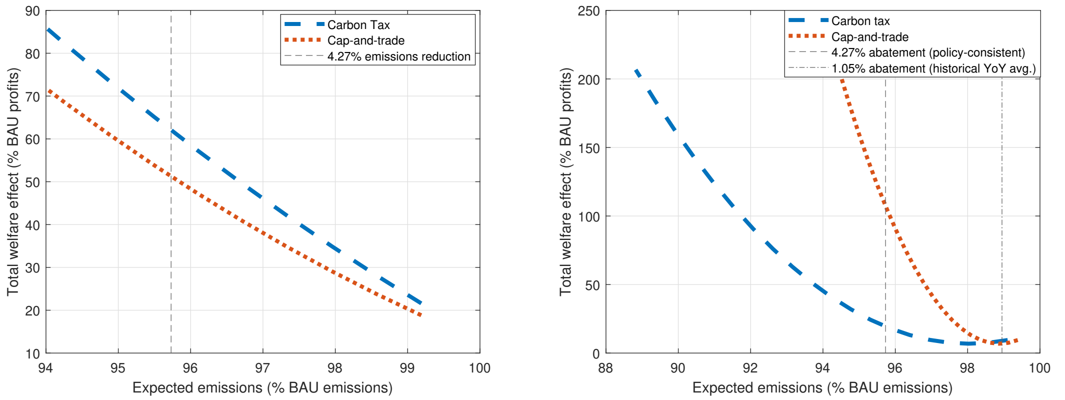
(a) Baseline parameters



(b) With 100% increase in natural gas prices

Figure 14. Energy Shares under Different in Natural Gas Prices

Note. This figure compares coal and natural gas shares under unit-level marginal cost parameters c_{is} consistent with different natural gas prices. Subfigures in the left column are fossil fuel shares consistent with baseline SMM cost parameters that were estimated in Section 1.4.3. Subfigures in the right column are fossil fuel shares under a hypothetical 100% increase in natural gas prices which would double estimated unit-level marginal cost parameters c_{is} at all natural gas power plants.



(a) Baseline parameters (b) With 100% increase in natural gas prices

Figure 15. Welfare Effects under Different in Natural Gas Prices

Note. This figure compares total welfare effects under unit-level marginal cost parameters c_{is} consistent with different natural gas prices. Panel (a) shows welfare effects consistent with baseline SMM cost parameters that were estimated in Section 1.4.3. Panel (b) shows welfare effects under a hypothetical 100% increase in natural gas prices which would double estimated unit-level marginal cost parameters at all natural gas power plants.

Results show that a 100% increase in average unit-level marginal costs at natural gas power plants reverts the welfare ranking that is consistent with baseline cost parameter estimates from Section 1.4.3. This implies that the welfare ranking between carbon taxes and permit systems depends crucially on the joint distribution of unit-level marginal cost parameters c_{is} across fuel types and firms. Specifically, for sufficiently high average marginal costs at natural gas units (for instance, because of increasing natural gas prices), permit systems have higher welfare than emissions-equivalent carbon taxes (and vice versa). This is because firms abate more emissions by switching production from coal-fired units to natural gas plants (which use a less emissions-intensive fossil fuel) in the case of a carbon tax (see discussion on differences in output allocations in Section 1.3.5 and Figure 14). Therefore, an increase in average marginal costs at natural gas units disproportionately affects the economy with price-based regulation and reverts the welfare ranking that was consistent with baseline estimates.

A.1.4 Distributions of key endogenous variables

A.1.4.1 Output

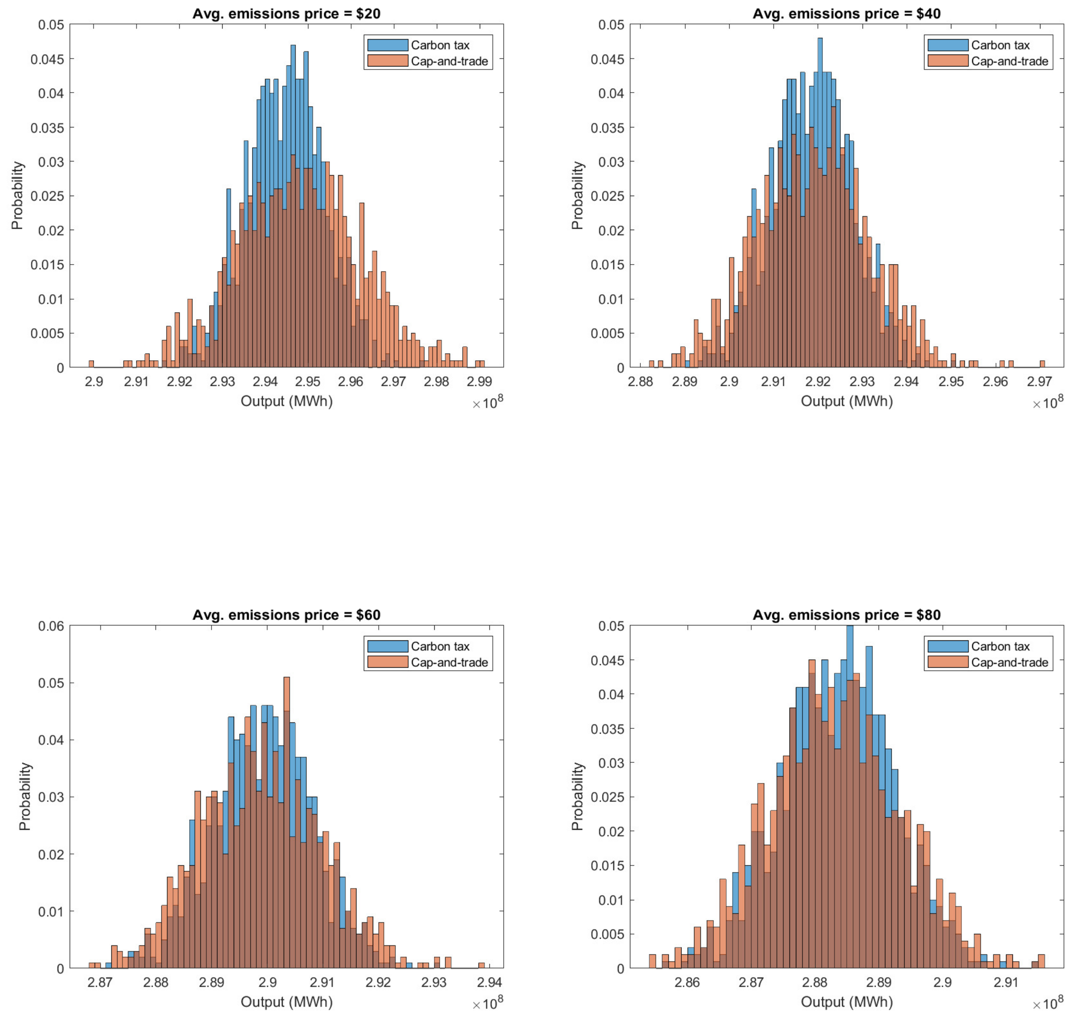


Figure 16. Probability Density Function of Total Generation

Note. This figure shows the probability density function of total generation under price-equivalent control modes for different levels of average emissions prices ($/ton). Blue histograms are for output with a carbon tax while orange histograms are for output with a permit system.

A.1.4.2 Electricity Prices

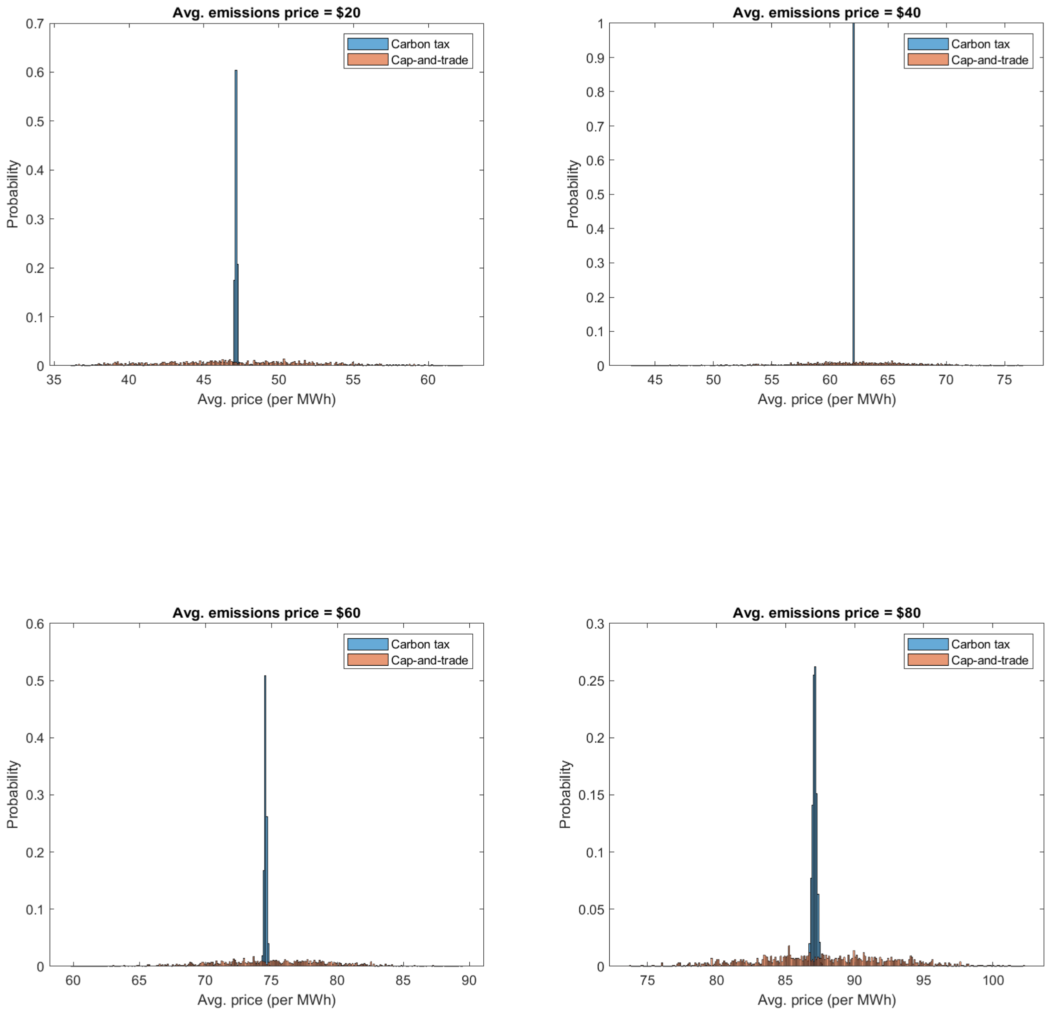


Figure 17. Probability Density Function of Avg. Hourly Electricity Prices

Note. This figure shows the probability density function of average hourly electricity prices under price-equivalent control modes for different levels of average emissions prices ($/ton). Each average hourly electricity price corresponds to the mean value of output hourly prices under a specific draw of the history of demand shocks. Blue histograms are for prices with a carbon tax while orange histograms are for prices with a permit system.

A.1.4.3 Emissions

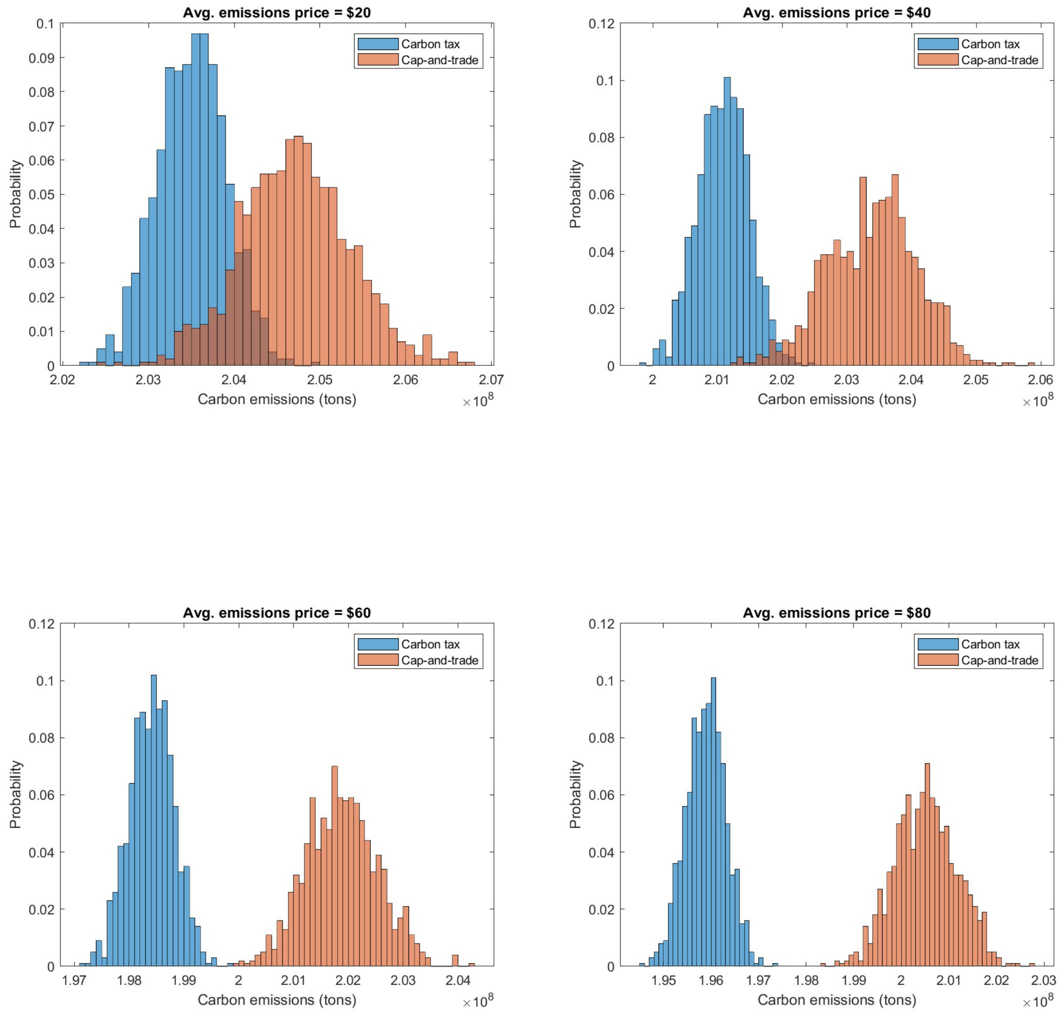


Figure 18. Probability Density Function of Total Emissions

Note. This figure shows the probability density function of total compliance cycle emissions under price-equivalent control modes for different levels of average emissions prices ($/ton). Blue histograms are for emissions with a carbon tax while orange histograms are for emissions with a permit system.

A.1.4.4 Permit prices

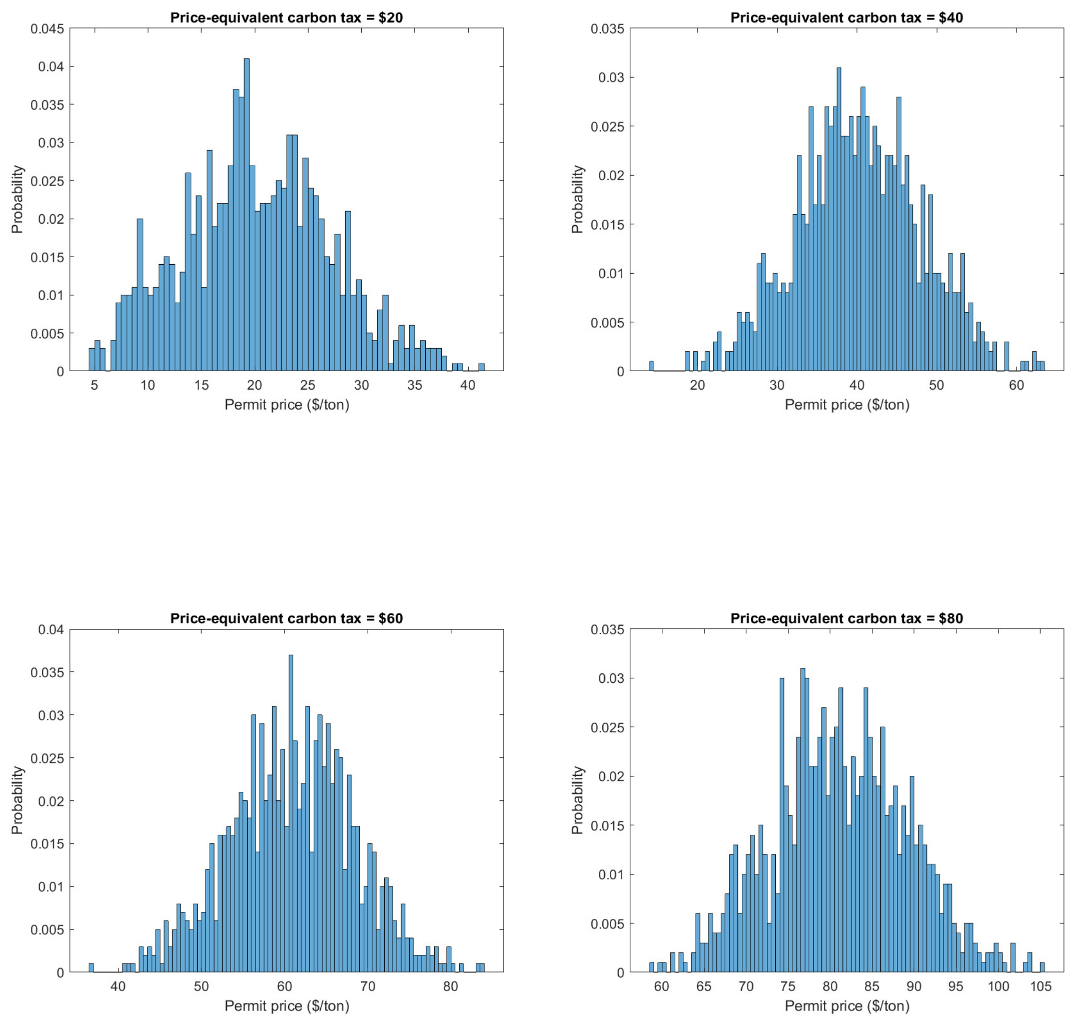


Figure 19. Probability Density Function of Permit Prices

Note. This figure shows the probability density function of allowance prices in a compliance cycle compared to different levels of a price-equivalent carbon tax ($/ton). A price-equivalent carbon tax is a counterfactual emissions fee equal to the price of permits *in expectation*. Probability density functions of permit prices associated to higher carbon taxes are consistent with lower emissions caps.

APPENDIX B

CHAPTER 2: DO VERTICAL ARRANGEMENTS MATTER FOR COST-EFFECTIVENESS OF OUTPUT SUBSIDIES?

B.1 Appendix

B.1.1 Derivation of Euler conditions (2.5) and (2.6)

Proof. Take the FOC of (2.3) w.r.t. m' to obtain,

$$-F_g - \frac{1}{m}G_g'\left(\frac{m'-m}{m}\right) + \beta\mathbb{E}_\theta\left[\frac{\partial V_g(m',\theta')}{\partial m'}\right] = 0$$

Moreover, applying the Envelope Theorem to (2.3) delivers,

$$\frac{\partial V_g(m,\theta)}{\partial m} = \theta p + F_g + \frac{m'}{m^2}G_g'\left(\frac{m'-m}{m}\right)$$

Iterate this Envelope Condition one period ahead and substitute into the FOC to obtain (2.6). An analogous procedure applied to (2.2) yields (2.5).

$\square$

B.1.2 Decreasingness and continuity of $V_f(0,\cdot)$

Proof.

1. Decreasingness: Let T be the contraction operator defined by (2.2). By induction on n.
   - $n = 0$: Let $V_f^0(0,\cdot)$ be a decreasing function and consider $q_1 < q_2$. Then,

     $$\begin{aligned} &T\left[V_f^0(0,q_1)\right] \\ &= \max_{m'\geq 0}\left\{-F_f m' - G_f\left(\frac{m'-m}{m}\right) + \beta\mathbb{E}_q\left[V_f^0(m',q')|q_1\right]\right\} \\ &\geq \max_{m'\geq 0}\left\{-F_f m' - G_f\left(\frac{m'-m}{m}\right) + \beta\mathbb{E}_q\left[V_f^0(m',q')|q_2\right]\right\} \\ &= T\left[V_f^0(0,q_2)\right] \end{aligned}$$

     where in line three I used the assumption that $V_f^0(m',q')$ is decreasing in q.
   - $n \to n+1$: Analogous to the $n = 0$ step after changing $V_f^0(0,\cdot)$ for $T^n\left[V_f^0(0,\cdot)\right]$.

This implies that $T^n\left[V_f^0(0,\cdot)\right]$ is decreasing for all $n \in \mathbb{N}$. By the Contraction Mapping Theorem, it must be the case that $V_f(0,\cdot) = \lim_{n\to\infty} T^n\left[V_f^0(0,\cdot)\right]$ is decreasing.

2. Continuity: $V_f(0,\cdot)$ is continuous as a direct consequence of Berge's Theorem of the Maximum since the instant return function in (2.2) is continuous in m and q.

$\square$

B.1.3 Existence of reservation price $q^*(\theta)$

Proof. Let $\theta \in [0,1]$.

- Case 1: $V_f(0,0) \geq V_g(0,\theta)$. We know that $V_f(0,\cdot)$ is decreasing and continuous. Moreover, it is also the case that $\lim_{q\to+\infty} V_f(0,q) = 0$. Since $V_g(0,\theta) \geq 0$, by the Intermediate Value Theorem the set $\{q \mid V_f(0,q) = V_g(0,\theta)\}$ is non-empty. Since this set is bounded below, such reservation price exists.
- Case 2: $V_f(0,0) < V_g(0,\theta)$. The reservation price does not exist since the set $\{q \mid V_f(0,q) = V_g(0,\theta)\}$ is empty. In this case, it is optimal to build the green energy unit independently of q.

$\square$