Economic Policy in the Energy-Environment Nexus

by

David A. Bielen

Department of Economics
Duke University

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Christopher D. Timmins, Chair

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Andrew J. Yates

Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
in the Graduate School of Duke University
2015
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This dissertation studies the economic impacts of environmental policy on energy sectors. The first chapter pertains to climate change mitigation options through the Clean Air Act (CAA). Invoking Section 111(d) of the CAA, the Environmental Protection Agency (EPA) is currently developing regulations for carbon dioxide (CO₂) emissions from existing fossil fuel power plants. Due to the heavy carbon-intensity of coal as a fuel, the coal industry and related interests appear likely to bear much of the regulatory burden. In response, regulatory features aimed at mitigating some of the adverse impacts on coal and its constituents have been discussed, either in the interest of equity or as a means of easing political and legal opposition. This paper examines one approach motivated by the current EPA proposal: differentiation in the context of tradable performance standards, where the standard is relaxed for coal generation and tightened for natural gas generation. I explore the economic incentives induced by such a policy, and evaluate three key distributional outcomes: aggregate coal usage, coal plant profits, and regional wholesale electricity prices. To conduct the analysis, I first develop a simple analytic model of the electricity sector, showing that differentiation, when compared to a policy with the same standard for all fuel types, always increases coal usage, but price and profit changes depend on competing effects. To quantify these outcomes, I construct and implement a detailed simulation model of the U.S. wholesale electricity market. In the simulation results, I find that differentiation increases coal usage modestly, restores coal plant profits
beyond the no-regulation level, and increases electricity prices in almost every region of the country. The results imply that differentiation provides limited assistance to coal producers, and benefits coal-fired power plants at the expense of electricity consumers.

The second chapter, which is joint work with Richard Newell and William Pizer, capitalizes on the phaseout of a biofuels subsidy to empirically investigate the subsidy incidence. The subsidy in question is the Volumetric Ethanol Excise Tax Credit (VEETC), which had subsidized the blending of ethanol with gasoline but was allowed to expire at the end of 2011. During its tenure, the subsidy was the subject of intense scrutiny over which stakeholder groups benefited from its existence. Using commodity futures contract and spot prices, we estimate the subsidy incidence accruing to corn farmers, ethanol producers, gasoline blenders, and gasoline consumers around the time of expiration. We find compelling evidence that ethanol producers captured around two-thirds of the 45¢ per gallon of ethanol blended subsidy. We find suggestive, albeit not conclusive, evidence that at least some of this benefit was passed upstream to corn farmers. On the petroleum side, we find no evidence that oil refiners captured any part of the subsidy. In a longer-term analysis, we find evidence that the subsidy was largely pocketed by the blender, as any more than a 45% pass-through falls outside our estimated 95% confidence interval, though more work is necessary to validate this result. Our paper contributes to a growing literature on U.S. biofuels policy, as well as the literature on empirical estimation of economic incidence.

The third chapter, which is joint work with Andrew Yates, studies the optimal regulation of local air pollutants in an analytic model that incorporates insights from other disciplines. For one, epidemiologists have long recognized the existence of both acute short-term and chronic long-term damages associated with exposure to major types of pollutants. At the same time, atmospheric scientists have demonstrated...
that the extent of population exposure depends on meteorological conditions, which are stochastic. A small number of economic studies of optimal pollution regulation have incorporated one of these elements, but none have dealt with both simultaneously. Our paper fills this gap in the literature by first developing an analytic model with abatement costs, separate acute and chronic damage components, and stochastic pollution exposure. We analytically characterize the optimal path of pollution regulation in the presence of under three different scenarios regarding the regulator’s ability to update the policy and forecast the weather. We then compare the welfare outcomes across regulatory regimes, and perform comparative statics with respect to the key parameters of the model. We find that regulatory flexibility cost advantages are decreasing in the slope of marginal costs and increasing in the slope of marginal chronic damages. With respect to acute damages, the sign depends on which policies are being compared.
This dissertation is dedicated in loving memory to my late aunt, Donna Schiefer.
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Finally, I would like to thank my wife, Elise Francis Bielen, who has made every day for the past twelve years one worth living. Without her uncompromising patience, love, and support, I would have never reached this point.
1.1 Introduction

While academic economists have traditionally focused on the cost-effectiveness properties of environmental policy instruments, their distributional consequences are receiving increasing attention.\(^1\) With the United States Environmental Protection Agency (EPA) currently formulating regulations for carbon dioxide (CO\(_2\)) emissions from existing power plants, equity issues have emerged as a central issue in the policy debate. Here, the EPA and ultimately individual states must make choices that will determine the relative burden on the coal industry, coal regions, and downstream coal users. These choices will likely influence the ease or difficulty with which the policies are implemented as well as views about future policies to address climate change.

The options available for influencing distributional impacts depend on the type of policy under consideration. Under a cap-and-trade system, the allocation of permits

\(^1\) For example, see Bovenberg et al. (2005), Bushnell and Chen (2012), Rausch and Mowers (2014)).
can be manipulated to address equity concerns. The current regulatory process, however, leans towards rate-based standards that cap emissions per unit of electricity, rather than emissions (Burtraw et al., 2012). Trading is still possible and cost-effective, allowing low-mitigation-cost facilities to overcomply, in turn earning and selling credits to high-mitigation-cost facilities that undercomply. Under this type of policy, the analogy to using permit allocation for redistribution would seem to be manipulating the rate standard across facilities, yet the efficacy of this approach is neither demonstrated nor well understood. In our particular context, the question is whether “differentiation” helps coal and its constituents when the standard for coal-fired generation is relaxed while the standard for natural gas generation is tightened. Answering this question and quantifying the associated impacts is the central focus of this paper.

Does differentiation improve outcomes for various coal-oriented stakeholders under a tradable performance standard policy in the U.S. electricity sector? To answer this question, I start with proxies for improved outcomes. Aggregate coal usage, coal plant profits, and wholesale electricity prices represent the economic impacts on the interests of coal producers and laborers, coal-fired power plants, and electricity distributors and consumers in coal-heavy generation regions, respectively. The analysis begins with a simple analytic model to understand how differentiation affects these outcomes and what is theoretically possible. Where the theory is ambiguous, and in order to provide detailed quantitative estimates, I then turn to a state-of-the-art simulation model of the U.S. wholesale electricity market.

Using the analytic model, I demonstrate how, compared to a single standard policy, differentiation is expected to increase coal usage, but that the directions of price and profit changes depend on two competing effects. The coal usage result is driven by changes in emission reduction behavior: I show that differentiation prioritizes emission reductions from within-fuel switching of generation from dirty
to clean (coal) plants, versus between-fuel switching from coal- to natural gas-fired plants. This results in less coal displacement. Differentiation also results in higher prices for compliance credits.\footnote{2} As a result, relaxing the standard for coal-fired plants has the counteracting effects of requiring fewer credit purchases but raising the credit prices. I show how these competing cost effects are related to electricity price and plant profit outcomes, and how the net effects depend on the entire system of generating facilities and opportunities for various types of mitigation.

I use the simulation model to generate plausible quantitative impacts of differentiation under a national tradable performance standard policy. Consistent with the analytic results, I find that differentiation increases coal usage through an increase in dirty to clean plant switching within fuel categories. However, the extent is modest ($\approx 1\%$ in coal usage) due to the limited potential of within-fuel switching as a means of compliance. I also find that, on average, differentiation increases electricity prices in almost every region in the country, even regions that rely heavily on coal-fired generation. Increasing electricity prices help to bolster coal-fired plant profits. Additionally, more than half of the utilized coal plant capacity in the model faces decreasing per unit costs under differentiation. In the extreme, the combination of these two effects results in aggregate coal-fired plant profits that actually exceed the level in the absence of regulation.

Taken together, the results imply that differentiation of a tradable performance standard on the basis of fuel-type does little to aid coal producers and laborers, and hurts electricity consumers in coal-heavy regions even more. Unless the goal is to assuage coal-fired power plants, this type of policy is an ineffective one, at least in a short-run analysis. However, the analytic results suggest that differentiation could
be more effective in situations where switching between differentiated facilities (e.g., from coal to gas in this case) is not the overwhelming source of mitigation. For example, this might be the case for programs with regional- rather than fuel-based differentiation, an area that I plan to investigate in future work.

The paper is organized as follows. In Section 1.2, I describe the policy setting for CO$_2$ regulation in the electricity sector. Section 1.3 reviews the existing literature on tradable performance standards and other similar policies. In Sections 1.4 and 1.5, I develop a simplified version of the simulation model and use it to examine how differentiation could impact coal usage, coal plant profits, and electricity prices. Section 1.6 describes the construction of the simulation model, the equilibrium conditions, and the policies for which I report results. Those results are described in Section 1.7. This section also contains discussion relating the analytic section to the simulation results. Section 1.8 concludes with a discussion of the implications of the model results.

1.2 Carbon Policy in the U.S. Electricity Sector

In this section, I describe the policy setting for the EPA’s existing power plant regulations, focusing on recent developments in the executive and legislative branches of the U.S. government. I briefly explain the mechanics of regulating through the Clean Air Act Section 111(d), which is what the EPA will use for the existing source rulemaking. The background provided will provide a more comprehensive motivation for the policy design feature studied in this paper.

Until recently, greenhouse gas policy seemed to be most likely introduced through legislative action. The American Clean Energy and Security Act of (2009), also known as the Waxman-Markey Bill, proposed an economy-wide cap-and-trade program for CO$_2$; it was narrowly approved by the House of Representatives but comparable legislation was never brought to a vote in the Senate. Since then, several
clean energy standards have been proposed, including the Clean Energy Standard Act of 2012, known as the Bingaman Proposal. Unlike the Waxman-Markey Bill, the Bingaman Proposal focused solely on the electricity sector. The Proposal also suggested a crediting system for each megawatt-hour (MWh) of electricity produced below a given emissions intensity standard, rather than establishing a cap-and-trade system. Although such a clean energy standard is not dissimilar from what is expected from the EPA process, attempts to establish one on a national basis through legislation proved unable to break through congressional gridlock.

Though attempts to regulate GHGs through new legislation failed, an older piece of legislation, the Clean Air Act (1970), would eventually prove to be a vehicle for executive branch action. At the same time that climate policy was being debated in Congress, there were several interesting developments regarding the EPA’s ability to regulate greenhouse gases. First, the Supreme Court ruled in Massachusetts v. EPA (2007) that the Clean Air Act gave the EPA authority to regulate GHGs under its Section 111(d). Two years later, EPA released a formal “endangerment finding,” which relied on scientific evidence to establish that GHGs are air pollutants. These two events have since initiated a string of rule-makings as set out by the Clean Air Act. First, the EPA dealt with the transportation sector by establishing vehicle emission standards. The next step was to address the electricity sector, which is currently the focus of the EPA.

Before addressing existing power plants, the EPA needed to first regulate new power plants, and the result of that process helped to motivate the policy studied here. In its New Source Performance Standards, the EPA established different emis-

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3 For a detailed discussion of the merits of a clean energy standard similar to the Bingaman Proposal, see Aldy (2011). Simulation results for various clean energy standards using Resources for the Future’s Haiku model are featured in Paul et al. (2013b,a).

4 The intensity standard is denoted in terms of emissions, e.g., metric tons of CO₂, per MWh. Such a standard is also often referred to as an efficiency or performance standard; this paper utilizes the latter.
sion rate targets for natural gas and coal plants. This outcome suggested that a similar distinction could be applied under the existing source regulation. This is exactly what occurred in the EPA’s initial proposal, albeit in indirect fashion.

The distinction between natural gas and coal in the EPA’s initial proposal is manifested in state-specific targets. The Clean Air Act is set up so that the EPA sets emission rate regulations, and the individual states construct State Implementation Plans (SIP) that inform the EPA how the state intends to comply; additionally, states are encouraged to form coalitions and submit joint plans. In the proposal, the specific rates were highly correlated with the amount of coal generation resources the state has, as states with more coal-fired plants received higher, i.e., more tons of CO$_2$ per MWh, standards. This suggests a few ways in which differentiated standards could be applied in the implementation phase. For one, individual states or coalitions could choose to treat coal and natural gas differently within their own tradable performance standard policy. Also, coalitions could differentiate on the basis of state, using the EPA’s specific rates as a benchmark for crediting. Even though the national policy modeled in this paper is unlikely to arise in the current CAAA regulatory framework, the intuition developed here is a useful aid to understanding the impacts of any style of differentiated policy.

My focus on tradable performance standard policies as a means of achieving compliance is supported by the structure of the Clean Air Act regulations. Because the EPA specifies targets in terms of emission rates rather than levels, tradable standards are a natural candidate for a flexible, market-based implementation policy (Burtraw et al., 2012). However, to be clear, the initial proposal included a provision that would allow states or coalitions to translate rates into levels. The extent to which states will choose to exercise that option remains to be seen. As will be demonstrated in the next section, tradable standard policies have become ubiquitous in energy sectors. The working assumption motivating this paper is that, at the very
least, they will play a role in regulating existing sources.

1.3 Literature Review

Despite the emergence of tradable performance standards in a variety of contexts, the vast majority of research on market-based policies has focused on cap-and-trade. This paper contributes to an emerging literature on tradable performance standards, as well as a literature concerned with the distributional impacts of environmental policy. In this section, I demonstrate how my paper fits into those two literatures. I also establish a conceptual link between differentiated performance standard policies, and cap-and-trade policies that allocate permits according to a benchmarking rule.

One of the few early studies of tradable performance standards is Helfand (1991), which theoretically studies simultaneously the output, profit, and efficiency properties of a variety of emission policies, including a rate-based standard. More recently, Fischer (2001) performed a theoretical comparison of schemes with a revenue rebating feature, including tradable performance standards and cap-and-trade programs with output-based allocations. The author demonstrates how each of these policies results in inefficient outcomes by shifting abatement efforts away from demand contraction and towards emission rate reduction. Fischer (2011) extends the theoretical analysis of this type of policy to markets with imperfect competition, while Fischer (2003) examines the environmental consequences of allowing trading across sectors with rate-based and cap-and-trade regulations. Finally, Fischer and Fox (2007) considers the tax interaction effects of tradable performance standards for both efficiency and distribution of rents.

The work described so far has focused on either general theory or economy-wide policy; other work has focused on the application of tradable performance standard policies in a variety of specific contexts. For example, Holland et al. (2009) and Lemoine (2014) both analyze tradable performance standards applied to transporta-
tion fuels, referred to as low-carbon fuel standard policies, focusing on theoretical efficiency properties. Lemoine (2014) in particular points out that the regulator can achieve higher welfare by choosing each fuel's emission ratings rather than just setting the level of the standard, which is akin to a result we see in the next section that a differentiated standard policy can yield efficiency gains relative to a single tradable standard policy. Tradable performance standards have also been addressed in the context of regulating the energy efficiency of automobiles, or Corporate Average Fuel Economy (CAFE). For instance, Rubin et al. (2008) considers the implications of various market structures in the CAFE compliance credit market on cost-savings, while Ito and Sallee (2014) analyzes the welfare properties of attribute-based standards in the context of Japanese fuel-economy standards. Regarding the latter work, differentiated standards can be considered a special case of attribute-basing in which the attributes are simply the fuel-types or automobile class in the cases of electricity and transportation, respectively. This paper is most similar to Lemoine (2014) and Ito and Sallee (2014) in terms of the type of policy under consideration, but the context is different and my primary focus is on distributional effects rather than cost-effectiveness or efficiency.

Another related paper is Bushnell and Chen (2012), which performs a simulation study of cap-and-trade programs in the western United States. Although much of the authors’ focus is on leakage, they also compare a few different permit allocation rules, including one that is “fuel-based.” This allocation design is similar to an output-based scheme, but the number of permits allocated per megawatt hour is higher for coal-fired plants than for natural gas-fired plants. Citing Bohringer and Lange (2005), the authors note that relative to a pure output-based design, under fuel-based allocation electricity prices rise and many of the benefits to firms with an abundance of coal-fired capacity are limited by rising permit prices. This paper builds on the work of Bushnell and Chen (2012) by investigating a related policy.
analytically and extending the simulation to the entire country. In addition to the mid-stream electricity generators, I also extend the analysis to coal producers and electricity consumers.

1.4 A Simple Electricity Market Model

In this section, I develop a framework for analyzing a differentiated standard policy in the U.S. electricity sector. The analytic model presented here is constructed to capture key stylized features of the power market. To build intuition, I demonstrate how the model works in the absence of regulation. I then introduce the performance standard policies to draw conclusions about the impact of differentiation on aggregate coal usage, regional electricity prices, and coal plant profits.

The analytic model is a static representation of an electricity sector with perfect competition in both the product (electricity) and credit markets. Electricity markets are region-specific in the sense that electricity cannot be traded across regions. Each region is endowed with many generating plants that supply electricity. Individual plants are indexed by region \( r \), fuel type \( f \), and unit number \( i \). For simplicity, the analytic model only considers coal (subscript \( \text{coal} \)) and natural gas plants (\( \text{gas} \)) as distinct fuel types.\(^5\) The collection of electricity generators in each region faces a downward-sloping demand curve represented by the function \( P_r(\cdot) \).

Each plant is endowed with a capacity \( K^i_{f,r} \), emission rate \( \sigma^i_{f,r} \), and unit cost of generation \( c^i_{f,r} \). All plant-specific parameters do not vary with generation; for costs, this is equivalent to assuming an elastic supply of fuel. Additionally, in accordance with the short-run nature of the model, plant capacities, unit costs, and emission

\(^5\) Other plant types, such as nuclear and renewables, are typically run at full capacity due to their low marginal costs. They are also not subject to any regulatory costs that would change the plant economics. Therefore, in a short run analysis of emissions policy, the relevant economic features of the policy are captured by the tradeoffs between coal and natural gas plants.
rates are held fixed, and no new plants are built. The endogenous variable associated with each plant is its generation level, denoted by $q_{f,r}$, which is bounded below by zero and above by the plant capacity. Total plant emissions and costs of generation are linear functions of the generation level: $\sigma_{f,r} \cdot q_{f,r}$ and $c_{f,r} \cdot q_{f,r}$, respectively.

1.4.1 No Regulation

To form a basis for comparison, I present the model first in the absence of regulation, a scenario that I refer to as business-as-usual (BAU). The social welfare function is given by the sum of consumer and producer surplus:

$$W_{p,q_i{f,r}} = \sum_r \left[ \int_0^{q_{f,r}} P_r(u)du - \sum_i \sum_f c_{f,r} \cdot q_{f,r} \right].$$

(1.1)

The social planner’s program is given by

$$\text{maximize} \quad W(q_{f,r})$$

subject to $0 \leq q_{f,r} \leq K_{f,r} \quad \forall i, f, r.$

(1.2)

Thus, the social planner’s objective is to choose plant-specific generation levels so that social welfare is maximized subject to the constraints on plant capacities. Given the structure of the model, the solution to (1.3) will be equivalent to a competitive market equilibrium.

Alternatively, production decisions can be presented from the perspective of the individual price-taking plants. The objective is to choose the generation level that maximizes profits subject to the capacity constraint:

$$\text{maximize} \quad p_{r} \cdot q_{f,r} - c_{f,r} \cdot q_{f,r}$$

subject to $0 \leq q_{f,r} \leq K_{f,r}.$

(1.3)

---

6 Although this paper does not explicitly model the dynamic effects of a differentiated policy, it does provide insight into what would be. I provide a discussion of how the results inform dynamic incentives at the end of the paper.
Profits are the difference between total revenues and total costs. From the plant perspective, the electricity price is given by a parameter, $p_r$. The Lagrangian associated with this program is defined as follows:

$$
L(q^i_{f,r}, \lambda^i_{f,r}) \equiv p_r \cdot q^i_{f,r} - c^i_{f,r} \cdot q^i_{f,r} - \lambda^i_{f,r}(q^i_{f,r} - K^i_{f,r}).
$$

(1.4)

Each plant faces the following first-order conditions (FOCs):

$$
q^i_{f,r} \geq 0 \quad \quad \quad \quad \lambda^i_{f,r} \geq 0
$$

$$
p_r - c^i_{f,r} - \lambda^i_{f,r} \leq 0 \quad \quad \quad \quad q^i_{f,r} - K^i_{f,r} \leq 0
$$

$$
q^i_{f,r}(p_r - c^i_{f,r} - \lambda^i_{f,r}) = 0 \quad \quad \quad \quad \lambda^i_{f,r}(q^i_{f,r} - K^i_{f,r}) = 0.
$$

(1.5)

Market equilibria are defined by the above conditions for each plant, as well as an aggregate resource constraint for each region that ensures that aggregate supply quantity equals the demand quantity.

On the individual plant level, generation decisions can be distilled into three possibilities. First, it is not economical for the plant to generate, and so $q^i_{f,r} = 0$. This will be the outcome if the equilibrium electricity price exceeds the plant’s unit cost of generation. Second, the plant generates up to its capacity so that $q^i_{f,r} = K^i_{f,r}$. This will occur if the equilibrium price is greater than the cost of generation, and so the plant will receive a rent ($\lambda^i_{f,r} > 0$) for each unit it generates. Finally, the plant might be on the margin where it’s cost of generation sets the equilibrium price. In this case, it will be the case that $0 < q^i_{f,r} < K^i_{f,r}$ and $\lambda^i_{f,r} = 0$.

One possible business-as-usual equilibrium is illustrated in Figure 1.1. The graphical example demonstrates the outcome for a particular two-region, two-plant scenario. Region 1 is endowed with a low-cost coal plant and a higher-cost gas plant. Region 2 generates its electricity at two coal plants, one which has lower costs of generation than the other. For simplicity, electricity demand is modeled as perfectly inelastic.
In both regions, electricity supply is an increasing step-function; costs for gas and coal plants are represented by red and black lines, respectively. To meet electricity demand (represented by the vertical blue line), units are “dispatched” in order of increasing unit cost. The more expensive plants in each region set the equilibrium price of electricity. The cheaper plants are used to capacity, and accrue profits equal to the shaded areas.

1.4.2 Tradable Performance Standard Policies

Now imagine that the social planner seeks to reduce emissions through a tradable performance standard policy. Initially, the policy under consideration sets a single standard for all fuel types. As demonstrated by Holland et al. (2009), the performance standard chosen by the regulator must be below the aggregate emission rate in order to change firm behavior. If the quantities $q_{i,bau}^{f,r}$ represent plant generation levels in the absence of regulation and $s$ represents the standard, this means that the inequality

$$\frac{\sum_r \sum_i \sum_f \sigma_{i}^{f,r} q_{i,bau}^{f,r}}{\sum_r \sum_i \sum_f q_{i,bau}^{f,r}} < s \quad (1.6)$$

FIGURE 1.1: Two-Region Business-As-Usual Electricity Market Equilibrium
must be satisfied. If it is, then I say that the standard is binding.

How will the market comply with the standard? In the electricity sector, I focus on two margins. The first is the coal-to-gas margin, in which coal-fired generation is displaced by gas-fired generation. The second is the within-fuel margin, either coal-to-coal or gas-to-gas, in which generation from a high emission rate plant is displaced by generation by a low emission rate plant within the same fuel category. These margins will be important when comparing a single standard to a differentiated policy.

Implementation of a (binding) tradable performance standard policy will add a (possibly negative) regulatory cost component to the economics of the individual plants. Plants with emission rates below the standard \( (\sigma_{f,r}^i < s) \) will be suppliers of compliance credits while plants with emission rates above the standard will be demanders. For the individual plant, the profit-maximization problem now has to account for credit sales/purchases:

\[
\begin{align*}
\text{maximize} & \quad p_r \cdot q_{f,r}^i - c_{f,r}^i \cdot q_{f,r}^i - \tau \cdot z_{f,r}^i \\
\text{subject to} & \quad 0 \leq q_{f,r}^i \leq K_{f,r}^i \\
& \quad (\sigma_{f,r}^i - s)q_{f,r}^i \leq z_{f,r}^i.
\end{align*}
\]  

\( (1.7) \)

Net credit demand is denoted by \( z_{f,r}^i \), and the equilibrium price for a credit is \( \tau \). If \( z_{f,r}^i > 0 \), then the plant will demand credits; otherwise, it will supply them. Because there is no benefit to not selling excess credits or purchasing more than is required to comply, the credit constraint will bind for all plants. As a result, credit demand can be substituted out of the objective function, and maximization occurs over a single
The FOCs for plants under the single standard policy account are

\[ q^i_{f,r} \geq 0 \quad \lambda^i_{f,r} \geq 0 \]
\[ p_r - c^i_{f,r} - \tau(\sigma^i_{f,r} - s) - \lambda^i_{f,r} \leq 0 \quad q^i_{f,r} - K^i_{f,r} \leq 0 \]
\[ q^i_{f,r}(p_r - c^i_{f,r} - \tau(\sigma^i_{f,r} - s) - \lambda^i_{f,r}) = 0 \quad \lambda^i_{f,r}(q^i_{f,r} - K^i_{f,r}) = 0. \]

The market equilibrium is defined by these conditions, the aggregate resource constraints for each region, and a credit market clearing condition that requires that the number of credits purchased must equal the number of credits sold. Mathematically, this is equivalent to

\[ \sum_r \sum_i \sum_f z^i_{f,r} = \sum_r \sum_i \sum_f (\sigma^i_{f,r} - s)q^i_{f,r} = 0. \]

1.4.3 Calculating the Credit Price

The only difference in between the business-as-usual and performance standard conditions from a plant’s perspective is the presence of the regulatory cost object \( \tau(\sigma^i_{f,r} - s) \). The emission rate and standard are exogenous in this setting, while the credit price is endogenously determined by the model. To see how the credit price is determined, imagine a low stringency policy such that the standard is set just below the business-as-usual aggregate emission rate.

Recalling our discussion of compliance margins, it must be the case that cheaper, higher emission rate generation is displaced by expensive lower emission rate generation. In order to maintain the same total level of electricity supply in each region, this displacement must occur between plants within the same region. Furthermore, because of the structure of the model with constant unit costs and fixed capacity, it must be the case that the displaced plant is operating at capacity, and the displacing plant is operating below capacity. For a low stringency policy, the level of displace-
ment could be fairly minimal so that both plants are operating yet below capacity. As implied by the FOCs, these plants will both be at the margin, i.e., their costs (including regulatory costs) will be equal to the equilibrium price level. We can use this fact to calculate the credit price:

\[
c^j_{f,r} + \tau(\sigma^j_{f,r} - s) = c^\sigma_{f,r} + \tau(\sigma^\sigma_{f,r} - s)
\]

\[
\Rightarrow \tau = \frac{c^\sigma_{f,r} - c^j_{f,r}}{\sigma^j_{f,r} - \sigma^\sigma_{f,r}}.
\]

(1.10)

Because the credit price is a function of plant-specific parameters, it follows that only two plants will be actively switching – across all regions – for any given level of the standard (unless there are two pairs of plants in different regions who have unit cost equalized by the same credit price). Going forward, I will refer to the plants on the switching margin as the *marginal switching pair*.

To illustrate the single-standard policy graphically, I return to the two-region example. Figure 1.2 demonstrates how generation, electricity prices, and profits are altered by implementing a performance standard. Consistent with the above discussion, the policy illustrated is of relatively low stringency; in the next section, I illustrate what happens as the standard is tightened.

The supply curves in each region under the policy are represented by the dashed lines. For comparison, the business-as-usual supply curves are reproduced as the solid lines. Because demand is inelastic, the only method of compliance is to switch generation from a high emission rate plant to a low emission rate plant, which is what happens in Region 1. Coal plant generation is displaced by generation from the natural gas plant. The unit costs of these plants are equal, as the coal plant is taxed and the gas plant is subsidized. The amount of displaced coal generation is given by the distance between the dotted vertical lines.

In Region 2, the marginal coal plant is subsidized under the standard while the
infra-marginal plant is taxed. This has the effect of lowering the electricity price while raising the cost of the low cost plant. As a result, the profits of this plant are reduced significantly.

1.4.4 Building Emissions Reductions

The policy applied to the two-region example in the previous section featured a single switching pair; however, meaningful aggregate emission reductions for the U.S. electricity sector would require switching among many pairs of plants. In the current setting, this requires tightening the performance standard. In this section, I examine what happens to the credit price as the policy becomes more stringent. The intuition developed here is useful in analyzing the impacts of a differentiated standard.

Using the equilibrium from Figure 1.2 as a starting point, suppose that the regulator tightens the standard slightly: I refer to this as a medium stringency policy. The result is depicted in Figure 1.3. The supply curves from the low stringency policy are represented by the solid lines, while the new supply curves are represented by the dashed lines. In order to comply with the new standard, there is additional switching from the coal plant to the gas plant in Region 1, as depicted by the dis-
tance between the vertical dotted lines. Because the credit price is purely a function of the parameters on the switching margin, meaning that it does not vary with the level of switching in response to the standard (as long as that pair continues to be actively switching). However, the unit costs do depend on the level of the standard: raising the standard means increasing unit costs for each plant, which is reflected as an upward shift in the supply curve. Therefore the electricity price increases in both regions, even though the credit price remains unchanged. Moreover, with the marginal switching pair in Region 1, generation in Region 2 does not change.

As the regulator continues to tighten the standard (high stringency), additional switching opportunities are undertaken. In the present example, this occurs when the single gas plant in Region 1 reaches capacity. Figure 1.4 demonstrates this graphically. The supply curves for the medium and high stringency standards are represented by solid and dashed lines, respectively. When the standard has been tightened sufficiently, the dispatch order in Region 1 flips: the coal plant is marginal and sets the electricity price and the gas plant now has the lower unit cost and accrues profits.
Region 2 supplies the additional compliance margin; the marginal switching pair is now the two coal units in Region 2. In order for this margin to exist, the higher cost coal plant must also have a lower emission rate (if not, there is no way to wring further emission rate improvements from this scenario). Additionally, this switching pair will now define the equilibrium credit price, which must be greater than the credit price defined by the Region 1 switching pair. That is, the credit price will jump discretely. For a larger electricity market, the compliance cost schedule will consist of an increasing function with many steps.

1.4.5 Differentiating the Standard

In this section, I describe what happens when the social planner differentiates the standard. The insights developed here build off of the developments from the previous section, and form the basis for the analytic results on coal usage, coal profits, and

---

8 To see this, I start by reiterating the well-known equivalence between the social planner’s optimal outcome and the competitive equilibrium outcome. The equilibrium credit price will be equal to the shadow value on the social planner’s credit constraint. Lagrangian duality implies that this credit price is the smallest such price that the emissions constraint is satisfied. Therefore, as the constraint becomes more and more stringent, the credit price must rise.
electricity prices provided in the next sub-section.

The impact of differentiated standards on electricity market economics requires an understanding of how they alter the compliance margins. Recall the emission rate constraint given by (1.9). Unlike in the previous section, however, imagine that the regulator provides coal and natural gas plants with different standards such that \( s_{coal} > s_{gas} \). As with the single standard, there is a single marginal switching pair associated with a particular choice of \( s_{coal} \) and \( s_{gas} \), and the plants in that pair have equal unit costs. In this case, the new equilibrium credit price when these two plants are providing marginal mitigation can be determined as follows:

\[
c_i^{f,r} + \tau (\sigma_i^{f,r} - s_f) = c_{p,r}^{d} + \tau (\sigma_{p,r}^{d} - s_p)
\]

\[
\Rightarrow \tau = \frac{c_i^{d} - c_i^{f,r}}{\sigma_i^{f,r} - \sigma_{p,r}^{d} - (s_f - s_p)},
\]

Compared to the single standard policy, the switching margins have been distorted by the parenthetic expression in the denominator. Note that if the switching margin is between two fuels of the same type, the associated credit price is unchanged by differentiation. However, in the case of a switch between coal and natural gas, the credit price increases unambiguously. The way to think about this is if you line up the switching pairs in the order of credit price they require, all else equal, within-fuel switches have become less costly relative to coal-to-gas switches. Moreover, as the level of differentiation increases, the penalty on coal-to-gas switches rises. In an absolute sense, all switches are at least as costly under differentiation, which cause the equilibrium price to rise for a given level of stringency.\(^9\) In the following sub-section, these credit price and switching behaviors will be illustrated graphically—and then linked to coal usage.

\(^9\) This result is reminiscent of the Bohringer and Lange (2005) result for bench-marked allocation in a cap-and-trade program.
1.5 Differentiating a Performance Standard: Impacts from Analytic Model

In this section, I use the framework developed previously to derive some basic facts about the potential impacts of differentiating the standard on coal usage, coal plant profits, and regional wholesale electricity prices. I also address the impacts on cost-effectiveness. The goal of this section is to demonstrate analytic results where possible and facilitate understanding of the simulation results presented later.

1.5.1 Coal Usage

Given relatively inelastic electricity demand and the fact that coal-fired power plants typically emit CO$_2$ at double the rate of natural gas plants, any regulation to reduce CO$_2$ will necessarily result in significant reductions in the amount of coal-fired generation. Accordingly, a tradable performance standard would have a negative effect on the demand for coal, leading to a decrease in coal consumption. The purpose of this section is to demonstrate how differentiating the standard will typically lead to a “less negative effect” on coal usage, which the simulation model will then quantify.

The mechanism through which differentiating an otherwise equivalent performance standard might increase coal usage can be seen by comparing within-fuel and coal-to-gas switching margins. Previously, I established that differentiation reduces the cost of within-fuel switches relative to coal-to-gas switches. This suggests that for a given level of emissions reduction, a greater proportion will be met by within-fuel “clean-to-dirty” switches. Such a switch will not change the composition of electricity generation by fuel. Therefore, the extent to which these types of switches are available will determine in part how much less coal generation is displaced by natural gas generation under the differentiated standard, and thus how much more coal is used.

The impact of differentiation on within-fuel switching frequency in a hypotheti-
The graph depicts the marginal compliance cost schedule against the level of emission reductions. Focus first on the black and red horizontal lines. Each step represents a different switching pair under a single standard policy. The black and red steps correspond to coal-to-gas and coal-to-coal switches, respectively. The vertical dashed line represents the emission reduction target of the policy. Though the $x$-axis measures emissions, each point has a one-to-one mapping to specific choice of the standard. The marginal compliance cost at the emission reduction target will yield the equilibrium credit price, as depicted by the horizontal dashed line. Two of the three coal-to-coal switches are not undertaken under the target.

![Figure 1.5](image)

**Figure 1.5**: Credit Price as a Function of Emission Reductions

The blue lines correspond to the marginal compliance costs under a differentiated standard policy. In the left panel, the pure cost effect is isolated. In mathematical terms, this is the impact of including the difference in the fuel-specific standards from the credit price expression in (1.11). This causes the costs to increase for all coal-to-gas switches while the costs for coal-to-coal switches remain the same. In the right panel, the marginal compliance costs are resorted into the new ordering that
will occur and the new equilibrium can be observed. As a result, the coal-to-coal switches that previously were not employed are used to achieve the same target. This results in less coal displacement, and therefore greater coal usage under the differentiated policy.

The graphic also demonstrates how the credit price will increase under a differentiated policy. This observation will be very important in understanding the impact of differentiation on plant unit costs, which will ultimately drive the price and coal plant profit results.

1.5.2 Per Unit Costs

In order to explain how differentiation impacts coal plant profits and regional electricity prices, it is necessary to understand how it affects plant unit costs. The framework developed here will guide our analysis of those other two distributional outcomes.

To analyze the cost impacts of a differentiated policy, I investigate what happens for an incremental increase in the coal standard. Mathematically, this can be seen by treating the credit price and the gas standard as functions of the coal standard. These functions are implicitly defined by the market equilibrium conditions on generation, the credit market constraint, and an equation specifying that emissions reductions are the same across all policies. Taking the derivative with respect to that standard, the resulting change (for representative coal and gas plants) is

$$\frac{\partial UC_{\text{coal},r}^i}{\partial s_{\text{coal}}} = \frac{\partial}{\partial s_{\text{coal}}} \left( c_{\text{coal},r}^i + \tau (\sigma_{\text{coal},r}^i - s_{\text{coal}}) \right) = \frac{\partial \tau}{\partial s_{\text{coal}}} (\sigma_{\text{coal},r}^i - s_{\text{coal}}) - \tau \quad (1.12a)$$

$$\frac{\partial UC_{\text{gas},r}^i}{\partial s_{\text{coal}}} = \frac{\partial}{\partial s_{\text{coal}}} \left( c_{\text{gas},r}^i + \tau (\sigma_{\text{gas},r}^i - s_{\text{gas}}) \right) = \frac{\partial s_{\text{gas}}}{\partial s_{\text{coal}}} \left( \frac{\partial \tau}{\partial s_{\text{gas}}} (\sigma_{\text{gas},r}^i - s_{\text{gas}}) - \tau \right) \quad (1.12b)$$

Note that the assumption of constant unit generation costs means that changes in plant unit costs will depend entirely on the net change in the unit costs of regulation.
Also, in order to keep emissions reductions fixed, the gas standard must tighten as the coal standard relaxes, i.e., $\partial s_{gas}/\partial s_{coal} < 0$.

For a “small” degree of differentiation, the net change in unit costs for both coal and gas plants depends on the relative magnitudes of two competing effects. As previously discussed, increasing the coal standard while keeping emission reductions fixed will result in an increasing credit price; this also implies that $\partial \tau/\partial s_{gas} < 0$. In isolation, the rising credit price results in larger per unit taxes for coal plants and subsidies for gas plants: this is captured by the first term of each equation in (1.12). However, an increasing coal standard also reduces the amount of compliance credit purchases for each unit generated at the coal plants, which reduces their per unit tax. For gas plants, the amount of compliance credits created (and hence sold) for each unit generated reduces, which reduces their per unit subsidy. This is captured by the “$\tau$” term in the parenthetical expression for both plant types. Ultimately, the net change in unit cost for a given plant will depend on which of these effects dominates.

Eventually, if the standards are differentiated to a sufficient degree, generation from low emission rate coal plants can become subsidized. Alternatively, generation from high emission rate gas plants can become taxed. For plants in those two categories, the impact of further differentiation on unit costs is unambiguous: they decrease for the coal plants and increase for the gas plants.

Because the expressions in (1.12) depend on plant-specific emission rates, it is possible, if not likely, that unit costs for some plants within a fuel category will increase while others will decrease. In any case, there is an emission rate in each category for which costs do not change. I refer to these rates, associated with a given level of differentiation, as iso-cost emission rates. Mathematically, they are defined
for both coal and gas plants by the following equations:

\[
\frac{\partial UC_{\text{coal},r}}{\partial s_{\text{coal}}} = 0 \Leftrightarrow \sigma^*_{\text{coal}}(s_{\text{coal}}) = \frac{\tau}{\frac{\partial \varepsilon}{\partial s_{\text{coal}}}} + s_{\text{coal}},
\]

(1.13)

and

\[
\frac{\partial UC_{\text{gas},r}}{\partial s_{\text{coal}}} = 0 \Leftrightarrow \sigma^*_{\text{gas}}(s_{\text{coal}}) = \frac{\tau}{\frac{\partial \varepsilon}{\partial s_{\text{coal}}}} + s_{\text{gas}}.
\]

(1.14)

Unit costs will be increasing for plant \( i \) if its emission rate exceeds the corresponding iso-cost emission rate at a given level of differentiation for its fuel type. Otherwise, unit costs will be decreasing. Note that the iso-cost rates will be complex functions of the universe of plants and mitigation opportunities.

The relationship between the degree of differentiation, iso-cost emission rates, and plant-specific emission rates is demonstrated graphically in Figure 1.6. The graphic is labeled in the context of coal plants, though the analysis for gas plants is equivalent. The vertical axis measures emission rates, and the horizontal axis measures the coal standard, which serves as a proxy for the level of differentiation. The dashed line represents a hypothetical path for the iso-cost emission rate. Note that this rate is a function of the coal standard, and hence moves vertically as the level of differentiation increases. For plants with high-emission rates, represented by the horizontal blue line, unit costs are increasing regardless of the level of the coal standard. The opposite is true for low-emission rate plants, represented by the red line. For medium-emission rate plants, such as the one represented by the purple line, it is possible that unit costs will be increasing for some levels of the standard and decreasing for others. For those plants, the sign of the net effect on unit costs of a particular level of differentiation (relative to the single-standard) needs to be calculated by integrating the marginal effects over all less differentiated policies.
Regional Prices

A fundamental feature of the U.S. electricity sector is regional segmentation. As a consequence, regulatory policies can have different impacts on different regions of the country. Analytically, the impact of differentiated standard policy on electricity prices in a given region is ambiguous. Furthermore, regional prices need not be monotonic in the degree of differentiation. Ultimately, it will depend largely on the joint distribution of the unit costs and emission rates for both gas and coal plants within the region. As I demonstrate below, in order for prices to not rise in a region, there must be sufficient capacity with low emission rates (conditional on fuel type) to replace relatively low-cost, higher-rate generation.

There are two avenues through which differentiation can alter electricity prices in a region. First, it can influence the unit cost of the marginal plant in the region,
as was discussed in the previous section. If the marginal plant has an emission rate below the iso-cost rate, then the wholesale price in the region will decrease, and vice versa for marginal plants above the iso-cost rate. For small changes in the degree of differentiation, this is the mechanism that would be expected to drive price changes. For larger changes, it is more likely that the marginal plant itself would change. How the dispatch order changes will depend on the changes in the compliance costs of switching opportunities within the region of interest, as well as those same changes across the entire sector.

Figure 1.7 illustrates how electricity prices might change with further differentiation in a hypothetical region at a particular level of regulation. The vertical axes represent net unit costs of generation under a given performance standard policy, and the horizontal axes represent observed plant emission rates. Unit cost and emission rate pairs for specific plants are represented by the blue dots, and the horizontal blue line represents the electricity price at the current level of differentiation. This price is, of course, determined by the unit cost of the plant at the margin.

The vertical dashed black lines represent three possibilities for the iso-cost emission rates, all of which have different implications for the electricity price. For simplicity, assume that these rates remain constant as the level of differentiation increases – this is equivalent to forcing the dashed line in Figure 1.6 to be horizontal. Under this assumption, both gas and coal plants can be represented on the same graph by pegging their emissions rate to their respective iso-cost rates. For plants with emission rates to the right of the dashed lines, unit costs increase with an increase in differentiation; for plants to the left, unit costs decrease.

Consider first the case in which iso-cost emission rates are depicted by the line labeled $\sigma_h^*$. Here all currently employed plants are to the left of the dashed line,10

10 One way to accomplish this transformation would be to subtract $\sigma_{coal}^* - \sigma_{gas}^*$ from the coal plant emission rates. This generates a standardized emission rate for those plants that can be used to plot gas and coal plants on the same axes.
meaning that their unit costs are decreasing in the coal standard. Therefore, prices will decrease monotonically with the degree of differentiation, even if the identity of the marginal plant changes. Conversely, suppose that the iso-cost emission rates are depicted by the $\sigma^*_l$ line. In this setting, all units with decreasing unit costs are producing at capacity, but additional generation is required to meet demand. The additional generation must come from plants with increasing unit costs, and so prices must increase monotonically with the coal standard.

In the first two scenarios, the effect of differentiation on prices in the region was straightforward. Now suppose the $\sigma^*_m$ line represents the iso-cost emission rate. In this case, a portion of currently employed capacity experiences increasing unit costs, while there is idle capacity with decreasing unit costs. The net effect on prices de-
pends on the magnitude of the rates of change in unit prices, which will determine at what point the low emission rate plant replaces the high rate plant. This ambiguity can result in non-monotonic responses in price to the degree of differentiation. Non-monotonicities can also result from the fact that the dashed lines are likely to shift with the degree of differentiation, which I have assumed away in this diagram.

1.5.4 Coal Generator Profits

The impact of differentiation on coal plant profits depends on factors described above: net unit costs and regional electricity prices. Compared with the business-as-usual equilibrium, it’s expected that imposing a single standard will likely have universally negative consequences for coal plant profits as it will tax all coal generation without increasing electricity prices appreciably.\(^{11}\) When the standards are differentiated, however, outcomes are less clear. Based on the preceding discussion, in this section I describe how differentiation influences plant profits at the individual unit, regional, and national levels.

From a profit perspective, differentiation will tend to enhance the economic position of plants with low emission rates while negatively impacting those with higher rates. In the context of utilization, some coal plants will benefit from differentiation. These plants tend to be relatively lower-emission rate units that are brought online through within-fuel switches. As was demonstrated in Figure 1.6, coal plants with particularly low emission rates will enjoy growing cost benefits from differentiation. As the degree of differentiation becomes very large, the plant economics can become even more favorable than in the case of no regulation for the cleanest of facilities. Whether this occurs or not depends also on the price impacts of differentiation.

To this point, the actual impacts of differentiation on output prices have been ac-

\(^{11}\) The muted impact of a (single) performance standard policy on prices, as opposed to, for instance, a cap-and-trade policy results from the implicit output subsidy established by the policy.
Acknowledged as ambiguous. In actuality, the simulation results will point to a nearly universal increase in prices, which will contribute further to the profit advantage of clean coal plants.

The aggregated impacts on coal plant profits both regionally and nationally are difficult to assess analytically, but there still are a few points to be made on those fronts. First, heterogeneity for aggregate coal profits across regions could be quite significant. For instance, consider a region with a large endowment of low emission rate coal capacity, but even greater electricity demand. If the resources available to meet that residual demand are high-emission rate natural gas plants, prices will increase while unit coal costs will decrease, leading to substantial profit improvements for coal plants in that region. On the other hand, imagine a region with cheap, high emission rate coal plants and expensive, low emission rate natural gas plants, with the latter on the margin. Under a single standard policy, the coal plants might still be utilized heavily if coal-to-gas switches in other regions are relatively cheaper. As demonstrated previously, differentiation will result in unit cost decreases for the low emission rate units (which are on the margin) and increases for the high emission rate plants. The result will be decreasing electricity prices and increasing coal plant costs, and so regional coal profits will decrease as a result of differentiation. In a national market with both types of regions, as well as regions between these extremes, it is difficult to assess the aggregate effect on coal profits nationally; doing so will require implementation of a numerical model.

1.5.5 Cost-Effectiveness

It is well-established in the environmental regulation literature that tradable performance standards are second-best instruments for pollution abatement if demand has any price response (see, e.g., Fischer (2001) and Holland et al. (2009)). This is because the implicit output subsidy that they establish results in less than opti-
mal reductions through conservation; instead, an inefficient proportion of emissions reduction comes from supply-side measures such as fuel-switching. The lack of conservation under a tradable, single standard policy leaves room for improvements through differentiation. While I only briefly address the cost-effectiveness issue here, a thorough analysis can be found in Lemoine (2014).

To demonstrate how differentiation can improve cost-effectiveness outcomes, I frame the problem in Stackelberg fashion. Taking the market equilibrium as given, the social welfare function is defined as a function of the coal standard, assuming that the gas standard is a function of the coal standard:

\[
W(s_{\text{coal}}) = \sum_r \left[ \int_0^{\sum_i q^i_{r,r}(s_{\text{coal}})} P_r(u) \, du - \sum_i \sum_f c^i_{f,r} \cdot q^i_{f,r}(s_{\text{coal}}) \right]. \quad (1.15)
\]

The question is what happens to welfare as the coal standard is increased by a small amount. Taking the derivative yields

\[
W'(s_{\text{coal}}) = \sum_r \sum_i \sum_f (P_r(q_r) - c^i_{f,r} - \lambda^i_{f,r}) \cdot \frac{\partial q^i_{f,r}}{\partial s_{\text{coal}}}, \quad (1.16)
\]

where \( q_r = \sum_i q^i_{\text{gas},r}(s_{\text{coal}}) + \sum_i q^i_{\text{coal},r}(s_{\text{coal}}) \). For small changes in the standard, only the marginal units will respond, meaning that \( \partial q^i_{f,r}/\partial s_{\text{coal}} = 0 \) for all units such that \( \lambda^i_{f,r} > 0 \). Removing those units and plugging in the first-order conditions for the marginal generators yields

\[
W'(s_{\text{coal}}) = \sum_r \sum_i \sum_f \tau(\sigma^i_{f,r} - s_f) \cdot \frac{\partial q^i_{f,r}}{\partial s_{\text{coal}}} \]

\[
= \sum_r \sum_i \sum_f \tau(\sigma^i_{f,r} - s_f) \cdot \frac{\partial q^i_{f,r}}{\partial s_{\text{coal}}} \quad (1.17)
\]

\[
= \tau \left( \sum_r \sum_i \sum_f \sigma^i_{f,r} \cdot \frac{\partial q^i_{f,r}}{\partial s_{\text{coal}}} - \sum_r \sum_i \sum_f s_f \cdot \frac{\partial q^i_{f,r}}{\partial s_{\text{coal}}} \right).
\]
Note that the first term in parentheses is the change in emissions in response to a change in the standard. Assuming, as has been the case to this point, that the coal and gas standards are changed in such a way that emissions are held constant, that term drops out of the equation, leaving

$$W'(s_{coal}) = -\tau \left( \sum_r \sum_i \sum_f s_f \cdot \frac{\partial q_{i,r}}{\partial s_{coal}} \right). \quad (1.18)$$

Solving at the single-standard rate such that $s_f = s$ for all $f$, the equation reduces further to

$$W'(s_{coal}) = -\tau \cdot s \left( \sum_r \sum_i \sum_f \frac{\partial q_{i,r}}{\partial s_{coal}} \right). \quad (1.19)$$

The summation term in the above equation is simply the change in aggregate generation. This implies that the change in welfare due to an incremental increase of the coal standard at the single standard level is a decreasing function of the change in output. Therefore, the initial effect of differentiation away from a uniform standard can yield increases in welfare if and only if it induces an increase in conservation. Accordingly, if demand is assumed to be perfectly inelastic, then aggregate generation is fixed and differentiated policies are less cost-effective.

1.6 Simulation Model

Here I describe the construction of my detailed electricity sector model, and how I use it to simulate a suite of performance standard policies. The simulation model allows me to calibrate the policies to forecasted supply and demand and quantify their impacts. Several data sources, each with relative strengths and weaknesses, are used in the parameterization of the model in an effort to mirror actual conditions in 2017.
1.6.1 Model Structure and Equilibrium Conditions

The simulation model structure is essentially a more detailed version of the model presented in Section 1.4. Electricity can now be transferred across regions (still denoted by \( r \)) to meet demand. Due to the non-storable nature of generated electricity, the market is also broken into time segments (\( s \)). This feature reflects the necessity for supply to meet demand instantaneously as well as the seasonal and daily fluctuations in demand. Adding these features to the model introduced in Section 1.4, the social welfare function can be the following:

\[
W(q_{j,r,s}^i, t_{r,r',s}) = \sum_r \sum_s \left[ \int_0^{\sum_j q_{j,r,s} + \sum_{s'}(1-\ell_{r,r',s})t_{r',r,s} - t_{r,r',s}} P_{r,s}(u) du \right] - \sum_i \sum_{j} c_{j,r,s} \cdot q_{j,r,s} - \sum_{r'} w_{r',r} \cdot t_{r',r,s}.
\]

The social planner’s objective function is now maximized over unit-specific generation \((q_{j,r,s}^i)\) and the level of electricity transfer \((t_{r,r',s})\) from region \( r' \) to region \( r \) within each time segment. Transfers between regions are subject to losses and wheeling costs, denoted by \( \ell_{r',r,s} \) and \( w_{r',r} \), respectively.

Without regulation, the social planner solves the following program:

\[
\begin{align*}
\text{maximize} & \quad W(q_{j,r,s}^i, t_{r,r',s}) \\
\text{subject to} & \quad 0 \leq q_{j,r,s}^i \leq K_{j,r,s}^i \quad \forall i, j, r, s \\
& \quad 0 \leq \sum_{s \in S} q_{j,r,s}^i \leq A_{j,r,s}^i \quad \forall i, j, r, S \\
& \quad 0 \leq t_{r,r',s} \leq T_{r,r',s} \quad \forall r, r', s.
\end{align*}
\]

Inter-regional transmission capacity limits are given by \( T_{r,r',s} \). In addition to a capacity constraint within time segments, generation units also have a seasonal availability constraint to reflect forced outages for maintenance, where seasons are denoted by \( S \).
Availability is specified as a proportion of the sum of capacity over all time segments:

\[ A_{j,r,S}^i = a_{j,r,S}^i \sum_{s \in S} K_{j,r,s}^i, \]  

(1.22)

where \( a_{j,r,S}^i \in (0, 1). \)

The program under regulation is analogous to the one described in Section 1.4. Seeking to meet an emissions target through tradable performance standards, the regulator seeks to maximize the following Lagrangian:

\[
\mathcal{L}(q_{j,r,s}^i, t_{r,r',s}^i, \lambda_{j,r,s}^i, \mu_{j,r,S}^i, \gamma_{r,r',s}^i, \tau) \equiv W(q_{j,r,s}^i, t_{r,r',s}^i) - \sum_r \sum_{s} \sum_i \sum_j \lambda_{j,r,s}^i (q_{j,r,s}^i - K_{j,r,s}^i) \\
- \sum_r \sum_S \sum_i \sum_j \mu_{j,r,s}^i \left( \sum_{s \in S} q_{j,r,s}^i - A_{j,r,s}^i \right) - \sum_r \sum_{s'} \sum_s \gamma_{r,r',s}^i (t_{r,r',s}^i - T_{r,r',s}) \\
- \tau \left( \sum_r \sum_{s} \sum_i \sum_j (\sigma_{j,r,s}^i - s_j) q_{j,r,s}^i \right),
\]

(1.23)

---

12 The approach to modeling seasonal availability is similar to the EPA’s Base Case v.5.13, which uses ICF International’s Integrated Planning Model (IPM) (U.S. Environmental Protection Agency, 2013). Alternatively, models such as the one developed in Bushnell and Chen (2012), specify a similar availability constraint in each time segment. As a result, the capacity constraint becomes superfluous. Conceptually, the seasonal approach reflects the ability of the unit operator to schedule maintenance strategically to minimize lost profits, while the per-segment approach reflects the unexpected nature of some outages.
The associated Kuhn-Tucker conditions, given in complementarity form, include the following.\(^{13}\)

\[
q_{j,r,s}^i \geq 0 \quad \perp \quad P_{r,s}(i) - c_{j,r,s}^i - \lambda_{j,r,s}^i - \mu_{j,r,s}^i - \tau(s_{j,r,s} - s_j) \leq 0 \quad \forall i, j, r, s \\
\lambda_{j,r,s}^i \geq 0 \quad \perp \quad q_{j,r,s}^i - K_{j,r,s}^i \leq 0 \quad \forall i, j, r, s \\
\mu_{j,r,s}^i \geq 0 \quad \perp \quad \sum_{s \in S} q_{j,r,s}^i - A_{j,r,s}^i \leq 0 \quad \forall i, j, r, S \\
t_{r,r',s} \geq 0 \quad \perp \quad (1 - \ell_{r,r',s})P_{r,s} - P_{r',s} - w_{r,r',s} - \gamma_{r,r',s} \leq 0 \quad \forall r, r', s \\
\mu_{r,r',s} \geq 0 \quad \perp \quad t_{r,r',s} - T_{r,r',s} \leq 0 \quad \forall r, r', s \\
\tau \geq 0 \quad \perp \quad \sum_r \sum s \sum i \sum j (\sigma_{j,r,s}^i - s_j)q_{j,r,s}^i 
\]

(1.24)

Missing from this system is an aggregate resource condition, which mandates that the quantity of generation meets demand in each region and time segment. Under an assumption of constant demand elasticity, the appropriate condition is

\[
P_{r,s} \geq 0 \quad \perp \quad Q_{s,r,s}^0 (P_{r,s}/P_{r,s}^0)^{\epsilon_{r,s}} - \sum_i \sum q_{j,r,s}^i - \sum_{r'} ((1 - \ell_{r',r,s})t_{r',r,s} - t_{r,r',s}) \leq 0 \quad \forall r, s, 
\]

(1.25)

where \(Q_{s,r,s}^0\) and \(P_{r,s}^0\) represent the equilibrium electricity demand and price, respectively, at the business-as-usual level. The constant elasticity in region \(r\) for time segment \(s\) is denoted by \(\epsilon_{r,s}\). Under the assumption of perfectly inelastic demand, \(\epsilon_{r,s} = 0\) for all \(r, s\); in this case, the model reduces to a simple linear program.

1.6.2 Data Sources and Model Parameterization

In this section, I describe the data and assumptions utilized in my simulation model. The model is constructed to provide a detailed yet transparent exploration into static performance standard policies for CO\(_2\). Overall, the model structure is similar in

\(^{13}\) Complementarity form here means that the product of the left-hand side of each pair of inequalities is equal to zero.
spirit to the dispatch module of several other electricity market models, such as the U.S. Energy Information Administration’s National Energy Modeling System and ICF International’s IPM (U.S. Energy Information Administration, 2013).

**Electricity Demand**

Demand for electricity in the model is adapted from EPA Base Case v.5.13 (U.S. Environmental Protection Agency, 2013). Each region has an hourly demand profile, also referred to as a load curve, that chronologically specifies a demand level of electricity for each hour in the year. For computational reasons, I first sort the load curve (within seasons) from highest to lowest demand, and then I aggregate those profiles into representative time segments. Demand is split into eight time segments within two seasons ("Summer" and "Winter"), meaning that there are 16 total segments. The segments are chosen that there are fewer hours at the high and low ends and more hours in the intermediate sections of the curve. Hourly demand within each segment is summed for each region.

**Unit-Specific Attributes**

Electricity supply is modeled at the individual generating unit level. This is possible because of the availability of fairly reliable and specific data collected by the EIA, EPA, and U.S. Federal Energy Regulatory Commission. The key characteristics of each unit are the region, fuel type, capacity, availability, and variable operations and maintenance (VOM) costs. Fossil units also have heat rates, which are a measure of efficiency, and emission factors. Below I describe where these data are obtained, and how they are incorporated into the model.

Data for basic unit characteristics come from a variety of sources. The overall universe of generating units comes from SNL Financial. Units that are expected to retire prior to 2017 are omitted from the model, while units that are characterized
as being “under construction” with an in-service date prior to 2017 are included. Fuel type and capacity data is also extracted from SNL Financial. The set of units is merged with the EPA’s NEEDS v.5.13 database to place each unit in a region; unmatched units are placed into regions based on additional grid interconnection data from SNL Financial (U.S. Environmental Protection Agency, 2013). Finally, unit availability data is extracted from the NEEDS database.

Individual unit costs are assumed to be linear for all levels of generation. Generating unit costs per Mwh are constructed as VOM costs plus the product of the heat rate \((HR)\) and the fuel price \((FP)\):

\[
c_i^{j,r,s} \equiv VOM_i^{j,r} + HR_i^{j,r} \cdot FP_i^{j,r,s}.
\]

The heat rate is defined in terms of mmBtu (million British thermal units) per MWh, i.e., the amount of primary heat energy required by the plant to produce a unit of electricity. Fuel prices are measured by $ per mmBtu, i.e., the price per unit of heat; they are assumed to be zero for non-thermal units (e.g., nuclear and renewables). Heat rates and VOM costs are taken from SNL Financial data whenever possible; otherwise, they are extracted from the NEEDS database. Fuel prices are collected from a combination of EPA Base Case v.5.13 and the 2014 North American Database for EPIS’s Aurora software.

Emission rates, defined in terms of pounds of CO\(_2\) per MWh, are the product of the heat rate of the generating unit and an emissions factor that measures the CO\(_2\) intensity of the associated fuel:

\[
\sigma_i^{j,r} \equiv EF_i^{j,r} \cdot HR_i^{j,r}.
\]

The emissions factor is defined in terms of pounds of CO\(_2\) per mmBtu. For natural gas generators, this factor is assumed to equal across all units. For coal plants, this factor defers depending on the type of coal that the unit burns. Emission factors are
extracted from SNL Financial when possible; otherwise, an average factor based on the unit’s fuel type is used.

*Transmission Network*

A key feature of the U.S. electricity sector is the interconnectness of the transmission grid. Using data from EPA Base Case v.5.13, I divide the lower 48 U.S. states into 66 model regions. Sixty-one of these regions are power market regions which have a positive demand for electricity. The remaining five regions are power-switching regions for which demand is zero. These regions are used to capture units with the ability to provide electricity to multiple regions. Transmission flows across regions are subject to capacity constraints, wheeling charges, and transmission losses; all of these parameters are supplied by EPA Base Case v.5.13.

1.7 Simulation Results

In this section, I describe the results of several different tradable performance standard policies. The results suggest that, as expected from the analytic model, implementing a tradable standard policy causes coal usage to decline significantly. Relative to a single-standard baseline, differentiation leads to a modest increase in coal generation and usage. Under a single-standard, electricity prices either decrease or increase depending on the region. Differentiation from the single standard causes prices to rise in almost every region. While single-standard policies result in substantial profit gains for natural gas plants and losses for coal units, differentiation leads to improved profit outcomes for low emission rate units in both categories. Overall, the distribution of profits within categories widens considerably as the degree of differentiation becomes large. Finally, differentiation is slightly more cost-effective for small degrees. As the standards become greatly differentiated, the differentiated policy becomes significantly more costly than the single standard.
Using the model described in the previous section, I simulate generation for the U.S. wholesale electricity market under a variety of tradable performance standard policies. I establish two reference cases: a business-as-usual scenario without an emissions constraint and a single-standard scenario that achieves a given emission reduction target. The differentiated-standard policies are calibrated to achieve the same target. Since the vast majority of switching behavior is driven by the difference between the coal and gas standards, the various differentiated-standard policies are described in terms of this parameter, i.e., $\Delta \equiv s_{\text{coal}} - s_{\text{gas}}$. Therefore, single-standard policies will correspond to the case where $\Delta = 0$. The procedure for identifying the exact levels of the standards at each emission target and differentiation degree pair is straightforward. Given a particular value for $\Delta$, I find the smallest gas and coal standard pair that achieves the business-as-usual equilibrium. This can be found by solving the following equation for $s_{\text{gas}}$:

\[
(s_{\text{gas}} + \Delta)q^0_{\text{coal}} + s_{\text{gas}}q^0_{\text{gas}} = s^0q^0 \\
\Rightarrow s_{\text{gas}} = \frac{s^0q^0 - \Delta q^0_{\text{coal}}}{q^0},
\]

where $q^0_{\text{coal}}$, $q^0_{\text{gas}}$, and $q^0$ represent business-as-usual aggregate levels for coal, gas, and fossil generation, respectively, and $s^0$ represents the emission rate at business-as-usual. After obtaining a value for $s_{\text{gas}}$, which also yields the value for $s_{\text{coal}}$ since $\Delta$ is fixed, I increase the stringency of the policy incrementally by reducing both standards symmetrically. The stringency is tightened until the emission reduction target is achieved.

The model can be simulated for any degree of differentiation and policy stringency; I illustrate a few examples in Figure 1.8. In the figure, I plot fuel-specific, capacity-weighted kernel density estimates of emission rates for all natural gas and coal units in the model. The red distribution is natural gas, and the blue distribution
is coal. The vertical dashed lines represent various performance standards. The black line is placed at the single-standard level for a 5% emissions reduction. For the most part, this line divides the coal and gas distributions; the gas units to the right of the line are typically idle in the simulations. Under this regulation, coal-fired power plants have higher unit costs and gas plants have lower unit costs. The green lines represent the differentiated coal and gas standards when $\Delta = 600$. This captures a substantial level of differentiation where production from the lowest-emitting coal plants is actually subsidized and have lower unit costs compared to BAU. The orange lines represent an even more extreme degree of differentiation ($\Delta = 1200$) for which a significant proportion of the coal units are being subsidized. Correspondingly, a large measure of natural gas units are taxed at this degree. Beyond this degree of differentiation, meaningful emission reduction targets cannot be achieved.

Figure 1.8: Illustrating Differentiated-Standard Policies

Consistent with the goal of this paper, I report results under each policy scenario
for coal usage, electricity prices, and coal generator profits. The results are simulated at a fairly specific level of geographic detail, and some aggregation is necessary. The model contains 61 market regions; I aggregate the model regions into 17 “reporting” regions on the basis of the electricity transmission system architecture. In the context of the model, market regions among which large volumes of electricity is transferred tend to be grouped together. The reporting regions are illustrated in Figure 1.9. I also aggregate across time segments in the main results. This means that, in the case of electricity prices, that the reported value is a weighted average of prices within each time segment and reporting region. Because there are 16 time segments for each market region, if a reporting region consists of 4 market regions, then the given price is the demand-weighted average of $4 \times 16 = 64$ equilibrium prices. My aggregation strategy attempts to capture the most relevant trends in price changes across regions at the time segment-level.

![Figure 1.9: Reporting Region Map](image)
The main results are summarized in the next three subsections. In addition to simply describing the key results, I explain the underlying economic factors that drive these key results. In doing so, I rely on the intuition developed in the analytic sections.

1.7.1 Coal Usage

As a measure of the impact on upstream coal interests, most notably coal producers and laborers, I present aggregate results for the change in coal usage as the coal and gas standards are increasingly differentiated. I then explain the simulation outcomes in the context of the analytic discussion of switching margins.

Results

The primary coal usage result is captured in Figure 1.10. Unlike in the case of electricity prices and generator profits, I emphasize the impact on coal usage at the national rather than the regional level. This is because the origin of the fuel is not necessarily confined to the region in which it is produced. Coal usage and generation have been standardized to their percentages of business-as-usual levels. Both series are plotted on the vertical axis against the corresponding degree of differentiation.

The graph shows that differentiation increases coal generation and usage by a modest amount. As expected, implementing the single-standard causes usage and generation to drop; both quantities are reduced by more than 10% from business-as-usual, which is demonstrated by the levels of the curves when $\Delta = 0$. Both series are increasing and primarily convex as the degree of differentiation increases. As a result, substantial increases don’t occur until the standard is highly differentiated. However, even for the most extreme differentiation, the increase in usage from the single-standard level is relatively small ($< 1\%$ relative to business-as-usual). The increase in generation is slightly larger ($\approx 1.5\%$).
Discussion

The positive relationship between degree of differentiation and coal usage and generation was predicted in Section 1.5. Due to rising costs of coal-to-gas switches in response to increased differentiation, it was shown that less coal would be displaced in favor of gas generation for a given emissions target. Using the simulation model, I investigate how the composition of emission reductions from each of the switching types changes as the degree of differentiation increases.

The simulation results for switching types, which are summarized in the pie charts in Figure 1.11, match the theory and empirical plot of usage and generation. In the single-standard case, nearly all emission reductions come from coal-to-gas switching. A small slice is the result of coal-to-coal switching.\footnote{The blue sliver results from replacing coal generation with dispatchable biomass-fueled generation. I assume that biomass plants, which contribute a very small fraction of U.S. electricity} For a moderate level of differ-
entiation ($\Delta = 600$), a small portion of the reductions achieved through coal-to-gas switches is displaced by additional coal-to-coal switching. This is consistent with Figure 1.10, which shows that coal generation and usage increase at an extremely slow rate up to the point when the degree of differentiation is large. That scenario is captured by the final pie chart. For extreme differentiation, the amount of coal-to-coal switching increases significantly, and some reductions are achieved by gas-to-gas switching. From the aggregate perspective, however, the overwhelming majority of emission reductions are the result of coal-to-gas switches even for the most differentiated policy. This explains why even though coal usage increases with differentiation compared to a single standard, the extent is modest compared to the original decline associated with the single standard.

1.7.2 Per Unit Costs

In order to explain the output price and coal plant profit results, I first demonstrate the effect of differentiation on unit costs in the context of the policy simulations. More than half of the utilized coal capacity experiences decreasing costs for almost all differentiation degrees, while most natural gas capacity experiences increasing costs.

As discussed in Section 1.4, the effect of differentiation on per unit cost for any particular plant depends on the plant emission rate and the behavior of the credit price, as well as, in the case of gas plants, the relationship between the coal and gas standard. The latter two elements are equilibrium results from the model simulations; both are displayed graphically in Figure 1.12, plotted against the coal standard. As expected, the credit price, represented by the blue line, not only increases with the coal standard, but exhibits substantial convexity. For instance, the credit price for the most extreme degree of differentiation in the figure ($\Delta = 1200$) is around six generation, are not covered by the emission regulation.
times larger than the value at the single standard. The red line demonstrates the
relationship between the two standards. As a function of the coal standard, the gas
standard is decreasing and concave.

The empirical versions of $\tau(s_{coal})$ and $s_{gas}(s_{coal})$ are used to construct the iso-cost
emission rates for the simulation model; the results are plotted in Figure 1.13. The
left-hand graphic pertains to coal plants, while the gas results are depicted on the
right side. The paths of the iso-cost emission rates are given by the dashed lines.

Figure 1.11: Emission Reductions by Switching Type
Close to the single-standard level, the paths fluctuate greatly, but the paths smooth out for greater degrees of differentiation. Roughly speaking, the iso-cost emission rate functions for gas and coal hover near 800 and 2,200 lbs. of CO$_2$ per MWh.

To get a sense for how much fuel-specific capacity is above and below the iso-cost emission rates, the capacity-weighted 5th, 50th, and 95th emission rate percentiles for
both fuels are imposed on the graphs. The 95th percentile emission rates, represented by the red lines, are well above the dashed lines for both coal and gas; costs for plants with emission rates in this neighborhood will be increasing for all differentiation degrees. At the clean end of the distribution, represented by the red lines, coal plant costs are decreasing regardless of the coal standard. Contrast this to the gas diagram, which shows that the iso-cost emission rate is largely straddling the 5th percentile emission rate. This suggests that even for the cleanest gas plants, cost movement is roughly neutral as the standards are increasingly differentiated. To get a sense for behavior at the middle of the distributions, the 50th percentiles are displayed as purple lines. In the case of coal, costs are decreasing for almost all differentiation degrees. The opposite is true for natural gas. Consequently, on an average basis, this graphic suggests that coal plants benefit more from differentiation than natural gas plants.

1.7.3 Prices

In this section, I report and explain the results for the effect of differentiation on regional wholesale electricity prices. Differentiation causes prices to increase relative to the single-standard price in almost every region, including those that rely heavily on coal for generation. The price increases are the result of increasing unit costs for plants near the margin (both coal and gas) in most regions.

Results

The main results for the policy impacts on electricity prices are given in Table 1.1. As a reference, the overall size of each region is included in Column 2. This value is the level of business-as-usual generation within each region, denoted in million MWh. Column 3 records the percentage of this generation from coal units. In Column 4, I report the demand-weighted average annual prices in the absence of regulation.
Column 5 gives the percentage deviation from the business-as-usual price level for the single-standard policy. Columns 6 and 7 give the incremental percent changes from the single-standard price level under two differentiated-standard policies, relative to the business-as-usual price. Mathematically, I implement the formula

\[ \% \text{ Change in Column 5 or 6} = 100 \times \frac{P_{ds} - P_{ss}}{P_{bau}}, \]  

(1.29)

where \( ds \) represents the associated differentiated-standard policy. As a result, adding Column 5 or 6 to Column 4 yields the percent change from business-as-usual prices for the differentiated standard policy.

Within Table 1.1, the dispersion in region size, fuel mix, and business-as-usual price levels can be seen. Some regions, such as the Mid-Atlantic, are much larger than others, such as the Rocky Mountains, and will therefore have more influence on national price changes. Also, regions have different fuel mixes. For example, regions such as New England, Florida, and California rely heavily on natural gas for generation, while regions such as the Midwest and the Southwest rely heavily on coal. From a price perspective, natural gas-heavy regions tend to have higher electricity prices than coal-heavy regions.

When the single-standard policy is implemented, prices in most regions decrease. In extreme examples, like Texas and the Pacific Northwest, they decrease by 5-6%. In contrast, prices increase in other regions such as the Midwest-West and -East. Overall, most regions experience price changes, either negative or positive, in the range of 2-4%. For the entire country, average prices decrease modestly.

The magnitude of the price impacts of differentiation depend largely on whether \( \Delta = 600 \) or 1200, but the direction is almost uniformly positive. For the \( \Delta = 600 \) case exhibited in Column 5, prices increase from the single-standard level in almost every region; the exceptions are the Carolinas and Rocky Mountain regions. In all cases, the price change is less than a percentage point, including the national average.
Table 1.1: Regional Price Impacts of Performance Standard Policies

<table>
<thead>
<tr>
<th>Region</th>
<th>Size (TWh)</th>
<th>% Coal</th>
<th>BAU $/MWh</th>
<th>SS $/MWh</th>
<th>$\Delta$ = 600</th>
<th>$\Delta$ = 1200</th>
</tr>
</thead>
<tbody>
<tr>
<td>Texas</td>
<td>332</td>
<td>44%</td>
<td>34</td>
<td>-4.9%</td>
<td>0.9%</td>
<td>8.7%</td>
</tr>
<tr>
<td>Florida</td>
<td>230</td>
<td>3%</td>
<td>38</td>
<td>-3.1%</td>
<td>0.7%</td>
<td>3.9%</td>
</tr>
<tr>
<td>Midwest-North</td>
<td>176</td>
<td>60%</td>
<td>32</td>
<td>-2.4%</td>
<td>0.8%</td>
<td>5.9%</td>
</tr>
<tr>
<td>Midwest-West</td>
<td>98</td>
<td>70%</td>
<td>29</td>
<td>4.2%</td>
<td>0.2%</td>
<td>3.4%</td>
</tr>
<tr>
<td>Midwest-East</td>
<td>409</td>
<td>64%</td>
<td>33</td>
<td>4.2%</td>
<td>0.3%</td>
<td>3.0%</td>
</tr>
<tr>
<td>New England</td>
<td>128</td>
<td>3%</td>
<td>44</td>
<td>-2.7%</td>
<td>0.2%</td>
<td>4.5%</td>
</tr>
<tr>
<td>New York</td>
<td>149</td>
<td>4%</td>
<td>45</td>
<td>-2.0%</td>
<td>0.5%</td>
<td>4.3%</td>
</tr>
<tr>
<td>Mid-Atlantic</td>
<td>708</td>
<td>47%</td>
<td>38</td>
<td>-1.2%</td>
<td>0.5%</td>
<td>4.2%</td>
</tr>
<tr>
<td>Tennessee Valley</td>
<td>231</td>
<td>43%</td>
<td>35</td>
<td>2.7%</td>
<td>0.2%</td>
<td>1.6%</td>
</tr>
<tr>
<td>Delta</td>
<td>103</td>
<td>28%</td>
<td>37</td>
<td>-1.8%</td>
<td>0.7%</td>
<td>5.4%</td>
</tr>
<tr>
<td>Southeast</td>
<td>256</td>
<td>21%</td>
<td>39</td>
<td>-2.0%</td>
<td>0.6%</td>
<td>0.2%</td>
</tr>
<tr>
<td>Carolinas</td>
<td>229</td>
<td>27%</td>
<td>43</td>
<td>3.3%</td>
<td>-0.2%</td>
<td>-3.3%</td>
</tr>
<tr>
<td>Heartland</td>
<td>263</td>
<td>64%</td>
<td>33</td>
<td>-3.2%</td>
<td>0.9%</td>
<td>6.7%</td>
</tr>
<tr>
<td>California</td>
<td>279</td>
<td>1%</td>
<td>42</td>
<td>-4.8%</td>
<td>0.6%</td>
<td>4.7%</td>
</tr>
<tr>
<td>Southwest</td>
<td>197</td>
<td>47%</td>
<td>34</td>
<td>-4.2%</td>
<td>0.8%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Rocky Mountains</td>
<td>71</td>
<td>72%</td>
<td>31</td>
<td>0.4%</td>
<td>-0.4%</td>
<td>2.1%</td>
</tr>
<tr>
<td>Pacific Northwest</td>
<td>191</td>
<td>17%</td>
<td>32</td>
<td>-6.0%</td>
<td>0.6%</td>
<td>4.6%</td>
</tr>
<tr>
<td>United States</td>
<td>4,048</td>
<td>39%</td>
<td>37</td>
<td>-1.4%</td>
<td>0.5%</td>
<td>3.8%</td>
</tr>
</tbody>
</table>

For the larger degree of differentiation reported in Column 6, the price changes are positive in all regions except for the Carolinas. Note that prices in the Rocky Mountain region are not monotonic in the degree of differentiation, a possibility we highlighted in the analytic discussion. In terms of magnitude, the impacts are much larger in almost all regions (the Southeast region is the lone exception). In most cases, the price increases by 3-5%; however, Texas experiences an increase of almost 9% relative to the single-standard level. Price changes purely relative to business-
as-usual, which can be determined by summing Columns 4 and 6, are in most cases positive. For the Midwest-West and -East regions, the price increases under the single-standard policy and continues to increase as the standards are differentiated, resulting in significant positive price movement from the business-as-usual level. Nationally, prices increase by just under 4%.

Discussion

The effect of differentiation on the electricity price in a particular region depends on the unit cost behavior of plants near the margin. In most regions, unit costs increase for the marginal plants, regardless of whether they are gas or coal. The lone exception occurs in the Carolinas; I demonstrate in Figure 1.14 why this region experiences falling prices by contrasting it with a more “typical” region (Texas). A primary reason for why unit costs tend to increase for marginal plants is because overall per unit costs tend to be correlated with emission rates so (relatively) higher emitting plants are on the margin – but not always.

The price impacts of differentiation for the Carolinas (right panel) and Texas (left panel) are demonstrated graphically in Figure 1.14. The vertical axes represent per unit generation costs at the single-standard equilibrium, while the horizontal axes represent emission rates standardized by the fuel-specific iso-emission rates, as was the case in Figure 1.7.\(^\text{15}\) This allows the gas (red markers) and coal (blue markers) plants to be combined on a single graph; the size of the markers reflects the plant capacity, with larger markers representing larger plants. The blue horizontal lines denote the market-clearing electricity price in each region at the single-standard. The vertical dashed lines split the units into two categories: plants to the left have costs

\(^{15}\) Recall that iso-cost emission rates are a function of the level of the coal standard, or equivalently, the degree of differentiation. To construct this diagram, I use the iso-cost emission rates corresponding to the case where $\Delta = 1200$. For gas and coal, this implies rates of 767 and 2,212 lbs. of CO\(_2\) per MWh. As demonstrated in Figure 1.13, these rates are not constant for all differentiation degrees, but they serve as a useful proxy for the purposes of illustration.
that are decreasing with differentiation, while plants to the right have increasing costs. In the Carolinas, all plants near the margin have decreasing unit costs. As a result, electricity prices are decreasing as the standards are differentiated. However, this scenario is atypical. As Table 1.1 demonstrated, prices generally increase with differentiation. This is what occurs in Texas, where most of the units at the margin have increasing costs.

Figure 1.14: Texas versus Carolinas: Price Impacts of Differentiation

Figure 1.14 also demonstrates the typical relationship between unit costs and emission rates. Within fuels, these parameters are positively correlated. As a result, plants near the margin are more likely to have costs that increase with differentiation, regardless of whether those plants are coal or gas. This effect should be even more pronounced for higher levels of demand, as the additional plants brought on-line will tend to have greater emission rates. By looking at summer peak demand prices, I demonstrate that this occurs in the context of the simulation model.

The increase in average prices with differentiation was demonstrated in Table 1.1; I use Figure 1.15 to convey the influence of high demand time periods on this increase. In the graphic, the horizontal axis denotes the summer peak price difference under
extreme differentiation ($\Delta = 1200$) versus the single-standard policy, i.e., $P_{ds} - P_{ss}$.
The plot is the density of this object for all regions. Clearly, the peak price difference
is typically well-above the average price increase under differentiation. This supports
the notion that higher emission rate units are utilized to meet higher levels of demand.
The result is that prices tend to increase with differentiation, regardless of whether
coal or gas is on the margin.

\begin{figure}[h]
  \centering
  \includegraphics[width=0.5\textwidth]{plot.png}
  \caption{Comparing Summer Peak Prices}
\end{figure}

\subsection{1.7.4 Coal Profits}

The previous section documented the adverse consequences of differentiation on electricity prices, a proxy for effects on consumers. In this section, I report the positive
\begin{figure}[h]
  \centering
  \includegraphics[width=0.5\textwidth]{plot.png}
  \caption{Comparing Summer Peak Prices}
\end{figure}

\section{1.7.4 Coal Profits}

The previous section documented the adverse consequences of differentiation on electricity prices, a proxy for effects on consumers. In this section, I report the positive
effect that differentiation has on coal plant profits. This is due to a combination
of higher electricity prices (discussed in Section 1.7.3) and reduced unit generation
costs for coal plants (discussed in Section 1.7.2).
Results

The main profit results are recorded in Table 1.2. The first three columns are the same reference columns from the price impacts table. Unlike the price table, all results in this table are given in levels, including the differences. The units for profits are millions of dollars ($M). As was the case for price impacts, Column 5 denotes the difference between coal profits under the single-standard policy versus the business-as-usual scenario. Columns 6 and 7 report the additional difference between the differentiated standard policies and the single-standard policy. The sum of either of these columns and Column 5 yields the coal unit profit deviation for the differentiated-standard scenario relative to the business-as-usual level.

Coal profits at the business-as-usual level vary greatly across regions. Not surprisingly, larger regions and regions with higher proportions of generation from coal tend to yield higher aggregate coal profits. The relationship is not linear, however. For example, consider the Midwest-East and Heartland regions. Both regions produce 64% of their electricity through coal, and the Midwest-East region generates more than 1.5 times the amount of electricity, yet Heartland coal units generate almost $300M more in aggregate profits. Overall, coal units generate almost $11B in profit in the absence of regulation.

Under a single-standard policy, coal unit profits decrease substantially as expected as coal plant unit costs go up. Heavy coal generation regions such as the Mid-Atlantic, Texas, Heartland, and the Southwest experience the largest absolute decreases in profits. On a percentage basis, coal units in Texas suffer the most, with region-wide profits decreasing by more than half. Compare this, for example, to the relatively mild decrease in profits within the Midwest-East. A large portion of this disparity is due to the disparity in price changes that were reported in Table 1.1.

Differentiating the standards improves regional coal unit profits across the board,
### Table 1.2: Regional Profit Impacts of Performance Standard Policies

<table>
<thead>
<tr>
<th>Region</th>
<th>Size (TWh)</th>
<th>% Coal</th>
<th>BAU (Π\textsubscript{BAU})</th>
<th>SS (Π\textsubscript{SS})</th>
<th>Δ = 600 (Π\textsubscript{ds} - Π\textsubscript{ss})</th>
<th>Δ = 1200 (Π\textsubscript{ds} - Π\textsubscript{ss})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Texas</td>
<td>332</td>
<td>44%</td>
<td>1,101</td>
<td>-573</td>
<td>22</td>
<td>285</td>
</tr>
<tr>
<td>Florida</td>
<td>230</td>
<td>3%</td>
<td>24</td>
<td>-5</td>
<td>4</td>
<td>23</td>
</tr>
<tr>
<td>Midwest-North</td>
<td>176</td>
<td>60%</td>
<td>663</td>
<td>-290</td>
<td>16</td>
<td>119</td>
</tr>
<tr>
<td>Midwest-West</td>
<td>98</td>
<td>70%</td>
<td>648</td>
<td>-73</td>
<td>12</td>
<td>129</td>
</tr>
<tr>
<td>Midwest-East</td>
<td>409</td>
<td>64%</td>
<td>1,310</td>
<td>-192</td>
<td>51</td>
<td>452</td>
</tr>
<tr>
<td>New England</td>
<td>128</td>
<td>3%</td>
<td>11</td>
<td>-8</td>
<td>2</td>
<td>17</td>
</tr>
<tr>
<td>New York</td>
<td>149</td>
<td>4%</td>
<td>23</td>
<td>-13</td>
<td>2</td>
<td>16</td>
</tr>
<tr>
<td>Mid-Atlantic</td>
<td>708</td>
<td>47%</td>
<td>2,218</td>
<td>-655</td>
<td>148</td>
<td>1,137</td>
</tr>
<tr>
<td>Tennessee Valley</td>
<td>231</td>
<td>43%</td>
<td>552</td>
<td>-91</td>
<td>22</td>
<td>180</td>
</tr>
<tr>
<td>Delta</td>
<td>103</td>
<td>28%</td>
<td>117</td>
<td>-65</td>
<td>2</td>
<td>15</td>
</tr>
<tr>
<td>Southeast</td>
<td>256</td>
<td>21%</td>
<td>558</td>
<td>-143</td>
<td>16</td>
<td>48</td>
</tr>
<tr>
<td>Carolinas</td>
<td>229</td>
<td>27%</td>
<td>229</td>
<td>-9</td>
<td>31</td>
<td>171</td>
</tr>
<tr>
<td>Heartland</td>
<td>263</td>
<td>64%</td>
<td>1,602</td>
<td>-544</td>
<td>46</td>
<td>376</td>
</tr>
<tr>
<td>California</td>
<td>279</td>
<td>1%</td>
<td>15</td>
<td>-6</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Southwest</td>
<td>197</td>
<td>47%</td>
<td>912</td>
<td>-319</td>
<td>40</td>
<td>282</td>
</tr>
<tr>
<td>Rocky Mountains</td>
<td>71</td>
<td>72%</td>
<td>493</td>
<td>-118</td>
<td>2</td>
<td>112</td>
</tr>
<tr>
<td>Pacific Northwest</td>
<td>191</td>
<td>17%</td>
<td>244</td>
<td>-116</td>
<td>2</td>
<td>25</td>
</tr>
<tr>
<td><strong>Unreg. Regions</strong></td>
<td><strong>2,645</strong></td>
<td><strong>44%</strong></td>
<td><strong>6,685</strong></td>
<td><strong>-1,902</strong></td>
<td><strong>277</strong></td>
<td><strong>2,238</strong></td>
</tr>
<tr>
<td><strong>United States</strong></td>
<td><strong>4,048</strong></td>
<td><strong>39%</strong></td>
<td><strong>10,723</strong></td>
<td><strong>-3,218</strong></td>
<td><strong>418</strong></td>
<td><strong>3,407</strong></td>
</tr>
</tbody>
</table>

as prices largely rise and costs largely fall. For the lower degree of differentiation, coal unit profits increase in all regions, but by small amounts relative to the lost profits from implementing the single-standard. The Carolinas is the only region in which profits increase beyond the single-standard level. For a large degree of differentiation, regional coal unit profits increase dramatically in all regions. Relative to business-as-usual profits, aggregate profits in many regions actually increase. On a
percentage basis, the largest increase occurs in the Carolinas, where profits are nearly doubled. In Texas and the Midwest-North, however, large profit losses brought on by regulation are not recouped through differentiation. On a nationwide-basis, profits increase beyond business-as-usual levels.

**Discussion**

The results for coal plant profits immediately make sense in light of the results presented in the unit cost and price sections. For modest degrees of differentiation, prices increase by a small amount, and profits increase accordingly. For more differentiated policies, the price increases are substantial, as are the profit increases. At the same time, unit costs are decreasing for more than half of the available coal capacity. Like the price effect, this effect becomes more profound as the degree of differentiation increases. Additionally, as evidenced in Figure 1.8, for largely differentiated policies, part of the coal distribution is subsidized relative to the no regulation case.

**1.7.5 Cost-Effectiveness**

In this section, I report the effect that differentiation has on aggregate cost-effectiveness. Two different cases are considered: one in which demand is perfectly inelastic, and one with a small demand elasticity. In both cases, the most extreme level of differentiation ($\Delta = 1200$) increases overall program costs significantly (57 to 79 percent).

The program cost results are displayed in Figure 1.16. The metric used to evaluate aggregate cost (plotted on the vertical axis) is the additional cost introduced by differentiation relative to the cost imposed by the single standard policy. Mathematically, I calculate

$$Add. \; Cost_{ds} = \frac{Cost_{ds} - Cost_{ss}}{Cost_{ss} - Cost_{bau}},$$

(1.30)

which provides a unit-free measure of how much cost distortion is introduced by differentiation. The additional cost value is plotted against the level of differentiation.
under three different assumptions about the price elasticity of demand. The green line represents the simulation results when demand is perfectly inelastic, as labeled on the figure. The demand elasticity is relaxed as the lines move in a southeast direction across the figure.

**Figure 1.16: Cost-Effectiveness With Inelastic and Elastic Demand**

In general, differentiation increases the costs of the performance standard policy, for all versions of the simulation model. As demonstrated in the theoretical section (Section 5.5), differentiation can lower program costs compared to a single-standard policy, but only when it induces additional conservation. When demand is perfectly inelastic, the conservation margin is eliminated, resulting in necessarily higher costs. In Figure 1.16, the green line shows that the simulation results match the theory. Moreover, when demand elasticity is relaxed, the additional induced conservation offsets to some degree the additional costs of differentiation. In fact, although it is difficult to see in the figure, the cost-minimizing version of the policy when demand is elastic is slightly differentiated. However, to keep the model realistic, even the most demand-elastic version of the model is parameterized with very low values of elasticity, and so the improvement induced by differentiation is extremely small.
1.8 Conclusion

Recent climate change policy discussions, both in the United States and abroad, have underscored the importance of accounting for distributional impacts in proposals. Economists have long touted the virtue of cost-effectiveness in policy, and for good reason, but often equity, legal, and political constraints necessitate deviations from first-best solutions. Ultimately, when it comes to emissions policy, sacrificing a certain degree of cost-effectiveness is preferable to failing to address the issue entirely.

This paper studies a key design feature in a tradable performance standard policy aimed at addressing potential inequities between coal and natural gas interests. By relaxing the coal standard while simultaneously tightening the natural gas standard, I analyze a continuum of differentiated policies aimed at achieving a fixed emission target while mitigating windfall welfare transfers from upstream, midstream, and downstream coal-oriented stakeholders to their natural gas counterparts. I examine the effects of differentiation through both analytic and simulation models with the same essential structure.

In the analytic model, I show that coal producers and laborers benefit from increased coal usage under differentiated policies, while the impacts on electricity consumers and coal-fired power plants through prices and profits, respectively, are ambiguous. The increase in coal usage is the result of a change in the relative cost of two compliance margins: within-fuel switching becomes less expensive relative to coal-to-gas switching under a differentiated policy. The ambiguity of the price and profit outcomes is shown to be the result of increasing compliance credit prices coupled with decreasing credit purchases/sales for coal-/natural gas-fired power plants.

To develop a quantitative sense of the impact of differentiation, I construct and implement a detailed short-run dispatch model of generation in the U.S. wholesale electricity market. The results suggest that differentiation does little to alter
outcomes until the distance between the coal and gas standards is significant. However, once the standards are sufficiently differentiated, coal-fired power plants benefit greatly at the expense of electricity consumers. Increasing electricity prices, coupled with decreasing per unit costs for most coal capacity, results in aggregate profits beyond business-as-usual levels. For coal producers, the benefit to differentiation remains modest at any level of differentiation, as they regain less than one percent of the 10 percent market decrease they observed under the single standard policy.

The results suggest that if the purpose of differentiation is to aid coal producers and electricity consumers, then it is a poor mechanism. Going forward, it would be interesting to use the framework developed in this paper to compare to other versions of differentiated policy. For instance, one might consider how the results change when differentiation is made on the basis of states, rather than fuels, as suggested by the initial existing source proposal by the EPA. Differentiation could also be studied outside of the electricity context: for instance, CAFE standards already differentiate on the basis of vehicle class. There is potential for interesting research on differentiated standards in automobile markets, since (1) they already exist; and (2) electricity and automobile markets differ in interesting ways.
2

Analyzing VEETC: Who Benefited?

2.1 Introduction

“It might cost you more to fill up with gas as early as New Year’s Day. If all other variables stay the same, gas prices should be higher since the tax credit oil companies have received to blend ethanol with their petroleum won’t be available.”

Jeff Scates, Illinois Corn Growers Association President

“As a result, oil companies have been able to set demand and price levels for ethanol, keeping prices low and pocketing much, if not all, of the VEETC as profit.”

Natural Resource Defense Council Policy Fact Sheet

The energy sector in the United States is host to a myriad of policies – regulations, taxes, and subsidies – that shift behavior away from a free-market outcome. Such
policies are often motivated by the association of different forms of energy use with significant non-market consequences related to the economy, security, and environment. An important question is whether the benefits from these policies exceed the costs, requiring a careful analysis of non-market benefits (National Research Council, 2010).

Often missing from the aggregate benefit-cost analysis are distributional assessments of who pays or, in the case of a subsidy, who benefits. Incidence is not obvious, as burdens and benefits can accrue to both producers and consumers depending on relative elasticities, and may be passed up and down a particular supply chain. Moreover, for market-based policies, including taxes and subsidies, the distinct consequences for winners and losers can be many times the aggregate cost or benefit (Burtraw and Palmer, 2008). In many policy debates, it is these consequences for particular stakeholders that help determine both enactment and survival, regardless of the aggregate net benefit analysis. For both equity in its own right and equity’s link to acceptance, we need to consider these distributional effects.

Perhaps nowhere is this more evident than ethanol, which was the object of the single most expensive energy subsidy in recent history, the Volumetric Ethanol Excise Tax Credit (VEETC).\(^1\) Regardless of one’s stance on whether more ethanol is good or bad, or whether the subsidy was effective at encouraging more ethanol, advocates claimed the subsidy lowered motor fuel prices for consumers while critics claimed the subsidy simply enriched ethanol producers. What is the truth?

Policy effects are often difficult to measure because the no-policy counterfactual cannot be observed. Further complicating matters, multiple policies often target the same objective, making it difficult to disentangle the effects of any single policy. This is particularly evident in the case of policies that promoted ethanol, where three dif-

\(^1\) The VEETC accounted for $5 billion per year, or roughly one-quarter of all energy related, non-stimulus subsidies in 2007 and 2011 (U.S. Energy Information Administration, 2011).
ferent policies were in place from 2005, when both ethanol mandates and a ban on MTBE as a fuel additive began, until the end of 2011, when the VEETC was ended.

Nonetheless, the sudden end to the VEETC on December 31\textsuperscript{st}, 2011, offers a unique opportunity to observe the incremental consequences of a single policy among the mix of three. In particular, at the time of its termination, was the ethanol subsidy benefiting ethanol producers or ethanol consumers? Was the value being passed further up or down the supply chain? By comparing prices along the supply chain immediately before and after the last date of the subsidy, we can isolate the effect of the subsidy termination holding other influences constant, and thereby determine the subsidy incidence.

Our results suggest that most – perhaps two-thirds – of the subsidy accrued to ethanol producers. Moreover, we find suggestive evidence that at least some of the benefits were passed up the supply chain to corn farmers, although data limitations prevent us from making more confident statements on this front. Random variation in prices for petroleum products makes it difficult to estimate the incidence on oil refiners or gasoline consumers precisely, but our point estimates suggest that these stakeholders received very little, if any, benefit from the subsidy. This refutes the notion that the subsidy largely benefited consumers.

Based on the above evidence, we conclude that the remaining third of the subsidy was likely being captured by fuel blenders at the time the subsidy expired. We do find evidence that blenders captured a larger portion of the subsidy over a longer horizon. However, more work is needed to integrate and validate these results.

In order to estimate the ethanol subsidy incidence, we use several data sources and empirical techniques. When possible, we use one-month calendar spreads constructed from the futures markets for ethanol, corn, and gasoline blendstock (petroleum). These spreads provide a means to differentiate sharply between the prices of products that could be used to claim the tax credit, and those that could not. For com-
modities without exchange-traded futures markets, specifically finished gasoline, we use standard time-series regression techniques on spot price data to analyze whether the subsidy expiration coincided with a significant change in the gasoline blending margin around the time of expiration.

This paper is organized as follows: Section 2.2 provides background on the industry structure for gasoline production and biofuels policy in the United States. Section 2.3 summarizes the related literature on renewable fuel policies and event studies of policy changes. Section 2.4 lays out our conceptual framework and discusses how the subsidy might manifest in commodity prices. Section 2.5 presents our empirical approach and model, describes the data, and provides the results. Section 2.6 concludes.

### 2.2 Background

In this section, we introduce background information about gasoline production and biofuels policy in the United States. The details will motivate our approach to measuring subsidy incidence and provide a basis for certain model assumptions.

#### 2.2.1 Making Gasoline

Gasoline production in the United States involves the convergence of two supply chain branches: one that involves petroleum and one that is agricultural in nature. At the most basic level, the process can be described by the schematic outlined in Figure 2.1. This section describes the figure in detail, and provides a description of how the entities might be connected at the corporate level.

On the agricultural side, production begins on the farm and ends with blending at the fuel terminal. Corn is harvested, and then shipped to ethanol production facilities for processing. The amount of corn used for fuel production is significant: in 2011,

---

2 Our focus for this paper is restricted to corn-derived ethanol. The use of other feedstocks is, for the most part, in the research or early commercialization phase, but not yet commercially

---
which was the last year for the VEETC, ethanol production accounted for about 40 percent of corn consumption in the United States (Brester, 2012). The other major input in ethanol production is fuel used to generate electricity for the plant, typically natural gas. The major outputs of the production process are ethanol and distillers grains, which can be sold as animal feed. Once production has occurred, the ethanol is shipped, typically via truck or railcar, to fuel terminals to be blended into gasoline.

Meanwhile, on the petroleum side, production begins with fossil fuel extraction

and, as with ethanol, ends with blending at the fuel terminal. Crude oil is removed from the ground and shipped via pipeline to oil refineries. Refiners process crude oil into several different products, one of which is a precursor to finished gasoline. Reformulated blendstock for oxygenated blending (RBOB) and conventional blendstock for oxygenated blending (CBOB) are refined products specifically engineered

Figure 2.1: A Diagram of Gasoline Production in the U.S.
to be blended with an oxygenate, such as ethanol.\textsuperscript{3} These products are then transported, usually via pipeline, to the fuel terminal. From a performance standpoint, the reason behind oxygenate blending is to increase the octane of the fuel, which serves the dual purpose of preventing engine “knock” in motor vehicles and creating a cleaner-burning fuel. However, when used in blends higher than about 5 percent, ethanol transitions from a complement to petroleum to a substitute.

Finished gasoline is the product of combining fuel ethanol with gasoline blend-stock. Once both products are in storage at the terminal, they are blended in one of two ways. Either both fuels are combined in a designated blending tank, or they are “splash” blended aboard a fuel truck.\textsuperscript{4} The blended fuel, while still at the terminal, is referred to as wholesale finished gasoline. The proportion of ethanol in a gallon of finished gasoline can vary: the most common forms are a 10\% ethanol blend (called E10), usable in most passenger cars, and an 85\% blend (E85), which can only be used in certain “flex fuel” vehicles. Transportation of the fuel from the terminal to the retail gas station, typically via a fuel truck, transforms wholesale gasoline into retail gasoline.\textsuperscript{5} Retail gasoline prices also incorporate federal and state fuel taxes and retail distribution margins.

Although we will treat ethanol producers, oil refiners, and fuel blenders as if they are unique entities, the corporate structures are actually quite varied and complex. Often, oil refiners are also fuel blenders. Moreover, some refiners are not only blenders, but ethanol producers as well. Fuel terminals are owned and operated by refiners, blenders, or neither. For particularly large entities, such as Valero, the cor-

\textsuperscript{3} RBOB is used in the production of reformulated gasoline, a product blended to burn more cleanly than conventional gasoline (produced from CBOB). The Clean Air Act requires reformulated gasoline to be used in cities with high smog levels, since petroleum combustion contributes to ground-level ozone formation.

\textsuperscript{4} A small number of retail stations, primarily located in the Midwest, perform splash blending at the pump.

\textsuperscript{5} For a more detailed schematic and description of the gasoline production process, refer to (Bullock, 2007).
porate structure can include refineries, ethanol production facilities, blending plants, and retail distribution facilities. However, while there is a significant amount of vertical integration in the gasoline supply chain, there are many entities that specialize in production of a particular commodity. For most products along the supply chain, well-defined spot and futures markets exist.

2.2.2 U.S. Biofuels Policy

The United States government has long provided support for the biofuels industry – particularly corn ethanol. The justifications for supporting the domestic ethanol industry are varied and have not changed much over time. Perhaps the most popular is reducing U.S. dependence on imported oil, though rural development, enhancing farm incomes, and reduced air pollutant emissions are often invoked as well. Historically, the bulk of support for ethanol was provided in the form of subsidies and import tariffs. Over the past decade tax credits have given way to mandates, particularly the federal Renewable Fuel Standard (RFS).

The VEETC, and a complementary ethanol import tariff, were initially put in place more than three decades ago, though the level of support has varied over time. Initially, The Energy Tax Act of 1978 established a 40¢ per gallon tax credit for ethanol blending, regardless of where or how the ethanol was produced.\(^6\) Shortly thereafter, an import tariff of 40¢ per gallon was established to prevent subsidization of imports and protect the domestic industry from Brazilian sugarcane-derived ethanol. Over the years, the levels of the tax credit and the tariff were adjusted. At the time of expiration, the tax credit was at 45¢ per gallon of ethanol and the tariff was at 54¢ per gallon.

In addition to the VEETC and import tariffs, the ethanol industry has also ben-

\(^6\) Information in this section summarizes discussions in Duffield et al. (2008) and De Gorter and Just (2008), for instance.
elected from mandated blending. With the passage of the Energy Policy Act of 2005, the RFS was born. The RFS mandate is administered as a minimum percentage of ethanol in finished gasoline for all obligated parties, specifying a lower-bound for the level of ethanol that must be blended. Compliance can be achieved by blending ethanol or purchasing credits (called Renewable Identification Numbers, or RINs) from other obligated parties. At the time of the VEETC expiration, the price of a RIN was effectively zero, suggesting that the mandate was not binding; that is, blending was above the lower-bound (Irwin and Good, 2013).\footnote{At the same time that the RFS sets a lower-bound on ethanol blending, an upper-bound exists as well in the form of an E10 “blend wall,” which prevents the aggregate proportion of ethanol in the gasoline supply from rising much above ten percent. Infrastructure, legal, and regulatory limitations have limited sales of higher ethanol blends such as E15 and E85 and are expected to continue to do so, at least in the short-run (Babcock and Pouliot, 2014; Irwin and Good, 2015).}

Beyond direct subsidization and import protection, the ethanol industry has also enjoyed increased demand for its product due to local air and water pollution policies. The Clean Air Act Amendments of 1990 required that gasoline be reformulated to reduce smog, which promoted ethanol and MTBE use. By 2006, however, MTBE had been phased out due to concerns over groundwater contamination, leaving ethanol as the oxygenate of choice in the United States.

These policies, together with a significant increase in oil prices over the past decade, have led to substantial growth in the ethanol industry. By 2011, fuel ethanol consumption had reached 12.9 billion gallons, up from 83.1 million gallons in 1981 (Koizumi, 2014). With the advent of the RFS, critics of ethanol policy maintained that the VEETC had become a wasteful policy, providing a subsidy for an activity that had become mandatory. The expansion of ethanol production also caused the total tax expenditure on the subsidy to expand to about $5 billion per year. The subsidy was ultimately allowed to expire at the end of 2011.
2.3 Literature Review

In this section, we discuss how our paper relates to two distinct literatures. Topically, our paper adds to the renewable fuel policy literature. This literature consists largely of welfare studies of biofuel policies and empirical studies of the connections between agricultural markets. Methodologically, our empirical approach is more closely related to those implemented in the literature on event studies of policy changes.

Over the past decade, a substantial literature has emerged that analyzes the welfare and distributional consequences of biofuel policies, primarily through analytic and simulation models. Many of these papers, particularly in recent years, focus on the impacts of a mandate such as the RFS, but we will limit our review to papers that specifically address the VEETC. De Gorter and Just (2008) analyze the joint impact of an import tariff and ethanol subsidy on prices and output in the ethanol and fuel markets using an analytic model, which they parameterize to simulate the effect of removing the policies. Taheripour and Tyner (2007) investigate the incidence of the ethanol subsidy in an analytic framework, testing their results over a wide-range of parameter values. Gardner (2007) compares the impact of an ethanol subsidy to a direct corn subsidy on farmers and ethanol producers in a stylized setting, and simulates the short- and long-run outcomes resulting from removal of the ethanol subsidy. Babcock (2008) performs a similar analysis to study the distributional consequences of removing the tax credit, assuming a closed economy. Kruse et al. (2007) and McPhail and Babcock (2008) simulate removal of the tax credit and/or tariff in a stochastic, short-run setting. All of these studies focus on prospective outcomes of policy changes using assumed supply and demand elasticities.

Most empirical studies of the corn-ethanol-petroleum complex focus on testing for long-run cointegrating relationships and price volatility transmission. A notable

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8 For a recent review of empirical work on the relationships between food and fuel prices, see Serra and Zilberman (2013).
exception is Abbott (2014), who develops a simple analytic model of corn supply, ethanol production, and gasoline blending. Combining model implications with price and quantity data, the author investigates regime-switching behavior in corn and fuel markets from 2005-2012. Using crude changes in commodity price levels, the author posits that the blenders captured 15¢ of the 45¢ per gallon subsidy, and that the rest was passed along to ethanol producers. Although the empirical strategy differs from the one implemented in this paper, the conclusions are similar.

Our paper also contributes to the literature on event studies of policy changes. For example, Bushnell et al. (2013) look at stock market valuations of affected firms before and after a sharp devaluation in CO₂ permit prices in the EU ETS. Changes in valuations provide insight into market beliefs about the impact of permit prices on firm profitability. If those beliefs are correct, then the changes reflect changes in the expected discounted future profits of the firms. In the current study, we rely on commodity futures prices before and after subsidy expiration to gauge the markets’ beliefs about the incidence of the VEETC. Differences in these prices provide evidence as to which parties the market believed to be benefiting from the subsidy. If the market beliefs are correct, then our study allows us to estimate the incidence of the subsidy. To our knowledge, our approach of using future price spreads for event analysis is novel and unique in the literature.

2.4 Subsidy Incidence

In this section, we formalize our assumptions about fuel production and blending economics. We cover a variety of scenarios that describe how we might expect the subsidy to be passed along to various parties. The assumptions made in this section motivate our empirical approach, and our discussion of subsidy incidence frames how

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9 For other examples of event study approaches to evaluating impacts of environmental policy on firm profits, see Kahn and Knittel (2006) and Linn (2006, 2010).
we view our empirical results.

The VEETC is a subsidy provided to fuel blenders for each gallon of ethanol used to produce gasoline. As noted by Bullock (2007), the incidence of a tax or subsidy is often passed along a vertically-linked market chain, manifesting in deviations of equilibrium prices and quantities from the non-distortionary environment. In the case of the supply chain for blended ethanol depicted in Figure 2.1, this suggests potential deviations in corn, ethanol, RBOB, and retail gasoline prices and quantities. Depending on how these different prices and quantities change, the incidence of the subsidy will vary across corn farmers, ethanol producers, fuel blenders, oil refiners, and consumers.

We make several assumptions regarding behavior of supply and demand in these markets in order to estimate the subsidy incidence. First, we assume simple linear production technologies for ethanol, RBOB, and gasoline, with

\[
\begin{align*}
C_{ethanol} &= 0.37P_{corn} + C_{0,ethanol}; \\
C_{RBOB} &= P_{oil} + C_{0,RBOB}; \\
C_{gasoline} &= 0.1(P_{ethanol} - S_{ethanol}) + 0.9P_{RBOB} + C_{0,gasoline};
\end{align*}
\] (2.1)

where \( C \) represents the unit (per gallon) cost of production for each commodity, \( P \) represents market prices for inputs (per gallon or per bushel, for corn), and \( C_0 \) represents other per unit costs. In other words, a gallon of ethanol requires 0.37 bushels of corn, a gallon of blendstock requires a gallon of crude oil, and a gallon of gasoline blends 10% ethanol and 90% blendstock. \( S_{ethanol} \) is the ethanol subsidy – either 45¢ per gallon before or zero after expiration.

Our second assumption is that prices generally exceed unit costs due to capacity constraints, so \( P_{ethanol} > C_{ethanol}, P_{RBOB} > C_{RBOB}, \) and \( P_{gasoline} > C_{gasoline} \). If prices substantially exceed unit costs, we would expect investment to occur and capacity to expand.
Related to this assumption, we assume consumption and production decisions are largely fixed over the short run and unrelated to price changes (here, short run is the one- to two-month horizon that we examine once the subsidy is removed). Instead, exogenous short-run deviations in supply and demand of ethanol, blendstock, and gasoline are met through changes in inventories of each commodity rather than price changes in consumption or production. Storage capacity is typically one month’s supply and stocks are typically 50 percent of capacity (U.S. Energy Information Administration, 2014). By examining both price and stockpile changes, producers can adjust future production; persistent price changes will ultimately influence demand as well.

In this way, price changes largely reflect expectations about what is necessary to balance supply and demand over time, rather than immediately changing production or consumption. As a result, our incidence calculations can be accomplished by focusing solely on price changes, as quantity is not changing. Moreover, the price changes can be interpreted not just as a short-term phenomenon, but as a somewhat longer-term signal about the appropriate prices to balance supply and demand.

Given our supporting assumptions, we proceed with a discussion of subsidy incidence. As a starting point, we consider what the price consequences are for removing the subsidy in the case where the incidence accrues entirely to one party, ceteris paribus. The result will provide upper bounds on the incidence for each party, which will guide our empirical analysis. This information is summarized in Table 2.1 and is described as follows:

- (Upstream of the subsidy – Ethanol Producers) Subsidy expiration means that each gallon of ethanol blended effectively costs blenders 45¢ more per gallon in terms of foregone subsidy receipts, and so their willingness-to-pay (WTP) for ethanol reduces by that amount. As a result, the market price of ethanol
decreases by 45¢ per gallon. Note that this assumes that ethanol producers are unable to pass their loss in margin further up the supply chain to corn farmers.

- (Further upstream of the subsidy – Corn Farmers) As in the case where ethanol producers capture the entire subsidy, subsidy expiration means that ethanol producers receive 45¢ less per gallon of ethanol because of the reduced WTP for ethanol by blenders. If the incidence is passed entirely up the chain to corn farmers, expiration means that ethanol producers WTP for corn decreases by the amount of the subsidy. As a result, the price of corn also decreases by 45¢ per gallon of ethanol. In the data, this requires translating corn prices from per bushel to per gallon of ethanol (approximately 0.37 bushels per gallon of ethanol).

- (Upstream of the subsidy – Oil Refiners) Without the subsidy, it costs blenders 45 more per ten gallons of gasoline produced. Under the fixed ratio, nine of those gallons are RBOB. If the refiner is able to extract the entire subsidy, the blender’s WTP for RBOB decreases by 45¢ for nine gallons of RBOB, or 5¢ per gallon of RBOB. As a result, the price of RBOB per gallon decreases by 5¢.

- (Downstream of the subsidy – Gasoline Consumers) From the standpoint of the blender, subsidy expiration makes each gallon of ethanol effectively 45¢ more expensive, and ethanol makes up 10% of each gallon of gasoline. The price of gasoline therefore rises by 4.5¢ per gallon if consumers capture the entire subsidy.

- (Origin of the subsidy – Blenders) If the blender simply pockets the subsidy, there are no changes in the commodity price levels. Instead, upon subsidy expiration, the blender’s margin falls by the amount of the subsidy, 45¢ per
Table 2.1: Relationships Between Incidence and Price Changes Upon Subsidy Expiration if the Subsidy Went Entirely to One Stakeholder Group

<table>
<thead>
<tr>
<th>Incidence Recipient</th>
<th>$\Delta P_{\text{corn}}$</th>
<th>$\Delta P_{\text{ethanol}}$</th>
<th>$\Delta P_{\text{RBOB}}$</th>
<th>$\Delta P_{\text{gasoline}}$</th>
<th>Blender’s Take</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ethanol Producers</td>
<td>0</td>
<td>$-45$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Farmers</td>
<td>$-45$</td>
<td>$-45$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Oil Refiners</td>
<td>0</td>
<td>0</td>
<td>$-5$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Blenders</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>$-45$</td>
<td>0</td>
</tr>
<tr>
<td>Consumers</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>$+4.5$</td>
</tr>
</tbody>
</table>

Notes: All values in ¢/per gallon; corn prices are translated to per gallon of ethanol equivalent. We assume a 1:9 ratio of ethanol to RBOB in each gallon of finished gasoline and 0.37 bushels of corn in each gallon of ethanol.

gallon of ethanol blended.

Table 2.1 illustrates the following principle of removing a subsidy in the context of a market supply-chain: prices decrease upstream of the point where the subsidy had entered the market and increase downstream. It also demonstrates the difference between economic incidence, which is a calculation of the welfare distribution resulting from a tax or subsidy, and statutory incidence, which is simply an accounting of who physically pays the tax or receives the subsidy.

As noted previously, however, it is likely the case that the incidence of the subsidy didn’t go entirely to one stakeholder group. Table 2.2 demonstrates how to calculate, for each stakeholder group, the change in welfare per gallon of ethanol blended resulting from the aggregation of observed price changes in the supply chain. First, note that the overall change in welfare must add up to the full value of the subsidy. Again, this is a consequence of our assumption that in the short run, quantities are fixed. The welfare changes for gasoline consumers, oil refiners, and farmers are
straightforward because their incidence will simply reflect the change in the price of the commodity that they produce or consume. In each case, the price change in Table 2.2 is multiplied by a constant to reflect the incidence per gallon of ethanol, e.g., consumers must consume ten gallons of gasoline in order to consume one gallon of ethanol.

The welfare change calculations for blenders and ethanol producers must take into account multiple price changes. For ethanol producers, the incidence from the subsidy will be reflected by any price change in their product, ethanol, minus any price change in their input, corn. Upon subsidy removal, to the extent that the ethanol price decrease exceeds the corn price decrease (in per gallon terms), we will observe a decrease in welfare for ethanol producers. The welfare change calculation for blenders is determined by the price changes for ethanol, RBOB, and gasoline. Any portion of the subsidy not passed either upstream or downstream of blending
through commodity prices will represent, under our assumptions, lost blender welfare due to the subsidy expiration. With Tables 2.1 and 2.2 in mind, we proceed by outlining our empirical approach and describing the data.

2.5 Empirical Methods, Data, and Results

In this section, we describe our empirical approach, data, and results on a commodity-by-commodity basis. Because the approaches for ethanol and RBOB are similar and indicative of our preferred approach, we begin with these markets. We then describe our approaches for corn and finished wholesale gasoline, which are complicated by data limitations. We synthesize the results into an overall assessment in the concluding section.

2.5.1 Ethanol and RBOB

Our empirical approach for both ethanol and RBOB relies upon the existence of futures contract markets for each commodity. We exploit the design of these contracts to conduct an analysis similar in concept to an event study. Ultimately, our evidence suggests that a significant portion of the subsidy was passed up the agricultural branch of the supply chain (our point estimate is 30¢ per gallon), while we find no indication that any part of the subsidy was passed up the petroleum refining branch, except through potential ownership of blending operations.

Each futures contract is defined by a month-year combination, with a market that begins daily trading many months before the contract comes due (the “delivery” month). As an example, we might observe that the December 2011 futures contract opens for trading in November 2009 and continues to trade until November 30th, 2011. At this point delivery must be completed by December 3rd, 2011. For each commodity, a standardized contract determines the closing day of the contract month.
Conceptually, the price of the futures contract at a given point in time can be assumed to reflect the expected spot price of the commodity at the time of maturity. For example, if the contract is set to mature at time $T$, then the future price at time $t$ is given by the equation

$$F(t, T) = \mathbb{E}_t[S(T)],$$

where $F$ represents a future price, and $S$ represents a spot market price. We exploit the combination of this expectation, along with the monthly structure of the futures contract, to examine the subsidy incidence.

Consider a set date for policy expiration. In the case of VEETC, the policy was allowed to expire on December 31st, 2011. Ethanol blended into motor fuel before this date received the tax credit, and ethanol blended afterwards did not. If we assume as above that the subsidy incidence manifests in commodity prices, then we should see price differences between the December and January futures contracts to the extent that the subsidy was having an effect on ethanol or RBOB prices. The difference in price is due to the fact that the commodity in December is eligible to receive the subsidy whereas the commodity in January is not. Because the future prices for December and January contracts are being observed at the same point in time prior to these dates, the difference in the future prices is not confounded by changes in market conditions that unfold in actual calendar time.

The price we are interested for this identification strategy in is known as a one-month calendar spread. For a given point in time $t$, the one-month calendar spread is the difference in the price of two adjacent futures contracts (with prices denoted by $F$). If those futures contracts expire on dates $T$ and $T - 30$ (about one month difference), then mathematically the calendar spread is given by

$$CS(t, T) = F(t, T) - F(t, T - 30),$$

(2.3)
where $C'S$ denotes “calendar spread.” In the case of the VEETC, the calendar spread of interest would be the January 2012 - December 2011 spread (hereafter, Jan12-Dec11). We refer to December’s contract as the “leading contract,” and January’s as the “trailing contract.” For RBOB and ethanol, which are produced upstream of the subsidy, we would expect this price spread to be negative as a result of subsidy expiration.

We construct a time series of the Jan12-Dec11 price spread and assess how it evolves over time. We would expect the spread to widen as the market incorporates information that the subsidy is likely to expire. In addition, to distinguish change in the price spread due to policy expiration from other unobserved factors, we estimate the degree of noise in the series in a simple and flexible way. First, we construct calendar spreads for ethanol and RBOB for several years both prior to and after December 2011. This approach provides a sense for how spreads typically behave, so that we can see if the subsidy expiration induced extraordinary behavior beyond what can reasonably be attributed to typical variation. For the purpose of comparing calendar spreads, we define the object $s = T - t$, which represents the number of days until maturity of the leading contract. For both commodities, we construct separate samples of calendar spreads for each $s$ value. We then order the calendar spreads (excluding Jan12-Dec11) within each group, and calculate the 2.5th and 97.5th percentiles. This gives us a non-parametric version of a 95 percent confidence band that runs from the first day in which the spread can be calculated up to the day of maturity.

In the case of ethanol, we use the exact procedure just described. For RBOB, the procedure is slightly more complicated. As we demonstrated in Table 2.1, any price change in RBOB due to VEETC expiration will be at most 5¢. This is a small price change relative to common fluctuations in petroleum markets. In order to gain a more precise estimate, we assume that any incidence accruing to oil refiners did not
get passed further upstream in the form of higher crude oil prices. Because crude oil is sold in a global liquids market of which ethanol is about two percent, it is reasonable to assume that the VEETC would not have any influence on oil prices. This allows us to control for changes in oil prices in our RBOB analysis, thereby removing the main source of RBOB price volatility.

We control for oil price variation by estimating the following model:

\[
CS_{RBOB}(t, T) = \beta_0 + \alpha_1 CS_{oil}(t, T - 11) + \alpha_2 CS_{oil}(t - 1, T - 11) \\
+ \alpha_3 CS_{oil}(t - 2, T - 11) + \beta_1 CS_{oil}(t, T + 11) \\
+ \beta_2 CS_{oil}(t - 1, T + 11) + \beta_3 CS_{oil}(t - 2, T + 11) + \epsilon(t, T),
\]

(2.4)

where \(CS_x(t, T)\) represents a calendar spread for commodity \(x\) on date \(t\) for which the trailing contract matures on date \(T\). Because oil futures contracts mature in the middle of the month prior to the contract month, i.e., around eleven trading days, it is not obvious whether to include the leading oil spread or the trailing spread, where the term leading is again meant to express a contract that matures first. Therefore, we include both contracts as regressors.\(^{10}\) We also included one- and two-day lags for both types of contracts. We estimate the model separately for each calendar spread in the sample period, in order to create a set of conditional RBOB price spreads that are analogous to the ethanol price spreads discussed above. We then use these spreads to create a confidence interval in order to gauge whether the RBOB spread behaves atypically near the point of subsidy expiration.

Given the approaches described above, the only data we require are futures contract price data for ethanol, RBOB, and crude oil. We use daily price data on futures

\(^{10}\) When including the leading calendar spread as a regressor, we encounter an additional difficulty with timing. The leading contract of the leading spread matures about half a month prior to the leading contract of the RBOB spread. Therefore, if we use the pure calendar spread model, the best we can do is measure the RBOB price change around eleven trading days prior to maturity. Alternatively, we can replace the price of the leading contract of the leading spread with the oil spot price for the last half month. We implement both procedures, neither of which produces significantly different results.
contracts from January 2007 through July 2013. The ethanol and corn futures contracts are traded on the Chicago Mercantile Exchange (CME), while the RBOB and crude oil (Brent) futures contracts are traded on the New York Mercantile Exchange (NYMEX). All futures price series were accessed via Bloomberg. As noted above, the delivery dates for the futures contracts vary across commodities. For ethanol, the contracts mature on the third trading day of the contract month. Brent contracts mature on the last business day prior to the 15th day of the month prior to the contract month, i.e., the December Brent contract matures in mid-November. RBOB contracts mature on the last day of the month prior to the contract month.

The behavior of ethanol futures contracts around the VEETC expiration is demonstrated graphically in Figure 2.2. The figure plots the spot price of ethanol (dashed line) as well as the futures strip for August 2011 through April 2012 as of several different dates during that time period. For contract months prior to January 2012, the ethanol futures market was backwardated, meaning that contracts for more distant delivery dates traded at lower prices. For contract months after February 2012, the market traded in contango, meaning that contracts in the more distant future traded at higher prices. Prior to maturity of the near contract, the January 2012 contract traded above the February 2012 contract. The black dots in the figure represent the prices of the December 2011 and January 2012 contracts at the time that the December 2011 contract expired (December 5th, 2011). In noting the vertical distance between the two points, we can see how stark the price difference was between those contracts relative to the price spreads both before and particularly after that time. Comparing the Jan12-Dec11 spread at earlier dates suggests the possibility that subsidy expiration might have begun being reflected in the market as early as the beginning of September 2011 and increased as the year as the year progressed.

11 We chose to begin our exploration with 2007 data rather than 2006 (the earliest year for which a market existed for ethanol futures) to avoid noise occurring as a result of MTBE phaseout and participants acclimating to a new market.
The notion of lingering, but decreasing, uncertainty over subsidy expiration is reasonable, especially because of the last minute extension that had been granted to the VEETC just one year earlier.\textsuperscript{12} It could also be the case that the futures market gained information over time about the incidence of the subsidy captured by ethanol producers.

\textbf{Figure 2.2: Ethanol Futures Strip Around Subsidy Expiration}

While Figure 2.2 suggests a reaction in ethanol futures markets to the VEETC expiration, it doesn’t say much about how atypical the calendar spread behavior was at that point relative to the rest of our 2007-2013 estimation window. To get a better sense of how significant the size of the Jan12-Dec11 spread was statistically, we calculate the 2.5\textsuperscript{th}, median, and 97.5\textsuperscript{th} percentile calendar spreads. The results are plotted in Figure 2.3, along with the Jan12-Dec11 spread. The vertical axis represents price spreads, in dollars per gallon of ethanol, while the top horizontal axis represents the number of days until maturity of the lead month contract (since they all mature at different dates) of the price spreads used to construct the confidence

\textsuperscript{12} For this reason, one could also posit that the effect of the subsidy expiration wasn’t fully reflected in the ethanol futures market by December contract maturity. If this is the case, then we are underestimating the benefit of the policy to ethanol producers.
interval. The bottom horizontal axis tracks the evolution of the Jan12-Dec11 spread over calendar time.

Overall, the ethanol price series appears to exhibit a very slight degree of backwardation. The median (or 50th percentile), represented by the black line in the figure, hovers at 0¢ until around 90 days until maturity, at which point it decreases slightly and remains negative. The red lines capture the empirical 95th percentile of spreads, and demonstrate that the distribution of spreads is skewed downward (negatively), a feature that appears stronger as the leading contracts approach maturity. The Jan12-Dec11 spread, represented by the blue line, declines steeply as the December delivery date draws near, finishing at about 30¢ per gallon, which is well beyond the lower bound of the 95% confidence interval. This suggests that ethanol producers received about two-thirds of the 45¢ subsidy at the time it expired, some of which could have in turn been passed upstream to corn farmers.

Figure 2.3: Ethanol Spread for January 2012 - December 2011
To investigate whether any incidence was passed up the petroleum branch, we present an analogous illustration for the RBOB market in Figure 2.4. However, unlike ethanol, we do not construct our plots directly from the RBOB spreads. Instead, we first estimate (2.4) to control for oil price changes, and then perform the same analysis as we did for ethanol, but on the RBOB regression residuals. As a result, the vertical axis in the figure represents RBOB price spreads after removing the variation in price spreads due to oil price changes. The black median line is around zero for all days to maturity. The Jan12-Dec11 spread maintains a price near zero until mid-September 2011. It then drops as low as around 3¢ in early October before climbing back up above zero during the month of November. By the last trading day for the December contract, the spread is negative, but by less than a cent. The confidence interval depicted by the red lines shows some downward skewness, particularly as maturity of the lead contract approaches.\textsuperscript{13} We note that the lower bound of the interval exceeds the maximum incidence that could accrue to oil refiners (5¢) for almost all measurements in the last 30 days of the contracts, which negates our ability to find any statistical evidence that the VEETC expiration resulted in a price change for RBOB. Nonetheless, while we can’t say definitively that there was no effect on RBOB prices as a result of the VEETC expiration, the evidence we do have suggests very little, if any, impact.

2.5.2 Corn

Since our evidence suggests that a significant portion of the subsidy was passed upstream to ethanol producers, we next investigate whether some of it was passed further upstream to corn farmers. We find some suggestive evidence that this occurred, and in fact it might have been the case that all of the incidence passed up the

\textsuperscript{13} For the day of maturity, this skewness is illustrated by the lower bound on the interval, which is almost three times further away from zero than the upper bound.
Figure 2.4: RBOB Spread for January 2012 - December 2011 RBOB Spread, Controlling for Oil Prices

agriculture branch of the supply chain went to farmers. However, because of data limitations due to the nature of corn futures markets, our evidence is more suggestive than conclusive.

As with ethanol, standardized futures contracts exist for corn and are traded through the CME, which we collected via Bloomberg for January 2007 through July 2013. These contracts mature on the business day immediately preceding the 15th day of the contract month. Unlike ethanol and RBOB, however, there are not corn futures contracts for every calendar month. Instead, corn futures contracts exist only for March, May, July, September, and December. This fact, coupled with the highly seasonal nature of agricultural commodity markets, forces us to alter our approach to calculating price changes in the corn market.

The approach that we use instead, as well as the accompanying results, is demonstrated in Figure 2.5. In lieu of a Jan12-Dec11 spread, which cannot be constructed
for the corn market, we base our analysis on the Mar12-Dec11 spread. The concept behind using this spread is the same as before, but our procedure could be more prone to picking up non-VEETC effects than the single month spread. In Figure 2.5, we plot the spreads for all March-December spreads from March 2008 to March 2013. We focus only on the March-December spreads due to the existence of highly seasonal effects in corn futures spreads. For example, the typical March-December spread exhibits much different behavior than the typical September-July spread. Because of this more limited set of observations, we look at all of the available series of spreads, rather than summarizing in a confidence interval.

The vertical axis in the figure once again represents the spread in contract prices between adjacent months. For the sake of comparison, the prices have been converted to per gallon of ethanol equivalent, assuming a 0.37 bushels per gallon conversion. For the four earliest contracts, the spreads exhibit varying degrees of contango (i.e., all spreads are positive), which is typical behavior in grains markets. Because crops are costly to store, a premium, often called the carry, is provided as compensation.\textsuperscript{14} When the leading contract is between 150 and 180 days to maturity, the premium appears to be about 30\textcent per gallon. The final premium at maturity over this time horizon appears to have increased to around 40\textcent per gallon. Our spread of interest, Mar12-Dec11, exhibits similar behavior until around 30 days before maturity, at which point it decreases sharply and eventually finishes below 10\textcent per gallon, or about 30\textcent per gallon lower than is typical. The Mar13-Dec12 spread exhibits atypical behavior as well, trading in an atypically low degree of contango or even backwarcation for most of the last 120 days until maturity of the December 2012 contract. Right before that maturity date, however, the Mar13-Dec12 spread converges rapidly toward a more typical carry premium. The atypical behavior of this spread can be explained by drought conditions in 2012 that resulted in a short supply of new corn

\textsuperscript{14} For example, see Yoon and Brorsen (2002).
to be sold in December of that year, causing prices for near-contract corn to increase.

Our takeaway from this analysis is that there is some suggestive evidence that the subsidy incidence was being passed upstream from ethanol producers to corn farmers, as the corn spread for Mar12-Dec11 at maturity is about 30¢ per gallon lower than normal, but it is difficult to make any strong statements because of the lack of sufficient data.

![Figure 2.5: Corn Spreads for March - December](image)

### 2.5.3 Finished Gasoline

Unlike in the cases of ethanol, RBOB, and corn, there are no standardized futures contracts for finished gasoline. As a result, our previous approach is not feasible. As an alternative, we turn to spot market prices to provide insights. Ultimately, we find no evidence that any incidence was passed downstream through wholesale gasoline prices and hence eventually to consumers. We also find evidence to suggest that blenders might have been pocketing more of the subsidy in the long-run, though this requires us to make stronger assumptions about quantity behavior.

Conceptually, our approach to estimating downstream incidence is to look for
changes in the blender margin around the time of the subsidy. The blender margin is defined as the price per gallon of finished gasoline less the prices per gallon of ethanol and RBOB, weighted by their volumetric contributions to the finished product. Mathematically, we can express this as

\[ BM = P_{\text{gasoline}} - 0.1P_{\text{ethanol}} - 0.9P_{\text{RBOB}}, \]  

(2.5)

where \( BM \) is the blender’s margin. We can decompose prices into two components:

\[ BM = (\bar{P}_{\text{gasoline}} - s_{\text{gasoline}}) - 0.1(\bar{P}_{\text{ethanol}} + s_{\text{ethanol}}) - 0.9(\bar{P}_{\text{RBOB}} + s_{\text{RBOB}}), \]  

(2.6)

where \( \bar{P}_x \) is the price net of the subsidy for commodity \( x \) and \( s_x > 0 \) is the portion of the subsidy passed along through price of commodity \( x \). It follows that for the period after the subsidy expired, all \( s_x \) are equal to zero and \( P_x = \bar{P}_x \) for all \( x \).

We motivate our empirical model by considering the extremes of (2.6). If all the subsidy incidence was passed along the supply chain, either upstream or downstream, then it will be the case that \( s_{\text{gasoline}} + 0.1s_{\text{ethanol}} + 0.9s_{\text{RBOB}} = 4.5\)¢. Therefore, the blender’s margin prior to subsidy expiration will be lower than the margin after expiration. On the other hand, if none of the incidence is passed along, then all \( s_x \) are equal to zero. This means that the blender’s margin will not change as a result of subsidy expiration.

Our econometric specification follows from re-writing (2.6) as

\[ \bar{P}_{\text{gasoline}} - s_{\text{gasoline}} = BM + 0.1(\bar{P}_{\text{ethanol}} + s_{\text{ethanol}}) + 0.9(\bar{P}_{\text{RBOB}} + s_{\text{RBOB}}), \]  

(2.7)

This can be thought of as defining a cointegrating relationship between gasoline, ethanol, and RBOB. To test for how much of the subsidy was passed along either upstream or downstream, we can either estimate or impose the theoretical relationship, and look for an increase in the blender’s margin, \( BM \). Note that doing so changes our focus from a very short term study to a longer term study and makes
our assumption that all of the incidence manifested in price changes stronger.

To estimate this model on the relationship of finished gasoline, RBOB, and ethanol prices, we use daily wholesale spot price data on the three commodities from May 11th, 2007 through December 31st, 2012.\textsuperscript{15} The ethanol and RBOB data are both New York Harbor spot prices acquired from Bloomberg, while the gasoline data are reformulated E10 rack prices in New York City acquired from Oil Price Information Service (OPIS). We chose prices in the same market in order to estimate any effect as precisely as possible, and we chose to work with wholesale prices for the same reason.

The price series over our sample period are plotted in Figure 2.6. Ethanol, RBOB, and gasoline prices are identified as the blue, orange, and green lines, respectively. The date of subsidy expiration on December 31st, 2011 is marked by the vertical gray line. Right before this cutoff, ethanol spot prices decline sharply, consistent with our earlier results. The prices for all three commodities evolve according to a random walk.\textsuperscript{16} Unsurprisingly, gasoline and RBOB prices move very closely together. Ethanol prices generally follow a similar path, but the relationship is not as tight. In fact, there are several periods (e.g., around early 2010 and 2012) where ethanol prices move counter to the petroleum prices. A formal Johansen test for cointegration between the three series suggests the existence of one cointegrating vector of the form $P_{\text{gasoline}} = 0.09 - 0.11P_{\text{ethanol}} - 0.89P_{\text{RBOB}}$, which is statistically indistinguishable from the theoretical relationship between the price series that we laid out in (2.5), with a mean blender margin of 9¢ per gallon of finished gasoline over the entire period.\textsuperscript{17}

Because our estimated cointegrating vector generates coefficients on $P_{\text{ethanol}}$ and $P_{\text{RBOB}}$ that are close to the theoretical relationship, we simply impose the relation-

\textsuperscript{15} The beginning date was chosen because it was the first day available for our ethanol price series. The end date was chosen because it preceded a rapid rise in the price of RFS RINs, which would
ship and use standard autoregressive modeling techniques to estimate the blender margin over time. Specifically, we estimate the following model:

\[ BM_t = \varphi_0 + \varphi_1 \mathbb{1}\{t > \text{Dec. 31, 2011}\} + \sum_{i=1}^{P} \varphi_i BM_{t-i} + \epsilon_t, \]  

(2.8)

where

\[ BM_t = P_{\text{gasoline},t} - 0.1 P_{\text{ethanol},t} - 0.9 P_{\text{RBOB},t} \]  

(2.9)

and \( \epsilon_t \) is white noise, and \( \mathbb{1}\{\cdot\} \) is an indicator function that evaluates to one if the condition inside the brackets is satisfied. In our model, this corresponds to a dummy variable that will be equal to one for dates after subsidy expiration. We are complicate our analysis.

\textsuperscript{16} For each commodity, Phillips-Perron tests fail to reject the null hypothesis of a unit root.

\textsuperscript{17} The confidence intervals for the coefficients on \( P_{\text{ethanol}} \) and \( P_{\text{RBOB}} \) contain 0.1 and 0.9, respectively, for any reasonable \( \alpha \)-level.
interested in the change in the unconditional mean of the blender’s margin resulting from subsidy expiration. Under our model specification, this is estimated by the following transformation of the parameters:

\[
\Delta BM = \frac{\hat{\varphi}_e}{1 - \sum_{i=1}^{P} \hat{\varphi}_i}.
\]  

(2.10)

where \(\Delta BM\) is the estimated change in the blender’s margin resulting from expiration.

Our constructed blender’s margin variable is plotted in Figure 2.7. The figure suggests that the blender margin series is stationary, and in fact a unit root null is soundly rejected.\(^{18}\) It also does not suggest any obvious visible change in the pre- and post-expiration blender’s margin, though this is still an issue to be resolved through rigorous statistical analysis.

Consistent with our visual interpretation, estimation of (2.8) fails to identify any significant increase in the blender’s margin constant, which is calculated according to equation (2.10). We find a point estimate of 0.0002 with a 95% confidence interval of \([-0.02, 0.02]\). The point estimate suggests that very little of the incidence was passed along through price changes, which clearly contradicts some of our earlier evidence. However, our previous estimates were based on a short-run analysis right around the time of expiration, while this section focuses on a longer-term analysis. Further research is required to validate, integrate, and reconcile the results.

2.6 Conclusion

This paper describes the mechanics of fuel blending and how the incidence of the VEETC could have manifested in price changes. We collected futures and spot price data on each commodity in the supply chain and used them to empirically estimate

\(^{18}\) The standard Box-Jenkins approach to model specification suggests an AR-model with \(P = 4\).
price changes before and after the subsidy expiration. For the futures price data, we used an event-study style of analysis using one-month calendar spreads. This approach gave us a clean indication of how the market perceived the incidence to be distributed among various industries. Since futures price data was not available for measuring downstream incidence, we instead empirically estimated the blender’s margin using spot price data.

The analysis to date yields different findings for the upstream versus downstream methods. Using the ethanol futures data, we found compelling evidence that around two-thirds of the subsidy was passed up the agriculture chain to ethanol producers. Moreover, we found suggestive evidence that this portion of the subsidy was further passed upstream to corn farmers, though the data is more limited. Finally, we find no evidence that oil refiners captured any portion of the subsidy, though our error bounds exceeded the maximum incidence they could have theoretically collected.
This suggests that blenders or consumers captured perhaps one-third of the subsidy.

The more downstream-oriented analysis of blender margins suggested that blenders, rather than ethanol producers or corn farmers, captured most (if not all) of the subsidy. Our estimate of the change in the blender margin as a result of subsidy expiration yielded a point estimate of essentially zero, which implies that none of the subsidy was passed along through price changes. Furthermore, the upper bound of the 95% confidence interval on this estimate only covers around 45% of the subsidy, which is smaller than our point estimate of the incidence going up the agricultural chain resulting from our upstream analysis. Further research is required to validate, integrate, and ideally reconcile these results.
3.1 Introduction

The ultimate impacts of emissions of local air pollutants such as \( \text{SO}_2 \) and \( \text{NO}_x \) on the environment and human populations remain a matter of significant scientific inquiry. For one, the relationship between emissions levels and eventual exposure in the form of ambient concentrations depends largely on meteorological conditions, which can be forecasted but are still subject to substantial uncertainty (Hodan and Barnard, 2004). Moreover, the resulting exposure is largely considered to result in acute, short-term and chronic, long-term damages, though the relative magnitude of each type of damage remains an on-going question (Kloog et al., 2013, 2012). Presumably, optimal regulation of emissions should take into account each of these phenomena. Yet, to date, these are considerations that have been largely ignored by the existing economics literature.

We contribute to the literature on optimal environmental regulation by developing and analyzing a dynamic model with abatement costs, acute and chronic damages.
from pollution, and stochastic exposure. We consider three types of regulation which
differ with respect to the amount of control and information available to the regula-
tor: perfect forecasts, uninformative forecasts, and ex ante regulation. With perfect
forecasts, the regulator knows with certainty at the beginning of each period how
current emissions map to current exposure. Under uninformative forecasts, the reg-
ulator only knows the distribution of possible exposures associated with a given level
of emissions. For both forecasting cases, regulation can be updated dynamically
according to the current stock of exposure. This differs from ex ante regulation, in
which the regulator does not know with certainty the future exposures and cannot
update the regulation dynamically.

After analyzing the first-order conditions of a general model, we turn to an ana-
lytically tractable version with specific functional forms for costs, damages, and the
relationship between emissions and exposure. Using stochastic dynamic program-
ming techniques, we determine the optimal feedback regulation as a function of the
current exposure stock for both the perfect and uninformative forecasts scenarios.
For ex ante regulation, we determine the optimal regulation path as a function of the
model parameters. We then derive and compare the expected total costs associated
with each type of regulation. Finally, we perform comparative statics on the cost
comparisons to see how they change as the parameters of the model change.

Our model specification combines elements from models developed in Leiby and
Rubin (2001) and Hamilton and Requate (2012). Similar to our approach, Leiby
and Rubin (2001) consider a model with abatement costs and both stock and flow,
i.e., chronic and acute, damages. Unlike the current paper, however, they focus on
characterizing the optimal intertemporal trading ratio for the banking and borrowing
of emissions permits and do not incorporate uncertainty over pollution exposure. On
the other hand, Hamilton and Requate (2012) analyze a model with abatement costs
from emissions and damages from exposure, where the latter depends on a stochastic
process for environmental services, which is akin to our specification of meteorological conditions. Unlike the current paper, the model is static, and the authors focus on the the regulator’s choice between emissions versus ambient quality standards.

Our model was developed with local air pollutants such as SO$_2$ and NO$_x$ in mind, though it could also apply to water pollutants. Emissions of these pollutants are known to contribute to increased ambient concentrations of criteria air pollutants such as particulate matter (PM$_{2.5}$ and PM$_{10}$) and ozone. The process in which, for example, sulfur oxides are converted through chemical reactions to damaging small particulate matter is known as secondary formation. Often, these pollutants are thought of, at least by economists, as flow pollutants. However, the previously mentioned epidemiology literature suggests that such pollutants have stock-like effects. Instead of the stock building up in the atmosphere, it builds up inside human beings. As a result, regulatory approaches that ignore these chronic impacts will underestimate the deleterious effects on the environment and population.

For the applications we have in mind, the dynamic regulation would require that regulator update quite frequently. Presumably the period length could be as short as one or two days. Under this type of scenario, abatement would most likely have to come through the electric power sector, where short-term abatement is possible subject to grid stability requirements (Sun et al., 2012). Furthermore, implementing the perfect forecasts regulation (or at least, more precise forecasts regulation) requires the ability to precisely predict pollution exposure in the short-term. In fact, IBM has recently reached an agreement with the Beijing government for a project that requires doing exactly that (IBM Corporation, 2014).

Our results derive several properties of the optimal regulation paths and associated total expected emissions costs. The emissions path for perfect forecasts is the same as the path for a baseline perfect certainty case (for which the stochastic variable is known to be equal to its expected value in all periods), plus a correction term
that can be either positive or negative depending on the realization of the stochastic variable. As expected, total expected costs under perfect forecasts are lower than under uninformative forecasts, which are lower than under ex ante regulation. From the comparative statics results, we see that the expected cost benefits to having more regulatory flexibility decline as the marginal abatement cost slope becomes larger relative to the marginal damage slopes and increase as the marginal chronic damage slope becomes larger relative to the marginal acute damage and marginal abatement cost slopes. The same analysis with respect to the marginal acute damage slope depends on the comparison being considered.

The paper is organized as follows. In Section 3.2, we describe the most general form of the model and the regulation scenarios; we also derive and interpret the first-order conditions. Section 3.3 defines a tractable version of the model and derives and interprets the optimal regulation path. In Section 3.4, we solve for and compare the expected total costs under our three scenarios, and calculate and provide intuition for the associated comparative statics. We conclude in Section 3.5.

3.2 General Model

In this section, we introduce and discuss the most general form of our model. We also describe our three different regulatory scenarios, and derive and interpret the first-order conditions under each.

We consider a finite-horizon dynamic program with \( T \) periods. The regulator chooses the level of pollution emissions, \( x_t \in \mathbb{R}_+ \), associated with each time period. The emissions level at time \( t \) enters directly into a period specific aggregate cost function, \( C_t(x_t) \). Costs are assumed to be decreasing and convex with respect to emissions, i.e., emissions abatement is costly.

Emissions are also associated with pollution exposures, which determine the amount of damages (in dollars). The mapping between emissions and exposure,
$e_t \in \mathbb{R}_+$, is defined through a dispersal function, $f$. We assume that the dispersal function has a stochastic component in each period, defined by $\varphi_t$. These random variables are assumed to be independent and identically distributed with known distribution $G_t(\cdot)$. Mathematically, we can represent the relationship as follows:

$$e_t = f(x_t, \varphi_t),$$

where we assume that $f$ is increasing in its arguments. Under this formulation, the interpretation of the dispersal function is that greater emissions lead to greater exposure in the same period, subject to uncertainty over meteorological conditions. Furthermore, a higher realization of the “weather” variable $\varphi_t$ is associated with conditions that result in higher exposure, such as high temperatures and low wind speeds (Tai et al., 2010; Cheng and Li, 2010).

We assume the existence of two linearly separable, increasing, and convex damage functions, representing acute and chronic damages. Acute damages are a time-varying function of current period exposure only and are defined as $D_{a,t}(e_t)$. Intuitively, they reflect damages that occur as a result of particularly severe short-run phenomenon, such as heat inversions that trap pollutants closer to ground-level. Additionally, we define chronic damages by $D_c(\sum_{t=1}^{T} e_t)$, as they are defined as a function of the sum of exposures over all periods. These reflect the additional “stock” effects that result from repeated pollution exposures over time.

The regulator’s objective is to minimize the expected sum of total costs and damages. Mathematically, we can express the program at its outset as follows:

$$\min_{\{x_t\}_{t=1}^{T}} \mathbb{E}_0 \left[ \left( \sum_{t=1}^{T} C_t(x_t) + D_{a,t}(e_t) \right) + D_c\left( \sum_{t=1}^{T} e_t \right) \right].$$

(3.2)

The inclusion of the chronic damage component makes the regulator’s problem dynamic, since it ties together emissions across all time periods. A particularly large
realization of \( \varphi_t \) in one period will impact the optimal regulation in other periods.

Given our model set-up, we examine three different scenarios regarding the regulator’s knowledge of the weather variable and ability to update the policy. In the case of dynamic regulation, the optimal level of pollution is chosen at the beginning of each period \( t \). This allows the regulator to incorporate previous realizations of the weather variable into the time \( t \) decision. In actuality, those previous realizations could be expected to provide information about the current stock of exposure, which matters for the chronic damage term, and the distribution \( G_t \). For our analysis, we will assume that dynamic regulation allows for perfect information about the stock, but we will separate the weather variable distribution effect into two extreme scenarios. In one case, the regulator learns the realization of \( \varphi_t \) before making a decision at time \( t \), but does not learn anything about future realizations. We call this scenario perfect forecasts. In the other case, the regulator makes the decision at time \( t \) without learning any additional information about \( \varphi_t \); we call this scenario unininformative forecasts. Under the third scenario, we assume that, in addition to not gaining information over time about the weather variables, the regulator is unable to dynamically update the policy. Therefore, all decisions must be made at the outset of the program. Accordingly, this scenario is called ex ante regulation.

We now derive the first-order conditions of the model under the three scenarios.

### 3.2.1 Perfect Forecasts

When the regulator has access to perfect forecasts, decisions at each period incorporate the current value of the stock of exposures as well as the current period weather realization. Incorporating the Bellman Principle, the regulator’s objective at each time \( t = 1, \ldots, T \) is as follows:

\[
V_t(d_t, \varphi_t) = \min_{x_t} C_t(x_t) + D_{a,t}(f(x_t, \varphi_t)) + \mathbb{E}_t[V_{t+1}(d_{t+1}, \varphi_{t+1})],
\] (3.3)
where $d_t$ is the stock of exposure at time $t$ and evolves according to the state equation

$$d_{t+1} = d_t + e_t. \quad (3.4)$$

We define the terminal value function as the chronic damages associated with the program, i.e.,

$$V_{T+1}(d_{T+1}, \varphi_{T+1}) \equiv D_c(\sum_{t=1}^T e_t). \quad (1)$$

Assuming an interior solution, the first-order condition is given by

$$C'_t(x_t) + D'_{a,t}(f(x_t, \varphi_t)) \cdot f_x(x_t, \varphi_t) + \mathbb{E}_t \left[ \frac{\partial V_{t+1}}{\partial d_{t+1}} \right] f_x(x_t, \varphi_t) = 0, \quad (3.5)$$

where $f_x$ is defined as the partial derivative of the dispersal function with respect to its first argument. Interpreting $-C'_t(x_t)$ as the marginal abatement cost, this condition states that the optimal level of emissions will equalize marginal abatement cost with the sum of marginal acute damage and the expected marginal impact on the next-period value of the program.

Because the regulator knows $\varphi_t$, we can use the envelope theorem to further analyze the first-order conditions. Taking the derivative of (3.3) at the optimal value of $x_t$ with respect to the state, we obtain

$$\frac{\partial V_t}{\partial d_t} = \mathbb{E}_t \left[ \frac{\partial V_{t+1}}{\partial d_{t+1}} \frac{\partial d_{t+1}}{\partial d_t} \right], \quad (3.6)$$

which after rolling forward and taking expectations, yields

$$\mathbb{E}_t \left[ \frac{\partial V_{t+2}}{\partial d_{t+2}} \right] = \mathbb{E}_t \left[ \frac{\partial V_{t+2}}{\partial d_{t+1}} \frac{\partial d_{t+1}}{\partial d_t} \right]. \quad (3.7)$$

Noting that $\frac{\partial d_{t+2}}{\partial d_{t+1}} = 1$ and combining with the first-order condition (and suppressing arguments where clear), we get

$$C'_t + D'_{a,t}f_x(x_t, \varphi_t) = \mathbb{E}_t \left[ \frac{f_x(x_t, \varphi_t)}{f_x(x_{t+1}, \varphi_{t+1})} \left( C'_{t+1} + D'_{a,t+1}f_x(x_{t+1}, \varphi_{t+1}) \right) \right]. \quad (3.8)$$

\footnote{This definition implies that there is no randomness to account for in the terminal period, i.e., $\mathbb{E}_T[V_{T+1}(d_{T+1}, \varphi_{T+1})] = V_{T+1}(d_{T+1}, \varphi_{T+1})$.}
This equation tells us that, under the optimal policy, the regulator will equate the marginal flow costs today (given by the sum of marginal costs and acute damages) to expected marginal flow costs tomorrow, with the latter weighted by the ratio of the marginal effect of emissions on exposure today to the marginal effect of emissions on exposure tomorrow.

### 3.2.2 Uninformative Forecasts

Under the uninformative forecast scenario, the regulator is able to choose the pollution level at the beginning of each period, but only the distribution of the current period weather variable is known. As a result, there is only one state variable, which still evolves according to (3.4). Applying the Bellman Principle again yields

\[
V_t(d_t) = \min_{x_t} C_t(x_t) + \mathbb{E}_t[D_{a,t}(f(x_t, \varphi_t))] + \mathbb{E}_t[V_{t+1}(d_{t+1})],
\]  

(3.9)

where we define the terminal value function as before. The associated first-order condition is given by

\[
C_t'(x_t) + \mathbb{E}_t[D_{a,t}'(f(x_t, \varphi_t)) \cdot f_x(x_t, \varphi_t)] + \mathbb{E}_t\left[\frac{\partial V_{t+1}}{\partial d_{t+1}}\right] f_x(x_t, \varphi_t) = 0.
\]

(3.10)

This has a similar interpretation to the first-order condition under perfect forecasts, but now the optimal regulation sets the marginal abatement cost equal to the expected current-period acute damages plus the expected marginal impact of additional pollution on the next period value of the program. Also, because the current period weather variable is unknown, we cannot use the envelope theorem to get an Euler equation.

### 3.2.3 Ex Ante Regulation

In the ex ante regulation scenario, the regulator selects the full set of \(x_t\) values in advance. These decisions are made with the information set at time-0, and so the
regulator’s program is given by (3.2). The first-order condition for \( x_t \) is given by

\[
C'_t(x_t) + \mathbb{E}_0[D'_a(t, \varphi_t)] \cdot f_x(x_t, \varphi_t) + \mathbb{E}_0[D'_c(t) \cdot f_x(x_t, \varphi_t)] = 0. \tag{3.11}
\]

Thus, the optimal pollution level is set such that marginal abatement costs at time \( t \) equal the expected sum of marginal acute damages at time \( t \) and the marginal contribution of time \( t \) emissions to chronic damages.

### 3.3 Quadratic Model

In this section, we introduce a special case of the general model considered in the previous section. We choose specific functional forms for costs, damages, and the dispersal function that allow us to draw out the fundamental features of the model while maintaining tractability. The optimal path of regulation for each scenario is also laid out, which sets up our comparison of expected total program costs and derivation of associated comparative statics in the next section.

First, we define the dispersal function and its components. We assume that it takes on the following linear form:

\[
e_t = f(x_t, \varphi_t) \equiv \gamma x_t + \varphi_t. \tag{3.12}
\]

As before, \( x_t \) is the level of emissions and \( \varphi_t \) is the weather variable at time \( t \). Because the weather variables are assumed to be i.i.d., we only need to specify the unconditional mean and variance, defined as \( \mu \) and \( \sigma^2 > 0 \), respectively.\(^2\) To facilitate the interpretation of our model, we also define a deterministic scaling parameter, \( \gamma \).

This parameter defines concisely the relationship between an emissions and exposure level; for example, we could think of the emissions as tons of SO\(_2\) from power plants and the exposure as concentration (in parts per billion) of PM\(_{2.5}\). The weather

\(^2\) We assume that the random variable \( \varphi_t \) has bounded support such that exposure must be positive within the range of emissions we consider.
variable then plays the role of a stochastic additive shifter in that relationship.

We also choose tractable functional forms for costs, acute damages, and chronic damages. Respectively, we define them as follows:

\[ C(x_t) = \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 \]

\[ D_a(e_t) = \frac{1}{2} \delta_a e_t^2 \]

\[ D_c \left( \sum_{t=1}^{T} e_t \right) = \frac{1}{2} \delta_c \left( \sum_{t} e_t \right)^2. \]

In addition to specifying specific functional forms for costs and damages, we have also removed the time dependency of the functions. While this is an analytic convenience that will allow us to solve the model, it is not necessarily a realistic assumption.\(^3\)

Given our functional form assumptions, we now describe the optimal emission paths for our three scenarios. First, however, we describe the path under perfect certainty as a way to benchmark the other scenarios.

### 3.3.1 Certainty

In the case of perfect certainty, we assume that the realizations of the weather variables are known with perfect certainty at the outset of the program. This differs from the perfect forecasts scenario, where the regulator is uncertain about all weather variables beyond the current period. To further facilitate comparison, we assume that all weather variables are realized at their mean, \( \mu \). Allowing \( x^c_t \) to denote the optimal pollution at time \( t \) under certainty, we show in Appendix A that

\[ x^c_t(d_t) = \frac{\theta - \gamma (\delta_c d_t + \mu (\delta_a + (T - (t - 1)) \delta_c))}{\lambda + \gamma^2 (\delta_a + (T - (t - 1)) \delta_c)}. \]  

\(^3\) For example, imagine that regulation is being imposed on the electricity sector. The shape of the cost curve will depend, for instance, on the time of year. This is because summer and winter months tend to be correlated with high electricity demand, which will increase the costs associated with all levels of abatement as fewer units are idle and hence able to replace generation from low-cost and heavily polluting units.
This represents the closed-loop solution to the dynamic program, as the optimal emissions level is specified in terms of the current stock of pollution. It also depends on the model parameters and \( s = T - (t - 1) \), which is the number of periods remaining until the final period.

Because we are assuming perfect certainty, we can combine (3.13) with the state equation (3.4) to solve for \( x_t^c \) in terms of the initial stock and model parameters:

\[
x_t^c = \frac{\theta - \gamma(\delta_c d_1 + \mu(\delta_a + T\delta_c))}{\lambda + \gamma^2(\delta_a + T\delta_c)}.
\]  

(3.14)

Since the weather realization is the same in each period and the cost and damage functions are stationary and convex, the optimal level of emissions is the same in each period. Not surprisingly, the optimal per period emissions level will be decreasing in the initial stock of exposure. Going forward, we will simplify the analysis by assuming \( d_1 = 0 \).

We now turn to the optimal regulation in the three scenarios with weather uncertainty.

3.3.2 Perfect Forecasts

Under the perfect forecasts scenario, the regulator knows the realization of the current period weather variable when making a decision on emissions, but only the distribution of future weather variables is known. The optimal solution can be found by starting at the terminal period and solving through backward induction. As demonstrated in (3.5), this requires knowledge of the derivative with respect to the current stock of pollution of the next-period value function. We perform the derivation in Appendix A, and report the solution \( (x_t^p) \) under perfect forecasts:

\[
x_t^p(d_t, \varphi_t) = x_t^c(d_t) + (\mu - \varphi_t)\kappa_t,
\]  

(3.15)
where

\[
\kappa_t = \frac{\gamma(\gamma^2(\delta_a(\delta_a + s\delta_c) + \lambda(\delta_a + \delta_c))}{(\lambda + \gamma^2\delta_a)(\lambda + \gamma^2(\delta_a + s\delta_c))}.
\]  

(3.16)

Our solution (3.15) describes a complete solution to the dynamic program: given a value of the stock of exposure and the current period weather variable, the regulator can calculate the optimal level of emissions.

The optimal solution under perfect forecasts is equal to the optimal forecast under certainty, plus a correction term that depends on the difference between the realization of current period weather and its expected value. If the realization is the expected value, then the optimal solution is the same level of emissions. If the realization is above the expected value, then the optimal emissions level under perfect forecasts is less than it is under certainty. The opposite is true if the realization is above the mean.

The weight on the correction term \( \kappa_t \) is time-dependent. Moreover, the derivative with respect to \( s \) is negative. This means that as we move further away from the terminal date, the regulator should react less strongly to deviations in weather conditions. In the extreme, as \( s \to \infty \), the value of \( \kappa_t \) approaches \( \frac{\gamma\delta_a}{\lambda + \gamma^2\delta_a} \). In this case, the chronic damage parameter becomes insignificant in determining the optimal regulation.

3.3.3 Uninformative Forecasts

With uninformative forecasts, the regulator makes a decision on the emissions level without knowledge of the current period weather variable realization. Once again, we can solve for the optimal regulation (denoted by \( x^u_t \)) as a function of the state:

\[
x^u_t(d_t, \varphi_t) = x^*_t(d_t).
\]  

(3.17)

In this scenario, the optimal solution is the same as in the certainty case. In light of (3.15), this makes sense. Without knowledge of the weather variable realization,
the best the regulator can do is to assume it is equal to its expected value. This will eliminate the correction term.

3.3.4 Ex Ante Regulation

Under ex ante regulation, the regulator must decide on the level of emissions for each period at the outset of the program. It is straightforward to verify that the best the regulator can do is to assume that the weather variable realization in each period is equal to its expected value. Thus, the solution (denoted by $x_t^a$) is given by

$$x_t^a = x_t^c,$$  

(3.18)

which does not depend on any state variables because the regulation is not dynamic.

Even though the optimal regulation appears identical under the uninformative forecasts and the ex ante regulation scenarios, the expected total program costs at the outset will not be the same. Under uninformative forecasts, the regulator responds to past realizations of the weather variable through their impact on the current period exposure stock. In contrast, under ex ante regulation the regulator “winds back” $x_t^c(d_t)$ at the outset of the program into a non-state-dependent regulation and does not react to weather variable realizations. Not surprisingly, this leads to higher total expected program costs.

3.4 Analytic Results

In this section, we compare expected total program costs under our three scenarios, which requires us to characterize the value function for each scenario. After deriving the differences in expected total costs, we calculate and interpret their comparative statics with respect to the fundamental model parameters.
3.4.1 Welfare Comparisons

In order to demonstrate our procedure for calculating expected program costs under our three scenarios, we again start with the certainty case. Consistent with our functional form assumptions, we hypothesize that the value function at time $t$ can be written as a quadratic function of the state variable:

$$V_t(d_t) = \frac{1}{2} a_t d_t^2 + b_t d_t + c_t,$$

(3.19)

where $a_t$, $b_t$, and $c_t$ are parameters to be solved for using the terminal conditions $a_{T+1} = \delta_c$, $b_{T+1} = 0$, and $c_{T+1} = 0$. We insert our hypothesized value function into the Bellman equation, take the first-order conditions, and solve for the optimal regulation, $x_t(d_t)$ as a function of the value function and model parameters. Plugging the solution back into the Bellman equation and matching up the coefficients of $d_t^2$, $d_t$, and the constant yields a series of recursive equations that can be used to verify our guess and solve for the value function parameters. Finally, we impose the condition that $d_1 = 0$, which means that $V_1(0)$ will represent the total expected costs for the program.

Our solution method can be applied to all three regulatory scenarios in addition to the certainty baseline. We define the total expected program costs for perfect forecasts, uninformative forecasts, and ex ante regulation as $V^p$, $V^u$, and $V^a$, respectively. These symbols represent period one value functions under the assumption that the initial exposure stock is zero. We derive the expressions for these quantities in Appendix A. The following propositions describe the differences across the quantities, which is our primary interest.

**Proposition 1.** The difference in expected total program costs between uninformative
and perfect forecast regulation is given by

\[
V^u - V^p = \frac{\gamma^2 \sigma^2}{2} \left( \frac{T \delta_a^2}{\lambda + \gamma^2 \delta_a} + \frac{T \delta_c^2}{\lambda + \gamma^2(\delta_a + T \delta_c)} + \frac{\delta_a \delta_c (2 \lambda + \gamma^2 \delta_a)}{\lambda + \gamma^2 \delta_a} \sum_{i=1}^{T} \frac{1}{\lambda + \gamma^2(\delta_a + i \delta_c)} \right)
\]  

(3.20)

Every term in the parentheses is positive, so the difference \(V^u - V^p\) is positive. In terms of the model, it represents the upper bound on the value of improving forecasts, which is a reduction in total expected costs. If the regulator benefits from improved, but not necessarily perfect, forecasts, costs will still be reduced, but not by as much.

**Proposition 2.** The difference in expected total program costs between ex ante and uninformative forecast regulation is given by

\[
V^a - V^u = \frac{\gamma^2 \sigma^2}{2} \left( \sum_{i=1}^{T} \frac{i \delta_c^2}{\lambda + \gamma^2(\delta_a + i \delta_c)} \right)
\]  

(3.21)

The difference \(V^a - V^u\) is also positive. As expected, there are cost benefits to dynamic regulation, even when the regulator does not learn anything new about the distribution of the current period weather variable.

**Proposition 3.** The difference in expected total program costs between ex ante and perfect forecast regulation is given by

\[
V^a - V^p = \sigma^2 \left( \frac{\lambda^2}{\delta_a + \lambda} \right) \sum_{i=1}^{T} \left( \frac{\gamma^2 \delta_a^2 + \gamma^2 \delta_a \delta_c + \lambda \delta_c}{\lambda^2} - \frac{\delta_c}{\lambda + \gamma^2(\delta_a + i \delta_c)} \right)
\]  

(3.22)

Based solely on (3.22), the sign is not immediately obvious. However, we know that \(V^a - V^p = (V^a - V^u) + (V^u - V^p)\), and so it follows immediately based on the previous propositions that this difference is positive.

Due to the complexity of the total expected cost comparison expressions, we turn to comparative statics to yield further insights.
3.4.2 Comparative Statics

The comparative statics for the total expected cost comparisons are summarized in Table 3.1. The results for the number of periods, $T$, and the variance of the weather variable, $\sigma^2$, are straightforward. There is an informational advantage to the dynamic regulations, one which manifests in each period that the regulator makes a decision. In this case, more decisions (greater $T$) will increase the value of this advantage, and reduce expected total costs relative to the ex ante policy. For the same reason, we would expect perfect forecasts to become less costly relative to uninformative forecasts as $T$ increases. Although the regulator can use the value of the exposure stock to update regulations each period, there is still a disadvantage to having to guess at the current weather. Again, more periods will result in more guesses and therefore higher costs.

In the case of $\sigma^2$, the story is similar as it is for $T$. Both perfect and uninformative forecasts allow for accounting for past weather variable realizations, but uninformative forecasts result in less current period information. If the variance of the weather variable distribution is small, then this information is not as valuable and the cost difference between the scenarios will decrease. In the case of ex ante regulation, the decisions cannot be updated, so all realizations must be predicted in advance with no opportunity to make corrections. The result will be greater expected costs if the weather variables have greater dispersion.

For the slope parameters, the comparative statics represent the change in the comparisons due to making one of the parameters relatively larger, and hence more influential, relative to the others. For instance, the results for $\lambda$ represent the process of making the slope of the marginal cost larger relative to the slopes of acute and chronic damages. In this case, the total expected cost differences will decrease uniformly as we compare ex ante regulation to uninformative forecasts, and unin-
Table 3.1: Comparative Statics Results by Parameter and Regulatory Cost Comparison

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$\frac{\delta Y^{a}-Y^{u}}{\delta e}$</th>
<th>$\frac{\delta Y^{a}-Y^{p}}{\delta e}$</th>
<th>$\frac{\delta Y^{a}-Y^{p}}{\delta c}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\delta_a$</td>
<td>-</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>$\delta_c$</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

formative to perfect forecasts. If marginal cost considerations are weighing more heavily in the decision, then the informational advantage of knowing the current period weather realization decreases, since the cost function doesn’t incorporate this information directly. Likewise, dynamic regulation becomes less valuable since its main advantage is to account for past weather variable realizations, which are again less important if marginal cost considerations dominate.

Contrary to the results for $\lambda$, total expected cost differences will increase uniformly across our comparisons as $\delta_c$ increases. The primary advantage to dynamic regulation is to account for past exposures, and all of the exposures directly enter into the model through the chronic damage function. Therefore, as the weight on the slope of marginal chronic damages increases relatively, the advantage to updating regulation will increase as well. Furthermore, because the current period weather realization will impact not only the current stock of pollution but the future stocks, there is additional value to be realized from perfect forecasts when $\delta_c$ increases relatively.

The results for $\delta_a$ demonstrate the advantage of being able to forecast the cur-
rent period weather variable. When the slope of acute damages increases relatively, the advantage of uninformative forecasts over ex ante regulation decreases. This is because that advantage is based on being able to update the regulation, but acute damages are influenced by current exposure only, which is unknown in either scenario. On the other hand, when the slope of acute damages increases relatively, the advantage of perfect over uninformative forecasts increases. This occurs because the advantage of forecasting the current weather variable manifests directly within the acute damage term.

3.5 Conclusion

In this paper, we analyzed a dynamic analytic model with abatement costs, acute and chronic damages, and a pollution dispersal function with a stochastic component. We derived and interpreted the first-order conditions for a version of the model with general functional forms under three different regulatory scenarios: perfect forecasts, uninformative forecasts, and ex ante regulation. These scenarios corresponded to decreasing amounts of regulatory flexibility and information in the decision-making process.

To solve the model fully, we developed a tractable version with specific functional forms. We demonstrated the optimal regulation path under each regulatory scenario. Specifically, we demonstrated how the optimal level of pollution with uninformative forecasts is the same as the case in which the weather variable realizations are all equal to the expected value and known in advance with perfect certainty. In the perfect certainty case, the optimal level is equal to the certainty case plus a correction term that depended on the difference between the current period weather and its expected value.

Finally, we derived the total expected costs and calculated the differences in these quantities for each of our scenarios. We demonstrated, as expected, that total ex-
pected costs were decreasing in the amount of regulatory flexibility and information. We also demonstrated how the differences in costs across policies changed in response to changes in the cost and damage parameters. The takeaway is that regulatory flexibility cost advantages were decreasing in the slope of marginal costs and increasing in the slope of marginal chronic damages. With respect to acute damages, the sign depends on the comparison being done.

The model considered here was vastly simplified to enhance tractability and to study the informational effects in isolation. A more realistic representation would include spatial effects, which are important in the context of local air pollutants. It would also incorporate emissions and exposures for multiple pollutants. These considerations could be studied in an analytic model, but it might be more realistic to study them in a numerical integrated assessment framework.
A.1 Derivation of Value Functions

In this section, we demonstrate how we solve for the value functions associated with our four different scenarios: certainty, dynamic regulation with perfect forecasts, dynamic regulation with uninformative forecasts, and \textit{ex ante} regulation. Our general procedure is as follows: first, we hypothesize the form of the value function as a function of the state variable. Using the Bellman equation at time $t$, we then differentiate and solve for the optimal level of emissions as a function of the hypothesized parameters. Next, we plug the solution back into the Bellman equation and verify our hypothesized form of the value function. Finally, we solve for the hypothesized parameters using the resulting system of difference equations.

Once we’ve solved for the value functions, the expressions in Propositions 1-3 follow almost immediately by substituting $t = 1$ into the value functions and assuming $d_1 = 0$. 
A.1.1 Certainty

We hypothesize that the value function $V_t(d_t)$ can be written as a quadratic function of the state:

$$V_t(d_t) = \frac{1}{2}a_t d_t^2 + b_t d_t + c_t,$$

with the terminal conditions $a_{T+1} = \delta_c$, $b_{T+1} = 0$, and $c_{T+1} = 0$. Under certainty, we assume that $\varphi_t = \mu$ for all $t$. The resulting Bellman equation is

$$V_t(d_t, \varphi_t) = \min_{x_t} \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 + \frac{1}{2} \delta_a e_t^2 + V_{t+1}(d_{t+1}).$$

Using the hypothesized value function, this becomes

$$V_t(d_t, \varphi_t) = \min_{x_t} \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 + \frac{1}{2} \delta_a e_t^2 + \frac{1}{2} a_t d_t^2 + b_{t+1} d_{t+1} + c_{t+1}.$$

Substituting the state equation, we obtain

$$V_t(d_t, \varphi_t) = \min_{x_t} \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 + \frac{1}{2} \delta_a (\gamma x_t + \mu)^2 + \frac{1}{2} a_t d_t^2 + b_{t+1} d_{t+1} + c_{t+1}.$$

The first-order condition for $x_t$ is

$$x_t = \frac{\theta - \gamma (a_{t+1} d_t + b_{t+1} + \mu (\delta_a + a_{t+1}))}{\lambda + \gamma^2 (\delta_a + a_{t+1})}. \quad \text{(A.1)}$$

Substituting back into the objective function and simplifying yields

$$V_t(d_t, \varphi_t) = \frac{1}{2} d_t^2 \left( \frac{\lambda + \gamma^2 \delta_a a_{t+1}}{\lambda + \gamma^2 (\delta_a + a_{t+1})} \right) + d_t \left( \frac{\gamma \theta + \lambda \mu a_{t+1} + (\lambda + \gamma^2 \delta_a) b_{t+1}}{\lambda + \gamma^2 (\delta_a + a_{t+1})} \right)$$

$$+ \left( 2 \frac{(\gamma \theta + \lambda \mu)^2 (\delta_a + a_{t+1}) + 2 \lambda (\gamma \theta + \lambda \mu) b_{t+1} + \lambda \gamma^2 b_{t+1}^2}{2 \lambda (\lambda + \gamma^2 (\delta_a + a_{t+1}))} \right).$$
This defines the following set of three recursive equations:

\[ a_t = \frac{(\lambda + \gamma^2 \delta_a) a_{t+1}}{\lambda + \gamma^2 (\delta_a + a_{t+1})}, \]

\[ b_t = \frac{(\gamma \theta + \lambda \mu) a_{t+1} + (\lambda + \gamma^2 \delta_a) b_{t+1}}{\lambda + \gamma^2 (\delta_a + a_{t+1})}, \]

\[ c_t = c_{t+1} + \frac{(\gamma \theta + \lambda \mu)^2 (\delta_a + a_{t+1}) + 2\lambda (\gamma \theta + \lambda \mu) b_{t+1} + \lambda \gamma^2 b_{t+1}^2}{2\lambda (\lambda + \gamma^2 (\delta_a + a_{t+1}))}. \]

The explicit expressions for \( a_t \), \( b_t \), and \( c_t \) that solve the system are

\[ a_t^c = \frac{\delta_c (\lambda + \gamma^2 \delta_a)}{\lambda + \gamma^2 (\delta_a + (T - (t - 1)) \delta_c)}, \]

\[ b_t^c = \frac{(T - (t - 1))(\gamma \theta + \lambda \mu) \delta_c}{\lambda + \gamma^2 (\delta_a + (T - (t - 1)) \delta_c)}, \]

\[ c_t^c = \frac{(T - (t - 1))(\gamma \theta + \lambda \mu)^2 (\delta_a + (T - (t - 1)) \delta_c)}{2\lambda (\lambda + \gamma^2 (\delta_a + (T - (t - 1)) \delta_c))}. \]

Assuming that \( d_1 = 0 \), the value of \( V_t^c(0) \) gives the total costs over the entire regulation period. To obtain the explicit form of the optimal regulation \( x_t^c(d_t) \) given in the text, we substitute the expressions for \( a_t^c \) and \( b_t^c \) back into the solution to (A.1).

**A.1.2 Perfect Forecasts**

In this scenario, we hypothesize that the expected value of the value function, \( \mathbb{E}_{t-1}[V_t(d_t, \varphi_t)] \), can be written as a quadratic function of \( d_t \):

\[ \mathbb{E}_{t-1}[V_t(d_t, \varphi_t)] = \frac{1}{2} a_t d_t^2 + b_t d_t + c_t. \]

The resulting Bellman equation is

\[ \mathbb{E}_{t-1}[V_t(d_t, \varphi_t)] = \min_{x_t} \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 + \frac{1}{2} \delta_a e_t^2 + \mathbb{E}_t[V_{t+1}(d_{t+1})]. \]

Using the hypothesized value function, this becomes

\[ \mathbb{E}_{t-1}[V_t(d_t, \varphi_t)] = \min_{x_t} \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 + \frac{1}{2} \delta_a e_t^2 + \frac{1}{2} a_{t+1} d_{t+1}^2 + b_{t+1} d_{t+1} + c_{t+1}. \]
After substituting in the state equation as before, we get the first order condition for $x_t$,

$$x_t = \frac{\theta - \gamma(a_{t+1}d_t + b_{t+1} + \varphi_t(\delta_a + a_{t+1}))}{\lambda + \gamma^2(\delta_a + a_{t+1})}.$$ 

Substituting this back into the objective function and taking the expected value verifies that the hypothesis was correct, and yields a system of difference equations. The solution to that system is

$$a_t^p = a_t^c,$$
$$b_t^p = b_t^c,$$
$$c_t^p = c_t^c + \frac{\lambda \sigma^2}{2(\lambda + \gamma^2 \delta_a)}((T - (t - 1))\delta_a + \lambda \delta_c \Phi),$$

where

$$\Phi \equiv \sum_{i=1}^{T-(t-1)} \frac{1}{\lambda + \gamma^2 (\delta_a + i\delta_c)}.$$ 

Substituting the expressions for $a_{t+1}^p$ and $b_{t+1}^p$ into the optimal solution gives the expression for $x_t^p(d_t, \varphi_t)$ in the main text.

### A.1.3 Uninformative Forecasts

In this scenario, we hypothesize that the value function $V_t(d_t)$, can be written as a quadratic function of $d$:

$$V_t(d_t) = \frac{1}{2}a_t d_t^2 + b_t d_t + c_t.$$ 

The resulting Bellman equation is

$$V_t(d_t) = \min_{x_t} \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 + \mathbb{E}_t \left[ \frac{1}{2} \delta_a e_t^2 \right] + \mathbb{E}_t[V_{t+1}(d_{t+1})]. \quad (A.2)$$

Using the hypothesized value function, this becomes

$$\mathbb{E}_{t-1}[V_t(d_t, \varphi_t)] = \min_{x_t} \frac{\lambda}{2} \left( \frac{\theta}{\lambda} - x_t \right)^2 + \mathbb{E}_t \left[ \frac{1}{2} \delta_a e_t^2 \right] + \mathbb{E}_t \left[ \frac{1}{2} a_{t+1} d_{t+1}^2 + b_{t+1} d_{t+1} + c_{t+1} \right].$$

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After substituting in the state equation as before, we get the first order condition for $x_t$,

$$x_t = \frac{\theta - \gamma(a_{t+1}d_t + b_{t+1} + \mu(\delta_a + a_{t+1}))}{\lambda + \gamma^2(\delta_a + a_{t+1})}$$

Substituting this back into the objective function and taking the expected value verifies that the hypothesis was correct, and yields a system of difference equations.

The solution to that system is

$$a_t^u = a_t^p,$$

$$b_t^u = b_t^p,$$

$$c_t^u = c_t^p + \frac{\gamma^2 \sigma^2}{2} \left( \frac{(T - (t-1))\delta_a^2}{\lambda + \gamma^2 \delta_a} + \frac{\delta_a \delta_c (2\lambda + \gamma^2 \delta_a)}{\lambda + \gamma^2 \delta_a} \Phi \right) + \frac{(T - (t-1))\delta_c^2}{\lambda + \gamma^2 (\delta_a + (T - (t-1))\delta_c)} .$$

Substituting the expressions for $a_t^u$ and $b_t^u$ into the optimal solution gives the expression for $x_t^u(d_t)$ in the main text.

### A.1.4 Ex Ante Regulation

The Bellman under ex ante regulation is also given by (A.2), but we do not optimize over $x_t$. Instead, we set $x_t$ equal to the optimal ex ante values $x_t^a$. Following the same steps as for the other cases, we obtain a system of difference equations. The solution is

$$a_t^a = \delta_c,$$

$$b_t^a = \frac{(T - (t-1))(\gamma \theta + \lambda \mu)\delta_c}{\lambda + \gamma^2 (\delta_a + T\delta_c)} ,$$

$$c_t^a = c_t^u + \frac{(T - (t-1))(t-1)^2(\gamma \theta + \lambda \mu)^2 \gamma^2 \delta_c^2}{2(\lambda + \gamma^2 (\delta_a + T\delta_c))^2(\lambda + \gamma^2 (\delta_a + (T - (t-1))\delta_c))} + \frac{\sigma^2}{2} \Psi ,$$

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where
\[ \Psi \equiv \sum_{i=1}^{T-(t-1)} \frac{(i-1)\gamma^2\delta_c^2}{\lambda + \gamma^2(\delta_a + (i-1)\delta_c)}. \]

A.2 Comparative Statics

In this section, we derive the comparative statics results from Section 3.4.2. We start with the differences in total expected program costs for three different comparisons: uninformative forecasts versus perfect forecasts, ex ante regulation versus uninformative forecasts, and ex ante regulation versus perfect forecasts. We then calculate how those differences change with respect to changes in the slope of the marginal function (\( \lambda \)) and the slopes of the marginal damage functions (\( \delta_a \) and \( \delta_c \)).

A.2.1 Uninformative versus Perfect Forecasts

The difference in expected total costs between the uninformative and perfect forecast scenarios is given in Proposition 1.

Slope of Marginal Costs

\[
\frac{\partial V^u - V^p}{\partial \lambda} = \gamma^2\sigma^2 \left( - \frac{T\delta_a^2}{(\lambda + \gamma^2\delta_a)^2} - \frac{T\delta_c^2}{(\lambda + \gamma^2(\delta_a + T\delta_c))^2} \right) + \frac{\gamma^2\delta_a\delta_c}{(\lambda + \gamma^2(\delta_a + i\delta_c))^2} \sum_{i=1}^{T} \frac{1}{(\lambda + \gamma^2(\delta_a + i\delta_c))^2} \\
- \frac{\delta_a\delta_c(2\lambda + \gamma^2\delta_a)}{\lambda + \gamma^2\delta_a} \sum_{i=1}^{T} \frac{1}{(\lambda + \gamma^2(\delta_a + i\delta_c))^2} \right) \\
\left( \frac{T\delta_c^2}{(\lambda + \gamma^2(\delta_a + T\delta_c))^2} - \left( \frac{\delta_a^2}{(\lambda + \gamma^2\delta_a)^2} \sum_{i=1}^{T} \left( 1 - \frac{\gamma^2\delta_c}{\lambda + \gamma^2(\delta_a + i\delta_c)} \right) \right) \right) \\
- \frac{\delta_a\delta_c(2\lambda + \gamma^2\delta_a)}{\lambda + \gamma^2\delta_a} \sum_{i=1}^{T} \frac{1}{(\lambda + \gamma^2(\delta_a + i\delta_c))^2} \right) < 0.
\]
Slope of Acute Damages

\[
\frac{\dot{c}(V^u - V^p)}{\dot{\delta_c}} = \frac{\gamma^2 \sigma^2}{2} \left( \frac{T(2\lambda \delta_a + \gamma^2 \delta_a^2)}{(\lambda + \gamma^2 \delta_a^2)^2} - \frac{T \gamma^2 \delta_c^2}{(\lambda + \gamma^2(\delta_a + T \delta_c))^2} \right) \\
+ \frac{\lambda^2 \delta_c + (\lambda + \gamma^2 \delta_a)^2 \delta_c}{(\lambda + \gamma^2 \delta_a^2)^2} \sum_{i=1}^{T} \frac{1}{\lambda + \gamma^2(\delta_a + i \delta_c)} \\
- \frac{\delta_a \delta_c(2\lambda + \gamma^2 \delta_a)}{\lambda + \gamma^2 \delta_a} \sum_{i=1}^{T} \frac{\gamma^2}{(\lambda + \gamma^2(\delta_a + i \delta_c))^2} \\
= \frac{\gamma^2 \sigma^2}{2} \left( \frac{T(2\lambda \delta_a + \gamma^2 \delta_a^2)}{(\lambda + \gamma^2 \delta_a^2)^2} - \frac{T \gamma^2 \delta_c^2}{(\lambda + \gamma^2(\delta_a + T \delta_c))^2} \right) \\
+ \sum_{i=1}^{T} \frac{2\lambda^2(\lambda + \gamma^2 \delta_a) \delta_c + i \lambda^2 \gamma \delta_c + i \gamma^2(\lambda + \gamma^2 \delta_a)^2 \delta_c^2}{(\lambda + \gamma^2 \delta_a)^2(\lambda + \gamma^2(\delta_a + i \delta_c))^2} \\
+ \sum_{i=1}^{T} \left( \frac{i \gamma^2 \delta_c^2}{(\lambda + \gamma^2(\delta_a + i \delta_c))^2} - \frac{\gamma^2 \delta_c^2}{(\lambda + \gamma^2(\delta_a + T \delta_c))^2} \right) > 0
\]

Slope of Chronic Damages

\[
\frac{\dot{c}(V^u - V^p)}{\dot{\delta_c}} = \frac{\gamma^2 \sigma^2}{2} \left( \frac{\lambda (2\lambda \delta_a + \gamma^2 \delta_a + T \gamma^2 \delta_c)}{(\lambda + \gamma^2(\delta_a + T \delta_c))^2} + \sum_{i=1}^{T} \frac{\delta_a(2\lambda + \gamma^2 \delta_a)}{(\lambda + \gamma^2(\delta_a + i \delta_c))^2} \right) > 0
\]

A.2.2 Ex Ante Regulation versus Uninformative Forecasts

The difference in expected total costs between the ex ante regulation and uninformative forecast scenarios is given in Proposition 2.

Slope of Marginal Costs

\[
\frac{\dot{c}(V^u - V^u)}{\dot{\lambda}} = \frac{\gamma^2 \sigma^2}{2} \left( \sum_{i=1}^{T-1} \frac{i \delta_c^2}{(\lambda + \gamma^2(\delta_a + i \delta_c))^2} \right) < 0
\]
Slope of Acute Damages

\[
\frac{\partial (V^a - V^u)}{\partial \delta_a} = \frac{\gamma^2 \sigma^2}{2} \left( \sum_{i=1}^{T-1} \frac{i \gamma^2 \delta^2_c}{(\lambda + \gamma^2 (\delta_a + i \delta_c))^2} \right) < 0
\]

Slope of Chronic Damages

\[
\frac{\partial (V^a - V^u)}{\partial \delta_c} = \frac{\gamma^2 \sigma^2}{2} \left( \sum_{i=1}^{T-1} \frac{i \delta_c(2 \gamma^2 \delta^2_a + i \gamma^2 \delta^2_c + 2 \lambda)}{(\lambda + \gamma^2 (\delta_a + i \delta_c))^2} \right) > 0
\]

A.2.3 Ex Ante Regulation versus Perfect Forecasts

The difference in expected total costs between the ex ante regulation and perfect forecast scenarios is given in Proposition 3. Note that the results for the marginal cost and chronic damage slopes immediately follow from previous comparative statics.

Slope of Marginal Costs

\[
\frac{\partial (V^a - V^p)}{\partial \lambda} = \frac{\partial (V^a - V^u)}{\partial \lambda} + \frac{\partial (V^u - V^p)}{\partial \lambda} < 0
\]

Slope of Acute Damages

\[
\frac{\partial (V^a - V^p)}{\partial \delta_a} = \frac{\sigma^2}{2} \left( \sum_{i=1}^{T} \frac{\gamma^2 \delta^2_c \lambda^2}{(\lambda + \gamma^2 \delta_a)^2 (\lambda + \gamma^2 (\delta_a + i \delta_c))^2} + \frac{\gamma^2 \delta^2_c \lambda^2}{(\lambda + \gamma^2 \delta_a)^2 (\lambda + \gamma^2 (\delta_a + i \delta_c))^2} \right) \\
+ \frac{T \gamma^2 (2 \delta_a + \delta_c)}{\lambda + \gamma^2 \delta_a} - \frac{T \gamma^2 (2 \delta_a + \delta_c + 2 \lambda)}{(\lambda + \gamma^2 \delta_a)^2} \\
= \frac{\sigma^2}{2} \left( \sum_{i=1}^{T} \frac{\gamma^2 \delta^2_c \lambda^2 (2 \lambda + \gamma^2 (2 \delta_a + i \delta_c))}{(\lambda + \gamma^2 \delta_a)^2 (\lambda + \gamma^2 (\delta_a + i \delta_c))^2} \right) + \frac{\gamma^2 \delta_a (2 \gamma^2 \delta_a + 2 \lambda)}{(\lambda + \gamma^2 \delta_a)^2} > 0
\]

Slope of Chronic Damages

\[
\frac{\partial (V^a - V^p)}{\partial \delta_c} = \frac{\partial (V^a - V^u)}{\partial \delta_c} + \frac{\partial (V^u - V^p)}{\partial \delta_c} > 0
\]
Bibliography


Biography

David Allen Bielen was born on August 12th, 1986 in Wilkes-Barre, Pennsylvania. He spent most of his childhood in Cortland, New York and Danville, Pennsylvania. He attended the Pennsylvania State University and graduated in May of 2009 with a Bachelor of Science in Economics. He enrolled in the PhD program in Economics at Duke University the following summer, where he completed a Master of Arts in Economics in 2011. After graduating with a PhD in May 2015, Dave will join the National Renewable Energy Laboratory’s Strategic Energy Analysis Center in Golden, Colorado as an energy and environmental policy analyst.