Electricity Markets and Environmental Policy

by

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The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.
This thesis is comprised of three distinct chapters. In the first chapter, Gone with the Wind: Consumer Surplus from Renewable Generation, I show how more renewable generation can lead to less competitive behavior from traditional electricity generators. Because wholesale electricity markets are structured as multi-unit uniform price auctions, diverse market participants that own wind turbines and traditional resources (like coal and gas plants) have an incentive to withhold their output from their traditional resources to increase the revenue from their own wind turbines. As a result, these generators internalize the benefits of the low marginal cost, directly reducing consumer benefit. Using data from the Midwestern United States, I show that uncompetitive behavior from diverse market participants reduces consumer surplus by up to 3 billion USD from 2014 to 2016.

The second chapter, Concentration Effects of Heterogenous Standards: Refinery Response to the Clean Air Act Amendments, highlights the economic implications of environmental policies. I show how spatially differentiated environmental policies can create new product markets in which firms can compete. If investment is costly, this policy will segment the product market and allow firms to recover lost profits by competing in a more concentrated market. In the context of the boutique fuel standards associated with the 1990 Clean Air Act Amendments, I find that the refineries most exposed to counties where cleaner, more expensive, fuels were mandated were less likely to exit the market.

The final chapter, Demand Side Emissions Policies, evaluates alternative second best policies to address the emission externalities associated with the generation of electricity. I first show that there is significant heterogeneity in the marginal external damages per MWh of electricity in the United States. Next, I consider alternative policies to address the heterogeneity in emission externalities and find that demand side policies, such as energy efficiency investments, peak pricing,
or demand response, are much less effective than a simple plant specific emission tax. This suggests policy makers interested in addressing emission externalities should focus on policies directed at wholesale generation instead of utility distribution.
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Chapter 1

Gone with the Wind: Consumer Surplus from Renewable Generation

Abstract: I use a supply function equilibrium framework to show how increased renewable generation can increase electricity generators’ incentive to withhold capacity. As a result, strategic behavior from conventional generators attenuates the impact of low marginal cost generation on the market price. Taking advantage of detailed data on one of the largest wholesale electricity market in the United States, I provide direct evidence that horizontally integrated firms that own wind turbines and conventional generation will withhold their conventional generation when their own wind turbines are generating electricity. As a result, over 30% of wind generation is replacing withheld units suggesting a decrease in potential consumer surplus of 3.3 billion US Dollars from 2014 to 2016.

JEL classification codes: L13, Q42, D44

1.1 Introduction

Since 2008, over half of new electricity generation capacity in the US has been in the form of renewable energy (EIA, 2017). As a result, wholesale electricity markets have been inundated with a large quantity of electricity generated at a low marginal cost. This lower operating cost has created immense value and has the potential to have a large impact on the price of electricity.\footnote{Callaway, Fowlie, and McCormick (2018) show the value of renewable generation associated with avoided operating cost can be just as large, if not larger, than the public benefit of avoided emission externalities.} However, the extent to which the lower operating cost impacts the price of electricity depends on the conduct of the firms in the market. This is especially true in wholesale electricity markets,
where inelastic demand and capacity constraints allows market participants some degree of market power.

In this paper I evaluate the competitive effects of more renewable generation in wholesale electricity markets, and quantify the consumer surplus associated with the lower operating cost of renewable generation taking into account how market participants will strategically respond to renewable generation. I first use a simple equilibrium framework to derive a quantity pass-through equation, showing how more renewable generation should impact the price of electricity taking into account firm conduct. Modifying Klemperer and Meyer’s (1989) Supply Function Equilibrium framework, I show that diverse market participants, those that own wind turbines and other assets, have an incentive to withhold their other assets when their own wind turbines are generating electricity.² This physical withholding attenuates the consumer benefit associated with renewable generation, and showcases how firms can exert market power to internalize the benefits of a low cost technology.³

Leveraging hourly data on ex-ante generator-specific strategies from one of the largest wholesale electricity market in the United States, I show direct evidence of strategic withholding by diverse market participants. Identification comes from variation in the quantity offered by a market participant, to the wholesale market operator, at a given price within a year-month-hour (e.g. June, 2016, 4pm). While my empirical strategy is most similar to Fabra and Reguant’s (2014) analysis of emission cost pass-through, the use of within offer price variation is novel. I find the market participants that own more wind capacity withhold their output more in response to renewable generation, and they withhold their output more in response to their own wind generation relative to wind generation from wind turbines they do not own. This is robust to concerns regarding congestion constraints and net exports. With the detailed data on supply and demand for every hour, I am able to make rare and credible claims regarding consumer surplus from renew-

² Throughout, I use the term diverse to define market participants that own wind turbines and conventional electricity generators and the word conventional to describe electricity generators that are not wind turbines or solar panels.
³ Physical withholding is a reduction in the quantity offered to the market, at a given price, with the intent to influence the market price. This is in comparison to economic withholding, which involves bidding a generator’s quantity at a higher price.
able generation by re-constructing the market equilibrium and calculating an expression for the price reduction from renewable generation taking into account the strategic response by traditional electricity generators.

Overall I find that the potential consumer surplus from the low cost of renewable generation is large. In the Midcontinent Independent System Operator’s wholesale electricity market from 2014 to 2016, I find a potential consumer benefit of $69 per person per year associated with the low operating cost of renewable generation. However, estimated parameters of firm level withholding suggest only $47 per person per year of consumer benefit is realized. During the entire sample period, this suggests physical withholding associated with renewable generation reduced consumer surplus by over 3 billion US dollars.

With this paper I am making three contributions. First, I show the importance of understanding the incentives of the firm. Many papers have evaluated the integration of renewable generation in electricity markets, uncovering a “merit order effect” where renewable generation displaces high cost generation and lowers the market price, idealized in Figure 1.1.\(^4\) The results are location specific, often determined by the fuel mix and fuel prices, and are large.\(^5\) Overwhelmingly, these empirical papers do not consider how the increased renewable generation might change the strategies of electricity generators, but instead assume a perfectly competitive market or an economic dispatch of resources. This is despite theoretical importance of competitive conduct in how renewable generation can impact the price, as shown by Ben-Moshe and Rubin (2015); Acemoglu, Kakhabd, and Ozdaglar (2017).

This understanding of how a firm might change their strategy in response to a new technology extends its importance to policy design. A number of states with in the U.S. support renewable

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\(^4\) These papers either consider a simulation model (Sensfuß, Ragwitz, and Genoese 2008; McConnell et al. 2013), or estimate the reduced form change in price due to renewable generation (Woo et al. 2011; Cludius et al. 2014; Clé, Cataldi, and Zoppoli 2015; Woo et al. 2015, 2016).

\(^5\) For example, Woo et al. (2016) find that a one gigawatt hour (GWh) increase of wind generation in California lowers the wholesale market price by $1.5 to $11.4 per megawatt hour. This implies average hourly wind generation can lower total market revenue by millions of dollars per day assuming the average hourly wind generation in California during 2017 was around 1.5 GWh and the average hourly load is 24 GWh. If 1.5 GWh of wind generation reduces the price by 9.75 $/MWh, for 24,000 MWh in a hour, for twenty-four hours, revenue declines by 5.6 million USD that day.
Electricity markets are conceived as a Merit Order, where the lowest cost resources have merit and are dispatched first. When wind turbines generate electricity, it is believed they displace higher cost units as wind generation shift the supply curve to the right. As a result of the supply shift the equilibrium price of electricity decreases, from $P_0$ to $P_1$, displacing higher cost electricity generating units. This does not consider how increased wind generation might impact the incentive to withhold capacity.
generation for the benefit it provides to consumers, not necessarily because it reduces emissions from electricity generation. Not taking into account how existing electricity generators might internalize the benefits for renewable generation will cause these policies to under-deliver. Overall I show the cumulative strategic response by all electricity generators is large enough to decrease the realized consumer benefit by more than 30%.

My second contribution it to provide direct evidence of strategic bidding in multi-unit auctions. Wholesale electricity markets are multi-unit auctions where the uniform price is set by the marginal unit. In such markets there is a known incentive for market participants to withhold output to increase their own revenue (Ausubel et al., 2014). This incentive increases in proportion to the infra-marginal market share of the electricity generator (Wolfram, 1998). For the firms that own renewable resources, increased renewable generation is a large short-run increase in their infra-marginal market share, intensifying their incentive to withhold their generation. Because wind generation is determined predominately by weather patterns, this variation is as good as random.

While a number of papers have looked at strategic bidding in multi-unit auctions (Hortaçsu, Kastl, and Zhang, 2018; Doraszelski et al., 2017; List and Lucking-Reiley, 2002), and even in wholesale electricity markets (Hortacsu and Puller, 2008; Wolfram, 1998; Borenstein, Bushnell, and Wolak, 2002; Reguant, 2014; Ito and Reguant, 2016), they typically rely on structural models trying to uncover price-cost margins or underlying valuations. The exogenous nature of wind generation, in combination with the rich data on generator-specific strategies, allows me to substitute structural assumptions on firm conduct with parsimonious estimating equations that identify parameters of a firm’s underlying strategy. With these parameters, and the quantity pass-through equation, it is straightforward to make claims regarding consumer surplus in the spirit of Chetty (2009).

Finally, this paper provides an update on the status of competition in wholesale electricity markets. Ever since the California electricity crisis in the early 2000s, regulators and market monitors have worked to ensure that wholesale electricity markets approximate the competitive outcome. As a result, wholesale electricity markets in the US are currently perceived as competitive by economic researchers (Bushnell, Mansur, and Novan, 2017), regulators (FERC, 2011), and
independent market monitors (Potomac Economics, 2018). This is partly because of long term forward contracts, a forward wholesale market, and vertical commitments between producers and consumers of wholesale electricity. As the electricity grid transitions towards more renewable generation, it is important to consider the ways in which a firm’s ability and incentive to exert market power might change, and to develop tools to characterize and diagnose imperfectly competitive behavior.\(^6\) An immediate policy implication of this paper is better market monitoring for physical withholding of capacity. This can be accomplished using the methods outlined within this paper.

The paper proceeds as follows, section 1.2 outlines a general framework for understanding how renewable generation, in particular wind, impacts the price of electricity in wholesale markets. Section 1.3 provides context by describing key details regarding MISO including an introduction to the data. Section 1.4 focuses on estimating and calculating the how wind generation should impact the price of electricity. Section 1.5 turns to micro-data on firm strategies, showing evidence of physical withholding during windy hours. Section 1.6 summarizes the implications of withholding for consumer surplus, section 1.7 concludes.

### 1.2 Wind Generation in Wholesale Electricity Markets

The high fixed costs of electricity generation, transmission, and distribution lends itself to a model of natural monopoly and has historically been served by vertically integrated investor, or municipality, owned utilities operating under cost of service regulation. Since the 1980s the electricity industry has undergone deregulation and restructuring at the state and federal level largely motivated by the success seen in other industries (such as rail and natural gas), and analysis showing the potential for increased efficiency (for example Joskow and Schmalensee (1988)).\(^7\) Restructured wholesale electricity markets emerged, where competitive supply and demand bids

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\(^6\) Overall, Independent Market Monitors do a good job identifying and mitigating blatant exertion of market power in wholesale electricity markets. In Appendix B I outline exactly how this is done for the market I study, MISO, as well as characterize the market in terms of forward contracts and vertical commitments.

\(^7\) Public Utilities Regulatory Policy Act (PURPA) of 1978 encouraged alternative fuels and introduced independent power producers (IPPs). Federal Energy Regulatory Commission (FERC) orders 888 and 889 in 1996 laid the ground work for competitive wholesale electricity markets. FERC order 2000, promulgated in 1999, encouraged the formation of Regional Transmission Organizations to serve as planning bodies over a larger geographic area. State policies have introduced retail competition and forced divestiture of vertically integrated assets.
are submitted to a centralized and impartial Independent System Operator, who then decides which units to dispatch and the price they receive. As of 2012, these markets cover 60% of generation capacity within the US and they are effective in reducing production cost by reallocating output (Cicala, 2017).

The following is intended to model a wholesale electricity market operating as a multi-unit uniform price auction that allows for diverse market participants and a degree of low variable cost renewable generation. Demand for electricity is determined by Load Serving Entities, predominately utilities, that charge customers a rate for electricity in the retail market. These Load Serving Entities submit demand bids for each hour that can be price sensitive, but are overwhelmingly inelastic with respect to price. I model demand in the wholesale market at time \( t \) as \( D_t(p) = d_t(p) + \varepsilon_t \) where \( d_t(p) \) is the deterministic component of demand as a function of price that can be forecasted and \( \varepsilon_t \) is a random variable representing fluctuations in the quantity demanded. I model \( \varepsilon_t \) to be an i.i.d. random variable with expectation equal to zero.

Supply in the wholesale electricity market is provided by market participants, which I denote by the subscript \( o \), who own multiple electricity generating assets including coal, gas, nuclear, or hydrological based resources. Each conventional unit owned by market participant \( o \), denoted by the subscripts \( k \in K_o \), submits a unit-specific supply curve as a function of price, \( s_{kt}(p) \). This offer curve represents the quantity the market participant \( o \) is willing to produce from unit \( k \) at time \( t \) for price \( p \). As a simplification, I consider the market participant’s aggregate supply sans wind generation as \( S_{ot}(p) = \sum_{k \in K_o} s_{kt}(p) \). When the uniform market clearing price is \( \hat{p} \), the market participant will produce \( S_{ot}(\hat{p}) = \sum_{k \in K_o} s_{kt}(\hat{p}) \) with costs \( C_{ot}(S_{ot}(\hat{p})) \) and revenue \( \hat{p}S_{ot}(\hat{p}) \).

The quantity of electricity generated by wind turbines at time \( t \) is modeled by an aggregate quantity, \( W_t \). Because weather conditions are imperfectly forecast-able, it is most realistic to decompose wind generation into a deterministic forecast-able quantity and a random variable representing the forecast error. Here I abstract from the random component, as it does not con-

---

8 Load Serving Entities in wholesale markets can also be generators of electricity if they are vertically integrated. The commercial and retail rate of electricity is typically a time-invariant rate or increasing block pricing. Industrial consumers typically have peak demand charges as well.
tribute to any of the comparative statics in this section.\footnote{Acemoglu, Kakhbod, and Ozdaglar (2017) shows the incentives to withhold output remain when wind generation is a random value, is private information, and correlated across wind turbines.} The aggregate quantity, $W_t$, is common knowledge to all market participants and perfectly forecast-able. The proportion of wind that is owned by market participant $o$ at time $t$ is denoted by $\theta_{ot} \in [0,1]$, with $\sum_o \theta_{ot} = 1$. This implies the amount of wind generated by market participant $o$ at time $t$ is $\theta_{ot}W_t$. In this model I assume that wind generation always clears at the equilibrium because of its low variable cost.\footnote{I assume the variable cost of production for wind turbines is zero as it does not require fuel. There are other variable operation and management cost associated with wind turbines, but the Federal Renewable Energy Production Tax Credit is larger than these costs. It is possible that wind generation can be curtailed manually, however the market I study, MISO, has incorporated wind generation as part of the economic dispatch since 2011, resulting in a curtailment rate of less that 1%.}

The price concept most common in U.S. wholesale electricity markets is a Locational Marginal Price (LMP). This price represents the marginal cost of increasing energy production at any given moment and at any given location within the market, and therefore varies by location (at different pricing nodes) and by time (typically at 5 minute intervals). The LMP can be decomposed into three distinct components: the Marginal Energy Component (MEC) determined as the price where supply equals demand at a load-weighted reference node, marginal congestion cost associated with the shadow price of system transmission constraints and out of merit dispatch, and marginal losses associated with transmitting the electricity over long distances. At any given moment, the MEC is the same at every location within the market while the losses and congestion components vary by node.\footnote{Some markets are known for very high and negative prices at times, this is typically because of the congestion and loss components.} Analytically, I consider the price $p$ to represent the MEC of the LMP.\footnote{This is in contrast to Mercadal (2015), who explicitly uses the cross-sectional variance in transmission cost and losses to cluster MISO into multiple smaller markets.}

### 1.2.1 Market Equilibrium and the Analytical Merit Order Effect

Moving forward, I will suppress the time subscript for notational ease. The market operator takes the supply offers as given, observes the realized demand shock, $\varepsilon$, to solve for the dispatch quantity for each firm and the price received in accordance with a security constrained dispatch
algorithm. Outside of security constraints and reliability concerns, we can think of the market clearing as follows:

\[
\frac{d(p) + \varepsilon}{D(p)} = \sum_o S_o(p) + \frac{W}{wind}
\]  

(1.1)

Implicitly differentiating the market clearing condition with respect to total wind generation, \( W \), gives the equilibrium effect of increased renewable generation on wholesale market price.\(^\text{13}\)

\[
\frac{dp}{dW} = -\frac{1 + \sum_o \frac{\partial S_o(p)}{\partial W}}{\sum S_o'(p) - d'(p)}
\]  

(1.2)

Where ' denotes the partial derivative with respect to the function’s main argument. Equation 1.2 is the rate at which an increase in renewable generation impacts the equilibrium price, what I am calling the analytical merit order effect. This value depends on the supply function slope, demand slope, and the strategic response by market participants. The intuition of Equation 1.2, when the slope of demand and \( \frac{\partial S_o(p)}{\partial W} \) are equal to zero, is shown in Figure 1.1 where the change in the price of electricity is determined by the difference in price submitted for the marginal unit, \( -\frac{1}{\sum S_o'(p)} \).

This can be thought of as the pass-through of increased renewable generation. This is related to, but different from, the conventional pass-through rate of a cost shock or tax. To show this, consider the market equilibrium with a unit tax, \( d(p) = \sum S_o(p - t) \), under perfect competition. Implicitly differentiating the market equilibrium with respect to \( t \) uncovers the well-known pass-through formula \( \frac{dp}{dt} = \frac{\sum S_o'}{\sum S_o'^2} = \frac{1}{1 + \epsilon_S} \) where \( \epsilon_D \) and \( \epsilon_S \) denote the own-price and market supply elasticities respectively. The denominators of Equation 1.2 and the conventional pass-through equation are identical, representing a marginal deviation from the market equilibrium. This value will increase, decreasing the pass-through, when supply or demand is more inelastic. The numerator is different because the shock impacts supply differently. An increase in wind generation impacts the total quantity supplied, while the tax impacts the cost of production.\(^\text{14}\)

Electricity markets are often considered to be imperfectly competitive because of capacity

\(^{13}\) I assume that the quantity demanded does not depend on the quantity of wind generated, that is \( \frac{\partial D(p)}{\partial W} = 0 \).

\(^{14}\) This is related to the concept exogenous quantity pass-through described by Weyl and Fabinger (2013). It differs in that wind generation is an increase in the aggregate market quantity, while Weyl and Fabinger (2013) model the exogenous quantity as a firm specific quantity, identical across firms.
and transmission constraints, a degree of market power, as well as vertical and horizontal relations. I incorporate competitive conduct into Equation 1.2 with the inclusion of $\frac{\partial S_o(p)}{\partial W}$ in the numerator. Without placing structure on the market or market participants’ incentives it is impossible to sign this value. The sign of this term suggests the extent to which increased renewable generation has a pro- or anti-competitive effect on market participants’ behavior. If the term is positive the market participant offers more generation quantity to the market at any given price in response to increased renewable generation. This pro-competitive outcome arises if the firm is trying to ensure their generation clears in the market, and is not displaced by the increased renewable generation.\footnote{Ciarreta, Espinosa, and Pizarro-Irizar (2017) finds evidence of this in the Spanish electricity market by looking at the difference in the offer curves over long periods of time.}

The implications is that renewable generation would decrease the price by more than the change in cost. Conversely, when the term is negative, the supplier is offering less quantity to the market at any given price. This anti-competitive outcome could be an attempt by the firm to keep the price high, offsetting the lower price associated with increased renewable generation.

1.2.2 Market Participants’ Strategy and Testable Predictions

To understand how a firm might change their strategy in response to increased renewable generation, I consider two models of the market participants’ behavior. One model assumes that market participants choose their strategies as if they are in a perfectly competitive wholesale electricity market, the other uses a supply function equilibrium framework. These will provide two different predictions for $\frac{\partial S_o(p)}{\partial W}$, implying different values for the analytical merit order effect, $\frac{dp}{dW}$. For each prediction, I use the detailed data I have on market hourly supply and demand to explicitly calculate the analytical merit order effect. I then test which one is better realized in the observed market price.

In a perfectly competitive market, firms are price takers and submit a supply function that outlines the inverse of their marginal cost of production. This would be independent of $W$ implying
that $\frac{\partial S_o(p)}{\partial W} = 0$. Substituting this into Equation 1.2 we have that

$$\frac{dp_{\text{comp}}}{dW} = -\frac{1}{\sum S'_o(p) - d'(p)}$$

(1.3)

and for an observed quantity of wind based generation in an hour, the total price effect would be

$$dp_{\text{comp}} = -\frac{1}{\sum S'_o(p) - d'(p)} dW$$

(1.4)

From an incidence perspective, this represents the upper bound of the price reduction associated with increased renewable generation and can be used to calculate to the potential consumer surplus available.

Conversely a firm with market power might internalize the benefits associated with increased renewable generation. Figure 1.2 provides the intuition. When a market participant with market power is considering the incentives to withhold, they are comparing a higher price and smaller quantity to a lower price and larger quantity. When this market participant owns a wind turbine that is also generating electricity, they receive additional benefit of increasing the price directly proportional to the quantity of electricity generated by their wind turbine. This is because they receive additional revenue from the infra-marginal wind turbine but do not incur any cost.

I use the supply function equilibrium framework (SFE) outlined by Klemperer and Meyer (1989) to derive the market participant’s best response function. Market participants choose the $S_o(p)$ that maximizes their expected profit, with the expectation taken over the uncertainty in price due to demand shocks. Appendix A proves the optimal strategy of market participant $o$ with conventional assets and wind turbines can be characterized by

$$p - C'_o(S_o(p)) = \frac{S_o(p) + \theta_oW}{d'(p) - \sum_{j \neq o} S'_j(p)}$$

(1.5)

It is clear that an increase in the amount of electricity produced by wind, $W$, will be associated with a reduction in the supply curve offered to the market. For simplicity I assume that the marginal cost is constant near the equilibrium price, $C''_o(S(p)) = 0$, and that market participants do not change the slope of their offer curve in response to increased renewable generation, $\frac{\partial S'_i(p)}{\partial W} = \ldots$
When a firm with market power considers the incentives to withhold their output they trade off a lower price with a larger quantity with a higher price and a smaller quantity. This trade off is represented in the top figure, for the firm that submits a bid corresponding to the red step, by the area of the only blue cross hatch and the only red cross hatch rectangles. When the market participant is diverse, owning wind turbines and conventional generators, they receive additional revenue from a high price on their wind based assets. In the bottom panel, the green cross hatch represents the revenue from the wind turbine if the firm does not withhold and the additional red only cross hatch rectangle shows the revenue received from the wind based asset if they withhold their output.
0, ∀i, near the equilibrium price.\textsuperscript{16} This provides \( \frac{\partial S_o(p)}{\partial W} = -\theta_o \), a market participant will reduce their generation offer in response to a unit increase in renewable generation by the proportion of total wind generation they are producing.

More broadly, this comparative static suggests that a market participant will withhold their conventional generation by the quantity of wind generated, one for one.\textsuperscript{17} Overall they are generating the same quantity of electricity, however they are replacing their conventional generation with wind generation. From this we can get a number of testable predictions for how firm’s will respond to increased wind generation under a supply function equilibrium model:

Testable Predictions.

(A) Only market participants that own wind turbines will reduce their quantity offered in response to more wind generation. Market participants that do not own wind turbines will not change their offer curve in response to more wind generation. For these firms \( \theta_o = 0 \) at all times implying \( \frac{\partial S_o(p)}{\partial W} = 0 \) always.

(B) Market participants that generate a larger share of the total wind generation will reduce the quantity offered by a larger amount in response to more wind generation. This follows from \( \frac{\partial^2 S_o(p)}{\partial W \partial \theta_o} = -1 < 0 \)

(C) Market participants will only change their offer curve in response to their own wind generation, not in response to the wind generation of other market participants. This can be seen by noting that only the market participant’s own wind generation, \( \theta_o W \), appears in Equation 1.5. Their optimal strategy does not depend on \( \sum_{j \neq o} \theta_j W \).

Substituting the values of \( \frac{\partial S_o(p)}{\partial W} \) into Equation 1.2, we have that the analytical merit order

\textsuperscript{16} This assumption greatly simplifies the analysis. In the context of forward markets, an “additive separability” assumption with similar implications is common (Hortacsu and Puller, 2008; Mercadal, 2015). In application, I find some market participants do change the supply slope, in-line with the theoretical prediction on bid shading. I consider it to be a second order effect, and the assumption plays no direct role in any of my results.

\textsuperscript{17} In particular we are talking about physical withholding, where the quantity offered is reduced. This is in comparison to economic withholding, in which market participants are submitting their offer curves above the marginal cost of production.
The effect is

\[
\frac{dp_{SFE}}{dW} = - \left( 1 - \sum_{o \in V} \theta_o \right) \frac{1}{\sum S'_o(p) - d'(p)}
\]

(1.6)

where \( V \) is the set of market participants that own both wind turbines and conventional assets. In aggregate this strategic withholding implies increased renewable generation will have the following impact on the market price

\[
\frac{dp_{SFE}}{dW} = - \left( 1 - \sum_{o \in V} \theta_o \right) \frac{1}{\sum S'_o(p) - d'(p)} dW
\]

(1.7)

This shows the impact on the price paid by consumers in wholesale electricity markets depends on the ownership of the wind turbines. If all wind turbines are owned by market participants that also own conventional assets, then \( \sum_{o \in V} \theta_o = 1 \) and there would be no effect on price. Conversely, if wind turbines were owned exclusively by independent producers that own only wind turbines, then \( \sum_{o \in V} \theta_o = 0 \) and the expected price change would be identical to Equation 1.4.

1.3 The Midcontinent Independent System Operator and Data

The Midcontinent Independent System Operator (MISO) was formed in 1998 and approved as the first Regional Transmission Organization in the US by the Federal Energy Regulatory Commission in 2001.\textsuperscript{18} The operator serves as a non-profit organization managing transmission and dispatch of electricity generating units within its footprint through a variety of market operations, focusing on reliability, efficiency, and the development of electricity resources. Since the incorporation of the Southern Region in 2013, MISO has become the largest wholesale electricity market in the United States with a total of 180 gigawatts of generation capacity, and conducts market operations from Montana to Michigan to Louisiana as shown in Figure 1.3. The distribution of wind turbines and conventional electricity generating assets within MISO is shown in Figure 1.4. The largest concentration of wind turbines in the United States is in the Great Plains, extending from Iowa to Texas.

\textsuperscript{18} MISO was formerly known as the Midwest Independent System Operator up until 2013.
MISO’s footprint and nodal prices in MISO during one moment during the sample period. Cross sectional variance is determined by congestion and transmission losses. Lower prices are darker in color.

The locations of all electricity generating units in MISO according to the Energy Information Agency form 860 for the year 2016. Wind turbines are blue diamonds while conventional generators are red circles. The size of the point is proportional to the log of the generating unit’s capacity.
MISO operates a number of markets in combination with planning and oversight to achieve its goals in distribution and reliability including a day ahead and real time wholesale electricity market similar to the model described in section 2. These markets capture almost all electricity generation and transmission activities within MISO’s footprint that are not part of bilateral contracts. Supplemental information on MISO, its markets, regulated utility operations, wind turbine ownership, and market monitoring are provided in the Appendix B.

MISO publishes data regarding their market operations on their website as Market Reports. The primary data I use are the daily real time generation offers by generation units from January of 2014 to December of 2016. I focus on the real time market because there are no purely financial players in the real time market, increasing the benefits from withholding output. These data provide, for every hour, a time consistent unit and owner identification code, the generating unit type (steam, combustion, wind turbine, hydro), the ex-post quantity generated and LMP received at five minute intervals, as well as details on the generating unit’s supply bid. Unit-level data on the hourly LMP received and the quantity generated for all units are summarized in Table 1.1. The sample average unit LMP is $27.42/MWh with wind turbines receiving a lower than average LMP and combustion turbines receiving the highest LMP on average. This is because the LMP is lower when wind turbines generate electricity, while the combustion turbines only generate electricity when the LMP is high. In terms of unit level generation, steam turbines and combined cycle units produce the most electricity per hour. To give context to the units, households in the United States consume approximately 1 MWh of electricity in a month on average. Overall I observe a total of 1,324 units during the sample, of which 211 are wind turbines.

As show by Equation 1.7, the impact of renewable generation on the price of electricity can depend on who owns the wind turbines so it is important to know the portfolio of unit types owned by every market participant. I take advantage of the time-invariant owner code associated with

---

19 A market report from 2011-2012 suggests 20 to 30% of electricity generated in a year is through bilateral contracts. These bilateral contracts include agreements with groups outside of MISO as well as grandfathered contracts within MISO.

20 The start date is a few months after when the Southern Region was integrated into MISO. The end date is when MISO stopped reporting unit specific identification numbers to preserve the privacy of the asset owners.
<table>
<thead>
<tr>
<th></th>
<th>Unit-Hour LMP</th>
<th></th>
<th>Unit-Hour MWh</th>
<th></th>
<th>Num. Units</th>
<th>Unit-Hour Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steam Turbine</td>
<td>28.55</td>
<td>29.01</td>
<td>224.14</td>
<td>235.98</td>
<td>411</td>
<td>6,072,029</td>
</tr>
<tr>
<td>Combustion Turbine</td>
<td>34.91</td>
<td>46.19</td>
<td>148.07</td>
<td>157.24</td>
<td>441</td>
<td>981,114</td>
</tr>
<tr>
<td>Hydro Powered</td>
<td>29.87</td>
<td>33.06</td>
<td>23.08</td>
<td>45.06</td>
<td>83</td>
<td>1,252,130</td>
</tr>
<tr>
<td>Combined Cycle</td>
<td>29.55</td>
<td>28.91</td>
<td>299.35</td>
<td>146.04</td>
<td>76</td>
<td>672,407</td>
</tr>
<tr>
<td>Wind Turbine</td>
<td>22.97</td>
<td>26.80</td>
<td>28.75</td>
<td>39.44</td>
<td>211</td>
<td>4,504,944</td>
</tr>
<tr>
<td>Other</td>
<td>31.97</td>
<td>39.91</td>
<td>33.66</td>
<td>65.56</td>
<td>102</td>
<td>292,701</td>
</tr>
<tr>
<td>Total</td>
<td>27.42</td>
<td>30.73</td>
<td>136.17</td>
<td>194.97</td>
<td>1,324</td>
<td>13,775,325</td>
</tr>
</tbody>
</table>

Notes: Unit-Hour observations come from MISO Real Time Cleared Offers Market Report From January 1, 2014 to December 24, 2016. The sample includes all electricity generating units that produced positive output. LMP stands for location marginal price and is given in USD per MWh. The MWh produced and price received are reported at 5 minute intervals within a single hour. The Unit-Hour observations are the hourly average of these values.
the generating units in the supply offer data to measure market participants portfolios, as all units with the same owner code are owned by the same market participant. I consider the maximum quantity generated by a unit during the sample period as a measure of its capacity to calculate the portfolio of assets for every owner code. Figure 1.5 shows the portfolio for the thirty largest market participants and their corresponding owner code. It is evident that almost all of these market participants have diverse assets, and that some of the largest market participants own a sizable amount of wind generation capacity.

Figure 1.5: Capacity and Portfolio of Market Participants in MISO.

The capacity and portfolio of the thirty largest market participants in MISO. Capacity is measured as the maximum MWh produced by a unit during the entire sample period. The bar labels are the Market Participant’s coded identification number. This shows large market participants own wind generation and conventional assets. There are approximately 220 small market participants that appear during the sample period.

In addition to the micro-data on unit level offers, MISO’s market reports include hourly market level information on average LMP, the marginal energy component (MEC) of the LMP, the hourly fuel mix, the number of binding transmission constraints, the shadow price of relieving the
binding constraints, wind forecasts, and net exports. I supplement these data with daily weather measures from the National Oceanic and Atmospheric Administration averaged across all states in MISO, as well as daily day-ahead natural gas prices at Henry Hub from the Intercontinental Exchange. The first panel in Table 1.2 summarizes these data. This market is large, clearing 71 GWh in a hour on average. A little more than half this is provided by coal based generators, and a fourth by natural gas. Wind generation provides almost 5 GWh on average, with a maximum of 13.7 GWh. While wind generation is a small portion of the market overall, there are moments when wind turbines produce more electricity than all the nuclear plants within MISO, and wind can meet up to 20% of load during periods of low demand.

Hourly unit level supply offer data include up to ten price-quantity pairs that outline the quantity each unit is willing to produce at a given market price. Additional data include minimum and maximum generation quantities, a flag if the unit ‘must run’, and a flag if the offer curve is a piece-wise linear or step function. I reconstruct unit specific supply curves for the hour by interpolating the price-quantity pairs on a common support (e.g. from -10 dollars to 100 dollars at an interval of 1 dollar). When appropriate, I extrapolate or truncate the quantity offered using the maximum and minimum quantity available. To ensure the function is everywhere differentiable and monotonic I smooth the offer curve using a normal kernel following Wolak (2001). For a set of price and quantity pairs, \((p_{ikt}, q_{ikt})\), \(i = 1 \ldots N\), for unit \(k\) at time \(t\), the smoothed supply function is

\[
\hat{s}_{kt}(p) = \sum_i q_{ikt} \Phi \left( \frac{p - p_{ikt}}{h} \right)
\]

where \(\Phi\) is the standard normal cumulative distribution function and \(h\) is smoothing parameter.\(^{21}\)

I aggregate these unit level supply functions by market participant. Figure 1.6 shows all offer curves of two sample market participants for one hour of the day in a month.

To find the slopes at equilibrium, I aggregate all of the generating unit supply curves within MISO to obtain a market supply curve.\(^{22}\) I go through an identical process of interpolating and

---

\(^{21}\) I use a bandwidth of three dollars, as does Kim (2017). Changing the bandwidth does not alter the results presented below.

\(^{22}\) Here I define the entire MISO region as a single market. I’ve considered other market definitions including
Table 1.2: Market Level Summary Statistics.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market LMP, USD/MWh</td>
<td>27</td>
<td>20.8</td>
<td>-26.8</td>
<td>23.7</td>
<td>1,571</td>
<td>26,117</td>
</tr>
<tr>
<td>Market MEC, USD/MWh</td>
<td>29.9</td>
<td>22.7</td>
<td>-28.7</td>
<td>25.8</td>
<td>1,806</td>
<td>26,117</td>
</tr>
<tr>
<td>Market GWh Generated</td>
<td>71.4</td>
<td>12.6</td>
<td>42.1</td>
<td>70.4</td>
<td>116</td>
<td>26,117</td>
</tr>
<tr>
<td>Coal GWh</td>
<td>36.8</td>
<td>8.46</td>
<td>16.5</td>
<td>36.6</td>
<td>56.8</td>
<td>26,117</td>
</tr>
<tr>
<td>Gas GWh</td>
<td>15.9</td>
<td>6.21</td>
<td>4.57</td>
<td>15.3</td>
<td>43.4</td>
<td>26,117</td>
</tr>
<tr>
<td>Hydro GWh</td>
<td>.988</td>
<td>.5</td>
<td>.305</td>
<td>.843</td>
<td>3.29</td>
<td>26,117</td>
</tr>
<tr>
<td>Nuclear GWh</td>
<td>11.4</td>
<td>1.23</td>
<td>6.1</td>
<td>11.7</td>
<td>13.3</td>
<td>26,117</td>
</tr>
<tr>
<td>Other GWh</td>
<td>1.35</td>
<td>.852</td>
<td>.295</td>
<td>1.07</td>
<td>7.74</td>
<td>26,117</td>
</tr>
<tr>
<td>Wind GWh</td>
<td>4.96</td>
<td>2.79</td>
<td>.132</td>
<td>4.61</td>
<td>13.7</td>
<td>26,117</td>
</tr>
<tr>
<td>Wind GWh, Diverse</td>
<td>3.58</td>
<td>2.1</td>
<td>.0551</td>
<td>3.29</td>
<td>10.2</td>
<td>26,117</td>
</tr>
<tr>
<td>Wind GWh, Independent</td>
<td>1.37</td>
<td>.722</td>
<td>.0693</td>
<td>1.3</td>
<td>3.61</td>
<td>26,117</td>
</tr>
<tr>
<td>Shadow Price of Constraints</td>
<td>-.947</td>
<td>1.28</td>
<td>-17.3</td>
<td>-.506</td>
<td>0</td>
<td>26,117</td>
</tr>
<tr>
<td>Number of Binding Constraints</td>
<td>3.79</td>
<td>2.65</td>
<td>0</td>
<td>3.17</td>
<td>19.2</td>
<td>26,117</td>
</tr>
<tr>
<td>Max Daily Temperature, C</td>
<td>17.6</td>
<td>10.4</td>
<td>-11.7</td>
<td>19.5</td>
<td>33.4</td>
<td>26,117</td>
</tr>
<tr>
<td>Natural Gas Price, USD/MMBtu</td>
<td>3.13</td>
<td>1.01</td>
<td>1.49</td>
<td>2.84</td>
<td>7.88</td>
<td>26,117</td>
</tr>
<tr>
<td>Net Exports GWh</td>
<td>4.41</td>
<td>1.99</td>
<td>-1.77</td>
<td>4.27</td>
<td>11.6</td>
<td>26,117</td>
</tr>
<tr>
<td>Wind Forecast Error, GWh</td>
<td>-.00594</td>
<td>.965</td>
<td>-4.13</td>
<td>.00101</td>
<td>4.32</td>
<td>26,093</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equilibrium Price, USD/MWh</td>
<td>28.8</td>
<td>8.47</td>
<td>17</td>
<td>26</td>
<td>118</td>
<td>26,117</td>
</tr>
<tr>
<td>Supply Slope, $\Delta \text{MWh} / \Delta \text{USD}_{\text{MWh}}$</td>
<td>2.627</td>
<td>1.512</td>
<td>17.5</td>
<td>2,307</td>
<td>7,432</td>
<td>26,117</td>
</tr>
<tr>
<td>Demand Slope, $\Delta \text{MWh} / \Delta \text{USD}_{\text{MWh}}$</td>
<td>-4.98</td>
<td>7.49</td>
<td>-67.7</td>
<td>-1.25</td>
<td>0</td>
<td>26,117</td>
</tr>
</tbody>
</table>

Notes: Market-Hour observations from January 1, 2014 to December 24, 2016. Market LMP, from the Nodal LMP Market Report, is taken as the average of all LMPs with an hour. The MEC is found by subtracting the Loss and Congestion Component from the LMP for each hour. Generation quantity in GWh comes from the Fuel Mix Market Report. The decomposition of Wind into Diverse and Independent Owners comes from the Cleared Offers Market Report. Diverse is defined as wind generation that is owned by a market participant that owns assets other than wind turbines. Independent wind comes from market participants that own only wind-based resources. Shadow Price, in thousand USD, and Number of Binding Constraints comes from MISO’s Real Time Binding Constraint Market Report. Temperature data is an average of all temperature readings within MISO’s footprint from the Global Historical Climatology Network operated by NOAA. Wind Forecast Error and day ahead Henry Hub natural gas price and comes from Yes Energy. The wind data is missing one day of data from June of 2015. Equilibrium Price, Supply Slope, and Demand Slope are recovered from the offer supply and demand curves. The equilibrium is where the offered supply net of wind equals the demand less of net exports.
Set of all offer curves by two market participants in a single year-month-hour. An offer curve is the hourly supply curve offered by the market participant for a given hour, this represents the ex-ante quantity they are willing to produce across all units for a given market price. This also showcases the type of variation used in the bid level regression that include year-month-hour fixed effects. Darker lines are associated with windier hours.
aggregating using the demand bids by the Load Serving Entities. To find the market equilibrium, I find the price where supply is equal to demand as shown in Figure 1.7. At this equilibrium I calculate the local slope of supply and demand as the difference in the quantity, along the curve, for a one step increase in price. The equilibrium prices and slopes are summarized in Panel B of Table 1.2. This price should correspond to the Marginal Energy Component of the LMP.

Figure 1.7: Reconstructed Equilibrium.

The reconstructed market supply and demand curves, in black, for a sample hour form the equilibrium price. The equilibrium is denoted by the dashed blue lines. The calculated merit order effect for a one unit increase is shown by the dashed red line. Walking down the merit order effect from the equilibrium shows the expected price reduction at with the yellow dashed lines.

subregions within MISO and price clusters similar to Mercadal (2015). Because the Marginal Energy Component is the same for all units in MISO, and I am interested in how wind impacts the Marginal Energy Component, any other market definition is inappropriate.

Because I am interested in the impact of wind on the price of electricity, I define the equilibrium without using the supply bids by the wind generating units. In addition I use generation within the market instead of demand, as this is a measure of demand net of imports. I consider alternative equilibriums, including wind and ignoring exports, and the results presented below do not change.
1.4 Empirical Impact on Price

I use the slope of supply and demand, summarized in Panel B of Table 1.2 to calculate an exact expression of Equation 1.3 for every hour in my sample. I do the same for Equation 1.6 where I use the fraction of wind owned by diverse market participants in that hour for the value of $\sum_{o \in V} \theta_o$. Table 1.2 shows that on average the proportion of wind owned by diverse market participants is 72%. The resulting values are summarized as “Analytical Merit Order Effect, Competitive” and “Analytical Merit Order Effect, SFE” respectively in Table 1.3. For a one GWh increase in wind generation for a given hour, we’d expect the price to decrease by $0.65/MWh if market participants were acting competitively, and $0.19/MWh if market participants were withholding according to their incentives. For context, the same increase in wind has been associated with a 3.18% price decline in Spain (Böckers, Giessing, and Rösch, 2013), 0.8 to 2.3 €/Mwh price decline in Germany (Cludius et al., 2014), 1.5 to 11.4 $/Mwh price decline in California (Woo et al., 2016), and 3.9 to 15.2$/Mwh price decline in Texas (Woo et al., 2011).

To find the total price effect, I take the analytical merit order effect for an hour and multiply this by the quantity of electricity generated by wind for that hour. This provides values of $dp_{\text{comp}}$ and $dp_{\text{SFE}}$ from Equation 1.4 and Equation 1.7. The total price effect is $3.7/MWh in a perfectly competitive market and around $1/MWh according to the supply function equilibrium framework. These values vary tremendously, ranging from near zero to over $100/MWh. This is consistent with the wholesale market where prices fluctuate greatly and can reach over $1,000/MWh.

As a validity check, I also estimate the empirical merit order effect for MISO. I consider the following equation to estimate the reduced form price effect of increased renewable generation:

\[
\text{Price}_t = \beta_1 \text{WindGWh}_t + \beta_2 \text{ClearedGWh}_t + \beta_3 \text{NetExports}_t + \beta_4 \text{WindForecastError}_t + \beta_5 \text{GasPrice}_d + \beta_6 \text{Temperature}_d + \lambda_{ymh} + \varepsilon_t
\]  

where $\text{Price}_t$ is the hourly, market wide, price measured as the Marginal Energy Component  

\(^{24}\) It is important to note these numbers include the impact on wind generation on congestion and transmission. Which in part explains why the estimates are different. In addition, the fuel mix in MISO is more coal heavy than in the other regions.
Table 1.3: Analytical Merit Order Effect.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Analytical Merit Order Effect, Competitive</td>
<td>-0.65</td>
<td>1.05</td>
<td>-57.10</td>
<td>-0.13</td>
<td>26,117</td>
</tr>
<tr>
<td>Analytical Merit Order Effect, SFE</td>
<td>-0.19</td>
<td>0.29</td>
<td>-15.64</td>
<td>-0.03</td>
<td>26,117</td>
</tr>
<tr>
<td>(dp_{comp,USD} )</td>
<td>-3.73</td>
<td>8.87</td>
<td>-477.07</td>
<td>-0.04</td>
<td>26,117</td>
</tr>
<tr>
<td>(dp_{sfe,USD} )</td>
<td>-1.02</td>
<td>2.36</td>
<td>-130.66</td>
<td>-0.02</td>
<td>26,117</td>
</tr>
</tbody>
</table>

Notes: Analytical Merit Order Effect comes from the theoretical prediction of the impact of 1 GWh of wind on the price of electricity with the corresponding assumptions on the price of electricity. Competition corresponds to Equation 1.3, the supply function equilibrium (sfe) corresponds to Equation 1.6. The values of \(dp_{comp,sfe} \) come from Equation 1.4 and Equation 1.7 respectively, where the analytical merit order effect is multiplied by the GWh of wind based electricity. The slopes of supply and demand come from the equilibrium without wind bids and demand less of net exports. The value of \(\sum_{o \in V} \theta_o \) is set equal to the proportion of wind that is generated by diverse market participants in a hour.
(MEC) or the mean Locational Marginal Price (LMP). \( \beta_1 \), the coefficient on the quantity of wind energy generated for hour \( t \), is the parameter of interest. \( ClearedGWh_t \) in combination with \( NetExports_t \) control for demand within the market and addresses any simultaneity issues. The remaining variables, hourly wind forecast error, daily gas price, and daily temperature are important determinants of the price of electricity. Month of sample by hour fixed effects control for omitted trending variables that might be correlated with wind generation and electricity prices. As an example, these fixed effects compare the market price during windy instances of 4pm in September of 2014 to the less windy instances of 4pm in September of 2014. Since wind generation is determined by the weather patterns, the remaining variation is as good as random.

Table 1.4: Estimated Merit Order Effect.

<table>
<thead>
<tr>
<th></th>
<th>(1) Market LMP, USD/MWh</th>
<th>(2) Market MEC, USD/MWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind GWh</td>
<td>-1.345***</td>
<td>-0.765***</td>
</tr>
<tr>
<td></td>
<td>(0.167)</td>
<td>(0.127)</td>
</tr>
<tr>
<td>Market GWh Generated</td>
<td>0.749***</td>
<td>0.839***</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Net Exports GWh</td>
<td>0.390</td>
<td>0.329</td>
</tr>
<tr>
<td></td>
<td>(0.222)</td>
<td>(0.215)</td>
</tr>
<tr>
<td>Max Daily Temperature, C</td>
<td>-0.476*</td>
<td>-0.394</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.215)</td>
</tr>
<tr>
<td>Natural Gas Price, USD/MMBtu</td>
<td>3.508</td>
<td>4.136</td>
</tr>
<tr>
<td></td>
<td>(2.286)</td>
<td>(2.070)</td>
</tr>
<tr>
<td>Wind Forecast Error, GWh</td>
<td>0.296</td>
<td>0.557*</td>
</tr>
<tr>
<td></td>
<td>(0.175)</td>
<td>(0.226)</td>
</tr>
<tr>
<td>Year-Month-Hour Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>26,093</td>
<td>26,093</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.36</td>
<td>0.36</td>
</tr>
</tbody>
</table>

Notes: Market-hour data comes from MISO Market Reports and NOAA, from January 1, 2014 to December, 24, 2016. Column one estimates the effect of 1 GWh of wind generation on the hourly Locational Marginal Price (LMP). Column two estimates the impact of 1 GWh wind on the Marginal Energy Component (MEC) of the LMP. Standard errors, in parenthesis, are clustered by month of sample. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for hypothesis test \( H_0 : \beta = 0 \) vs. \( H_1 : \beta \neq 0 \).
Table 1.4 shows the results from estimating Equation 1.8 on the full sample. I observe a one GWh increase in wind generation is associated with a decline in price of 1.35 $/MWh on average if considering the LMP, and 0.77 $/MWh if looking at the MEC. The difference in these values is the average effect that wind generation has on the congestion and transmissions losses component of the LMP. This estimated change in price is the same order of magnitude and sign as the analytical merit order effect in Equation 1.2. Although comparable, the estimates of the merit order effect presented in Table 1.3 and Table 1.4 are conceptually different. The measure from Equation 1.8 is the average effect of wind on price conditional on other factors that are observed in the data. In contrast, the expression calculated from Equation 1.3 and Equation 1.6 is the theoretical price change if there were a unit increase in wind generation based only on the slope of supply and demand.

1.4.1 Pass-through of Analytical Merit Order Effect

To test which assumption on conduct, price taking competition or the supply function equilibrium with withholding, better characterizes the change in price from increased renewable generation, I estimate the following equation

\[
Price_t = \rho_1 \left[ dp_{(comp,SFE)} \right]_t + \rho_2 ClearedGWh_t + \rho_3 NetExports_t + \rho_4 WindForcastError_t + \\
\rho_5 GasPrice_d + \rho_6 Temperature_d + \rho_7 ShadowPriceofConstraints_t + \lambda_{mhy} + \varepsilon_t
\]

(1.9)

with identification, notation, and covariates similar to Equation 1.8. Here I include the analytical total price effect \( dp \) calculated from equations Equation 1.4 and Equation 1.7 instead of the quantity of wind generation. The shadow price of constraints is included as a control to account for how wind impacts congestion and dispatch that is out of merit order. I am interested in the coefficient \( \rho_1 \) and how close it is to one. If the analytical price change is perfectly represented in the market price, \( \rho_1 \) is equal to one exactly. Comparing the value of \( \rho_1 \) between assumptions on conduct informs which assumption on firm conduct best represents the market.
Table 1.5 presents the results from estimating Equation 1.9 on the full sample using the MEC as the price measure. Because there are a number very large negative values for the analytical merit order effect, columns 2, 3, 5, and 6, show the estimates from a 1% left tail winsorized sample. This effectively replaces any values of $dp$ less than the first percentile with the first percentile. Overall the estimate of $\rho_1$ is closer to one for $dp_{SFE}$ than $dp_{comp}$. Consider the hypothesis test $H_0 : \rho_1 = 1$ versus $H_a : \rho_1 \neq 1$. For the winsorized sample can reject the null hypothesis at the 0.01 significance level under the assumption of perfect competition, but fail to reject the null hypothesis at the 0.1 under the assumption of strategic withholding in a supply function equilibrium framework.

Overall, the estimates imply 45 to 54 % of the expected price change under perfect competition is realized in the market price, while over 100 % of the expected price change is observed under the assumption of strategic withholding. This suggests that the true price effect is somewhere between the perfectly competitive price change and the supply function equilibrium price change. Columns (3) and (6) of each table shows how the estimate of $\rho_1$ changes during peak and off peak hours. It is clear that the analytical merit order effect is realized in the market price more so during the off-peak hours when it more difficult to exert market power. However, the point estimate for the supply function equilibrium model during on peak hours is equal to one suggesting that the price effect of renewable generation with strategic withholding is fully realized when market participants benefit the most from strategic withholding.

### 1.5 Evidence of Strategic Witholding

While the merit order effects presented in Table 1.3 are informative, they rely on modeling assumptions. Here, I instead use detailed data on the strategies of all market participants for all hours to directly test for physical withholding. I begin by aggregating the conventional unit supply curves, described in section 1.3, by owner codes for every hour. This gives me a hourly

---

25 The first percentiles are the −30.10 and −8.08 for the competitive and supply function equilibrium analytical merit order effects respectively. The large negative values are a result of $dp$ being a local approximation to the price change and the supply curve being convex.

26 I define peak hours as 3pm to 8pm inclusive.
### Table 1.5: Pass-through of Calculated Merit Order Effect on Market Level Prices.

<table>
<thead>
<tr>
<th></th>
<th>MEC, USD/MWh</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$dp_{\text{comp}, \text{USD}}$</td>
<td></td>
<td>0.10***</td>
<td>0.45***</td>
<td>(0.04)</td>
<td>(0.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$dp_{\text{sfe}, \text{USD}}$</td>
<td></td>
<td></td>
<td></td>
<td>0.31***</td>
<td>1.41</td>
<td>(0.15)</td>
<td>(0.48)</td>
</tr>
<tr>
<td>Off Peak $\times dp_{\text{comp}, \text{USD}}$</td>
<td>0.54***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On Peak $\times dp_{\text{comp}, \text{USD}}$</td>
<td>0.32***</td>
<td></td>
<td></td>
<td>(0.12)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Off Peak $\times dp_{\text{sfe}, \text{USD}}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.70</td>
<td>(0.59)</td>
</tr>
<tr>
<td>On Peak $\times dp_{\text{sfe}, \text{USD}}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.00</td>
<td>(0.39)</td>
</tr>
<tr>
<td>Market GWh Generated</td>
<td></td>
<td>0.45***</td>
<td>0.47***</td>
<td>0.47***</td>
<td>0.45***</td>
<td>0.47***</td>
<td>0.47***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Net Exports GWh</td>
<td></td>
<td>0.55*</td>
<td>0.51*</td>
<td>0.50*</td>
<td>0.55*</td>
<td>0.52*</td>
<td>0.52*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.22)</td>
<td>(0.22)</td>
<td>(0.22)</td>
<td>(0.23)</td>
<td>(0.22)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Max Daily Temperature, C</td>
<td>-0.45*</td>
<td>-0.46**</td>
<td>-0.46**</td>
<td>-0.45*</td>
<td>-0.46**</td>
<td>-0.46**</td>
<td>-0.46**</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Natural Gas Price, USD/MMBtu</td>
<td>2.69</td>
<td>3.14</td>
<td>3.21</td>
<td>2.68</td>
<td>3.08</td>
<td>3.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.33)</td>
<td>(2.26)</td>
<td>(2.25)</td>
<td>(2.34)</td>
<td>(2.29)</td>
<td>(2.28)</td>
<td></td>
</tr>
<tr>
<td>Wind Forecast Error, GWh</td>
<td>0.61***</td>
<td>0.52**</td>
<td>0.51**</td>
<td>0.62***</td>
<td>0.55**</td>
<td>0.54**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.15)</td>
<td>(0.16)</td>
<td>(0.17)</td>
<td>(0.16)</td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>Shadow Price of Constraints</td>
<td>-6.80***</td>
<td>-7.00***</td>
<td>-7.01***</td>
<td>-6.78***</td>
<td>-6.93***</td>
<td>-6.93***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.05)</td>
<td>(1.09)</td>
<td>(1.09)</td>
<td>(1.05)</td>
<td>(1.07)</td>
<td>(1.07)</td>
<td></td>
</tr>
<tr>
<td>Year-Month-Hour Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>$dp$ Winsorized</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>26,093</td>
<td>26,093</td>
<td>26,093</td>
<td>26,093</td>
<td>26,093</td>
<td>26,093</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.44</td>
<td>0.45</td>
<td>0.45</td>
<td>0.44</td>
<td>0.44</td>
<td>0.44</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Data comes from MISO market reports, NOAA, and Yes Energy from January 1, 2014 to December 24, 2016. The sample includes all market-hour observations from January 1st 2014 to December 24th. Peak hours are between 3pm and 8pm, inclusive. Standard errors, in parenthesis, are clustered by month of sample. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for each hypothesis test. The hypothesis test conducted on the coefficients of $dp_{\text{comp}, \text{sfe}}$ and its interactions is $H_0 : \rho = 1$ vs. $H_1 : \rho \neq 1$. The hypothesis test for all other coefficients is $H_0 : \beta = 0$ vs. $H_1 : \beta \neq 0$. The sample size varies because of missing wind forecast observations.
supply curve of the conventional assets for every market participant on a common support, every $3 interval between 0 and 60 dollars. These curves are defined by a set of \( b = 1 \ldots 21 \) price quantity pairs, \((p_b, q_{ob})\), for owner \( o \) at time \( t \). The set of \( p_b \) are the same for all market participants, for all hours, only the quantities offered at these prices change.

To directly test for strategic physical withholding, I see how the quantity offered at a given price changes in response to increased renewable generation. The general estimating equation of interest is

\[
q_{otb} = \gamma_0 \text{ClearedGWh}_t + \gamma_1 \text{NetExports}_t + \delta \text{WindGWh}_t + X \beta + \eta_{op_bymh} + \varepsilon_{otb} \quad (1.10)
\]

where \( q_{otb} \) is the quantity offered, in MWh, by market participant \( o \) at time \( t \) and price bin \( p_b \). \( X \) represents other determinants of a market participant’s strategy including daily temperature measures, daily natural gas prices, the hourly number of binding constraints in MISO, and the hourly shadow price of all constraints. Identification comes from owner specific, month-of-sample by hour, fixed effects for every price bin, \( \eta_{op_bymh} \). This captures the average quantity offered by market participant \( o \) at price \( p_b \) within a month-of-sample hour (e.g. September 2014, 4pm). Therefore the coefficient \( \delta \) is identified off the deviation from the market participants month-of-sample hour average supply curve. Because these data represent the ex-ante strategy of a firm, withholding the quantity offered at a given price would imply that \( \delta < 0 \). The supply function equilibrium theory presented in section 1.2 suggests the coefficient of \( \delta \) should be (A) negative only for diverse market participants that own both wind turbines and conventional assets, (B) increasing in the share of total wind owned by the diverse market participant, and (C) negative only in response to a market participants own wind generation.

Table 1.6 shows the estimate of \( \delta \) in Equation 1.10 is negative. Overall, a 1 GWh increase in wind generation in an hour is associated with a 2.8 MWh reduction it the quantity offered at a given price on average across all market participants. In column (2), I interact \( \text{WindGWh}_t \) with a indicator variable for if a market participant owns wind turbines and conventional assets. This shows that diverse market participants reduce the quantity offered by 13 MWh on average,
Table 1.6: Withholding of Offer Curve in Response to Wind Generation.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market GWh Generated</td>
<td>3.345***</td>
<td>3.345***</td>
<td>3.347***</td>
</tr>
<tr>
<td></td>
<td>(0.536)</td>
<td>(0.536)</td>
<td>(0.535)</td>
</tr>
<tr>
<td>Wind GWh</td>
<td>-2.787***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.736)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not Diverse Owner × Wind GWh</td>
<td></td>
<td>-1.256***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.258)</td>
<td></td>
</tr>
<tr>
<td>Diverse Owner × Wind GWh</td>
<td></td>
<td>-13.23**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.665)</td>
<td></td>
</tr>
<tr>
<td>Not Diverse Owner × Wind GWh, Independent</td>
<td>-2.653</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.586)</td>
<td></td>
</tr>
<tr>
<td>Diverse Owner × Wind GWh, Independent</td>
<td>-8.437</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(12.26)</td>
<td></td>
</tr>
<tr>
<td>Not Diverse Owner × Wind GWh, Diverse</td>
<td>-0.778</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.631)</td>
<td></td>
</tr>
<tr>
<td>Diverse Owner × Wind GWh, Diverse</td>
<td>-14.85*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6.283)</td>
<td></td>
</tr>
<tr>
<td>Owner-Price-Year-Month-Hour Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>28,777,140</td>
<td>28,777,140</td>
<td>28,777,140</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.97</td>
<td>0.97</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Notes: Data comes from MISO Real Time Offer Market Reports January 1, 2014 to December 24, 2016. This sample is all offers by market participants during peak hours, defined as 3pm to 8pm inclusive. Offer curves are are interpolated and defined at 3$ intervals between 0 and 60 USD. All unit level offers are aggregated to the market participant. One observation is the quantity offered by all units owned by the same market participant at a given price for that hour. Diverse market participants own wind turbines and conventional electricity generating assets. Wind Based GWh, Independent, is wind based electricity generated by market participants that own only wind turbines. Likewise, Wind Based GWh, Diverse is wind based electricity generated by diverse market participants. All specifications include fixed effects for the average quantity offered by the market participant at the price for a given month-hour. Other controls include daily temperature, daily natural gas price, hourly number of binding constraints, hourly shadow price of all constraints. Standard errors, in parenthesis, are clustered by month of sample and owner. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for each hypothesis test. The hypothesis test for all coefficients is $H_0 : \beta = 0$ vs. $H_1 : \beta \neq 0$. 
while the independent market participants only reduce the quantity offered by 1.2 MWh. Finally, in column (3) I decompose $WindGWh_t$ into the quantity of electricity generated by independent wind turbines and the quantity of electricity generated by wind turbines owned by diverse market participants. This shows that the quantity offered by diverse market participants is reduced the most in response to diverse wind generation.

The estimates presented in Table 1.6 are the average effects for all market participants, or at best separated by if a market participant owns wind turbines. I expect there to be substantial heterogeneity in how market participants respond to increased renewable generations because they vary in the portfolio of wind based generation and their bidding sophistication. I interact $WindGWh_t$ in Equation 1.10 with the owner code of every market participant to get a unit specific estimate of $\delta_o$. In particular, I estimate the parameters in the following equation

$$q_{otb} = \gamma_0 \text{ClearedGWh}_t + \gamma_1 \text{NetExports}_t + \delta_o WindGWh_t \cdot OwnerCode_o + X \beta + \eta_{opb\gamma} + \epsilon_{otb}$$

and plot the density of the coefficients in Figure 1.8 by if the market participant is diverse. To ensure I am looking only at relevant bid prices, I discard any observations where the market price is more than the price bin plus three, $p_b + 3$. This shows the coefficients for the market participants that do not own wind generation are near zero, where as the density for diverse market participants has an obvious left skew and is centered below zero.

As shown in section 1.2, a firm’s incentive to withhold increases with the amount of electricity they generate from wind turbines. I match the estimates for owner-specific withholding coefficients for diverse market participants, $\hat{\delta}_o$, with the total capacity of all wind turbines owned by each market participant. Figure 1.9 shows how there are a few market participants that are withholding the most in response to wind generation, and these market participants also own the most wind turbine capacity.

---

27 Hortacsu and Puller (2008) show evidence of imperfect bidding behavior by market participants in Texas’s ERCOT market.
28 Both densities use an Epanechnikov kernel with a bandwidth of 2 MWh.
29 I add three to the price bin because the price bins are at three dollar intervals. Using the full sample provides a similar result.
Kernel density of withholding coefficients for ever market participant separated by the market participant’s portfolio diversity. Withholding coefficients are how the market participants offer curve changes in response to increased wind generation controlling for the month/year/hour/price/owner average quantity. Both densities use a Epanechnikov Kernal with a bandwidth of two dollars.
Figure 1.9: Withholding Coefficients and Owner Wind Turbine Capacity.

Owner specific withholding coefficient and owner total wind turbine capacity for diverse market participants. Withholding coefficients are estimates from Equation 1.11, turbine capacity is the sum of each turbine’s maximum output in the sample period. Note the horizontal axis is in \( \log_{10} \) and the vertical axis is \( \log_2 \).
Finally, we expect market participants to only withhold their output when their own wind turbines are generating wind. This is because they are withholding output to increase the revenue received by their wind turbines and not to prevent price suppression on the conventional assets. To show evidence for this I estimate the parameters from the following equation

\[ q_{otb} = \gamma_{0o} ClearedGWWh_t + \gamma_{1o} NetExports_t + \delta_{opb} OwnWindGWWh_t \cdot p_b + \chi_{opb} OtherWindGWWh_t \cdot p_b + X_{\beta o} + \eta_{pbymh} + \varepsilon_{tb} \]  

(1.12)

where \( \delta_{opb} \) represents how owner \( o \) changes the quantity offered at price \( p_b \) in response to electricity generated from their own wind turbines, and \( \chi_{opb} \) is how a market participant \( o \) changes the quantity offered in response to electricity generated by all other wind turbines. This is estimated separately for each market participant because it is computational intensive. Figure 1.10 shows these estimates for four market participants that own a large share of total and wind generation. It is clear that these market participants are responding more so to their own wind generation than the electricity generated from other wind turbines.

These results are robust to concerns regarding transmission congestion. Ideally, I would be able to spatially differentiate the electricity generators and see how their behavior depends on transmission congestion near their pricing node. Unfortunately, my data is not that granular in the cross section. In all the specifications I control the system wide number of binding constraints, and the total shadow price of the binding constraints, which captures some of the variation of interest. Re-estimating all of the equations above for the subsample of hours for which there are zero binding constraints, or a low shadow price, does not change the estimates significantly.

1.6 Implications for Consumer Surplus

Using the analytical merit order effect for the expected price change due to increased renewable generation it is possible to make claims regarding consumer surplus in the wholesale electricity market. I model consumer surplus from electricity during hour \( t \) at market price \( p \) as

\[ CS_t(p) = \int_p^{\infty} D_t(x) dx \]
Witholding coefficients at every price bin for a select number of large and diverse market participants. Estimates come from estimating Equation 1.10 with flexible price bins interacted with WindGWh, separately for each market participant. Confidence interval uses robust standard errors.
where $D_t(x)$ is the demand for electricity at time $t$ and price $x$. To see how consumer surplus changes due to an increase in the quantity of wind, $W_t$, I take the total derivative to get

$$\frac{dCS_t}{dW_t} = - D_t(p) \frac{dp}{dW_t}$$

implying the change in consumer surplus during the entire sample period would be

$$\Delta CS = - \sum_t D_t(p) \frac{dp}{dW_t} dW_t.$$ (1.13)

When calculating consumer surplus, I consider three alternative values for $\frac{dp}{dW_t}$. One is the prediction under the assumption of price taking behavior, where $\frac{dp_{\text{comp}}}{dW_t} = - \frac{1}{\sum_o S'_o(p) - d'(p)}$. For the second, I considered a supply function equilibrium framework with $\frac{dp_{\text{SFE}}}{dW_t} = - [1 - \sum_{o \in V} \theta_o] \frac{1}{\sum_o S'_o(p) - d'(p)}$ where $\sum_{o \in V} \theta_o$ is the proportion of wind owned by diverse market participants. Third, I use the estimates of physical withholding for diverse market participants from Equation 1.11 as an estimate of $\frac{\partial S_o}{\partial W}$. Table 1.7 shows the estimates of $\delta_o$ for all diverse market participants. The sum of these estimates, presented in the bottom of Table 1.7, suggests that over 30% of wind generation is replacing withheld offers by diverse market participants.

All together this provides me with three separate estimates of consumer surplus, all varying in the degree to which market participants withhold their generation offer

$$\Delta CS_{\text{comp}} = \sum_t D_t(p) \frac{1}{\sum_o S'_o(p) - d'_o(p)} dW_t$$ (1.14)

$$\Delta CS_{\text{SFE}} = \sum_t D_t(p) \frac{1 - \sum_{o \in V} \theta_o}{\sum_o S'_o(p) - d'_o(p)} dW_t$$ (1.15)

$$\Delta CS_{\text{obs}} = \sum_t D_t(p) \frac{1 - \sum_{o \in V} \delta_o}{\sum_o S'_o(p) - d'_o(p)} dW_t$$ (1.16)

I calculate the value of Equation 1.14, Equation 1.15, and Equation 1.16 using all hours between January 1st 2014 and December 24th 2016. I do this in two ways to account for import and exports of electricity within MISO. One uses net generation within MISO as a proxy for demand net of imports. This is making claims on all electricity generated within MISO. The other considers total demand within MISO.

---

I consider alternative $\Delta CS_{\text{obs}}$ that weights the withholding estimate by the owner specific wind generation, but the results do not change.
Table 1.7: Owner Specific Withholding of Diverse Market Participants.

<table>
<thead>
<tr>
<th>Owner Code</th>
<th>Wind GWh</th>
<th>Quantity Offered, MWh</th>
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</thead>
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<tr>
<td></td>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Owner Code=122062454</td>
<td>Wind GWh</td>
<td>-15.04*** (2.805) -20.84*** (3.220)</td>
</tr>
<tr>
<td>Owner Code=122062463</td>
<td>Wind GWh</td>
<td>0.235 (1.095) -1.194 (1.313)</td>
</tr>
<tr>
<td>Owner Code=122062474</td>
<td>Wind GWh</td>
<td>-1.798 (1.120) -3.010** (1.302)</td>
</tr>
<tr>
<td>Owner Code=122062480</td>
<td>Wind GWh</td>
<td>-19.03*** (3.394) -24.87*** (3.317)</td>
</tr>
<tr>
<td>Owner Code=122062486</td>
<td>Wind GWh</td>
<td>-2.111 (1.529) -3.115 (1.673)</td>
</tr>
<tr>
<td>Owner Code=122062512</td>
<td>Wind GWh</td>
<td>-13.64*** (1.627) -20.05*** (1.855)</td>
</tr>
<tr>
<td>Owner Code=122062521</td>
<td>Wind GWh</td>
<td>-1.291 (1.048) -2.459 (1.228)</td>
</tr>
<tr>
<td>Owner Code=122062548</td>
<td>Wind GWh</td>
<td>-1.809 (1.221) -3.042 (1.509)</td>
</tr>
<tr>
<td>Owner Code=122062550</td>
<td>Wind GWh</td>
<td>-33.76*** (1.912) -36.44*** (2.050)</td>
</tr>
<tr>
<td>Owner Code=122062561</td>
<td>Wind GWh</td>
<td>-3.642* (1.535) -5.146** (1.643)</td>
</tr>
<tr>
<td>Owner Code=122062564</td>
<td>Wind GWh</td>
<td>0.162 (1.131) -1.375 (1.347)</td>
</tr>
<tr>
<td>Owner Code=122062577</td>
<td>Wind GWh</td>
<td>-6.737*** (1.765) -7.468** (2.122)</td>
</tr>
<tr>
<td>Owner Code=122062590</td>
<td>Wind GWh</td>
<td>-97.41*** (3.234) -104.9*** (3.870)</td>
</tr>
<tr>
<td>Owner Code=122062603</td>
<td>Wind GWh</td>
<td>-1.814 (1.364) -3.690* (1.628)</td>
</tr>
<tr>
<td>Owner Code=122062624</td>
<td>Wind GWh</td>
<td>-1.824 (1.048) -2.815 (1.361)</td>
</tr>
<tr>
<td>Owner Code=122062627</td>
<td>Wind GWh</td>
<td>-0.524 (1.116) -2.029 (1.401)</td>
</tr>
<tr>
<td>Owner Code=122062642</td>
<td>Wind GWh</td>
<td>-8.172** (2.851) -7.649* (3.136)</td>
</tr>
<tr>
<td>Owner Code=122062646</td>
<td>Wind GWh</td>
<td>-1.437 (1.090) -2.513 (1.405)</td>
</tr>
<tr>
<td>Owner Code=122062647</td>
<td>Wind GWh</td>
<td>-3.649*** (0.688) -7.097*** (0.954)</td>
</tr>
<tr>
<td>Owner Code=122062649</td>
<td>Wind GWh</td>
<td>-14.39*** (1.660) -15.40*** (1.603)</td>
</tr>
<tr>
<td>Owner Code=125767546</td>
<td>Wind GWh</td>
<td>-1.519 (1.417) -2.416 (1.570)</td>
</tr>
<tr>
<td>Owner Code=576468110</td>
<td>Wind GWh</td>
<td>-62.20*** (2.516) -66.40*** (2.737)</td>
</tr>
<tr>
<td>Owner Code=576468116</td>
<td>Wind GWh</td>
<td>-11.70*** (2.082) -14.57*** (1.771)</td>
</tr>
</tbody>
</table>

| Owner-Price-Year-Month-Hour Fixed Effects | Yes | Yes |
| Controls for Demand | Yes | Yes |
| Peak | No | Yes |
| Sum of Coefficients | -303.10 | -351.40 |
| Standard Error of Sum | 14.36 | 17.10 |
| Observations | 9,532,246 | 2,596,242 |
| R-squared | 0.97 | 0.97 |

Notes: Data comes from MISO Real Time Offer Market Reports January 1, 2014 to December 24, 2016. This sample is all offers by diverse market participants. Column (1) uses the full sample, while column (2) is only for peak hours, defined as 3pm to 8pm inclusive. Offer curves are are interpolated and defined at $3 intervals between 0 and 60 USD. All unit level offers are aggregated to the market participant. One observation is the quantity offered by all unit owned by the same market participant at a given price for the hour. Sample includes all diverse market participants. All specifications include a fixed effect for the average quantity offered by the market participant at the price for a given month-hour, and control for demand. Other controls include daily temperature, daily natural gas price, hourly number of binding constraints, hourly shadow price of all constraints. Standard errors, in parenthesis, are clustered by month of sample and owner. *, **, *** denote p-value less than 0.1, 0.05, and 0.01 respectively for each hypothesis test. The hypothesis test for all coefficients is $H_0 : \beta = 0$ vs. $H_1 : \beta \neq 0$. 


Table 1.8 presents all estimates of the total change in consumer surplus, as well as market revenue over the sample period. I normalized these totals to a value per person per year assuming 50 million people live within MISO’s footprint. The potential consumer surplus from increased renewable generation, according to Equation 1.14, is huge, seven to ten billion USD over three years, equivalent to 50 to 69 USD per person per year. This number is greatly diminished if diverse market participants withhold perfectly, as calculate by Equation 1.15. The total consumer surplus would be only 2 to 2.8 billion USD, or 14 to 19 USD per person per year. Using the observed withholding coefficients to calculate consumer surplus, as in Equation 1.16, the surplus per person per year is 34 to 47 USD, suggesting that observed withholding by diverse market participants reduces consumer surplus by 16 to 22 USD per person per year.

<table>
<thead>
<tr>
<th></th>
<th>Net Demand</th>
<th>MISO Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total, Bil.USD</td>
<td>USD/person-year</td>
</tr>
<tr>
<td>Revenue</td>
<td>55.33</td>
<td>371.34</td>
</tr>
<tr>
<td>$\Delta CS_{comp}$, no curtail</td>
<td>7.38</td>
<td>49.51</td>
</tr>
<tr>
<td>$\Delta CS_{obs}$, observed</td>
<td>5.01</td>
<td>33.60</td>
</tr>
<tr>
<td>$\Delta CS_{sfe}$, full curtail</td>
<td>2.03</td>
<td>13.61</td>
</tr>
<tr>
<td>$\Delta CS_{comp} - \Delta CS_{obs}$</td>
<td>2.37</td>
<td>15.91</td>
</tr>
<tr>
<td>$\Delta CS_{comp} - \Delta CS_{sfe}$</td>
<td>5.35</td>
<td>35.90</td>
</tr>
</tbody>
</table>

Notes: Time period of interest is from January 1st, 2014 to December 24th, 2016. All calculations come from Equation 1.14, Equation 1.15, Equation 1.16. Revenue is the sum of Market MEC and market generation quantity in MWh for all hours. “Net Demand” uses the analytical merit order effect and production quantity at the equilibrium where supply net of wind equals demand less net imports. “MISO Demand” uses the equilibrium where supply net of wind equals total demand within MISO. Bil. stands for billion. Annual per person calculations divides the total quantity by 2.98 years and 50 million people. This number is the authors best guess for the population within MISO’s footprint based on the cumulative population of 61 million in the states of Arkansas, Illinois, Indiana, Iowa, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, Wisconsin according to the 2016 US Census Bureau estimates. All numbers are in nominal US dollars.

31 This population estimate is my best guess given that 61 million individuals live in the states of Arkansas, Illinois, Indiana, Iowa, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, Wisconsin according to the 2016 US Census Bureau estimates.
1.7 Conclusion

The increase in renewable generation capacity within the United States has created immense value by providing low marginal cost electricity. I first derive an analytical expression for how increased renewable generation should impact the price of electricity. I show the strategic response of conventional electricity generators to increased wind generation is an important factor to consider in price formation. In particular, a supply function equilibrium model with horizontally integrated generating units predicts that diverse market participants will reduce their generation offer in response to an increase of their own wind generation. Using detailed data on supply and demand from 2014 to 2016 in MISO’s wholesale electricity market, I quantify the expected price reduction under a model of perfect competition and a supply function equilibrium model with withholding.

I directly test for evidence of physical withholding by diverse market participants using month-of-sample by hour, price, owner fixed effects. Indeed, it is the diverse market participants that reduce the quantity offered, and they do it more in response to their own wind generation. This has important implications for consumer surplus and overall economic efficiency if this withholding leads to less efficient units having merit in the dispatch order. The analytical merit order effect I calculate and withholding coefficients I estimate imply increased renewable generation has the potential to increase consumer surplus by 50 to 69 USD per person per year, however observed withholding by diverse market participants reduces consumer surplus by 16 to 22 USD per person per year. This has implications for the market monitor in these wholesale electricity markets, as increased renewable generation might be associated with anti-competitive behavior.

There are several policy implications that come from these results as well as avenues for future research. For one, the ownership of the renewable generation assets is not neutral to the incidence of consumer and producer surplus. Wind turbines and solar panels owned by diverse market participants in wholesale markets will not reduce the price of electricity by as much as the same assets owned by independent market participants or assets compensated by purchasing power agreements. Moving forward, it is important to quantify how renewable generation impacts
producer surplus in these wholesale electricity markets. Producers can benefit from increased renewable generation because it reduces their fuel cost, or can be harmed if it decreases the price they receive. With accurate information on the cost of production, it would be straightforward to calculate producer surplus and compare them to my estimates of consumer surplus. Finally, this paper shows that wind generation might not be replacing the most inefficient generation units because of profit motives. There might be technical reasons for this in addition to the economic incentives shown here. Better understanding why this might be the case can increase the value derived from renewable generation.
Chapter 2

Concentration Effects of Heterogeneous Standards: Refinery Response to the Clean Air Act Amendments

Abstract Environmental regulations can alter the geographic and product markets in which firms compete. This can impact a firm’s ability to exercise market power, and profits subsequently. The boutique fuel standards related to the 1990 Clean Air Act Amendments is one such regulation that did this to the petroleum refining industry by mandating unconventional, cleaner burning, gasoline to be sold in certain counties of the United States. While the production of the cleaner fuel increased the fixed and variable cost of refineries, it also allowed them to recuperate lost profits by selling their product in a more concentrated market with a higher markup. I use a simulation to show evidence that the concentration effect can offset investment cost, and provide empirical evidence to suggest the refineries most exposed to the boutique fuel standards benefited the most from the policy.

JEL classification codes: L13, Q58, L71

2.1 Introduction

Environmental policies have the goal of increasing total welfare by correcting for an externality that is not addressed by the market. More often than not there are unintended economic consequences that result from the implementation of an environmental policy. These unintended consequences have the potential to be large, and can influence much of the political economy regarding the implementation of differing policies. In this paper I document one such policy, the
boutique fuel standards associated with the 1990 Clean Air Act Amendments (CAAA). I show how this policy influenced the market structure for petroleum refineries by segmenting the product market, and what the implications were for the profitability of refineries that were exposed to the standard.

These standards required specialized, cleaner burning, fuel to be sold in a patch work of densely populated areas within the United States, illustrated by Figure 2.1. These specialized fuels had a higher variable cost of production and required investment into particular production technologies (Office of Technology Assessment, 1990; Sweeney, 2014). Industry publications at the time claimed this regulation had “a more significant impact on refinery operations and capital expenditures than any environmental legislations since . . . 1976” (Scherr, Smalley Jr, and Norman, 1991). Typically, an increase in the cost of production would cause more firms to exit the market in the long run. Industry publications painted a grim picture, with one editorial column stating petroleum refineries “either retooled . . . or shutdown . . . invested . . . or shutdown . . . bought oxygenate or the ability to make it or shut down” (Oil & Gas Journal, 1997). In this paper, I show that the concentration effect associated with segmented product markets offset some of these industry concerns.

Although the boutique standards associated with the 1990 CAAAs did increase the costs of production, they also segmented the product market into “conventional” gasoline and “reformulated” gasoline. The segmentation of the product market, in addition to the costly investment in production technologies, allowed petroleum refineries to compete in more concentrated markets where they could exert more market power and charge a higher markup of price over the cost of production. We might expect the “concentration effects” of these standards to be large as the number of refineries has decline over time (shown in Figure 2.2) and these refineries already compete in relatively concentrated markets.\(^1\)

In the paper, I explore the extent to which the concentration effects of the boutique fuel

\(^1\) Using data on petroleum refinery capacity by Unit States state from 1987 to 2008, the average Herfindahl-Hirschman Index is approximately 0.56, indicating high concentration.
Figure 2.1: Product Markets Resulting from the 1990 CAAAs. 

Map is from Brown et al. (2008).

Figure 2.2: Number of Operating Refineries in the US by Year.

The vertical bar approximates the introduction of Boutique Fuel Standards associated with the Clean Air Act Amendments. Source: EIA-820.
standards offset the higher cost of production in influencing the profitability of petroleum refineries in the United States (US). I do this by first considering a simple model of Cournot competition in which petroleum refineries can sell two different products to geographic markets. In this model I explicitly model transportation costs, so the geography of production and consumption is important. I use this model to focus on the dynamics of investment in a technology that allows production of the higher cost good, and how the profitability of different refineries changes under different investment scenarios. Next, I turn to annual data of refinery capacity and operation status from the Energy Information Agency to look for evidence consistent with the theory. Using a hazard function approach in a difference-in-differences type framework, I show that refineries that were most exposed to Boutique Fuel Standards were the least likely to exit the market after the standards went into place. Interpreting this from a latent profits perspective, the additional profits from market segmentation offset investment and production costs.

Most directly, this research addresses the dynamic implications of environmental policies and the spatial issues relating to environmental federalism. The use of dynamic industry models to understand the long term implications of environmental regulations is “[p]erhaps the most striking gap in the literature” despite investment, research and development, and entry-exit decisions being the major mechanism in which a regulation can impact industry (Millimet, Roy, and Sengupta, 2009, p.113). Recent work, using the dynamic discrete choice framework of Maskin and Tirole (1988); Ericson and Pakes (1995), has been used to simulate the resulting change in market power due to environmental regulations (Ryan, 2012; Fowlie, Reguant, and Ryan, 2015). While informative, this type of analysis requires data that are often confidential and a number of assumptions regarding market conduct and economic primitives.\(^2\) Though less structured, similar dynamic information can be inferred from robust reduced form specifications or through the use of survival analysis as in Deily and Gray (1991); Helland (1998); Snyder, Miller, and Stavins (2003).

From a regulatory perspective, the CAAAs and their impact on refinery closures can be con-

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\(^2\) The data to do this analysis for the petroleum industry exists, however the EIA has changed its data sharing policy as of 2017.
ceived as an issue within Environmental Federalism (Millimet, 2014). The boutique fuel standards were primarily designed to reduce ozone, and since ozone pollution depends on the local mix of nitrogen oxides (\(NO_x\)) and volatile organic compounds (VOCs), heterogeneous fuel standards at the county level make sense in the context of Oates’ Decentralization Principle - the scale of the regulation should match the scale of the externality (Oates, 1972). For this policy in particular, however, the production and transportation network do not match the scale of the regulation. The incongruence between policy and production can create risk of supply interruptions, and contribute to other distortions that have economic consequence.\(^3\)

From a policy perspective, my study contributes to the evaluation of the CAAAs transportation fuel standards’ impact and efficacy. States subject to the fuel mandate have been associated with a positive and statistically significant increase in retail gasoline price when controlling for other factors (Chouinard and Perloff, 2007). Using a paired differences approach at the city level, Brown et al. (2008) shows that these boutique fuels cost an additional 3 cents per gallon in retail price on average. This cost is substantial given that the policy has been shown to have little to no impact on pollution levels except in the most strictly regulated state of California (Auffhammer and Kellogg, 2011). The extent to which this price increase is driven by an increase in the cost of production, or increased concentration, is a great avenue of future research.

This paper proceeds as follows, section 2.2 describes some key details on the regulation and industry. Section 2.3 presents an analytical model of spatially differentiated multi-product Cournot competitors who choose to invest in a new technology to produce a higher cost good, while subsection 2.3.4 simulates this model. Section 2.4 shows empirical evidence to support the model and the simulation. Section 2.5 concludes.

\(^3\) Muehlegger (2006) shows the boutique fuel standards can explain 70-90% of a price spike caused by an unexpected refinery outage in California, Illinois, and Wisconsin. This is driven by the difficulties in sourcing alternative fuels that meet the local standard.
2.2 Background on the Regulation and Industry

The CAAAs consist of three petroleum relevant regulations including maximum Reid vapor pressure to decrease volatile organic compounds, minimum added Oxygenate to reduce carbon monoxide, and a reformulated gasoline (RFG) standard to address ozone formation. While all three are significant, RFG has been most directly associated with increased costs and a change of refinery operations (Sweeney, 2014). My analysis will exclusively consider the impact of RFG, but can easily be extended to encompass alternative fuel policies.

Promulgated in 1990, Phase I RFG fuels were mandated in counties of severe ozone non-attainment in 1995. It is important to note there is a lag between policy creation and implementation, during which firms had the opportunity to adapt. The RFG standard consists of a fuel with a level of benzene, volatile organic compounds, and toxic air pollutants that is less than those of average gasoline products, however there are multiple ways a fuel can achieve this standard. Some counties opted into the fuel standard as part of their state’s implementation plan to achieve ozone compliance, while a few other counties chose to opt out.\(^4\) Notably, the entire state of California adopted reformulated fuel standards and enforced a standard stricter than Federal guidelines. Because these regulations were mandated in disproportionately populated areas, over 30% of domestic consumption of gasoline includes these fuels. Phase II introduced in 2000 involved stricter standards addressing \(NO_x\). The implications for refineries consist of increased fixed and variable costs as well as the segmentation of a once homogeneous product market into a patchwork of specialized fuels.

As an industry, refining possess unique characteristics. It is the intermediate production process between crude extraction and retail sale of petroleum products (predominately distillate, gasoline, diesel, jet fuel), as shown in Figure 2.3. Firms in this industry are both vertically and horizontally integrated, owning upstream exploration, downstream retail, and multiple refineries. Gasoline accounts for the most significant share of output from a refinery, typically over 40%, while

\(^4\) A complete list of counties and their adoption date is available at [http://www.epa.gov/gasoline-standards/reformulated-gasoline](http://www.epa.gov/gasoline-standards/reformulated-gasoline), accessed 2/28/2016
distillate fuels (diesel) typically account for an additional 30%. Various technologies are employed at variable capacities to transform crude into refined products. The basic process involves a distillation tower to separate elements of crude oil, an upgrading of the distillation vapors, and then a host of process to purify the product. While certain technologies, such as upgrading and desulphurization, have been associated with RFG, there is no singular technology that produces RFG exactly (Office of Technology Assessment, 1990). This is in part due to the various ways in which fuel can meet RFG requirements in addition to the ambiguous engineering relationship between technologies and pollutants.⁵

![Figure 2.3: Supply Chain for Reformulated Gasoline.](image)

The geography of petrol production and distribution is not uniform across the US and incongruent with RFG markets. Figure 2.4 shows the refinery locations in addition to operating pipelines for finished products. Aggregate markets commonly used in analysis are referred to as Petroleum Administrative Defense Districts (PADD). A majority of production is accomplished in PADD 2 (Midwest) and PADD 3 (Gulf Coast), primarily because these market’s proximity to waterways that are connected to crude production areas. PADD 4 (Rockies) and PADD 5 (West Coast) are largely isolated, in part because of the difficulty crossing the Pacific Ocean and the Rocky Mountains. The largest net importer is PADD 1 (East Coast), as there is not much conventional oil produced in this area, and there is a high demand for oil products. During the study period gasoline was predominately transported via petroleum product pipelines, however shipments by barge, rail, or transport truck do happen, albeit with higher transportation costs.

The dynamics of this industry are particularly interesting, the number of refineries has declined considerably and consistently since domestic price supports and subsidies were dismantled

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⁵ For example, hydro-treating reduces aromatics (good) and hydro-cracking increases concentration of olefin (bad), catalytic reforming increases aromatics (bad) and reduces the concentration of olefin (good) (Office of Technology Assessment, 1990).
Data is publicly available from the EIA. Colors represent PADD regions, dots represent refinery with the diameter proportion to refinery capacity, and the lines represent pipelines for transporting crude and gasoline products.
in 1981 as shown in Figure 2.2. Chesnes (2009) considers the dynamic investment decision of refineries, emphasizing the high capacity utilization rates despite a declining number of plants. Empirical work looking at the refining industry from 1947 to 2013 finds refinery size and the degree of multiple plant ownership as major drivers of plant closure, with multiplant owners choosing to close the smaller plants (Meyer and Taylor, 2015). Considering the importance of policy, Chen (2002) uses survival analysis to determine plants that were subsidized in the 1970s were more likely to close once the subsidies were dismantled in the 1980s. Breaking down the number of refineries by PADD, as in Figure 2.5, shows the geographic distribution of exit varies more after the Phase 1 or RFG was implemented. Exit trends since the end of the price supports equalize across PADDs. Most of the refineries that exited were in PADD 3, while very few refineries exited in PADD 1 and PADD 4.

Figure 2.5: Number of Refineries by PADD.

This figure shows the number of refineries by PADD per year as a percentage of the number of refineries in that PADD in 1995 when RFG Phase I went into effect.

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2.3 Modeling Refinery Response

2.3.1 Baseline Model

I model \( N \) petroleum refineries competing in \( M \) geographic markets.\(^7\) Refinery \( n \) chooses to sell \( q_{nm} \) units of gasoline to market \( m \), however incurs a transportation costs equal to \( \tau_{nm} \) for every unit sold. Inverse demand in each market, \( m \), is given by \( P(Q_m) \) where \( Q_m = \sum_n q_{nm} \) denotes aggregate gasoline sold in market \( m \) with \( P'(Q_m) < 0 \). The cost of producing gasoline is convex, to characterize the capacity constraints associated with petroleum refineries, and a function of the total amount of gasoline sold by firm \( n \): \( C(q_n) \) where \( q_n = \sum_m q_{nm} \) and \( C'(q_n) > 0 \) and \( C''(q_n) > 0 \).

All together, this implies the profits of firm \( n \) can be characterized by \( q_n = [q_{n1} \ldots q_{nM}]' \)

\[
\pi_n(q_n) = \sum_m [P(Q_m) - \tau_{nm}] q_{nm} - C(q_n)
\] (2.1)

Because demand is identical across markets, and cost of production are identical across refineries, the refineries are only differentiated by their transportation cost. The difference in transportation costs could be thought of firm’s having different costs of production to sell in different markets. The refinery will choose the set of \( q_{n1}, \ldots, q_{nM} \) to maximize their profits taking the quantities from the other refineries as given. The \( m \) first order conditions for firm \( n \) are

\[
P(Q_m) + P'(Q_m)q_{nm} - \tau_{nm} = C'(q_n), \quad \forall m
\]

This set of first order conditions depends on the production of other refineries in the same market through \( Q_m \), but also the production of this refinery in other markets, through \( q_n \). From this first order condition we can see that the refinery will set the marginal revenue net transportation costs equal to the same marginal cost across all markets. If competitors supply the same amount to market \( i \) and market \( j \), firm \( n \) will sell more in market \( i \) if \( \tau_{ni} < \tau_{nj} \). So each refinery will sell more gasoline to closer markets, all else equal.

The set of first order conditions for all refineries, across all markets, characterize the equilibrium quantities \( q_{nm}^* \). The prices per market will be determined by \( P(Q_m^*) \) and profits will be

\(^7\) The geographic markets can be thought of as counties within the United States.
be given by equation 2.1. Because of the asymmetry in transportation costs, an analytical Nash equilibrium is difficult to solve for. However, because transportation costs determine the quantity produced by every refinery, the aggregate quantity in a market $Q_m^*$ will depend on the transportation costs of all firms selling to that market, $\tau_1, \ldots, \tau_N$, and markets with smaller total transportation costs will have lower prices.

If inverse demand is linear, of the form $P(Q_m) = a - bQ_m$, and costs are quadratic, of the form $C(q_n) =cq_n^2$, the first order condition can be expressed as a system of equations in matrix form:

$$A = BQ_{N\times M} + Q_{N\times M}C$$

(2.2)

where element $(n, m)$ of $Q_{N\times M}$ is $q_{nm}$. Here $A = [1_{N\times M}a - \tau_{N\times M}]$, $B = b[1_{N\times N} + I_N]$, and $C = 2c[1_{M\times M}]$ where element $(n, m)$ of $\tau_{N\times M}$ is $\tau_{nm}$, $I_N$ is an identity matrix of size $N$ and $1_{N\times M}$ is a matrix of ones. This is a Sylvester equation and has a solution as long as the $B$ and $-C$ do not share an eigenvalue.

### 2.3.2 Introduction of New Product

I now model the market structure after a new, more expensive, product is mandated in some geographic markets. In the context of the reformulated gasoline standards of the 1990 Clean Air Act Amendments, this represents the counties in which only a cleaner burning fuel could be sold. I denote these markets by $M^r \subset \{1, \ldots, M\}$, and the conventional markets are denoted by $M^c = \{1, \ldots, M\} \setminus M^r$. The refinery now chooses how much to produce of each type of product, where $q^r_{nm}$ denotes the new product sold by refinery $n$ to market $m \in M^r$, and $q^c_{nm}$ is the quantity of the conventional fuel type sold by firm $n$ to market $m \in M^c$.

I first assume that it is costless to acquire the technology to produce and sell this product, however this product has an additional marginal cost of production $c_r$. Refineries now have the
following profit function

$$\pi_n(q_n) = \sum_{m \in M} [(P(Q_m) - \tau_{nm} - c_r) q_{nm}^r] + \sum_{m \in M_c} [(P(Q_m) - \tau_{nm}) q_{nm}^c] - C(q_n)$$

Choosing $q_{nm}$ to maximize their profits results in first order conditions

$$P(Q_m) + P'(Q_m) q_{nm}^c - \tau_{nm} = C'(q_n), \quad \forall m \in M^c$$

$$P(Q_m) + P'(Q_m) q_{nm}^r - \tau_{nm} - c_r = C'(q_n), \quad \forall m \in M^r$$

This can be incorporated into the Sylvester Equation 2.2 by redefining $A = [1_{N \times M} a - \tau_{N \times M}] - c_r 1_{N \times 1} R_{1 \times M}$ where element $m$ in $R_{1 \times M}$ equal 1 if market $m$ is subject to the regulation and 0 if it is not.

From these first order conditions we see that the refinery will choose to sell less in the markets where the higher cost gasoline is mandated ($m \in M^r$), all else equal, because the cost of production has increased in these markets. Because the quantity sold in markets $m \in M^r$ has reduced, the firm will increase in the quantity sold in $m \in M^c$. This happens because the marginal cost of production is a function of total quantity produced, and producing less in $m \in M^r$ decreases this marginal cost of total production, $C'(q_n)$, because costs are convex. In the markets where costs have not changed, $m \in M^c$, the refinery will choose to increase their quantity sold to match marginal revenue to the lower marginal costs. This static result of cross-product spillovers is the premise of Sweeney (2014).

### 2.3.3 New Product Requires Investment

I now consider the dynamic effects of the new product mandate by considering the incentives of refineries to expend a fix cost $F_r$ to have the ability to sell in the geographic markets where the more costly product is mandated. I denote whether refinery $n$ invests in the technology to produce the new product by the binary indicator variable $I_n$ which equals to 1 if refinery $n$ invests $F_r$ and 0 if they do not. As a result, there will two types of refineries, those that invest, and those that don’t. The refineries that invest receive revenue from both product markets, while those that don’t only receive revenue from the conventional product markets. So the general profit function is of
the form

$$\pi_n(q_n) = I_n \left[ \sum_{m \in M^r} [(P(Q_m) - \tau_{nm} - c_r) q_{nm}^r] - F_r \right] + \sum_{m \in M^c} [(P(Q_m) - \tau_{nm}) q_{nm}^c] - C(q_n)$$

The refinery’s decision to invest in the technology will depend on the additional variable profit they receive selling into \( m \in M^r \), the fixed cost \( F_r \), and how they substitute production away from \( m \in M^c \) and towards \( m \in M^r \). For a refinery to decide to invest, not only must the additional profit less the fixed costs be positive, but it must also be larger than the reduction in profits from selling less in the conventional markets. In equilibrium the decision to invest will not only depend on this trade off, but also the number of firms that are already selling into the reformulated market, as the revenues in the new product market will decrease with less market concentration.

Because the firms are only differentiated by their transportation costs, this will create a ranking that will determine which refineries will invest and which ones will not invest. For each refinery there is a vector of transportation costs \([\tau_{n1} \ldots \tau_{nM}]\). These vectors can be ordered based on the sum of total transportation costs to the markets with the new product \( m \in M^r \). The refinery that has the lowest total transportation costs to the new product market will invest first, followed by the refinery with the second most total transportation costs, and so on. This will continue until the marginal refinery becomes strictly worse off by expending the amount \( F_R \) to have access to the market.

I assume that the fixed costs are sufficiently high that there will be at least some refinery that will not want to invest in the new product. As a result, there will be less firms competing in the new product market. This concentration of the product market allows the refineries to charge a higher mark up than they would in the absence of the increase in the cost of production. This is because the new product has segmented the market. This increased mark up increases the profitability of the refinery, and reduces the probability that they will shutdown and exit the market. As a result, the refineries that are most exposed to the regulation can benefit the most by investing into the new product, which will be a more concentrated market. I will now illustrate this with a numerical example.
2.3.4 Numerical Simulation of the Model

I assume that there are three refineries spaced between two geographic markets, \( n \in \{1, 2, 3\} \), \( m \in \{A, B\} \). The transportation costs from firm \( n \) to market \( m \) are such that firm 1 is near market A, firm 3 is near market B, and firm 2 is in the middle. Illustratively, market A is a county in Wyoming and market B is Brooklyn, NY. Firm 1 would be a refinery in Denver, firm 2 would be a refinery in Louisiana, and firm 3 would be a refinery in New Jersey. Numerically, I choose

\[
\begin{align*}
\tau_{1A} &= \tau_{3B} = 10 \\
\tau_{2A} &= \tau_{2B} = 20 \\
\tau_{3A} &= \tau_{1B} = 30 
\end{align*}
\]

Inverse demand is identical at each geographic market and given as \( P(Q_m) = 100 - 10Q_m \). A firm produces a total of \( q_n \) in the absence of any policy, considered to be the baseline and incurs a cost of \( C(q_n) = \frac{1}{2}q_n^2 \). After the policy has been put in place, only a more expensive product can be sold in market B. Now, the total amount of quantity produced can be decomposed into the conventional product and the higher cost product: \( q_n = q_c^n + q_r^n \). The marginal cost of producing this more expensive unit is 10 dollars so that costs are now \( C(q_n, q_r^n) = \frac{1}{2}q_n^2 + 10q_r^n \).

I consider alternative investment scenarios and solve for the optimal quantity produced by each firm using according to Equation 2.2 with matrix \( A \) taking into account the additional marginal cost of producing the good for the regulated market. First I consider a “baseline” scenario in which there is no policy that mandates a cleaner product be sold in certain geographic areas. Next, I consider the variable profits when all three firms invest in the technology to produce the new product, when just the two closest firms invest in the technology to produce the new product, when only the closest firm invests, and finally when no firm invests. If firm \( n \) invested, then \( I_n = 1 \). I denote \( I = \{I_1, I_2, I_3\} \). The results are presented in Table 2.1.

We see that all firms are better off in the baseline scenario than when the higher cost product is mandated in certain counties and they all invest in the technology to produce the new product.
Table 2.1: Profits from Numerical Simulation.

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>${1, 1, 1}$</th>
<th>${0, 1, 1}$</th>
<th>${0, 0, 1}$</th>
<th>${0, 0, 0}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm 1</td>
<td>99.82</td>
<td>95.47</td>
<td>92.35</td>
<td>91.0</td>
<td>85.9</td>
</tr>
<tr>
<td>Firm 2</td>
<td>79.82</td>
<td>70.47</td>
<td>77.79</td>
<td>43.48</td>
<td>39.98</td>
</tr>
<tr>
<td>Firm 3</td>
<td>99.82</td>
<td>85.47</td>
<td>97.56</td>
<td>158.8</td>
<td>11.4</td>
</tr>
</tbody>
</table>

Notes: The Baseline simulation assumes there is only one product sold in all markets with identical costs. The other columns are the corresponding variable profits depending on which of the refineries, 1, 2, or 3, invested in the technology to produce the more expensive good, $I = \{I_1, I_2, I_3\}$

This is because the cost of production has increased. As expected, the refinery that is most exposed to the regulation, firm 3, loses the most profit after the policy has been put into effect and all firms decide to invest. If only the two refineries closest to the regulation decide to invest in the new technology, both of them will do better than if all three were to have invested in the technology, and firm 3 does better than firm 1. Although firm 3 is worse off relative to the baseline case, they are the most profitable of all three firms. This is because they are able to compete in a more concentrated market, and have the lowest transportation cost to this more concentrated market.

In the situation when only the closest refinery will sell into the new product market, their profit is the largest. It is even larger then the profit they would receive in the baseline scenario, when no higher cost product is mandated. This is because firm 3 is able to operate as a monopolist in market B. In the scenario in which no one invests in the technology to produce the higher cost market, all refineries are worse off because market B is effectively closed.

Which investment decision, and profits, are realized depends on the fixed cost $F_r$. In this simulation, firm 3 will invest as long as the fixed costs doesn’t exceed the increase in their profits relative to $I_n = \{0, 0, 0\}$, a total of $147.4$. Knowing that firm 3 has the bigger incentive to invest, and will invest first, firm 2 will only want to invest when the fixed costs is less than how their profits change going from $\{0, 0, 1\}$ to $\{0, 1, 1\}$, which equals $34.31$. In this particular scenario, firm 3’s variable profit are larger after the regulation goes into place as long as $34.31 < F_r < 147.4$. For their total profit, including the fixed costs, to be larger than the baseline, the fixed costs must not exceed $58.98$. 


The quantities each firm produces under the base line scenario, $I = \{1, 1, 1\}$, and $I = \{0, 1, 1\}$ are shown in Figure 2.6. This model illustrates how the segmentation of the product market associated with an environmental policy can offset the cost of compliance. Because a new product is introduced, and it is costly to obtain the ability to produce the new product, not all of the producers will decided to produce the new good. Although the variable costs of the new good are higher, the firms that decided to produce the good do so in a more concentrated industry. This concentration effect can increase the profits of the firm that is the most exposed to the policy, mitigating industry concern regarding the impact of the environmental policy.

Although it is not the main objective of this paper, it is worth while pointing out the total welfare effects of this policy taking into account the change in market structure. Although firm 3 is best off when $I = \{0, 0, 1\}$, consumers are worse off, as the prices are higher in market B. These higher prices are due to the higher cost of production and the concentration of the product market. Although the prices decrease in market A, the magnitude is much smaller relative to the price increase in market B. Overall, total welfare goes down because of the market concentration (not taking into account the benefits of reduced pollution). Because implementing environmental policies that harm industry are often more difficult, the reduction in consumer welfare due to market power might be admissible given political economy concerns.

2.4 Empirical Evidence

I now look at annual data on refinery operations in the United States from 1987 to 2008 to show evidence consistent with the theory outlined in section 2.3. Although the theoretical predictions in section 2.3 are regarding the profits of refineries with different exposure to the policy, I have limited information on the quantities prices of refinery sales, and the cost of operation. Instead, I take a latent profit approach and consider a refineries decision to shut down to be indicative of their profits.\footnote{The latent profits approach is motivated by Bresnahan and Reiss (1991).} In what follows, I take a few approaches to estimate the relationship between exposure to reformulated gasoline standards and the refineries decision to exit the market.
Figure 2.6: Prices and Quantities from Simulation.

Baseline Scenario

\[ p_A = 42.9 \quad p_B = 42.9 \]

2.90 \leftrightarrow 0.90

1.90 \leftrightarrow 1.90

0.90 \leftrightarrow 2.90

All Firms Invest

\[ p_A = 42.7 \quad p_B = 50.2 \]

2.91 \leftrightarrow 0.66

1.91 \leftrightarrow 1.66

0.91 \leftrightarrow 2.66

Only Firm 2 and 3 Invest

\[ p_A = 42.6 \quad p_B = 52.5 \]

2.97 \leftrightarrow 0

1.89 \leftrightarrow 1.87

0.89 \leftrightarrow 2.87

The arrows indicate the quantity supplied of to each market by each firm.
2.4.1 Data

EIA-820, published annually by the Energy Information Agency, provides firm-level data on operating status and capacity for various technologies of all refineries of the United States. While the refinery’s name and location is available for all years, the exact spelling varies significantly over time due to inconsistent form filing, mergers and acquisitions, and re-branding by the refinery’s parent company. I write an algorithm that probabilistically matches refineries based on the observation year, the refinery’s location, and a measure representing the similarities in name character string and capacity levels. This identifies all but 20 firms, who were subsequently identified manually. While a measure of exit can be inferred from these data, some firms still submit reports years after official closure. To ensure that refineries have exited, EIA-820 is cross referenced with closure listings from the American Petroleum Institute (API) annual data book. The present sample covers a period of 21 years from 1987 to 2008, with 211 plants in the beginning of the sample and a total of 147 in the final year. Of the 64 plants that exited the market during the sample period, 42 were before RFG phase I was implemented in 1995.

To measure capital technology, I calculate a index commonly used in the industry, the Nelson Complexity Index. Introduced in the 1960s, this index represents the financial investment per unit capacity and has often been used to measure refinery sophistication. Relative weights for capacity of different technologies are shown in Table 2.2. In general, less sophisticated refineries should be at a greater risk of exit. I measure investment of a refinery as the year-to-year change in the Nelson Index.

To measure the exposure of refineries to markets where the boutique fuels were mandated I use GIS to calculate a unit-less measure representing the proportion of the refinery’s consumer base that are in counties with fuel standards. Explicitly I calculate

\[
Exposure_n = \frac{\sum_{m \in M^r} \frac{Population_m}{\tau_{nm}}}{\sum_{m \in M^r} \frac{Population_m}{\tau_{nm}}}
\]

for every refinery \(n\), where \(Population_m\) is the population of county \(m\) from the 2014 census and \(\tau_{nm}\) is the transportation cost from refinery \(n\) to market \(m\) taking the least cost path through
Table 2.2: Nelson Complexity Index.

<table>
<thead>
<tr>
<th>Refining Process</th>
<th>Index per Unit Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distillation Capacity</td>
<td>1</td>
</tr>
<tr>
<td>Vacuum Distillation</td>
<td>2</td>
</tr>
<tr>
<td>Thermal Process</td>
<td>2.75</td>
</tr>
<tr>
<td>Coking</td>
<td>6</td>
</tr>
<tr>
<td>Catalytic Cracking</td>
<td>6</td>
</tr>
<tr>
<td>Catalytic Reforming</td>
<td>5</td>
</tr>
<tr>
<td>Catalytic Hydrocracking</td>
<td>6</td>
</tr>
<tr>
<td>Catalytic Hydrorefining &amp; Hydrotreating</td>
<td>2.5</td>
</tr>
<tr>
<td>Alkylation/Polemerization</td>
<td>10</td>
</tr>
<tr>
<td>Aromatics/Isomerization</td>
<td>15</td>
</tr>
<tr>
<td>Lubes</td>
<td>60</td>
</tr>
<tr>
<td>Asphalt</td>
<td>1.5</td>
</tr>
<tr>
<td>Hydrogen (MCfd)</td>
<td>1</td>
</tr>
<tr>
<td>Oxygenates (MTBE/TAME)</td>
<td>10</td>
</tr>
</tbody>
</table>

Adopted from Nelson (1976)
pipelines, barges, and highways. $Exposure_n$ varies over time as a few counties adopted boutique fuel standards after 1995, and is equal to zero prior to the implementation of the boutique fuel standards.

Following Muehlegger (2006), transportation costs are 2 and 4.5 cents per thousand mile-gallon (in 2003 dollars) for pipeline and barge respectively. Although Muehlegger (2006) employs a transportation cost of 30 cents per thousand mile-gallon of ground transportation, I separate this into 25 cents for major US highways and 40 cents for terrain absent of pipelines, barges, or highways. This reflects the difference in city and highway fuel economy. Lastly, elevation data are incorporated into transportation cost by multiplying the horizontal distance traveled by $1/cos(\theta)$, where $\theta$ is the slope of elevation derived from a Digital Elevation Model raster file. Figure 2.7 show examples of the cost distance maps used to calculate this measure for the a refinery in the Gulf Coast and California.

Other variables of interested include a PADD-level measure of profitability known as “crack spread” as well as industry specific cost factors such crude quality, electricity and natural gas prices sourced from the EIA. Although age is typically an important variable in exit analysis, is it hard to find public and reliable data on the age of refineries in the US. Further, papers estimating the determinants of refinery exit do not find age to be a statistically significant factor (Chen, 2002; Meyer and Taylor, 2015).

Table 2.3 and Table 2.4 show some summary statistics of the data. We see refineries vary greatly in the sophistication, as measured by the Nelson Index. Change in the Nelson Index, measured as Investment, also seems to vary significantly in the sample. The maximum exposure of refineries to RFG, $Expose_n$, during the sample period varies from 10 percent of the refineries cost discounted consumer base to up to 73 percent of the refineries cost discounted consumer base, showing a good deal of variation in exposure to the policy. The Herfindahl-Hirschman Index within a state varies from zero (no refineries exist in that state) to one (one refinery exists in that state),

---

9 3 barrels of crude typically product 2 barrels of gasoline and 1 barrel of distillate. The crack spread typically measures $2 \times (\text{Price of gas}) + (\text{Price of distillate}) - 3 \times (\text{Cost of Crude})$. I use a ratio of revenue to cost instead of the difference.
Figure 2.7: Cost Distance Map.

The color represents the cumulative cost path from the refinery to the county, taking the least cost path. The points in these maps represent counties, with the color of the point signifying if a fuel standard was ever required in that county.
Table 2.3: Refinery - Year Summary Statistics.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nelson Index</td>
<td>.794</td>
<td>.931</td>
<td>0</td>
<td>5.39</td>
<td>3,539</td>
</tr>
<tr>
<td>Investment</td>
<td>.0116</td>
<td>.0916</td>
<td>-1.7</td>
<td>1.64</td>
<td>3,327</td>
</tr>
<tr>
<td>Operating Capacity</td>
<td>102,369</td>
<td>106,028</td>
<td>0</td>
<td>590,500</td>
<td>3,539</td>
</tr>
<tr>
<td>Max Exposure to RFG</td>
<td>.263</td>
<td>.131</td>
<td>.102</td>
<td>.726</td>
<td>3,539</td>
</tr>
</tbody>
</table>

with an average of 0.55, indicating high concentration of the refinery markets at the state level on average.

2.4.2 Empirical Framework

The continuous decline of refineries since 1981 as shown in Figure 2.2 motivates the use of survival analysis to determine how RFG impacts a firm’s risk of exit. Survival analysis considers the risk of instantaneous exit conditional on the fact that the firm is still alive. The objective is to estimate a hazard function of the form

\[
\lambda(t) = \frac{f(t)}{1 - F(t)}
\]  

(2.4)

where \(F(t)\) and \(f(t) = \frac{d}{dt}F(t)\) are the cumulative and instantaneous probability of exit at time \(t\). The denominator is often called the survivor function. A key feature of hazard function is the assumption placed on the distribution of \(t\). A correct specification is necessary for consistent estimates. Broadly, there are two types of models employed in survival analysis. The proportional hazard and accelerated failure time model.

The proportional hazard specification is of the form \(\lambda(t|X'\beta) = \lambda_0(t)\phi(X'\beta)\) where \(\lambda_0(t)\) is the baseline hazard, independent of \(X'\beta\), \(X\) is matrix of control characteristics, and \(\beta\) is a vector

Table 2.4: State - Year Summary Statistics.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>State HHI</td>
<td>.555</td>
<td>.339</td>
<td>0</td>
<td>1</td>
<td>685</td>
</tr>
<tr>
<td>Crack Spread</td>
<td>1.68</td>
<td>.185</td>
<td>1.28</td>
<td>2.32</td>
<td>685</td>
</tr>
<tr>
<td>Crude Gravity</td>
<td>32</td>
<td>2.47</td>
<td>24.9</td>
<td>36.2</td>
<td>685</td>
</tr>
<tr>
<td>Crude Sulfur Content</td>
<td>1.18</td>
<td>.212</td>
<td>.76</td>
<td>1.7</td>
<td>685</td>
</tr>
<tr>
<td>Price of Gasoline</td>
<td>.892</td>
<td>.278</td>
<td>.48</td>
<td>1.82</td>
<td>563</td>
</tr>
<tr>
<td>Price of Electricity</td>
<td>5.3</td>
<td>.493</td>
<td>4.56</td>
<td>6.15</td>
<td>563</td>
</tr>
</tbody>
</table>
of parameters. \( \phi(X'\beta) \) shifts the baseline hazard up or down, depending of the parameter values and the values of \( X \). The distribution of \( t \) determines the functional form of the baseline hazard, \( \lambda_0(t) \). If \( t \) is exponential, the baseline hazard is constant, while a Weibull distribution of \( t \) implies a baseline hazard that is monotone increasing or decreasing. It is also possible to estimate a semi-parametric Cox Proportional Hazard model, where the estimates of \( \beta \) are recovered without specifying the functional form of \( \lambda_0(t) \).

In contrast to the proportional hazard model, the accelerated failure time model is of the form \( \lambda(t|X'\beta) = \lambda_0(t\phi(-X'\beta))\phi(X\beta) \), allowing for a non-monotonic \( \lambda_0 \). Common distributions employed include Log-normal or Gamma. Although the Weibull proportional hazard is most frequently used in the literature, the empirical distribution of the hazard function should help determine which specification is appropriate. Figure 2.8 shows the non-parametric estimate of the Kaplan-Meier survival function for the full sample. The linear trend over time suggest the Weibull proportional hazard function is an appropriate specification.

Figure 2.8: Kaplan-Meier Survival Estimate from the Full Sample.

Non-parametric estimates of the cumulative probability a firm is still operating. Analysis time is an annual count normalized such that 1986 is year zero.

I specify \( \phi(X'\beta) \) to be of the form \( e^{X'\beta} \) where \( X \) consists of determinants of a refinery’s decision to exit the market. This includes state level measures of crude quality and the crack
spread, a PADD-specific indicator variable, an indicator variable for if the year is before RFG phase I (1995) or a year-specific indicator variable, as well as a measure of refinery exposure to RFG, Equation 2.3, the exposure measure squared, and the maximum refinery level exposure during the sample period. The coefficients of interest are on the measure of refinery exposure, and the measure of refiner exposure squared. I include a squared term because of the non-linear relationship between refinery exposure to RFG and profits illustrated in section 2.3. One row in $X'\beta$ looks like

$$\beta_1 \text{Expose}_{nt} + \beta_2 \text{Exposure}_{nt}^2 + \beta_3 \text{MaxExposure}_n +$$

$$\beta_4 \text{Sulfur}_{st} + \beta_5 \text{Gravity}_{st} + \beta_6 \text{CrackSpread}_{st} + \gamma_t + \delta_P$$

Where $\text{Exposure}_{nt}$ is the exposure of refinery $n$ to the fuel mandate at time $t$ which equals to zero in the pre-period. $\text{MaxExposure}_n$ is a refinery specific measure of the maximal eventual exposure to the fuel standard. $\text{Sulfur}_{st}$, $\text{Gravity}_{st}$, and $\text{CrackSpread}_{st}$ are state-year control variables. Finally, $\gamma_t$ denotes a time period fixed effects (either yearly fixed effects or a pre-post fixed effect), and $\delta_P$ is a PADD specific fixed effect.

Identification of the effect RFG on the propensity of a refinery to shutdown comes from a difference in difference type argument in the potential outcomes framework. The variable $\text{Exposure}_{nt}$ measures the intensity of treatment for each refinery, and is time varying as new counties adopt boutique fuel standards, and zero prior to the policy implementation. By controlling for the pre and post policy average rate of exit (or annual average rate of exit), as well as the maximum eventual exposure of the refinery to the mandate, $\text{MaxExposure}_n$, I am able to estimate how more exposure to the regulatory fuel standard impacted the decision to exit taking into account general trends in the exit rate over time as well as time invariant determinants of exit that might be correlated with $\text{Exposure}_{nt}$. The PADD fixed effects take into account the time invariant average exit rate within a PADD, so that I am using the spatial variation in exposure to reformulated gasoline within a PADD.

Credible identification requires that there is no other determinant of exit that is correlated with a refineries exposure to the fuel standards. Table 2.5 shows that refineries are similar across
Table 2.5: Summary Statistics by Exposure Quartile.

<table>
<thead>
<tr>
<th></th>
<th>Quartile 1</th>
<th>Quartile 2</th>
<th>Quartile 3</th>
<th>Quartile 4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nelson Index</td>
<td>.706</td>
<td>.343</td>
<td>.392</td>
<td>.915</td>
<td>.582</td>
</tr>
<tr>
<td></td>
<td>(.67)</td>
<td>(.583)</td>
<td>(.655)</td>
<td>(1.04)</td>
<td>(.788)</td>
</tr>
<tr>
<td>Investment</td>
<td>.00937</td>
<td>.00675</td>
<td>.003</td>
<td>-.000824</td>
<td>.0045</td>
</tr>
<tr>
<td></td>
<td>(.0181)</td>
<td>(.0176)</td>
<td>(.0241)</td>
<td>(.0461)</td>
<td>(.029)</td>
</tr>
<tr>
<td>Operating Capacity</td>
<td>94,975</td>
<td>53,497</td>
<td>53,827</td>
<td>114,273</td>
<td>78,353</td>
</tr>
<tr>
<td></td>
<td>(83,391)</td>
<td>(75,658)</td>
<td>(80,157)</td>
<td>(114,379)</td>
<td>(92,973)</td>
</tr>
<tr>
<td>Max Exposure to RFG</td>
<td>.164</td>
<td>.201</td>
<td>.226</td>
<td>.455</td>
<td>.264</td>
</tr>
<tr>
<td></td>
<td>(.0279)</td>
<td>(.00559)</td>
<td>(.0119)</td>
<td>(.118)</td>
<td>(.13)</td>
</tr>
</tbody>
</table>

Standard errors are in parentheses.

quartiles of $MaxExpos{e}_{a}$, suggesting that they are similar on unobservable measures as well. One threat to identification is that the policy is endogenous, as emphasized by Besley and Case (2000).\footnote{To address this concern, non-attainment in National Ambient Air Quality Standards would be a source of exogenous variation, as it determines policy implementation but not the exit rate of refineries.}

Overall this is not a major concern; as the policy was federally mandated and on a downstream product. There are some concerns where counties opted in or out of the policy, or refineries lobbied for the policy, especially in the case of California. However, this concern only speaks to rent seeking behavior of the refineries, and is consistent with the results presented in section 2.3.

As in all difference in differences approaches, the key to valid estimates is that the treated group acts like the control group in the absence of treatment. We can look for similarities in the pre-treatment trends as done in Figure 2.9. All expect the lowest quartile of exposure to RFG shows similar trends prior to RFG Phase 1. Though it is clear that the post treatment trends differ from the pre-treatment, with less exits for the refineries in the outer quartiles. This suggest a non-linear effect of RFG exposure on refiner exit which can be tested in the data.

### 2.4.3 Empirical Results

I estimate the model using the annual data from EIA-820 with the Cox and Weibull proportional hazard specification, as well as with a probit and linear probability specification. The
Figure 2.9: Differential Exit by RFG Exposure Quartile.

Number Refineries Normalized to 1995
By Within PADD RFG Exposure Quartile

Annual level is the number of operating firms divided by the number of operating firm in 1990. Quartiles are defined by the RFG exposure measure described in the text.
coefficients in the proportional hazard and probit specifications are estimated using maximum likelihood and the coefficients in the linear probability model are estimated using ordinary least squares. The results, in terms of marginal effects, are presented in Table 2.6. Across all specifications the qualitative relationship between exposure to RFG and the hazard rate, or probability of exit, are similar.

Table 2.6: Regression Results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cox PH</th>
<th>Weibull PH</th>
<th>Probit</th>
<th>Linear P.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure to RFG</td>
<td>37.66*</td>
<td>34.86*</td>
<td>18.25**</td>
<td>0.280**</td>
</tr>
<tr>
<td></td>
<td>(20.38)</td>
<td>(18.66)</td>
<td>(8.297)</td>
<td>(0.101)</td>
</tr>
<tr>
<td>Exposure to RFG^2</td>
<td>-47.28*</td>
<td>-44.77*</td>
<td>-22.17**</td>
<td>-0.334***</td>
</tr>
<tr>
<td></td>
<td>(27.16)</td>
<td>(24.11)</td>
<td>(10.50)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>Nelson Index</td>
<td>-4.638***</td>
<td>-4.724***</td>
<td>-2.176***</td>
<td>-0.0158***</td>
</tr>
<tr>
<td></td>
<td>(0.739)</td>
<td>(0.758)</td>
<td>(0.335)</td>
<td>(0.00217)</td>
</tr>
<tr>
<td>Crack Spread</td>
<td>-0.808</td>
<td>1.250</td>
<td>-0.149</td>
<td>-0.0170</td>
</tr>
<tr>
<td></td>
<td>(2.587)</td>
<td>(0.783)</td>
<td>(1.430)</td>
<td>(0.0436)</td>
</tr>
<tr>
<td>Crude API gravity</td>
<td>-0.363</td>
<td>-0.529**</td>
<td>-0.188</td>
<td>-0.00242</td>
</tr>
<tr>
<td></td>
<td>(0.259)</td>
<td>(0.214)</td>
<td>(0.127)</td>
<td>(0.00259)</td>
</tr>
<tr>
<td>Crude sulfur</td>
<td>-2.460</td>
<td>-6.021***</td>
<td>-1.241</td>
<td>-0.0282</td>
</tr>
<tr>
<td></td>
<td>(2.340)</td>
<td>(1.539)</td>
<td>(1.025)</td>
<td>(0.0247)</td>
</tr>
<tr>
<td>Max Exposure to RFG</td>
<td>1.988</td>
<td>2.543</td>
<td>1.002</td>
<td>0.0297</td>
</tr>
<tr>
<td></td>
<td>(1.496)</td>
<td>(1.630)</td>
<td>(0.705)</td>
<td>(0.0313)</td>
</tr>
<tr>
<td>PADD Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pre/Post Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>3,495</td>
<td>3,495</td>
<td>3,004</td>
<td>3,539</td>
</tr>
<tr>
<td>R-squared</td>
<td></td>
<td></td>
<td></td>
<td>0.02</td>
</tr>
</tbody>
</table>

Robust standard errors in parenthesis. *, **, and *** denote 0.1, 0.05, and 0.005 level of significance respectively.

Interpreting the marginal effects for the proportional hazard models is not straightforward. These estimates represent the effect of a one unit increase in $\text{Exposure}_{nt}$ (going from 0 to 1) on the hazard ratio shown in Equation 2.4. While the units themselves are not meaningful, we can see the point estimates suggest the relationship is an inverted-U shape, with a peak at approximately
Exposure = 0.39. This general relationship can be said for the probit and linear probability model. This relationship is illustrated in Figure 2.10, where I’ve plotted the marginal effect of Exposure on the probability of exit for the probit and linear probability models. In these models, the coefficients are statistically significant from zero with a level of significance equal to 0.05.

These estimates suggest that the refineries that were most exposed to the reformulated fuel standards were less likely to exit the market, which would imply that they were relatively more profitable after the policy went into place. This is consistent with the model presented in section 2.3, where some refineries would invest in the technology to produce the higher cost product, but others would not. This market segmentation leads to concentration in the new product market, where refineries can now sell the product with a higher markup over the cost of production. As a final note of evidence, Figure 2.11 shows the average year-to-year change in the Nelson Index by quartile of Exposure. This represents the investment of refineries in new, more sophisticated technologies. We see that the quartile of refineries most exposed to RFG fuels invested much more than the others and this coincides with the RFG phase I and phase II, suggesting only they were able to sell the new product.

\[ y = ax^2 + b \]

For a polynomial of the form \( y = ax^2 + b \), the global maximum is \( -\frac{b}{2a} \). Taking the point estimates from columns one and two we find the maximum at \( 34.86/(2 \times 44.77) \) or \( 37.66/(2 \times 47.28) \).
Figure 2.11: Average Investment by RFG Exposure.
2.5 Conclusion

In this paper I show how environmental policies can impact the market structure in which firms compete. Looking at the Boutique Fuel Standards associated with the 1990 Clean Air Act Amendments, I show how the mandate of a cleaner burning fuel creates a new product market that segments the market. Using a model of Cournot competition, I simulate how the new standard can impact the profitability of refineries when producing the cleaner burning fuel requires a costly investment. Because not all refineries will decide to invest in the new technology, the new product market is more concentrated and refineries in this market can now charge a higher markup. Using data on annual refinery operations in the United States I show empirical evidence consistent with the theoretical predictions. The refineries that were most exposed to the environmental policy were less likely to exit the market.
Chapter 3

Demand Side Emissions Policies

Abstract: When implementing a Pigouvian tax to address an externality, a general principle is that the effectiveness of the policy is independent on where the tax is implemented. This would suggest that pricing the emissions associated with the generation, transmission, and distribution of electricity would be equally effective where the electricity is produced, or where it is consumed by residential, industrial, or commercial customers. I use hourly data on power plant generation and pollution emissions from 2010 to 2015 to evaluate alternative policies for addressing emission externalities associated with electricity generation. I show that the second best demand side policies, focusing on all generation within a given hour, are extremely ineffective in capturing the total variation in emission externalities. Conversely, a simple second best supply side policy can capture most of variation in emission externalities. This suggests that policies designed to address emission externalities should focus on wholesale markets operations and the generation of electricity, not utility retail pricing or demand response programs.

JEL classification codes: H23, Q48, Q58

3.1 Introduction

One of the preferred methods to address a market externality, going back to Pigou (1932), is to impose a tax on the transaction equal to the marginal external cost. Conventional wisdom suggests the physical incidence, on producer or consumers, should not impact the effectiveness of the externality correcting policy in competitive markets, as elucidated by Weyl and Fabinger
(2013). In the electricity industry, where there is a large potential for unpriced pollution emission externalities, there has been an abundance of policy proposals that depart from the ideal externality correcting tax, many of which focus primarily on changing consumer behavior. These policies that push for consumer responsibility include energy efficiency investments, retail rate design, and structuring demand response, are driven by utilities in the vacuum of State or Federal policy addressing emissions. While wide-spread, the ability of these demand side policies to address supply side emission externalities is not well characterized.

In this paper, I show the ‘second best’ demand side policies are not nearly as effective in addressing the emission externalities associated with the generation of electricity as the second best supply side policy. This is because there is significant heterogeneity in the marginal emissions across electricity generators within an hour, and consumers of electricity can not differentiate between different sources of electricity when they are making their consumption decision. Any policy that addresses the price paid by consumers, or the total demand within the electricity system, will not be able to directly address this heterogeneity. Instead, simple plant specific policies can address almost all of the variation in marginal external damages.

I show this using detailed data on plant-level hourly emissions in the United States from 2010 to 2015, and a new technique for evaluating alternative pricing structures as developed by Jacobsen et al. (2018). With these data and procedure, I am able to estimate the second best policy aimed at addressing emission externalities as a function of fundamental characteristics of electricity, such as it’s origin or the time of day that it is consumed. After making relatively weak assumptions about the substitution across electricity plants, the $R^2$ from the least-squares estimation of the second best policy represents the proportion of welfare that can be recovered by the second best policy relative to a benchmark policy that does not differentiate across product attributes. One benefit of this measure of relative policy effectiveness is that it doesn’t depend on the elasticity of demand or supply, or structural assumptions on pass-through.

These results are policy relevant. For one, these marginal external damages are large, surpassing the private marginal cost at times. If the policy design has significant implications on
policy effectiveness, it is important to design the best possible policy. Second, there is a current debate on which type of agent should address these externalities. Largely, utilities are pushing demand response and energy efficiency type programs while emphasizing consumer responsibility. Conversely, the wholesale electricity markets, like the New York Independent System Operator, are considering incorporating carbon damages into its decision to dispatch different units. My results suggest wholesale electricity market operators would be vastly more effective in addressing emission externalities than a distribution utility, and as such their role in policy making should be emphasized.

The impetus for related literature is Holland and Mansur (2008), which quantifies how real time electricity pricing would impact the average hourly emissions from producing electricity. Leveraging the fact that real time emissions policies will reduce variance in demand, they evaluate how less load variance impacts the average marginal emissions within a given area. Unsurprisingly, they find the relative effectiveness of real time electricity pricing on emission externalities depends on the local fuel mix. If the marginal units emit more pollution than the average unit, then real time electricity pricing reduced emission externalities. They find the effects to be small in magnitude, however by only looking at averages within a particular time frame, they are overlooking the cross-sectional variance of emission externalities. This paper revisits the effectiveness of retail pricing in addressing emissions externalities using a new technique, a richer and more recent data set.\footnote{Since Holland and Mansur (2008) there has been a rapid change in the mix of fuels used to generate electricity as natural gas prices have remained low and there has been more investment in renewable generation.}

In this paper, I not only evaluate how retail rates can impact emissions, but also explicitly recover retail rates that would be most effective in addressing emission externalities. This contributes to a more general, important, dialog on how can we design electricity rates to be more efficient.\footnote{Relevant papers for this discussion include Blonz (2016); Burger et al. (2019)}

Borenstein and Bushnell (2018) highlight the significant heterogeneity is hourly marginal social cost in generating electricity, as well as the incongruence of these real cost with the price paid by consumers. This hour-to-hour variation is primarily due to changes in the private marginal cost, not marginal emission damages. Despite this, there still is significant heterogeneity in marginal
external damages per unit of electricity and part of this paper is highlighting this feature of the US electricity grid.\textsuperscript{3}

Ideally, the price paid by a consumer would equal to the social marginal cost at any given time and any given location.\textsuperscript{4} My results suggest the only way to address the heterogeneity in emission externalities is to expose consumers to location specific retail rates, to have the ability to contract with specific electricity generators, or to have a supply side policy directed at each plant. Of these three, the supply side policy is the easiest to implement, and I recover the second best supply side policy which can address over 80\% of the variation in marginal external damages.

The paper proceeds as follows. Section 3.2 considers the theory behind second best policies to address emission externalities at both the demand and supply side. Section section 3.3 describes the data used in the analysis. Section 3.4 presents the second best emission policies, as well as the $R^2$ values representing the relative performance of the different second best policies. Section 3.5 explicitly calculates the absolute dead weight loss (DWL) associated with alternative policies with generous assumptions on supply and demand. Section 3.6 concludes the paper.

3.2 Modeling Second Best Emission Policies

The following closely resembles the theory presented by Jacobsen et al. (2018). Instead of the consumer choosing their optimal consumption bundle across multiple products, they choose a single amount to consume at a given time period and demand is independent across time periods. Importantly, this independence of consumption across periods excludes any inter-temporal substitution which is a critical assumption in the results that follow. Given the context of electricity markets, this is a reasonable assumption given the empirical evidence that consumers do not substitute across periods (Jessoe and Rapson, 2014; Gillan, 2017; Ito, Ida, and Tanaka, 2018; Allcott, 2011), as pointed out and emphasized by Jacobsen et al. (2018). My contribution is to model the

\textsuperscript{3} Commonly, when evaluating the impact of alternative policies on emissions, the approach is to average the emissions in a geographic area across all electricity used in that area and referring to this as the average marginal emissions rate. For example (Boomhower and Davis, Forthcoming; Holland et al., 2016; Fowlie and Muller, Forthcoming; Zivin, Kotchen, and Mansur, 2014). This averaging of the emissions greatly reduces the variance in emissions per MWh.

\textsuperscript{4} The idea of location based retails rates is termed Distributed Locational Marginal Price. For example, Li, Wu, and Oren (2014).
heterogeneity on the supply side in the marginal external emissions per unit produced. I assume there is independence of costs of production across periods, but not within periods.

With the assumption about independence across periods, I proceed considering the optimal choice of the producer, consumer, and social planner in a single period, then aggregate across periods. There is a representative consumer which consumes $X_j$ units of the good at time $j$ with $j = 1, ..., J$. This is produced from different production resources, denoted by the the subscript $i = 1, ..., I$, each of which produces a quantity $x_{ij}$ such that $X_j = \sum_i x_{ij}$. The costs of production are specific to the production resource, $c_i(x_{ij})$, and are additive across resource and over time. I assume cost are increasing for all $i$, $c_i' > 0$. In the context of electricity markets, $X_j$ is the total amount of electricity consumed in a given hour, and $x_{ij}$ is the amount of electricity produced by a particular plant.

Generating electricity creates pollution, $SO_2$, $PM_{2.5}$, $NO_X$, and $CO_2$ which can cause damage to human health and reduce productivity. I specify the total external damages associated with producing $x_{ij}$ units of the commodity as the value $\phi_{ij} x_{ij}$ so that $\phi_{ij}$ represents the marginal external damages of the good at time $j$ from producer $i$.\(^5\) I assume that the damages are linear so that the total damages during all time periods equals $\phi = \sum_j \sum_i \phi_{ij} x_{ij}$. In what follows, I assume the externality is ignored by the producers and consumers, however the social planner decides to address the externality through demand or supply side policies.\(^6\)

In a single periods, the representative consumer chooses the quantity $X_j$ according to their utility $U_j(X_j)$ for good $X$. I assume that utility is increasing and concave, $U_j' > 0, U_j'' < 0$ and that $U_j'(0) = \infty$. The consumer is endowed with a fixed income of $M$, and they can purchase an outside good $n$ which is the numeraire and enters their utility linearly. If the social planner introduces a tax, the revenue is returned to the consumer with a lump sum transfer of $D$.

While the setup of this model is motivated by the market for electricity, this general setting

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\(^5\) The marginal external damages clearly depend on the resource type, $i$, because each resource might invest in different production or abatement technologies. Having the marginal external damages vary over time, $j$, represents other determinants of economic damages from pollution including the heat rate of the plant, the temperature outside, rain, and the size of the exposed population.

\(^6\) In reality, some producers do care about emissions externalities when there are existing policies in place such as $SO_2$ trading, or a $CO_2$ cap and trade program.
can be seen elsewhere. A consumer will choose how much to consume of a particular good, however the good is composed of a number of inputs each with a different marginal external damages. Importantly, the consumer can not contract for the inputs of which the final good is composed.

3.2.1 Consumer’s and Producers’ Problem

The consumer solves the following problem when there is a per-unit demand side tax, \( t^d_j \):

\[
\max_{X_j} U_j(X_j) \tag{3.1}
\]

\[
\text{s.t. } (p_j - t^d_j)X_j + n \leq M + D \tag{3.2}
\]

The first order condition states the consumer will choose the optimal amount of \( X_j \) so that the marginal utility is equal to the unit price plus the per-unit tax given there is an interior solution: \( \frac{\partial U_j}{\partial X_j} = p_j + t^d_j \). If there is no demand side tax, the consumer will set the marginal utility equal to the per-unit price: \( \frac{\partial U_j}{\partial X_j} = p_j \).

Producers are competitive price taking profit maximizers in the short run.\(^7\) For every hour, they choose the quantity to maximize their profits for a given equilibrium price. If there is a unit production tax, \( t^s_{ij} \), this will increase their cost of production. Each producer \( i \) will choose \( x_{ij} \) at time \( j \) to solve

\[
\max_{x_{ij}} p_j x_{ij} - c_i(x_{ij}) - t^s_{ij} x_{ij} \tag{3.3}
\]

So they will choose to produce \( x_{ij} \) such that the marginal cost of production equals the price per unit less the unit production tax: \( \frac{\partial c_i(x_{ij})}{\partial x_{ij}} = p_j - t^s_{ij} \). If there is no production tax, they will produce where price is equal to the marginal cost of production: \( \frac{\partial c_i(x_{ij})}{\partial x_{ij}} = p_j \).

The equilibrium is defined by a market price, \( p_j \), such that the consumer is maximizing their utility, the producers are maximizing their profits, and the markets clear: \( X_j = \sum_i x_{ij} \). In what follows, I let \( \tilde{x}_{ij} \) and \( \tilde{X}_j \) denote these equilibrium quantities.

\(^7\) I do not consider entry or exit. Instead of profit maximizing, it is possible the supply side is determined by a central planner that is minimizing the cost of production across all resources. This is very close to reality in the setting of wholesale electricity markets.
3.2.2 Social Planner

The goal of the social planner is to maximize welfare, which is utility minus the cost of production and the damages from the externalities. Total welfare is the sum of per-period welfare across all periods:

\[ W = \sum_j W_j = \sum_j \left[ U(\tilde{X}_j) + M - \sum_i c_i(\tilde{x}_{ij}) - \sum_i \phi_{ij} \tilde{x}_{ij} \right] \]

The planner has the ability to introduce a tax \( t \) which can vary over time \( j \), and across units \( i \). They choose this tax to maximize the total welfare \( W \) such that total demand is equal to total supply \( \tilde{X}_j = \sum_i \tilde{x}_{ij} \).

If the social planner is unconstrained by the type of tax they introduce, they would choose to have a policy that is the most flexible, a separate tax per period, differentiated by the producer. As such the optimal supply side tax would be a set of \( t_{ij}^* \) that would maximize total welfare, \( W_j \).

The first order conditions for this problem are

\[
\frac{\partial W}{\partial t_{ij}^*} = \sum_j \frac{\partial W_j}{\partial t_{ij}^*} = \sum_j \left[ \frac{\partial U_j}{\partial X_j} \sum_{m=1}^I \frac{\partial \tilde{x}_{mj}}{\partial t_{ij}^*} - \sum_{m=1}^I \frac{\partial c_m(x_{mj})}{\partial x_{mj}} \frac{\partial \tilde{x}_{mj}}{\partial t_{ij}^*} - \sum_{m=1}^I \phi_{mj} \frac{\partial \tilde{x}_{mj}}{\partial t_{ij}^*} \right]
\]

in this expression, a tax on unit \( i \) will impact the equilibrium quantity produced by that unit through \( \frac{\partial \tilde{x}_{mj}}{\partial t_{ij}^*} \) when \( m = i \), and all other units when \( m \neq i \). In the presence of a supply side tax,\n
\[
\frac{\partial c_m(x_{mj})}{\partial \tilde{x}_{mj}} = p_j - t_{mj}^* \quad \text{and} \quad \frac{\partial U}{\partial X} = p_j,
\]

implying

\[
\frac{\partial W}{\partial t_{ij}^*} = \sum_j \sum_{m=1}^I \left[ t_{mj}^* - \phi_{mj} \right] \frac{\partial \tilde{x}_{mj}}{\partial t_{ij}^*}
\]

which will equal to zero when \( t_{mj}^* = \phi_{mj} \) for all \( m \) and all \( j \). This is first best, also referred to as the Pigouvian Benchmark. It is optimal to set the tax equal to the marginal external damages per unit of electricity from source \( i \) at time period \( j \).
3.2.3 Second Best Policies

If the social planner can only price the externality over time, as a demand side policy, or across plants, as a supply side policy, they will not be able to achieve the Pigouvian Benchmark. In this subsection, I consider alternative second best policies. If there is a demand side tax, $t_d^j$, which can not differentiate between plants, we have a similar first order condition

$$\frac{\partial W_j}{\partial t_d^j} = \frac{\partial U_j}{\partial X_j} \sum_m \frac{\partial \tilde{x}_{mj}}{\partial x_{mj}} - \sum_m \frac{\partial c_m(x_{mj})}{\partial x_{mj}} \frac{\partial \tilde{x}_{mj}}{\partial t_d^j} - \sum_m \phi_{mj} \frac{\partial \tilde{x}_{mj}}{\partial t_d^j}$$

where $\frac{\partial \tilde{x}_{mj}}{\partial t_d^j}$ denotes how the per unit tax on demand impacts the equilibrium quantity produced by plant $i$ through the market clearing condition. This relates to the combined supply and demand derivatives, as well as assumptions about pass-through. For the demand side policy, $\frac{\partial U_j}{\partial X_j} = p_j + t_d^j$, and $\frac{\partial c_i(x_{ij})}{\partial x_{ij}} = p_j$, so that

$$\frac{\partial W}{\partial t_d^j} = \sum_j \sum_m \left[ t_d^j - \phi_{mj} \right] \frac{\partial \tilde{x}_{mj}}{\partial t_d^j}$$

Here, it is impossible to set all $t_d^j = \phi_{mj}$, instead, the social planner with set $t_d^j = \frac{\sum_m \phi_{mj} \frac{\partial \tilde{x}_{mj}}{\partial t_d^j}}{\sum_m \frac{\partial \tilde{x}_{mj}}{\partial t_d^j}}$ which equals the weighted average marginal external damages across all electricity generating plants, with the weight equal to the plant’s responsiveness to the demand side tax. A higher tax will be set if dirtier plants are more responsive to the implementation of the tax.

If the planner can only choose a supply side policy, some $t_s^i$, which depends on the origin of the electricity but not on the time, the first order condition will be identical to the ones above however the policy is,

$$\frac{\partial W}{\partial t_s^i} = \sum_j \frac{\partial W_j}{\partial t_s^i} = \sum_j \sum_m \left[ t_s^i - \phi_{mj} \right] \frac{\partial \tilde{x}_{mj}}{\partial t_s^i}$$

To maximize total welfare the first order conditions imply the social planner will choose to have

$$t_s^i = \frac{\sum_m \phi_{mj} \frac{\partial \tilde{x}_{mj}}{\partial t_s^i}}{\sum_m \frac{\partial \tilde{x}_{mj}}{\partial t_s^i}}.$$  Similarly to the demand side policy, when the planner is constrained they will set the tax equal to some average of the marginal external damages. The tax for unit $m$ will be
larger if they pollute more during hours in which they are more responsive to a tax. If the plant’s responsiveness to the tax is independent over time, this second best policy would just be the average marginal emissions rate for the plant.

Noticing that \( t_{ij}^* \) does not equal \( t_j^d \) or \( t_i^* \), both limited supply and demand side policies are second best, there will be some welfare loss from this pricing imperfection.

### 3.2.4 Dead-Weight Loss and Regression Statistics

Consider the optimal supply side policy, \( t_{ij}^* = \phi_{ij} \), and some deviation from that policy \( \tau_{ij} \). Jacobsen et al. (2018) show how to recover an expression for dead weight loss. Consider a weighted average of the optimal policy, and the generic policy \( t_{ij} = (1 - \rho)\phi_{ij} + \rho\tau_{ij} \). Taking the derivative of total welfare with respect to the weight, \( \rho \), provides

\[
\frac{\partial W}{\partial \rho} = \sum_j \sum_i \sum_m \left[ t_{ij} - \phi_{ij} \right] \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}} \frac{\partial t_{mj}}{\partial \rho}
\]

Substituting \( t_{ij} = (1 - \rho)\phi_{ij} + \rho\tau_{ij} \) and \( \frac{\partial t_{mj}}{\partial \rho} = \tau_{mj} - \phi_{mj} \)

\[
\frac{\partial W}{\partial \rho} = \rho \sum_j \sum_i \sum_m \left[ \tau_{ij} - \phi_{ij} \right] \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}} \left[ \tau_{mj} - \phi_{mj} \right]
\]

The change in total welfare, or dead weight loss from some tax \( \tau_{ij} \neq \phi_{ij} \), equals the integral from \( \rho = 0 \) to \( \rho = 1 \). Assume that change in equilibrium output \( \tilde{x}_{ij} \) in response to a tax, and the externality \( \phi_{ij} \), are independent of \( \rho \).

\[
DWL(t_{ij} = \tau_{ij}) = -\frac{1}{2} \sum_{j=1}^{J} \sum_{i=1}^{I} \sum_{m=1}^{I} \left[ \tau_{ij} - \phi_{ij} \right] \left[ \tau_{mj} - \phi_{mj} \right] \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}}
\]

Define the tax error, \( e_{ij} \), as \( \tau_{ij} - \phi_{ij} \). Dead weight loss can be re-expressed as

\[
DWL(t_{ij} = \tau_{ij}) = -\frac{1}{2} \sum_{j=1}^{J} \sum_{i=1}^{I} e_{ij} \frac{\partial \tilde{x}_{ij}}{\partial t_{ij}} + \sum_{j=1}^{J} \sum_{i=1}^{I} \sum_{m \neq i} e_{ij} e_{mj} \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}}
\]

At this point, the expression will simplify greatly if a few conditions are met. Consider the following assumptions: (1) the tax error, \( e_{ij} \) is independent of the own-tax derivative \( \frac{\partial \tilde{x}_{ij}}{\partial t_{ij}} \) (2) The product of the tax errors, \( e_{ij} e_{mj} \), are independent of the cross derivatives, \( \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}} \). If (1) and (2) are
met, the expression for dead weight loss simplifies to

\[
DWL(t_{ij} = \tau_{ij}) = -\frac{1}{2} \left( \frac{\partial \tilde{x}_{ij}}{\partial t_{ij}} - \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}} \right) \sum_{j=1}^{J} \sum_{i=1}^{I} e_{ij}^2
\]

where \( \frac{\partial \tilde{x}_{ij}}{\partial t_{ij}} \) is the average change in the equilibrium quantity in response to the tax and \( \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}} = \frac{1}{I(I-1)} \sum_{i=1}^{I} \sum_{m \neq i} \frac{\partial \tilde{x}_{ij}}{\partial t_{mj}} \). This shows that the dead-weight loss is proportional to the sum of the squared tax error.

Before proceeding, it is important to evaluate the extent to which assumption (1) and (2) are met in the context of emission externalities associated with electricity generation. Although the total emissions per unit of production at a plant might be associated with the equilibrium response of that plant to a tax, it is reasonable to state that the residual emissions that are not addressed by the tax are independent of the plant’s responsiveness to the tax. In the context of a supply side policy, this assumption is stating that the plant is not more or less responsive to the tax when they are polluting more or less than their average amount per unit. For a demand side tax, this suggests that a plant is not more or less responsive when its emissions per unit deviate more or less from the average emissions in that hour.\(^8\) For assumption (2) to hold, it is necessary that two products that have (dis-)similar tax errors are not also more or less substitute-able.

We can think of a general tax policy that is linear in observable product attributes, \( \tau_{ij} = f(z_{ij}|\theta) = \alpha + \beta z_{ij} \), where the tax error would be equal to \( \phi_{ij} = f(z_{ij}|\theta) \). Finding the parameters values that minimize total dead-weight loss is equivalent to minimizing the sum of the squared tax errors, and can be found using ordinary least squares to project \( \phi_{ij} \) onto \( z_{ij} \). This dead weight loss minimizing tax policy, \( f(z_{ij}|\hat{\theta}) \), is the second best policy. Moreover, the \( R^2 \) from this regressions represents the percent of welfare that is recovered from the second best policy relative to a policy that does not differentiate over \( z_{ij} \), as the \( R^2 \) from this regression is equivalent to

\(^8\) Violation of this assumption might be reasonable for demand side policies. If so, the second best policy can still be recovered using a weighted least squares estimation procedure, where the weights are equal to the unit’s responsiveness to the tax.
\[ R^2 = 1 - \frac{SSR_{SecondBest}}{TSS_{SecondBest}} = 1 - \frac{SSR_{SecondBest}}{SRR_{Uniform}} = 1 - \frac{\text{DWL}(t_{ij} = f(z_{ij} | \hat{\theta}))}{\text{DWL}(t_{ij} = \bar{t})} \]

where \( \bar{t} \) is an average of all \( \phi_{ij} \), \( SSR \) stands for the Sum of Squared Residuals and \( TSS \) stands for the total sum of squares.

### 3.3 Data

The primary data are on the hourly operation of electricity generators from the EPA’s Continuous Emission Monitoring System (CEMS) from 2010 to 2015.\(^9\) These data report the hourly emissions of \( SO_2 \), \( CO_2 \), and \( NO_x \), as well as gross generation and net generation for each generator. These data are widely used.\(^{10}\) In what follows, I aggregate the generator level observations to the plant level. Particulate matter, like \( PM2.5 \), is a by product of burning fuel to generate electricity and can have an impact on human health, however is not reported in the CEMS database.\(^{11}\)

The CEMS data are hourly observations on 1482 electricity generating plants in the Continental United States structured as an unbalanced panel. When the electricity plant is not operating and not generating any pollution, the quantity of electricity generated and emissions are not reported.\(^{12}\) Table 3.1 tabulates the number of plants of each fuel type, as well as the average name plate capacity of the plants in Megawatts by fuel type.

Table 3.2 presents summary statistics for the average emissions per MWh for each plant. For

\(^9\) This includes all electricity generating generators in the United States over 25 megawatts that are not powered by Nuclear, Hydro, and Renewable resources.

\(^{10}\) See Davis and Hausman (2016) for a good outline on the accuracy of this data, as well as a list of publications that use these data.

\(^{11}\) It is possible to account for hourly \( PM2.5 \) emissions by calculating the average \( PM2.5 \) emissions per MWh according to annual data from the EPA National Emission Inventory, then calculating the hourly emissions as the average emission times the amount of MWh produced.

\(^{12}\) There are also times when the electricity generator is not producing any electricity, but emitting a large amount of pollution because it is still burning fuel to produce heat, but is not connected to the electricity grid.
Table 3.1: Plant Type and Size

<table>
<thead>
<tr>
<th>Main Fuel Type</th>
<th>Mean Capacity, MW</th>
<th>Number of Plants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>844.4</td>
<td>353</td>
</tr>
<tr>
<td>Gas</td>
<td>486.9</td>
<td>918</td>
</tr>
<tr>
<td>Other</td>
<td>1037.9</td>
<td>108</td>
</tr>
<tr>
<td>Petro</td>
<td>222.8</td>
<td>103</td>
</tr>
</tbody>
</table>

context, one MWh is the average amount of electricity consumed by a household in the US in one month. Significant heterogeneity in the average emissions per MWh across plants is evident. In particular, there is a long right tail, with a few plants emitting much more emissions per MWh on average than the rest. This across plant heterogeneity is important for the results that follow.

Table 3.2: Mean Plant Damages per MWh.

<table>
<thead>
<tr>
<th>Emission</th>
<th>Min</th>
<th>Q1</th>
<th>Mean</th>
<th>Median</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO2 ton per MWh</td>
<td>0</td>
<td>0.56</td>
<td>0.81</td>
<td>0.77</td>
<td>1.03</td>
<td>11.41</td>
</tr>
<tr>
<td>NOX lbs per MWh</td>
<td>0</td>
<td>0.01</td>
<td>2.03</td>
<td>0.01</td>
<td>1.40</td>
<td>66.86</td>
</tr>
<tr>
<td>SO2 lbs per MWh</td>
<td>0</td>
<td>0.33</td>
<td>1.58</td>
<td>0.91</td>
<td>2.12</td>
<td>35.65</td>
</tr>
</tbody>
</table>

The hourly emissions in the CEMS data are converted to economic damages using county-pollutant specific damages from the AP2 developed by Nick Mueller, as in Holland et al. (2016). This model is an integrated assessment air pollution model, and calculates the impact of a unit increase in $SO_2$, $NO_X$, and $PM2.5$ on human health, crop and timber yields, degradation of buildings and materials, and reduced visibility and recreation for every county in the US (Muller and Mendelsohn, 2007). This cross-sectional variation in pollution damages is driven primarily by population density, but is good in capturing how similar emissions profiles from plants located in different areas will have different impacts. Figure 3.1 shows the distribution of damages by county within the United States for one additional pound of $SO_2$ and $NO_X$, in 2011 USD. To account for the externalities of carbon emissions, I use the central estimate for the social cost of carbon developed by the Intergovernmental Working Group, $41/ton of CO2 in 2007 USD, inflated to $43.31 2011 USD (IWG, 2016). Because $CO_2$ is a greenhouse gas with global damages, I do not consider any cross-sectional variance in the damages from a ton of $CO_2$. 
Figure 3.1: A map of marginal external damages per pound of pollutant by county.

Data on marginal external damages per county comes from Holland et al. (2016).
The county specific $SO_2$ damages range from $2.02$ to $374.56$ per pound, with a mean of $14.10$ per pound. Likewise, county specific $NO_x$ damages range from $0.04$ to $22.03$ per pound, with a mean of $2.12$. Taking the mean emissions per MWh across all plants, and the mean damages, this suggest the average consumption of electricity in a month (one MWh) has a total external damages of $61.85$ on average.\footnote{This comes from $0.81 \times 43.31 + 2.03 \times 2.21 + 1.58 \times 14.10$.} Given the average wholesale price of electricity ranges for $30$ to $60$ per MWh, this suggests the marginal external damages associated with electricity generation are large. The social costs of one unit of electricity can be twice as large as the private costs in a given time period.

For every hour I calculate the total damages at an electricity generating plant as the sum of the marginal external damages from $CO_2$, $SO_2$, and $NO_X$. I denote the total damages at plant $i$ in hour $j$ as $TotDamages_{ij}$, with

$$TotDamages_{ij} = NO_xDamages_c \cdot NO_xlbs_{ij} + SO_2Damages_c \cdot SO_2lbs_{ij} + CO_2Damages \cdot CO_2tons_{ij}$$

The distribution on hourly plant damages per MWh, $TotDamages_{ij}/GrossGeneration_{ij}$, separated by NERC region are presented in Figure 3.2. The data in this figure represent the observations when electricity plants are producing more than 10 MWh of electricity, and only for the plants with more than 1000 observations. This subsample is what is used in the analysis that follows. Evident from these density plots is the heterogeneity in external damages per MWh, with multiple peaks and a wide spread. The values used to create the density plots are truncated to fit between 0 and 100 $$/MWh.

### 3.4 Second Best Emission Policies

In this section I consider alternative second best policies to address emission externalities associated with electricity generation. This builds off of the framework of evaluating imperfect pricing, first outlined by Jacobsen et al. (2018) and modified in section 3.2. I consider alternative
Figure 3.2: Damages per MWh by Plant-Hour

Density of plant, hour, damages. $/MWh

- ERCOT
- FRCC
- MRO
- NPCC
- RFC
- SERC
- SPP
- WECC
Source: EPA.gov. Broadly these regions can be matched to wholesale electricity markets. The TRE and SPP regions match with the Energy Reliability Council of Texas (ERCOT) and Souther Power Pool (SPP) wholesale markets respectively. MRO, matches with the most of the Midcontinent Independent System Operator’s (MISO) footprint prior to 2013. RFC is similar to the Pennsylvania-New Jersey-Maryland wholesale market. NPCC region consists of two market, the New England ISO and the New York ISO. Finally WECC includes the California wholesale market, CAISO, and the remaining western states. While MISO and PJM are partially within SERC, there are no wholesale markets in the South Eastern United States.
functions of product attributes to estimate the total damages from emission externalities. The results from ordinary least squares estimation represents the second best policy to address the emission externalities, and the $R^2$ from that regression is the percentage of the total welfare that is captured by this second best policy relative to flat tax that doesn’t differentiate across product attributes.

The second best policy is found by regressing the marginal external damages in an hour onto product attributes. Given true marginal external damages $\phi_{ij}$ and some product attributes $z_{ij}$, the second best policy based off of the product attributes is some function of the product attribute $f(z_{ij}|\theta)$ that tries to address the emission externalities $\phi_{ij}$, choosing $\hat{\theta}$ that minimize $(\phi_{ij} - f(z_{ij}|\theta))^2$.

In what follows, I consider $z_{ij}$ to be product attributes such as the time of day the electricity is produced or consumed as well as where the electricity was generated. In particular, when I consider demand side policies, I consider forms of $z_{ij}$ which depend only on the index $j$, as the consumer can not differentiate between the source of electricity. In variantly, these take the form of time periods fixed effects. For on-peak emission charges I let $f(z_{ij}|\theta) = \theta_p$ where $p \in \{\text{offPeak}, \text{onPeak}\}$, and the mapping between time period $j$ and peak $p$ is such that

$$p = \begin{cases} 
\text{onPeak}, & \text{if } 15 < \text{Hour}_j < 21 \\
\text{offPeak}, & \text{otherwise}
\end{cases}$$

One of the environmental factors that most impacts electricity plant operation is the temperature outside. To account for this I also consider a policy function that allows for a different emission price depending on if the hour is in a summer month. That is $f(z_{ij}|\theta) = \theta_{p,s}$ where $s = \text{onSummer}$ if the month associated with time period $j$ is in June, July, or August, and $s = \text{offSummer}$ otherwise.

The tax is differentiated across summer periods within a year and peak periods within a day.\footnote{This second best policy could consist of some base tax $\theta_0$, then a modifier depending summer periods within a year and peak periods within a day, however I do not incorporate a fixed amount so I can recover a separate value for every instance of $s$ and $p$. This affects the $R^2$ in that a model with no intercept will have an inflated $R^2$. I correct for this by calculating the $R^2$ manually using the total sum of squared difference from the average as the total sum of squares.}
Although less rare in practice, I consider demand side charges that are much more flexible including a separate per unit charge for every hour of the day by month of year \( f(z_{ij}|\theta) = \theta_{m,h} \), where \( m \) is the month associated with time period \( j \) and \( h \) is the hour of day associated with time periods \( j \).\(^{15}\) In the limit, I consider the most flexible demand side emission charges, a separate emissions price for every single hour of sample: \( f(z_{ij}|\theta) = \theta_j \), where \( j \) represents a year-month-day-hour unit of observation.

In terms of a supply side policy I consider one policy, a separate emissions charge for every single electricity plant that is time invariant. This is \( f(z_{ij}|\theta) = \theta_i \). In practice, this would be simple for a wholesale market operator to implement by adjusting the unit’s bid into the wholesale market. Alternative policies that can be considered include policies based on total load within the system, as well as retail rate policies that are based on the wholesale price.

In practice, I do not directly observe the marginal emissions per plant per hour. I observe the total emission, and the corresponding \( TotDamages_{ij} \), as well as the gross generation, \( GrossGen_{ij} \). To recover an estimate for the marginal external damages per unit I note that \( TotDamages_{ij} = \phi_{ij} x_{ij} \) and \( GrossGen_{ij} = x_{ij} \), so that taking the ratio \( TotDamages_{ij}/GrossGeneration_{ij} \) is a good approximation for \( \phi_{ij} \). In reality, this is the average emissions per unit per hour. In what follows I minimize the sum of the squared difference between \( TotDamages_{ij}/GrossGeneration_{ij} \) and \( f(z_{ij}|\theta) \).\(^{16}\)

### 3.4.1 Estimation Results

With the hourly plant-level data on electricity generation and emissions from 2010 to 2015, I estimate the second best policy functions outlined above separately for all 8 NERC regions in the continental United States.\(^{17}\) The recovered parameters represent the second best policy that can be used to address emission externalities associated with electricity generation. Looking at the simple

\(^{15}\) This is a total of \( 12 \times 24 = 288 \) parameters.

\(^{16}\) An alternative approach is to notice that minimizing the sum of the squared difference between \( \phi_{ij} \) and \( f(z_{ij}|\theta) \) is similar to minimizing the difference between \( TotDamages_{ij} \) and \( f(z_{ij}|\theta) \cdot GrossGen_{it} \). This works when \( f(z_{ij}|\theta) = \theta_j \), but not when \( f(z_{ij}|\theta) \) is across plants. In the latter case, the second best policy will be biased upward relative to the estimates I provide when dirtier plants are producing relatively more electricity.

\(^{17}\) I estimate it separately for each NERC region to reduce the computational intensity of the estimation.
demand side policies, $\hat{\theta}_{p,s}$ presented in Table 3.3, the second best emission charge per hour depends largely on the market. Interestingly, the second best policy to address emission externalities indicate that off peak prices should be lower than on peak prices, contra to conventional wisdom regarding peak pricing. This is because more electricity is generated from relatively cleaner resources, like natural gas plants relative to coal, during peak periods. This general result extends to summer periods, overall, the second best emission policy is a lower tax during the summer.

Table 3.3: Second Best Peak, Summer, Policies.

<table>
<thead>
<tr>
<th>Market</th>
<th>OffPeak,OffSummer</th>
<th>OffPeak,Summer</th>
<th>Peak,OffSummer</th>
<th>Peak,Summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERCOT</td>
<td>45.15</td>
<td>42.40</td>
<td>42.05</td>
<td>38.76</td>
</tr>
<tr>
<td>FRCC</td>
<td>43.08</td>
<td>40.79</td>
<td>42.83</td>
<td>40.46</td>
</tr>
<tr>
<td>MRO</td>
<td>98.55</td>
<td>96.50</td>
<td>93.25</td>
<td>87.46</td>
</tr>
<tr>
<td>NPCC</td>
<td>35.67</td>
<td>34.42</td>
<td>34.45</td>
<td>33.64</td>
</tr>
<tr>
<td>RFC</td>
<td>129.72</td>
<td>125.39</td>
<td>124.90</td>
<td>116.72</td>
</tr>
<tr>
<td>SERC</td>
<td>78.31</td>
<td>76.67</td>
<td>76.98</td>
<td>72.15</td>
</tr>
<tr>
<td>SPP</td>
<td>63.48</td>
<td>61.90</td>
<td>63.91</td>
<td>60.08</td>
</tr>
<tr>
<td>WECC</td>
<td>37.27</td>
<td>35.68</td>
<td>36.10</td>
<td>34.07</td>
</tr>
</tbody>
</table>

Looking at more flexible demand side policies Figure 3.4 shows the average values of $\hat{\theta}_{m,h}$ across hour of day and across months of the year for each NERC region separately. Similar to the results presented in Table 3.3, there is significantly more heterogeneity across markets than within markets. The second best hourly price is lowest during the peak of the day, and varies over the course of the year depending on the NERC region. Throughout the day, or over the course of the year, the second best policy to address the emission externalities doesn’t change considerably, which might suggest that there isn’t much to be gained from hourly policies to address emission externalities.

From the supply side estimation, I recover a set of plant specific $\hat{\theta}_i$ which are time invariant taxes used to address emission externalities. The densities of these plant specific tax rates, across NERC regions, are shown in Figure 3.5. In this diagram the largest 5% of values were winsorized so the tail of the distribution does not distort the image, and the color of the density represents the average value of $\hat{\theta}_i$ within the region. We see significant heterogeneity across plants within a
Figure 3.4: Second Best Demand Policies.

Second Best Policy by NERC Region and Hour

Second Best Policy by NERC Region and Month

market
- ERCOT
- FRCC
- MRO
- NPCC
- RFC
- SERC
- SPP
- WECC
NERC region. Largely, the plant specific emissions rate is centered around $25/MWh, however there are some regions with a more even distribution. Almost all of the regions have a long right tail, suggesting some plants create an exceptional amount of damage per MWh.

Figure 3.5: Second Best Supply Policies.

Given the connection to the model presented in section two, the $R^2$ from the OLS regressions represents the percentage of total welfare that is captured by the these second best policies relative to a policy that doesn’t differentiate across product attributes. Table 3.4 presents this information for four policies and by NERC region. We see that the demand side policies, $\theta_{s,p}$, $\theta_{m,h}$, and $\theta_j$ effectively address none of the large heterogeneity in emissions externalities. Even the policy that has a separate per unit tax for every single hour in the sample address at most 4% of the total variation in emissions. Given these are the best policies that price electricity over the course of the day, any other demand side policy would perform even worse. In contrast, the supply side policy, that simply charges each plant a separate time-invariate tax per unit can addresses 57 to 86% of the dead weight loss that remains after a uniform per unit tax.
Table 3.4: R-squared from Second Best Policies.

<table>
<thead>
<tr>
<th>NERC Region</th>
<th>Summer Peak</th>
<th>Month by Hour</th>
<th>Day by Hour</th>
<th>Plant Specific</th>
<th>N obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERCOT</td>
<td>0</td>
<td>0.00</td>
<td>0.01</td>
<td>0.77</td>
<td>3115739</td>
</tr>
<tr>
<td>FRCC</td>
<td>0</td>
<td>0.00</td>
<td>0.03</td>
<td>0.57</td>
<td>1881911</td>
</tr>
<tr>
<td>MRO</td>
<td>0</td>
<td>0.00</td>
<td>0.04</td>
<td>0.60</td>
<td>2651015</td>
</tr>
<tr>
<td>NPCC</td>
<td>0</td>
<td>0.01</td>
<td>0.04</td>
<td>0.60</td>
<td>3363451</td>
</tr>
<tr>
<td>RFC</td>
<td>0</td>
<td>0.00</td>
<td>0.02</td>
<td>0.71</td>
<td>7749748</td>
</tr>
<tr>
<td>SERC</td>
<td>0</td>
<td>0.00</td>
<td>0.02</td>
<td>0.63</td>
<td>8305699</td>
</tr>
<tr>
<td>SPP</td>
<td>0</td>
<td>0.00</td>
<td>0.01</td>
<td>0.86</td>
<td>2957715</td>
</tr>
<tr>
<td>WECC</td>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.80</td>
<td>6453583</td>
</tr>
</tbody>
</table>

3.5 Discussion

3.5.1 Dead-weight loss comparison

Similar to Borenstein and Bushnell (2018), it is possible to directly calculate the total dead weight loss from imperfectly pricing electricity if you are willing to make assumptions on the elasticity of demand and supply as well as pass-through. Although the method presented above is informative in which policy is relatively better in addressing the variation in emission externalities, there is no reference point for what is absolute dead weight loss associated with these alternative policies. More specifically, what is the dead weight loss associated with a uniform tax rate? If it is small, then the need to address the heterogeneity in emissions is small. In this section I will make generous assumptions on how the tax rate affects the production from each plant and overall all demand to answer this question.

First I assume that there are no cross effects, so that the dead weight loss associated with some policy $\tau_{ij}$ can be represented by

$$DWL(\tau_{ij}) = -\frac{1}{2} \sum_j \sum_i [\tau_{ij} - \phi_{ij}]^2 \frac{\partial x_{ij}}{\partial \tau_{ij}}$$

If I am willing to assume constant marginal cost, $\frac{\partial x_{ij}}{\partial \tau_{ij}}$ represents the average change in quantity demanded from plant $i$ in response to the tax. Assuming a constant elasticity of demand function,
this expression can be re expressed as \( \frac{\partial x_{ij}}{\partial t_{ij}} = \varepsilon \frac{d x_{ij}}{price_{ij}} \). Following Borenstein and Bushnell (2018), I assume an elasticity of demand equal to 0.2, which is in line with many empirical estimates.\(^{18}\)

For each hour, I let \( GrossGen_{ij} \) equal \( x_{ij} \) and use a fixed price of $50/MWh.

I consider three alternative values of \( t_{ij} \) motivated by the analytical second best policies derived in section 2. The first is an average emissions \( \tau = I^{-1} J^{-1} \sum_i \sum_j \phi_{ij} \) in the entire sample period, this represents the baseline dead weight loss which the policy differentiated by product attribute is improving over. Next, I consider a hour of sample specific policy, \( \tau_j = I^{-1} \sum_i \phi_{ij} \) and a plant specific policy \( \tau_i = J^{-1} \sum_j \phi_{ij} \). These are not the second best hour specific policy, as it doesn’t take into account how plant might be more responsive to the tax, however it is a close approximation. Finally, I consider the total dead-weight loss when there is no tax, \( \tau_{ij} = 0 \). I normalize the total dead weight loss to a per MWh value by dividing the sum by the total amount of electricity generated in the NERC region during the sample period.

Table 3.5 shows the total dead weight loss per MWh associated with a base policy of a flat tax. Given that this policy is addressing the externality, it is surprising that its inability to address the heterogeneity in emission externalities per MWh still results in dead weight loss on the order of 1 to $50/MWh. Importantly, doing this calculation shows which regions a differentiated policy could do the most benefit, e.g. RFC, and where it would do the least amount of benefit, e.g. WECC. In Table 3.5 I also calculate the % of the dead weight loss that is recovered from the differentiated supply side and demand side policy. Although not identical, the numbers are similar in magnitude to Table 3.4.

Figure 3.6 shows the total dead weight loss calculations for the four separate policies, across NERC regions, in absolute value. We see that going from no policy to an average tax can address around half of the total dead weight loss associated with electricity emission externalities. This amount, per MWh, is quite large. In RFC for example, an average price could reduce dead weight loss by $30 per MWh. Going from an average price to a extremely flexible demand side policy (one price for each hour of the sample), does very little to address the residual variation in emission

\(^{18}\) This is a central estimate for the elasticity of demand. See ?
externalities after an average emission price is imposed. Conversely, a plant specific price can address almost all of the dead-weight loss from emission externalities.

Table 3.5: DWL per MWh and % Welfare Recovered.

<table>
<thead>
<tr>
<th>NERC</th>
<th>DWL, average price</th>
<th>% Recovered, hour price</th>
<th>% Recovered, plant price</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERCOT</td>
<td>-11.16</td>
<td>0.01</td>
<td>0.94</td>
</tr>
<tr>
<td>FRCC</td>
<td>-5.32</td>
<td>0.03</td>
<td>0.72</td>
</tr>
<tr>
<td>MRO</td>
<td>-6.57</td>
<td>0.02</td>
<td>0.64</td>
</tr>
<tr>
<td>NPCC</td>
<td>-7.31</td>
<td>0.07</td>
<td>0.63</td>
</tr>
<tr>
<td>RFC</td>
<td>-49.99</td>
<td>0.01</td>
<td>0.74</td>
</tr>
<tr>
<td>SERC</td>
<td>-15.60</td>
<td>0.03</td>
<td>0.57</td>
</tr>
<tr>
<td>SPP</td>
<td>-3.94</td>
<td>0.01</td>
<td>0.85</td>
</tr>
<tr>
<td>WECC</td>
<td>-0.96</td>
<td>0.02</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Figure 3.6: Total DWL for Alternative Policies.
3.6 Conclusion

In this paper I show that demand side emissions policies do not do a good job in capturing the cross-sectional variance in emission externalities. Instead, supply side policies that take into account the average emissions of an electricity generating plant can address almost all of the variation in marginal external damages. As a result, policy makers concerned with the large emission externalities associated with electricity generation should focus on incorporating supply side policies, that differentiate across resources, instead of demand side policies such as real time pricing or demand response.
Bibliography


Appendix A

Firm’s incentives

Given the notation presented in 1.2, market participant $o$’s profit at time $t$ is characterized by

$$\Pi_o(S_o(p)) = p[S_o(p) + \theta_o W] - C_o(S_o(p))$$

(A.1)

Where $p$ is the market price, $\theta_o \in [0, 1]$ is the fraction of total wind generation produced by market participant $o$, $W$ is the perfectly forecast-able quantity of electricity generated by wind turbines, and $C_o(S_o(p))$ is the cost of producing $S_o(p)$.\(^1\) All market participants have perfect information on the cost of production of all other market participants.

Demand is composed of a forecast-able quantity and a random forecast error, $D(p) = d(p) + \varepsilon$, where $\varepsilon$ is an i.i.d. random variable with expectation equal to zero.\(^2\) Taking the strategies of the other market participants as given, all uncertainty in the market participant’s payoff is from the demand forecast error, $\varepsilon$. Market participants choose a supply function mapping the ex-post market price to the quantity they want to produce. The Nash-equilibrium is defined by all market participants choosing the supply function that maximizes their expected profits, taking the other (profit-maximizing) supply functions as given. Because the equilibrium in this model is defined by a system of differential equations with considerable asymmetry, I only consider the firm’s best response.

To characterize the equilibrium, I show that every realization of $\varepsilon$ is associated with one price-quantity pair which outlines the optimal supply function for that firm, following Klemperer and

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\(^1\) Cost are strictly increase and weakly convex in $S_o(p)$

\(^2\) Demand is strictly decreasing in price.
Meyer (1989). If we first assume the profit maximizing price-quantity pairs can be characterized by a supply function $q_o = S_o(p)$, the profit maximizing price associated with a realization of $\varepsilon$ will tell us the optimal profit maximizing quantity. Also noting that the quantity produced by market participant is defined by the residual demand $RD(p, \varepsilon) = d(p) + \varepsilon - \sum_{j \neq o} S_j(p) - W$, we can write the market participants profit function as

$$p[RD(p, \varepsilon) + \theta_o W] - C_o(RD(p, \varepsilon))$$

(A.2)

with the first order condition with respect to price provides

$$p - C'(RD(p, \varepsilon)) = -\frac{RD(p, \varepsilon) + \theta_o W}{RD_p(p, \varepsilon)}$$

(A.3)

where $RD_p(p, \varepsilon)$ is the slope of the residual demand with respect to price ($d'(p) - \sum_{j \neq o} S'_j(p)$).

This implicitly defines the optimal price as a function of the demand shock $\varepsilon$, $p^*_o(\varepsilon)$, taking forecast-able demand, the strategy of other players, and the forecast-able wind generation as given. The corresponding profit maximizing quantity is $RD(p^*_o(\varepsilon), \varepsilon) \equiv q^*_o(\varepsilon)$, providing a locus of parametrized profit maximizing price-quantity pairs: $p^*_o(\varepsilon), q^*_o(\varepsilon)$. As long as there is a one to one mapping between $\varepsilon$ and $p^*_o$, we have that $p^*_o(\varepsilon)$ is invertible and the optimal supply function is $S_o(p) = q_o((p^*_o)^{-1}(p))$.

Finally, substituting $S_o(p)$ for $RD(p^*_o(\varepsilon), \varepsilon) \equiv q^*_o(\varepsilon)$ and $d'(p) - \sum_{j \neq o} S'_j(p)$ for $RD_p(p, \varepsilon)$ in Equation A.3 we have

$$p - C'(S_o(p)) = -\frac{S_o(p) + \theta_o W}{d'(p) - \sum_{j \neq o} S'_j(p)}$$

(A.4)
Appendix B

Institutional Details on MISO

B.1 Markets in MISO

Markets in MISO include a day ahead and real time wholesale electricity market to balance generation supply and load demand, a market for financial transmission rights to manage the risk of congestion, a market for ancillary services that ensure reliability through frequency regulation, and an annual capacity market. Other important components of MISO include revenue sufficiency guarantee charges to those that are causing ramping and the related make-whole payments.

Both the day ahead and real time wholesale markets serve as multi-unit uniform price auctions. Each generation unit submits the amount they are willing to generate at a given price and a number of bid parameters for every hour.\footnote{These parameters include cost estimates, the minimum and maximum they can produce in economic and emergency scenarios, as well as if the unit must run.} The day ahead market serves as a forward market, with all bids submitted by 11 am the day before market operations. The quantities are cleared and the dispatch order is determined by 3 pm the day before market operations. The real time market serves as a spot market for last minute adjustments, with all bids submitted at least 30 minutes before the market hour. All quantities in the forward market are cleared again in the real time market unless modified.

Concurrently to the submission of generation offers, municipalities and other load serving entities may submit physical demand bids in the day ahead and real time market while financial market participants may submit virtual demand bids in the day ahead market only. A few of
the physical bids are price sensitive, however they are predominately price invariant representing inelastic demand for electricity in the short-run. Within MISO there are market participants offering demand response, however they bid into the supply side of the market with a curtailment price and target MW reduction.

A computer program uses the generation offers, demand bids, and constraint parameters to solve for the dispatch generation quantity for each unit and the market price they receive.\(^2\) MISO’s equilibrium concept is a set of locational marginal prices (LMP) at different geographic pricing nodes. The price at each node represents the market clearing price for that location as well as the marginal congestion cost and the cost of loss from transporting electricity over a significant distance. If there are no transmission constraints or transmission losses, the LMP will be the same at every location within that market.

Intermittent, or variable generation, can be a problem for the operators of transmission networks such as MISO, as unexpected deviations from the forecasted generation can impact the ability to meet security commitments. MISO addressed this in 2011 by integrating wind generating units as Dispatchable Intermittent Resources that can bid into the wholesale market. This has greatly reduced the number of manual curtailments.\(^3\) Relatedly, the day ahead forecasts that help determine the wind based generation offers have greatly increased in accuracy in recent years. A survey of the generation offers submitted by wind turbines show they are invariably inelastic, showing a fixed quantity, however their ex-post generation quantity does differ from their ex-ante supply offer.

### B.2 Utility Structure and Turbine Finance

Most states in MISO other than Michigan and Illinois never passed laws to de-regulate their electricity market. The implication is that a number of the electricity generating units are part

\(^2\) The current computer programs used to determine dispatch include Security-Constrained Unit Commitment (SCUC) and Security-Constrained Economic Dispatch (SCED). SCED is used in real time. This was changed in late 2014 to compensate quickly ramping technologies.

\(^3\) Wind turbines can curtail the amount of electricity they generate by changing the angle of their blades.
of a vertically integrated utility, buying the electricity they are selling within MISO’s wholesale market. This can mitigate the incentives to increase the wholesale price (Bushnell, Mansur, and Saravia, 2008). I use data from the U.S. Energy Information Agency to better characterize the operations of utilities. Table B.1 shows details on wind capacity for the ten utilities in MISO with the largest installed wind capacity in MISO according to EIA-860 form. I use EIA-861 form to show the total Tera-watt hours (TWh) of electricity they provide during the year 2016, as well as the percent of the total TWh that is sourced from wholesale markets and the percent that is deposited as sale for resale. The sale for resale percentage is the amount of electricity that is not sold to retail customers, and is instead sold to a third party like the wholesale market. We can see that for a number of large utilities, the quantity that is purchased from the wholesale market is less than the quantity that is sold into the wholesale market, on average in a year. This implies that these market participants would benefit from increasing the wholesale price within MISO.

Table B.1: Operations of Utilities with Large Wind Capacity in MISO, 2016

<table>
<thead>
<tr>
<th>Utility</th>
<th>Wind Capacity</th>
<th>TWh</th>
<th>% Wholesale Purchase</th>
<th>% Sale for Resale</th>
</tr>
</thead>
<tbody>
<tr>
<td>MidAmerican Energy Co</td>
<td>4083</td>
<td>33.2</td>
<td>0.12</td>
<td>0.26</td>
</tr>
<tr>
<td>Northern States Power Co - MN</td>
<td>852</td>
<td>48.6</td>
<td>0.27</td>
<td>0.26</td>
</tr>
<tr>
<td>ALLETE, Inc.</td>
<td>520</td>
<td>14.7</td>
<td>0.33</td>
<td>0.41</td>
</tr>
<tr>
<td>DTE Electric Company</td>
<td>449</td>
<td>47.3</td>
<td>0.21</td>
<td>0.05</td>
</tr>
<tr>
<td>Wisconsin Electric Power Co</td>
<td>339</td>
<td>36.8</td>
<td>0.29</td>
<td>0.26</td>
</tr>
<tr>
<td>Basin Electric Power Coop</td>
<td>287</td>
<td>29.6</td>
<td>0.37</td>
<td>0.94</td>
</tr>
<tr>
<td>Wisconsin Power &amp; Light Co</td>
<td>269</td>
<td>14.8</td>
<td>0.39</td>
<td>0.24</td>
</tr>
<tr>
<td>Consumers Energy Co</td>
<td>212</td>
<td>38.6</td>
<td>0.58</td>
<td>0.08</td>
</tr>
<tr>
<td>Interstate Power and Light Co</td>
<td>200</td>
<td>17.1</td>
<td>0.53</td>
<td>0.12</td>
</tr>
<tr>
<td>Montana-Dakota Utilities Co</td>
<td>157</td>
<td>3.5</td>
<td>0.25</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Notes: Wind capacity is the capacity of all wind turbines in megawatts. All data comes from EIA-860 and EIA-861 for the year 2016. TWh stands for terawatt-hour, and represents the thousand of gigawatt-hours sourced and dispositioned that year. Of the total amount sources, the % Wholesale Purchase represents the amount of electricity they purchased from the wholesale market, the remaining percent (from 100) is the share they generated. The % Sale for Resale is the percentage of total disposition that was sold to a third party (e.g. the wholesale market) the remaining share was sold to retail customers.
The predominate way to finance renewable energy electricity generation projects is through long term purchasing power agreements. Here the owner of the electricity generating resource signs a contract with an offtaker, who agrees to purchase a set amount of electricity at a fixed price. The electricity generators that sign this contract still sell in the wholesale market, in which case the off-taker pays the difference between the preset rate and the market rate. When the wholesale price is higher than the preset rate, the off-taker receives the revenue in excess of the preset rate. Projects financed in this way have no incentive to increase the market price. Ideally I would be able to identify these projects in the MISO data, however it is impossible given how the owner information is coded. Instead I present data from the American Wind Energy Association WindIQ database on all wind turbine projects on-line within MISO’s footprint.

Figure B.1 shows the total capacity in megawatts of all wind projects in MISO and the purchase type that finances them. Of the projects that are financed by only one purchase type, the most common purchase type is direct use by the utility that owns the wind project. To the extent to which the utility is selling the electricity in the wholesale market, these projects benefit from a higher wholesale market price. There are a number projects that are financed through merchant purchase type and purchase power agreements. Merchant projects, but not the power purchasing agreement projects, also benefit from a higher wholesale electricity price. With the data provided it is impossible to determine which percentage of the project is financed by a purchasing power agreement of through merchant sales.

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4 This differs from a hedge contract in that it is a purely financial arrangement.
Notes: The sum of total project capacity by generation purchase type, for purchase for all wind turbine projects online in MISO as of June 2018. Contract: Hedge is a physical contract for differences. Merchant projects sell electricity to the wholesale market. Direct Use: Utility-Owned is direct use of the wind turbine by the utility that owns the project. Contract: PPA is a purchasing power agreement that is a virtual contract for differences. There are a number of projects that have multiple purchase types listed.

B.3 Market Monitoring and Mitigation

To address concerns of uncompetitive conduct in the wholesale electricity market, independent system operators will contract with an independent market monitor. These monitors continuously monitor the market for uncompetitive conduct and release semi-annual reports detailing the overall competitiveness of the market. MISO’s independent market monitor is Potomac Economics. As of 2016, the assessment from Potomac is that MISO’s markets are competitive except for local
areas that experience chronic transmission constraints (Potomac Economics, June 2017). This is based off characterizations of the market structure and direct evaluation of market conduct.

The market structure is characterized by a Herfindahl-Hirschman Index (HHI) and the number of hours when at least one firm’s output is necessary to meet total demand. In MISO, the HHI varies from 600 (not concentrated) to over 3750 (very concentrated) depending on the region. While the number of pivotal firm’s is informative, a firm can still influence the price and not be pivotal.

Taking a more micro approach, Potomac directly looks the conduct of market participant by evaluating their price-cost markup, and looking for instances of economic and physical withholding.\(^5\)

The price-cost markup is found by comparing a simulated market price under two different scenarios, for all hours. One with the market participants actual bids, another using a “reference level” based on the suppliers start-up cost, no-load cost, and incremental energy cost. These two simulated market prices are averaged over a year, with the difference of the two averages being the price-cost markup. Overall MISO finds these mark ups to be small, almost zero (Potomac Economics, June 2017). This could be the case because only the averages are being compared.

A generation offer is considered to be an instance of economic or physical withholding if it fails a conduct threshold test. Potomac has different conduct thresholds depending on if a electricity generation facility is in chronically constrained area, call a Narrowly Constrained Area (NCA), or in an area that is temporarily constrained with a limited number of firms, called a Broad Constrained Area (BCA). For example, in a BCA, a plant fails the economic withholding conduct threshold if there is a binding transmission constraint and the energy offer is more than the minimum of the reference level generation price plus $100/MWh or the the reference level generation price times four. A market participant in a BCA fails the physical withholding conduct test if a plant is taking an unapproved deration or outage, there is a binding transmission constraint, and they are

\(^5\) Economic withholding is when a market participant submits an offer above their marginal cost in an attempt to increase the market price. Physical withholding is when a unit that should be able to produce at the prevailing market price instead withholds some or all of its output. The model presented in this paper is most concerned with physical withholding.
withholding the minimum of 5% of their portfolio or 200 MW (MISO, 2018). Overall, in 2016, Potomac identifies 5 to 10% of the total capacity in MISO was a derating or outage.

For Potomac to mitigate a generation offer, it must fail a conduct test for physical or economic withholding and it must fail an impact test. An impact test evaluates if the generation offer, instead of the reference level default bid, increases the market price beyond an acceptable level. For a Broad Constrained Area, the impact threshold is the minimum of 3 times the reference Energy LMP or the reference LMP plus $100/MWh. It’s likely that the type of anti-competitive behavior I model in this paper would not fail an impact test. This is because the incentive is to allow the wind generation to replace the market participants more expensive generation plants. This behavior would not create a significant increase in the market price, but instead prevent it from decreasing by the amount of the merit order effect. Table 1.3 suggest this value on average is $3.73/MWh.