ENVIRONMENTAL REGULATION AND FIRM BEHAVIOR

A Thesis
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Economics

Georgia Institute of Technology
August 2015

ENVIRONMENTAL REGULATION AND FIRM BEHAVIOR

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To Mitchell O. Galloway and Doris P. Galloway,

who always believed in me.

ACKNOWLEDGEMENTS

I would like to thank my committee, my family, Megan DeLockery, Lindsay McLellan, Christine Nguyen, Laura Garlock, and Danielle Godfrey for their continued support.

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SUMMARY

In three essays, I examine the impact of environmental regulation on the behavior of firms. First, I theoretically and empirically test the relationship between market power and cap-and-trade prices. Second, I demonstrate the potential for power plants to achieve efficiency gains and spillovers from changing environmental policy. Finally, I simulate the effect of new wind power on the decisions of power plants to invest in new capacity and to participate in reserve markets.

CHAPTER I

INTRODUCTION

The central theme of my research is the relationship between environmental regulation and the behavior of firms. The evaluation of environmental policy requires a thorough knowledge of the costs and benefits of implementing new programs. It is therefore important to understand how regulations change the decisions of regulated parties, and how these changes impact the costs or benefits of regulation.

To this end, I explore the relationship between a number of different regulatory changes and the actions of the affected firms in three essays, all related in part to the wholesale electricity industry. Electricity generation accounts for a significant portion of air pollution, and is consequently heavily regulated. The significant amount of regulation and the wealth of available data allow me to empirically test my theoretical models.

In my first chapter, I investigate the relationship between a firm's market power in their own product market and the prices in a regulatory market established by cap-and-trade programs. I predict, using a Cournot competition model, that increases in market power in the product market impact the demand for pollution permits provided that the marginal cost of abatement is increasing. I then examine this relationship empirically using RECLAIM in Southern California, a cap-and-trade program covering a narrow geographic region but a wide variety of industries. as a case study. I concentrate on measuring the degree of market power in three high-emitting industries: electricity generation, oil refining, and cement production. I find that a 1 standard deviation increase in the markup over marginal cost in these industries resulted in an increase in the price of RECLAIM permits by \$0.46, \$0.51, and \$3.52, respectively. Incorporating the California electricity crisis in 2000 and its impacts of the design and functioning of the program provides robustness to my results and illustrates the impact that large changes in market power can have on a regulatory market.

In my second chapter, I examine firm learning in response to environmental regulation. I theorize that regulation calls attention to existing inefficiencies within firms, allowing them to develop process innovations to improve their efficiency. Because power plants generally belong to a network of plants owned by a single firm, efficiency gains at one plant may result in innovations being transferred to other plants. I can test this relationship using the National Ambient Air Quality standards, which vary county-by-county. This country variation in regulatory stringency allows us to test the gains in efficiency of regulated plants as well as any gains at unregulated plants who belong to the same network as regulated plants. Using data from Energy Information Association on power plant efficiency from 1970-2010, I find that increases in regulatory stringency result in within-firm efficiency spillovers of about 1-2%. Additionally, consistent with the notion of firm learning, these spillovers tend to occur about 2 years after the change in regulation.

Finally, in my third chapter, I look at the impact of a result of regulation - the growth of wind power - on decision making processes in Texas electricity markets. There has been a recent push in Texas to implement capacity markets, an annual payment per-unit of capacity installed at power plants, in order to increase investment in new electric capacity. Opponents believe that the market provides enough incentives for innovation without subsidies. However, existing incentives to innovate are changing as a result of increasing wind penetration in the market. Using a simulation methodology, I translate a theoretical model into data and examine the comparative statics of a number of market outcomes with respect to wind power. I find that increased wind capacity results in divestment by fossil fuel plants and increases the risk of shortages. However, we also find that, due to the better preditive power of managers of the electricity grid when wind penetration increases, policy makers may be able to manipulate existing market mechanisms (in particular, the requirement for reserve capacity) foster investment without introducing subsidies through capacity markets.

Through these three essays, I discuss some of the unintended consequences of changing environmental policy on how firms make choices: cap-and-trade programs link together previously unrelated industries, resulting in manipulation of the permit price; attempts to meet air quality standards may result in innovation that benefits both regulated and unregulated plants; and growth in renewables affects the availability of the reserves necessary for electricity markets to operate.

CHAPTER II

THE IMPACT OF MARKET POWER IN THE PRODUCT MARKET ON CAP-AND-TRADE PRICES: EVIDENCE FROM RECLAIM IN SOUTHERN CALIFORNIA

Regulatory bodies often propose emissions trading schemes (also known as cap-and-trade programs) to curb emissions of harmful pollutants. The United States Environmental Protection Agency (EPA) has utilized cap-and-trade since 1995 via the Acid Rain Program (ARP) in order to cut the levels of nitrogen oxides (NOx) and sulfur dioxide air pollution. The European Union's Emissions Trading Scheme (ETS), established in 2005, strives to reduce greenhouse gas emissions in member nations via a cap-and-trade system. More recently, in 2012, the California Air Resources Board implemented a cap-and-trade program to meet the greenhouse gas reductions required by AB 32, the California Global Warming Solutions Act of 2006.

These regulatory programs share some similar characteristics. All involve the determination of some emissions cap, the distribution of allowances, or permits, for emissions amounting to this cap, and the ability of participating firms to trade these allowances amongst themselves to establish a market price. Proponents of cap-and-trade hail the flexibility of these programs, compared with command-and-control regulations, in terms of the actions a firm may take to reduce their emissions. Such flexibility reduces the cost of compliance with environmental regulation (Oates et al., 1989; Ellerman et al. 2000) [26, 6].

The market-based price of pollution may be affected by market failures, such as market power. This idea is consistent with Lipsey and Lancaster (1956)'s [21] Theory of the Second Best: any attempt to correct one market failure, like regulatory programs aimed at reducing pollutions negative externality, may produce a new market failure, like some new market power-related distortion. When permit trading programs cover more than one sector, they link previously unrelated industries through a new input market for permits. Connecting these industries allows the effects of market power in one industry to infiltrate other industries. The regulatory market and the product markets of regulated industries are thus inextricably linked. Even if firms do not behave strategically in the permit market, any existing product market failure that influences the demand for permits will also influence permit prices. The price in the multi-industry permit market transmits market failures to other industries.

The purpose of this paper is to examine the relationship between product market characteristics and permit prices in order to determine how market power in one industry has consequences in other industries. I develop a stylized theoretical model in which identical firms in a single sector exercise market power in the product market. In the model, an increase in market power decreases both the production of output and the use of abatement technology, creating two opposing forces acting on the demand for pollution permits. Provided that the marginal cost of abatement is increasing and the supply of permits is sufficiently low, the abatement effect is larger than the output effect and the net effect of an increase in product market power on permit demand is positive. Therefore, when firms have more market power, the shift in pollution demand increases the price of permits.

The theoretical model shows that, under some assumptions, market power in the product market has a positive effect on the price of cap-and-trade premits. Whether or not this is true in practice is an empirical question. I use data from the South Coast Air Quality Management District, the regulatory body responsible for a multiple industry cap-and-trade program called RECLAIM, to empirically test the relationship between market power in the electricity generation, the oil refining, and the hydraulic cement production industries and the price of RECLAIM permits. Using a panel of data from 1998-2003, I find that market power in these three industries significantly increased the price of permits over the sample period. Specifically, a 1 standard deviation rise in the industry markups over marginal cost increased the permit price by \$0.46, \$0.51, and \$3.52, respectively. That is, the actions of firms to increase profits in their own industry leak into to the regulatory industry and increase the costs of compliance with regulation.

Most of the literature involving market power and regulatory markets concentrates on the ability of firms to strategically manipulate permit markets in emissions trading schemes covering single industries, rather than examining how a market failure in an industry's market can create a spillover effect in the regulatory market. For example, van Egetern and Weber (1996) [36] examine the impact of permit market power on compliance decisions and permit prices, and found that the effect of permit market power depends on the compliance of powerful firms. Other research implies that permit markets may create market power in the product market. For example, Malik (2002) [24] suggests a firm may purchase more permits that necessary in order to restrict the output of its competitors. Hahn (1984) [8] models the introduction of a cap-and-trade regulation on an asymmetric market with a few powerful firms and many competitive firms. In this case, market power in the product market may translate into market power in the permit market. Depending on the initial allocation of permits, firms may act strategically to impact the permit market, creating distortions and inefficiency.

The paper proceeds as follows. First, I discuss the details of the RECLAIM program. A number of RECLAIM's characteristics simplify both the theoretical and the empirical analysis. Second, I propose a theoretical model in which identical firms have market power in the product market. I show that the price of permits, in most cases, increases when product market power increases. Finally, I empirically test this

Figure 1: Coverage of the RECLAIM program by the SCAQMD (Beychok, 2012) [2].

result using data from California's RECLAIM program.

2.1 About RECLAIM

The Regional Clean Air Incentives Market (RECLAIM)[1] began at the end of 1993 in California. The SCAQMD designed the program to reduce the emissions of nitrogen oxides (NOx)[2] in the Los Angeles area using market-based incentives. Figure 1 illustrates the portion of California regulated by RECLAIM, called the South Coast Air Basin. RECLAIM bears the basic structure of cap-and-trade systems. Regulators set an emissions cap for large NOx emitting facilities and distribute emissions permits, which sum up to this cap, to participating facilities. Facilities who have more permits than they need may then sell permits to facilities whose emissions while exceed their number of permits at some market price.

The program includes about 350 participants in the NOx market, including a large

[1]Information on RECLAIM from Israels (2002) [14], EPA (2006) [7] and Halmov et al. ([10].

[2]The program also creates the same mechanism for sulfur oxides (or SOx), which operates independently of the NOx and, unlike the NOx market, features a banking and borrowing system.

Table 1: Highest Emitting RECLAIM Industries

Industry	Average Quarterly NOx Emissions (lbs)
Cement, Hydraulic	306,228
Petroleum Refining	292,419
Electric Services	103,977
Glass Containers	89,071
Natural Gas Transmission and Distribution	58,265
Paper Mills	48,732
Natural Gas Transmission	43,921
Electric and Other Services, Combined	24,595
Paperboard Mills	16,672
Pharmaceutical Preparations	14,506

number of electric power generators. All electricity generating facilities in the regulated area are automatically included in the RECLAIM market, excluding facilities in Burbank, Glendale, Pasadena, and the Riverside County portions of the Mojave Desert Air Basin. These areas are under the jurisdiction of the SCAQMD, but are outside of the regulated zone, namely the Los Angeles Basin. The program does permit facilities in these regions to opt-in to the program, but opting-in makes future participation in the program mandatory. In addition to power plants, the program reaches a large variety of industries. Table 1 lists the ten participating industries with the highest level of NOx emissions, all of which are in the manufacturing factor. The three industries with the largest average quarterly NOx emissions are hydraulic cement production, oil refining, and electric services. RECLAIM also includes a number of service-based industries with NOx emissions, like savings institutions, though these have relatively small emissions levels.

Designers of the program based RECLAIM upon a theoretical economic model in which plant operators minimize costs by choosing to install new emission control technology, modify their processes to reduce emissions, or purchase credits (Halmov et al.) [10]. These credits represent reductions in emissions from other sources - they are sold by facilities who have reduced their emissions below their permit allocation.

Table 2: Annual RECLAIM Compliance Rates

Compliance Year	Compliance Rate
1994	86
1995	92
1996	85
1997	96
1998	94
1999	91
2000	88
2002	97
2003	97

The SCAQMD's model for RECLAIM assumes that plant operators always comply with the program, and have perfect informing on an infinite time horizon. In reality, compliance with the program is high. Table 2 reveals that compliance rates from 1994-2000 never fell below 86 percent and a 2007 audit report found that 94 percent of firms complied with the program in compliance year 2007. Non-compliant firms face a penalty of $500 per 1,000 pounds of emissions for each day it does not comply (Tietenburg, 2006) [34]. Additionally, future decisions of the SCAQMD about the firm (for example, the determination of allocations or the approval of new equipment) depend on the compliance of its facilities with the program. Therefore, though the average cost of emitting 1,000 pounds of NOx (approximately $1,880, according to Table 3) is greater than the monetary cost of non-compliance, the actual penalties of non-compliance may be much larger[3].

Prices in the permit market vary greatly seasonally and annually (Holland and Moore, 2012) [12]. In the early years of the program (1994-1999), regulators tested the program by choose a non-binding NOx cap (Tietenburg, 2006) [34], resulting in

[3]One common feature of cap-and-trade systems is a mechanism for the banking and borrowing of pollution permits. In such a mechanism, polluters can reduce their pollution today in order to "bank" permits for a later period, or borrow against future permits if they fail to meet their cap today. Interestingly, over the sample period, RECLAIM's NOx trading program did not include a banking and borrowing system (Parker, 2008) [28]. Regulators did not include this feature in the RECLAIM program because they were concerned that banking of RECLAIM trading credits (or RTCs) would lead to substantial increases in emissions in later years (Harrison, 2004) [11].

low permit prices. Then, beginning in the summer of 2000, permit prices spiked when there was a sudden shortage of emissions allowances, resulting from the California electricity crisis (Israels, 2002) [14]. The combination of the deregulation of the California electricity market and high summer electricity demand meant that power generators purchased an unusually large number of NOx permits. Initial allocations of permits, based on historical emissions, did not account for this large rise in demand. As a result, permit prices rose from $3,000 per ton at the beginning of the year to $70,000 per ton in August (Joskow and Kahn, 2002) [16]. Finally, in the period following the crisis, the SCAQMD made a number of changes to RECLAIM in order to prevent future crises, including the removal of 14 electricity generators from the primary permit market and a control technology requirement for large emitting facilities. During this period, prices were lower than during the crisis period, but higher than during the pre-crisis years as the emissions cap became binding.

2.2 *Stylized Theoretical Model*

To illustrate the impact that market power in the product market can have on the price in the regulatory market, I construct a stylized model of supply and demand for permits when firms are Cournot competitors in a single product market. This model serves to illustrate the hypothesized effect of product market power in the permit market in a simple competitive case, as well as to propose one potential mechanism for this relationship.

2.2.1 Equilibrium in the Permit Market

There are N Cournot competitors in a homogeneous goods industry. Firms face market demand of $P = 1 - Q$, where P is the market price and Q is the total industry output. All firms are identical, and have a marginal production cost of zero. In this market, the number of firms N acts as a proxy for the degree of market power in the industry. Each unit of output q_j produced by a firm j in this industry creates one unit of emissions of some pollutant. In order to reduce the level of air pollution, regulators establish a cap-and-trade program. The regulator distributes a total supply of permits S to the firms, where each permit allows the firm to emit one unit of pollution. Firms may buy and sell these permits amongst themselves in the permit market, for an endogenously determined price of r. Firms may also produce abatement, which lowers their total emissions and the total number of permits they must purchase. Each unit of abatement a_j reduces a firm's emissions by one unit, and the total abatement cost is $\frac{1}{2}a_j^2$. Firms face a trade-off between purchasing pollution permits and producing abatement.

The total amount of pollution produced by this industry is $Z = Q - A$ where $Q = \sum_{j=1}^{N} q_j$ and $A = \sum_{j=1}^{N} a_j$. The total amount of pollution is equivalent to the demand for permits by the firms. The price of permits, an implicit function of the permit market clearing condition, is a function of this demand. Firms consider the impact of total demand for permits on the price of permits in their optimization decision. Note that $\frac{\partial r}{\partial Q} = r'(Z)\frac{\partial Z}{\partial Q} = r'(Z)$ and $\frac{\partial r}{\partial A} = r'(Z)\frac{\partial Z}{\partial A} = -r'(Z)$. Equation 1 gives the profits of a representative firm in the industry.

$$\pi_j = (1 - Q)q_j - r(Z)(q_j - a_j) - \frac{1}{2}a_j^2 \tag{1}$$

The equilibrium permit demand function is defined by the optimal behavior of the firms in the market. Given this demand function, the market clearing condition defines the equilibrium permit price and, consequently, equilibrium firm choices. Each firm chooses its output and abatement in order to maximize its profits. The first order conditions describing their optimal choice are equations are given by:

$$1 - Q^* - q_j^* - r'(Z^*)(q_j^* - a_j^*) - r(Z^*) = 0$$

$$r'(Z^*)(q_j^* - a_j^*) + r(Z^*) - a_j^* = 0$$

Each of the N firms in the market have the same set of first order conditions. Summing up these first order conditions yields:

$$N(1 - Q^* - r(Z^*)) - Q^* - r'(Z^*)(Q^* - A^*) = 0$$

$$Nr(Z^*) + r'(Z^*)(Q^* - A^*) - A^* = 0$$

which define a system of equations describing the optimal total output and total abatement. Solving the system of equations gives the total output and total abatement as a function of the market clearing level of permits:

$$Q^* = \frac{N(1 + r'(Z^*) - r(Z^*))}{1 + N + r'(Z^*)(N + 2)}$$

$$A^* = \frac{N(r'(Z^*) + r(Z^*) + Nr(Z^*))}{1 + N + r'(Z^*)(N + 2)}$$

Symmetry of the firms implies that $Q^* = Nq_j^*$ and $A^* = Na_j^*$, giving the optimal choice of output and abatement for each firm.

$$q_j^* = \frac{1 + r'(Z^*) - r(Z^*)}{1 + N + r'(Z^*)(N + 2)}$$

$$a_j^* = \frac{r'(Z^*) + r(Z^*) + Nr(Z^*)}{1 + N + r'(Z^*)(N + 2)}$$

The total quantity demanded for pollution permits Z^* is the difference between total output Q^* and total abatement A^*. Solving for r gives the inverse demand function:

$$r(Z^*) = \frac{1}{N + 2} - \frac{1 + 2r'(Z^*) + N(1 + r'(Z^*))}{N(N + 2)} Z^*$$

To simplify the analysis, I make the assumption that the inverse demand function for pollution permits is linear, implying that $r''(Z) = 0$. Given the linear inverse demand assumption, the slope of the inverse permit demand function $r'(Z^*)$ is the coefficient of the Z^* term in the equation above. That is:

$$r'(Z^*) = -\frac{1 + 2r'(Z^*) + N(1 + r'(Z^*)}{N(N + 2)}$$

Solving this equation for $r'(Z^*)$ yields the actual slope of the inverse demand function $r(Z^*) = -\frac{1}{N+2}$. Therefore, the linear inverse demand assumption gives the final piece of information necessary to describe the permit demand derived from firm optimization behavior, and the inverse demand for pollution permits is described by equation 2.

$$r(Z^*) = \frac{1 - Z^*}{N + 2} \tag{2}$$

Assuming the perfect compliance of all firms with the cap-and-trade program, the total supply of permits S is equal to the total quantity demanded for permits Z. Proposition 1 describes the equilibrium in both the product and permit markets.

Proposition 1. *Assume the supply of permits $S < 1$. Then, the permit price, optimal output, optimal abatement, and equilibrium product market price are functions of the number of firms N and the supply of permits S:*

1. *The equilibrium permit price is $r(N, S) = \frac{1-S}{N+2}$.*
2. *The total output produced in equilibrium is $Q(N, S) = \frac{N+1-r(N,S)(N+2)}{N+2} = \frac{N+S}{N+2}$ and each firm produces $q_j(N, S) = \frac{1}{N}Q(N, S)$ units of output.*
3. *The total abatement produced in equilibrium is $A(N, S) = \frac{(N+1)(N+2)r(N,S)-1}{N+2} = \frac{N-S-NS}{N+2}$ and each firm produces $a_j(N, S) = \frac{1}{N}A(N, S)$ units of abatement.*
4. *The equilibrium product price is $P(N, S) = \frac{1+(N+2)r(N+S)}{N+2} = \frac{2-S}{N+2}$*

2.2.2 Product Market Power and the Permit Market

Market power may be defined using a concentration measure.[4]. In the Cournot model, changes in the number of firms change the level of market power in terms of concentration, as discussed in Lemma 1.

[4]In the empirical model, I also define market power as a Lerner index. In this particular model, the only marginal cost of production is r, and changes in r due to changes in the N offset changes in the price. The Lerner index is constant in N: $L = \frac{P-MC}{P} = \frac{P-MC}{P} = \frac{2-S-1+S}{N+2}\frac{N+2}{2-S} = \frac{1}{2-S}$. In a later section, I extend the above model to include increasing marginal production costs; in this case, the Lerner Index will no longer be constant in N.

Lemma 1. *Market power is decreasing in the number of firms because the Herfindahl-Hirschman Index (HHI) is decreasing in the number of firms.*

Proof. The HHI is given by $HHI = \sum_{j=1}^{N} s_j^2$ where $s_j = \frac{q_j}{Q}$ is the market share of the firm. Note that $s_j = \frac{q_j}{Q} = \frac{q_j}{Nq_j} = \frac{1}{N}$. Therefore, $HHI = \sum_{j=1}^{N}(\frac{1}{N})^2 = \frac{N}{N^2} = \frac{1}{N}$. Therefore, $\frac{dHHI}{dN} = -\frac{1}{N^2} < 0$ □

The key relationship of interest is the impact of changes in market power on the price in the permit market, discussed in Proposition 2:

Proposition 2. *The market permit price is decreasing in N and, consequently, increasing in the degree of market power.*

Proof. From Proposition 1, the equilibrium permit price is $r(N, S) = \frac{1-S}{N+2}$. Taking the derivative with respect to N gives $\frac{\partial r}{\partial N} = -\frac{1-S}{(N+2)^2} < 0$. Therefore, the permit price decreases when N increases. □

To understand the result in Proposition 2, I turn to the impact of changes in N on the market for pollution permits. Because of the perfect compliance assumption, the supply of permits is constant and any changes in N will only create a change in the demand for permits. Two competing forces are at work on the demand side: the output effect and the abatement effect.

The output effect is the standard Cournot result. An increase in the number of firms will increase the total output. The additional output by the new firm is greater than reduction in output by all firms due to the business stealing effect of greater competition. Increased output results in an increased demand for pollution permits. Conversely, a decrease the number of firms, representing an increase in the degree of market power in the industry, will reduce the total output, forcing the demand for pollution permits downward.

The abatement effect opposes the output effect. A larger number of firms also results in greater total abatement. As in the output case, the additional abatement

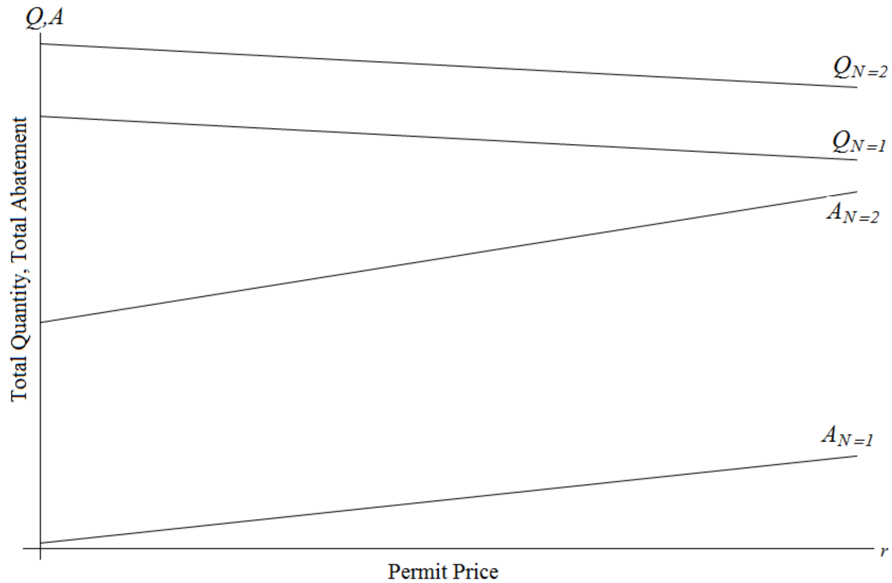


Figure 2: The effect of a shift in market power on total output and total abatement.

produced by the new firm will make up for the reductions in abatement in all firms. Increased total abatement works counter to the increased total output, reducing the demand for permits. Similarly, when firms have more market power, the total level of abatement falls. If the effect on output is greater than the effect on abatement, then demand for permits will increase with firm entry and fall with firm exit. However, as described in Lemma 2, the abatement changes resulting from changes in market power are larger than the changes in total output, so permit demand and market power move in the same direction.

Lemma 2. *The demand for pollution permits is decreasing in the number of firms N.*

Proof. Taking the derivatives of total output Q and total abatement A with respect to N yields $\frac{\partial Q}{\partial N} = \frac{1}{(N+2)^2}$ and $\frac{\partial A}{\partial N} = \frac{1}{(N+2)^2} + r$. Clearly, for any positive r, the rise in total abatement will be greater than the rise in total output, and the change in demand will be $\frac{\partial Z}{\partial N} = -r < 0$. □

Figure 2 illustrates the result in Proposition 2, showing the shift in abatement

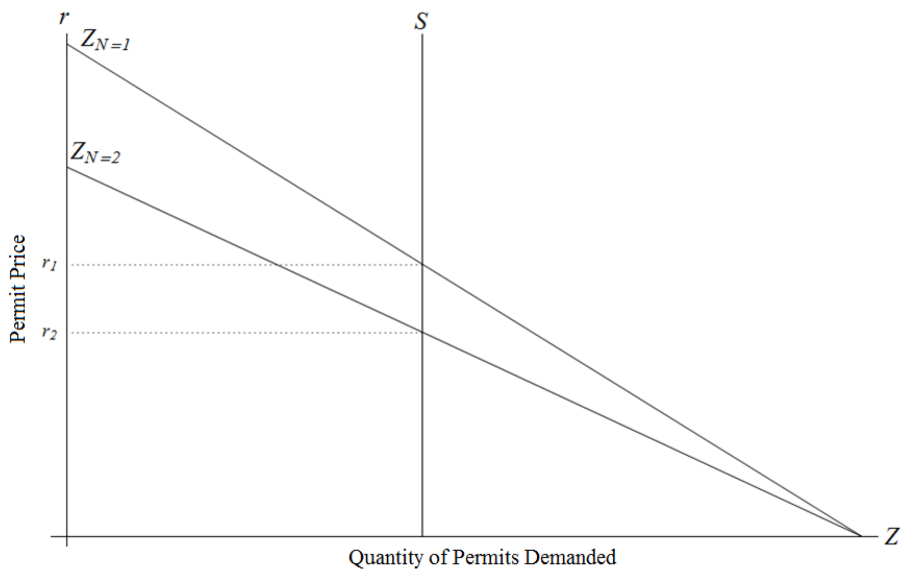


Figure 3: The effect of a shift in the market power on the equilibrium price of pollution permits.

and output for a constant level of r. For any given price r, a reduction in N shifts both the output-price curve and the abatement-price curve. In the relationship between output-price, the output effect suggests that an increase in N will increase in the total demand for permits due to output; therefore, the quantity curve shifts up. Similarly, the abatement effect states that a larger number of firms increases the total supply of permits through abatement, shifting the abatement supply curve upward as well. For any given permit price r, the abatement effect is larger than the output effect. Economies of scale in the production of abatement create this result. When firms have more market power, the total amount of output (and emissions) produced by each firm rises. To account for this increase, the firm must either purchase more permits or produce more abatement. Due to the increasing marginal cost of producing abatement, an increase in abatement makes the production of abatement more expensive relative to the price of permits. Therefore, individual firm abatement rise, but not by as much as individual firm output.

Because the demand for permits decreases with N and the supply of permits is constant, the price of pollution permits is decreasing in the number of firms. That is, when firms in the market have more market power, the price of permits will rise. Figure 3 illustrates the reduction in the equilibrium price due to greater competition. Note that in this model, I have assumed that the total allocation of permits does not change when a new firm enters the market. However, it is possible that the regulator may slightly increase S to accommodate firm entry. From Figure 3, it is clear that a shift in supply due to changes in N would simply serve to reduce the permit price even more. Therefore, the equilibrium outcome remains the same.

The fact that r increases with market power implies that the firms' marginal costs are decreasing in N. This result has implications for the effect of greater competition on the production price as well. In a case without the relationship between marginal cost and the number of firms, firms exercise their market power by reducing their quantity. When the marginal costs increase due to this reduction, the production price increases by a greater amount than it would otherwise. To illustrate this, consider the effect of a decrease in N on the price in an unregulated market with a constant marginal cost $0 < c < 1$. When the number of firms falls by one, the price of the product increases by $\frac{1}{(N+1)^2}$. Returning to the regulated market, the same fall increases the price by $\frac{2-S}{(N+2)^2}$. Since $S < 1$, it is clear that the price increases by more when market power increases when the market is regulated than when it is unregulated.

Returning to the RECLAIM permit market, it is possible that the increased ability of electricity firms to exercise market power during periods of high demand could have driven up the cost of NOx permits in the RECLAIM market and, consequently, driven up the price of electricity even further. That is, electricity market power has a feedback effect. Generators exercise market power in the product market, driving up the wholesale price of electricity. This market power also drives up the price of RECLAIM permits, also increasing the wholesale price of electricity. Therefore, when demand is high, the price of electricity may be greater than it would be without cap-and-trade NOx regulation.

Now, consider the implications of this relationship between market power and permit price when cap-and-trade programs involve multiple industries. Suppose an additional, perfectly competitive industry also participates in the cap-and-trade market, and that this industry has neglibily small emissions relative to the emissions of the other industry. When the first industry's market power increases, the price of permits rises, increasing the marginal costs (and the product prices) in the second industry. The cap-and-trade program connects these two industries, allowing the market failure in the first industry to impact the second industry. Multiple industry cap-and-trade programs may therefore create additional problems due to this ability of product market behaviors to influence the permit price.

2.2.3 The Role of the Elasticity of Product Demand

The key result of Proposition 2 is the fact that the total level of abatement increases more with N than the total level of output. However, if the price elasticity of demand for the product market is sufficiently negative, it may be possible that quantity increases by a greater amount when N changes than in the previous case. Therefore, now suppose that inverse demand for output is $P = 1 - bQ$, where $b > 0$. In this case, the elasticity of demand is given by equation 3. When b increases, demand becomes more elastic.

$$e_d = \frac{\partial Q}{\partial P}\frac{P}{Q} = \frac{1 - bQ}{bQ} \tag{3}$$

Proposition 3. *The price of pollution permits r is decreasing in N for all $b > 0$*

Proof. See Appendix A. □

Proposition 3 suggests that the result in Proposition 2 does not depend on the elasticity of demand. That is, the increase in abatement is always greater than the increase in output due to firm entry, regardless of the value of b. As in the previous case, changes in N simply shifts the output-permit price curve down while it shifts the abatement-permit price curve down *and* increases its slope. The elasticity of product demand does not change these two effects, so the demand for permits decreases in N, as does the price of permits.

2.2.4 Increasing Marginal Production Costs

The fact that changes in N only shift the quantity-price curve while they shift *and* change the slope of the abatement-price curve partially creates the results in Propositions 2 and 3. The assumption that the marginal costs of production are constant and zero drive this result. Therefore, I now assume that the total production cost is, like the total abatement cost, quadratic: $C_j(q_j) = \frac{1}{2}q_j^2$. Now, the marginal costs of production are increasing.

Proposition 4. *The price of pollution permits r is decreasing in N for all positive r where $S < \frac{(N+1)^2}{5+4N+N^2}$.*

Proof. See Appendix A. □

Now, when the number of firms decreases, when each individual firm produces a larger amount of output, the marginal cost of production increases. As a result, individual firm production will rise by a smaller amount than the case with constant marginal production costs and the output effect will be larger. However, the abatement effect will still dominate the output effect when the supply of permits is sufficiently low. When the permit supply is low, the price of permits is high. Because firms face a tradeoff between pollution permits and abatement, the higher the price of permits, the greater the incentives for firms to abate their emissions. For a given permit price, when N falls, firm abatement will not fall by much because the incentive to abate is still high.

There is a small range of S in which the increases in total quantity are greater than the increases in total abatement, so that the demand for permits increases when

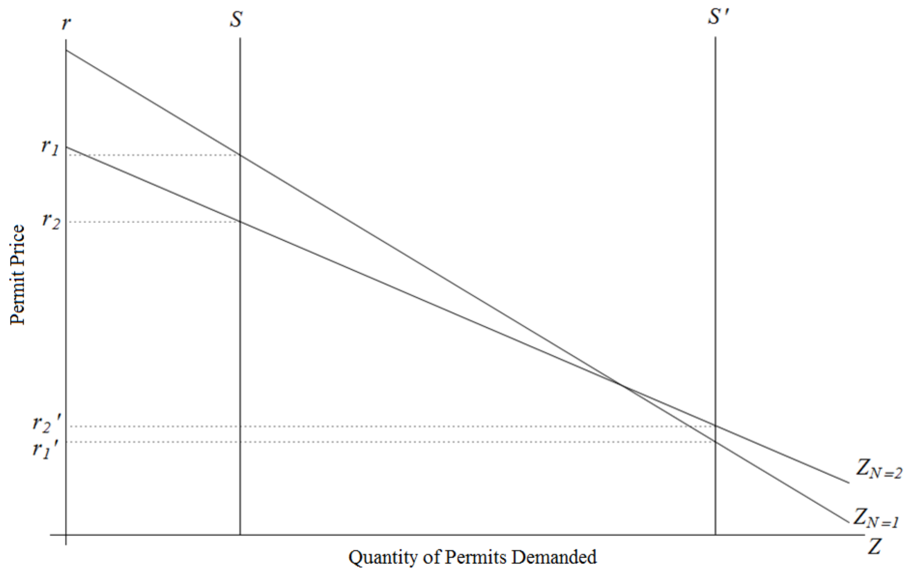


Figure 4: The effect of a change in market power on permit prices with increasing marginal production costs.

N increases. In this range, S is large enough that the equilibrium price of permits is small, so the incentives to incur the additional abatement cost in order to reduce the cost of pollution is low.

Figure 4 illustrates the two possible effects of N on r. When the supply of permits is S, an increase in N moves the equilibrium price from r_1^* to r_2^*, where $r_1^* > r_2^*$. Because a change in N shifts the permit demand curve down and changes the slope, at one point the two demand curves will intersect at a positive r. If the supply is large enough, say at $S' > S$, then the price of permits with fewer firms $r_1^{*'}$ is less than the price of permits with more firms $r_2^{*'}$. That is, when the market power of the firm increases, the price of permits decreases. In such a case, market power not only provides firms with additional revenue, but also with lower marginal costs of pollution.

2.3 An Empirical Test

To examine the empirical relationship between prices in the market for permits and levels of market power in the product market, I use information from the RECLAIM cap-and-trade program from the years 1998-2003. Note that the proposed output and abatement effects that result in the positive relationship between product market power and the price of permits is only one potential mechanism determining this relationship, and that this particular mechanism requires detailed information about plant marginal costs. I therefore concentrate more on the general predictions of the model. I estimate the effect of changes in market power on permit prices using variation over time.

I concentrate on measuring market power in 3 industries: the electricity generation industry, the hydraulic cement production industry, and the oil refining industry. According to Table 1, facilities in these three industries have the highest NOx emissions of all those industries that participate in RECLAIM. Because their emissions account for a large portion of the market for permits, they should have a greater ability to influence the market for permits than those industries will have relatively low emissions (like, for example, national commercial banks, which have average quarterly NOx emissions of approximately 25 pounds). Additionally, I include an average market power measure for all other industries to capture the ability of lower emitting industries to influence the permit market.

The basic relationship between permit prices and market power in the three main industries may be modeled as follows:

$$\ln(r_t) = \beta_0 + \sum_{i=1}^{3} \beta_i \ln(MP_{it}) + \beta_4 \ln(AMP_t) + \mathbf{x}_t \epsilon_t$$

where r_t is the price of RECLAIM permits, i indexes the industry (electricity, oil, and cement), MP_{it} is the degree of market power in industry i, and AMP_t is the average amount of market power in all other industries, $\mathbf{x}_t$ is a vector of control variables, and ϵ_t is an error term.

I choose the sample period to be 1998-2003 for a number of reasons. First, I start the sample in 1998, four years after the start of the RECLAIM emissions trading scheme, to allow participants to adjust to the implementation of the new regulation.

Additionally, the California electricity market was restructuring in 1998, decoupling electricity generation from transmission and distribution. Borenstein et al. (2002) [4] provides an excellent summary of the structure of the electricity market both before and after restructuring. The primary effect of restructuring was to change the nature of competition in the electricity industry, and therefore had a significant effect on the ability of firms to exercise market power. I therefore start my sample in 1998 to include only post-restructured electricity market power. Finally, I end the sample in 2003, splitting the data into three, two-year periods: the pre-crisis period (1998-1999), the crisis period (2000-2001), and the post-crisis period (2002-2003).

2.3.1 Data

From the South Coast Air Quality Management District, I obtained data on the price and quantity of RECLAIM trading credits (RTCs) in all trades that took place from 1998 to 2003. 1.4 percent of the registered trades were intra-firm trades. Additionally, 20.4 percent of transactions trade expired RTCs, in the few months following their expiration. The prices in such transactions are, in the vast majority of cases, zero. RTCs of this type have lower values and are, therefore, essentially traded in a different market. Thus, I drop expired and within-firm transactions from the data set. Using the remaining data, I construct a quantity-weighted, monthly average price. I weight by quantity in order to obtain the mean price per unit, as opposed to the mean price per transactions.[5]

For a relationship between price and market power to exist, the market for pollution permits must be sufficiently thick that a market price of permits exists. That is, there must be a large number of participants, both buyers and sellers, involved in the

[5]At the outset of the program, the SCAQMD sorted facilities into two cycles in order to stagger the introduction of the program. Cycle 1's compliance schedule runs from January to December of each year, while Cycle 2's schedule runs from July to June of the following year. Prices in transactions made on the June and December track are weighted equally, as are all RTCs with future expiration dates.

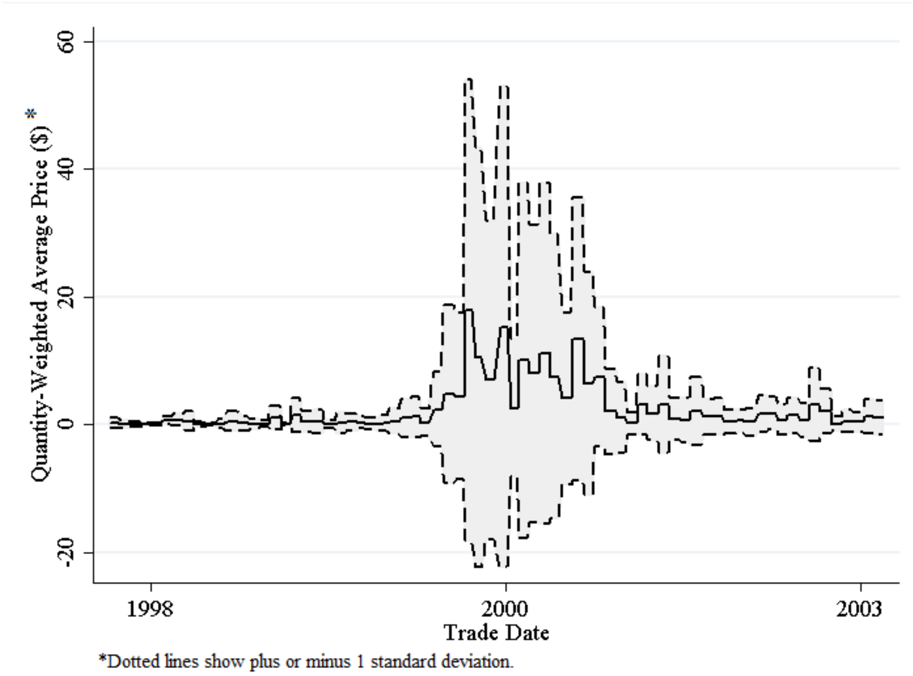


Figure 5: Establishing the existence of a market price in the permit market.

market. To establish the existence of this market price, I determined the weighted[6] standard deviation of the price in each month.

I then plot the monthly weighted average price, plus or minus one standard deviation, across time in the entire dataset in Figure 5. In general, the standard deviation is small, suggesting that there is a single market price for RTCs. However, a number of periods have larger standard deviations. Notably, in the summer of 2000, permit prices skyrocketed, creating a larger distribution of prices. This wide variation in the price of permits during the electricity crisis may indicate that the market was thick during this period or that a single market price did not exist due to uncertainty. As a result, the predictions of my theoretical model may not hold during the electricity crisis.

The South Coast Air Quality Management District also shared data on the characteristics of all RECLAIM facilities, including the SIC code, all registered equipment,

[6]Standard deviation is weighted in order to obtain the average deviation per unit traded, rather than per transaction.

and the registration date of all equipment. The SCAQMD divides equipment into "control" categories, describing the primary function of the equipment. These control categories include air filters, low-NOx burners, and scrubbers. I create a dummy variable for each control category that equals 1 in the time period in which a facility installs a type of equipment and in all following periods. Of course, much of this equipment may have been replaced or retired at some point during the time period. I do not have data on the expiration of the equipment permits, however, so I am unable to allow for the retirement of equipment.

To measure market power in the average RECLAIM industry as well as industry revenue, I use quarterly revenue data from Compustat.[7] I calculate the average industry revenue by SIC code for all firms across the country in an industry *and* for only firms with headquarters in California. For some industries local demand is more relevant than national demand. Other industries compete nationally, and national demand is more appropriate.

Compustat does not collect information on the market share of firms, or on firm output. Therefore, I use revenue data to calculate each firm's market share. If the prices of all goods in the industry are the same, then the market share calculated from revenue is the same as the market share calculated from output.[8]. However, if the prices are not the same, then these two measures are not equivalent, possibly biasing the results. The sign of such a bias is unclear. Equation **??** describes the formula used to calculate the market share of each firm j in a given industry i in each quarter, t. I calculate both the local market share and the national market share, in order to differentiate between firms that compete more nationally than locally and vice

[7]Note that Compustat contains data from only publicly traded companies. If publicly traded firms in any given industry are systematically different from privately traded firms, then average industry revenue may not accurately characterize an industry's demand. Also, if the private sector is sufficiently large, then I will over-estimate the market share of the publicly traded firms, possibly overestimating the market power index of the industry.

[8]$s^R_{ijt} = \frac{P_t Q_{ijt}}{\sum_{ijt} P_t Q_{ijt}} = \frac{P_t Q_{ijt}}{P_t \sum_{ijt} Q_{ijt}} = \frac{Q_{ijt}}{\sum_{ijt} Q_{ijt}} = s^Q_{ijt}$

versa. Using the market share, I calculate the Herfindahl index (HHI), a concentration measure commonly used to measure competition in an industry. Finally, I determine the number of firms in each industry at both the national level and at the California level. These variables serve as an additional possible measure of market power.

I obtain data from California's Independent System Operator (ISO), the operator of the electricity transmission grid in California on both the actual load on the grid and on the real-time, ex-post price in the electricity market in each hour. From the U.S. Environmental Information Administration (EIA), I obtain data on the capacities and fuel type of all generators in the state in each year, as well as the coal, petroleum, and natural gas prices. The EIA measures coal prices annually in dollars per short ton; I use the average unit cost of all types of coal as the fuel cost of coal-type generators. For the price of petroleum, I use the Daily Type 2 Petroleum Price from the New York Harbor, a spot-price measured by the EIA in dollars per gallon. Finally, the natural gas fuel price is the Henry Hub Gulf Coast natural gas spot price, measured daily by the EIA in dollars to MMBTU. Fuel prices should reflect the marginal fuel cost of production of a single unit of electricity; that is, they should be measured in dollars to MMBTU. I use conversion factors from the Environmental Protection Agency to convert the coal and petroleum prices to comparable units.[9] In the next section, I describe the methodology used to calculate market power in the electricity generation, oil refining, and cement production sectors in more detail.

The marginal fuel cost for a generator is the fuel cost per MWh produced. The heat rate of a generator gives the ability of a generator to convert fuel to power. I assume that, within an energy category, the heat rates of all generators are equal to the average heat rate for generators of that category. I use data from EIA Form-923 for the year 2001 to construct the average heat rate of generators for the three

[9] I calculate the average conversion factor over all types of coal used in electricity production to be 22.42 MMBtu per short ton. The average conversion factor of all types of petroleum used in electricity production is 0.122 MMBtu per gallon.

fossil-fuel categories I consider.

For the oil refinery market power measure, I obtain monthly data from the EIA on crude oil prices, crude oil yields, and motor gasoline prices. In order to convert crude oil prices into a measure of the marginal cost of the production of gasoline, I divide the price of crude oil by the average oil refinery yield in California (which is the number of gallons of gasoline produced per barrel of crude oil). This conversion yields marginal fuel cost of oil refining - the fuel price per gallon of gasoline produced.

Finally, I use coal and cement prices to measure market power in the cement industry. As with the electricity and oil refinery cost measures, a conversion is required to create a marginal cost from the fuel cost.[10] Additionally, only annual coal and cement prices are publicly available for the construction of a cement market power measure. To decompose annual prices into monthly prices, I use the monthly producer price indexes for coal and cement calculated by the Bureau of Labor Statistics.[11] I calculate the percent change of the monthly PPI from the annual PPI; the monthly price of coal (or cement) is then the annual price times one minus this percent change.

2.3.2 Measuring Industry Market Power

It is important to precisely measure market power in the electricity generation industry for the purpose of this analysis. The industry experiences large changes in the degree of market power of firms throughout the year. For example, market power is more likely to be exercised during the summer months. Many other industries, on the other hand, do not experience such large changes in market power over time, especially if the good produced is storable. Therefore, the electricity generation industry provides excellent inter-temporal variation for identification.

[10]The average heat content of coal is 22.42 MMBtu per short ton and the production of a unit of cement requires 4.7 MMBtu of fuel.

[11]According to the BLS, the PPI simply measures the changes in the price of a particular good relative to the prices in a base year of 100. The formula for the BLS' PPI is a weighted Laspeyres index, where sampled items are weighted by their size and importance.

Unfortunately, concentration measures, like the HHI, are not appropriate for the measurement of market power in the wholesale electricity industry (Borenstein et al., 1999) [3]. The demand for electricity is relatively inelastic and changes significantly over time. However, short-run capacity constraints limit the ability of individual generators to meet this demand, especially in combination with the inability to store generated electricity. Therefore, generators on the margin may be able to exhibit significant market power, even when their market share is relatively small.

To deal with the problems in the measurement of market power in the electricity market, I roughly follow the methodology of Borenstein et al. (2002) [4]. They create an approximate industry Lerner index by determining the marginal cost of the marginal generator required to meet the demand for fossil fuel generation and determine the difference between this marginal cost and the price of electricity.

Using the generation capacity data, I break generators into four groups depending on fuel type: coal, petroleum, natural gas, and alternative. Each category encompasses a number of different fuel types. I then determine the total capacity of each group in each year.

I assume the utility consumers of energy draw from all of the generators in the group with the lowest marginal fuel cost, before moving to the group with the next lowest marginal fuel cost if necessary to meet demand, and finally moving to the group with the highest marginal fuel cost if necessary. To illustrate the methodology, suppose that the fuel costs of coal, petroleum, and natural gas are, respectively, \$0.50 per MWh, \$1.00 per MWh, and \$1.50 per MWh, and each type has a capacity of 5 units. If the load is 3 units, then the fuel cost of the marginal unit is \$0.50. If the load is 8 units, then the fuel cost of the marginal unit is \$1.00. Finally, if the load is 14 units, then the fuel cost is \$1.50.

Figure 6 plots the prices of the three groups of generators across time. In general, coal is the cheapest means of producing electricity, followed by petroleum, and then

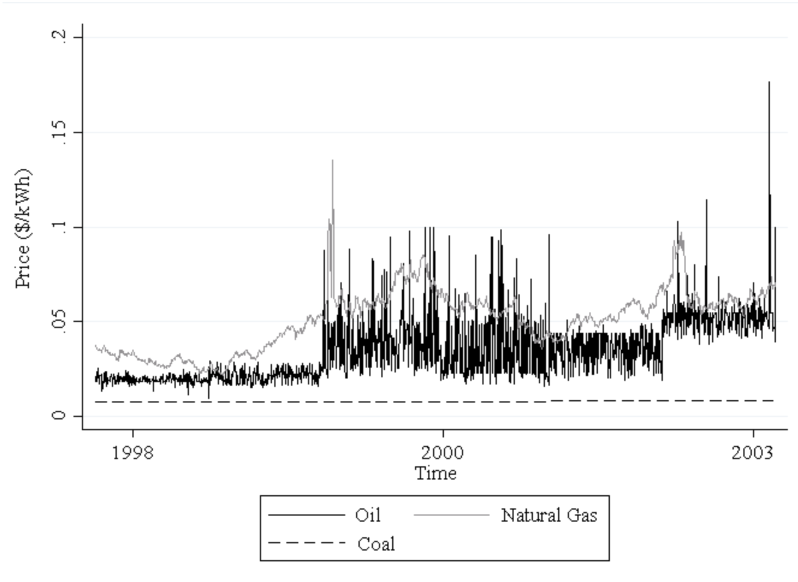


Figure 6: Determining the ranking of electricity generator fuel costs.

followed by natural gas. This ranking of marginal fuel costs holds for most of the days in the data set. For all other days, coal remains the cheapest, but natural gas is cheaper than petroleum. Therefore, I can concentrate on drawing from generators in these two orderings.

Once again, following the methodology of Borenstein et al. (2002) [4], I also assume that all out-of-state producers of electricity who export some of their generation to California are perfectly competitive. I use data from the California ISO on hourly electricity imports. Some of the days are missing import data. To fill in this data, I estimate that the missing imports are approximately the average imports of that hour of that specific day of the year over all years in the data set. Subtracting the estimated or actual imports of each hour from the actual load gives the estimated in-state demand for electricity production.

Note that, following Borenstein et al. (2002) [4] I concentrate on in-state fossil fuel production only. They conclude that non-fossil fuel generators face different incentives and are unlikely to exercise market power. In particular, regulations generally require nuclear generators to operate. According to a report from the California Energy

Commission[12], fossil fuel generation accounts for 39.6 percent of the electricity supply each year. Therefore, in order to only account for the load provided by fossil fuel generators, I deflate the total load by a factor 0.396.

Using the above methodology and the deflated load on the transmission grid, I determine the marginal fuel cost of the marginal generating unit at each hour. I then use the price of electricity in each hour to determine an average industry Lerner index at each hour.[13] Equation 4 gives the formula used to determine the Lerner index, where P_t is the price of electricity in hour t and MFC_t is the marginal fuel cost of the marginal generator:

$$L_t = \frac{P_t - MFC_t}{P_t} \tag{4}$$

Finally, I create two monthly electricity market power variables: the average market power and the average daily maximum market power. For the 3 months in the dataset prior to the restructuring of the electricity generation industry in California (that is, January, February, and March of 1998), I assume market power is zero, as the government regulated market power in the industry.

I also seperately estimate the effect of market power of oil refineries and cement producers on permit prices. As illustrated by Table 1, the three industries with the highest NOx emissions under the control of the SCAQMD are hydraulic cement production (with 306,228 quarterly lbs of NOx emissions on average), petroleum refining (with 292,419 lbs of emissions), and electric services (with 103,977 lbs of emissions). Because they trade a larger volume of permits that low-emitting industries, these

[12]From "Development of Energy Balances for the State of California: PIER Project Report." Prepared for the California Energy Commission by the Lawrence Berkeley National Laboratory in June, 2005.

[13]In periods when the price is negative or the marginal fuel cost is greater than the price of electricity, the Lerner index is set to zero. When the marginal fuel cost is greater than the price but the load is positive, it is likely that other factors are at work, and market power is negligible in determining the price. Similarly, when the price is negative, other incentives must be provided in order to ensure some supply of electricity, and the presence of market power is unlikely.

three industries have a greater opportunity to impact the market for permits. Therefore, in addition to creating a seperate measure for the market power in the electricity generation industry, I create Lerner indexes for market power in the oil refining and cement production industries.

The method for calculating this measure of the markup over marginal cost is much simpler than for electricity generation. The primary marginal cost for oil refineries is crude oil. The Lerner index given by equation 4 is also appropriate to calculate the markup for oil refineries, where P_t is the monthly price of motor gasoline and MFC_t is the monthly marginal cost of crude oil.

Fuel costs are also a major component of marginal cost for cement production; in particular, coal is primarily used to produce cement. However, hydraulic cement also requires multiple other inputs, including limestone, for which price data is unavailable. Therefore, the fuel cost forms only a portion of the marginal cost of production. The Lerner index constructed using equation 4 (where P_t is the monthly price of cement and MFC_t is the monthly price of coal) for cement is thus only a proxy for the degree of market power in the cement industry. Variation in the Lerner index captures variation in cement market power, but the magnitude of the Lerner index overestimates the markup over marginal cost in the industry.

Summary statistics for the key variables are in Table 3. Here permit price (1) is the quantity weighted average price of all permits, permit price (2) is the quantity weighted average price of only permits that retire within one year, Elec. LI (1) is the average electricity Lerner index, and Elec. LI (2) is the average daily maximum Lerner index. There are a number of important facts presented in Table 3. First, note that in both measures of permit prices, the price of permits rose significantly during the electricity crisis, from 1.88 to 7.51 and 2.24 to 6.86, respectively.

Secondly, the standard deviation of the market power measures for the average industry, the electricity industry, the oil refining industry, and the cement production

Table 3: Summary Statistics

	All Years		Crisis	
Variable	Mean	Std. Dev.	Mean	Std. Dev
Emissions (lbs)	16,119	62,682	24,117	86,169
Permit Price (1)	1.88	2.78	7.51	4.86
Permit Price (2)	2.24	3.00	6.86	4.21
HHI	0.434	0.283	0.470	0.283
Elec. Avg. Daily Max. LI	0.848	0.207	0.797	0.070
Elec. Avg. LI	0.927	0.202	0.942	0.041
Refinery LI	0.373	0.097	0.418	0.057
Cement LI	0.942	0.014	0.953	0.002

industry varies greatly. For example, the electricity Lerner index varies a lot over time, with a standard deviation of 0.183 for the average LI, while the refinery LI's standard deviation is 0.097 and the cement LI's standard deviation is 0.014. Therefore, a 1% change in the market power index means more for the cement industry than for the electricity industry; the standard deviation of electricity market power is about 22.5% of the mean, while the standard deviation of cement market power is only 1.49% of the mean. In order to accurately compare the magnitude of coefficients on these market power measures, I therefore use Z-scores of the HHI, the electricity LI's, the refinery LI, and the cement LI in the regression. I then estimate using the actual market power measures in order to determine the magnitude of the effects relative to the price of permits.

2.3.3 Empirical Specification and Results

In order to determine the effect of changes in market power on the price of permits, I estimate equation 5 using a fixed effects panel estimation to control for unobservable, time-invariant facility characteristics. Here, t indexes the month, j indexes the facility, and i indexes the industry.

$$\ln(r_t) = \beta_0 + \beta_1 \ln(ELI_t) + \beta_2 \ln(RLI_t) + \beta_3 \ln(CLI_t) + \beta_4 \ln(HHI_{it}) + \\ \beta_5 \ln(Demand_{it}) + \mathbf{a_{ijt}}\gamma + \mathbf{m_t} + \mathbf{y_t} + \delta_1 t + \delta_2 t^2 + \delta_3 t^3 + c_j + \epsilon_{ijt} \quad (5)$$

r_t is the weighted average price of NOx permits, ELI_t is the Lerner index for the electricity generation industry, RLI_t is the Lerner index for the oil refinery industry, CLI_t is the Lerner index for the cement industry, HHI_{it} is the Herfindahl index for industry i, $Demand_{it}$ is the revenue of industry i, and $\mathbf{a_{ijt}}$ is the vector of technology controls.

I include industry-level revenue to control for changes in industry demand, which may be related to both market power measures. Additionally, I include a cubic time trend term to control for changes in the permit price over time. I also control for month-of-year fixed effects and year fixed effects, represented by the set of dummy variables $\mathbf{m_t}$ and $\mathbf{y_t}$, respectively. Therefore, I identify the parameters of the equation using variation across industry and across time, controlling for month-of-year-specific and year-specific changes in the price of permits. For example, yearly changes in the regulation and the total allocation of permits will be captured by year fixed effects and month fixed effects capture seasonal variation like weather. Technology control variables capture the adoption of new technologies which may increase or decrease the emissions of individual facilities. In all estimations, I cluster standard errors by industry.

In the primary specifications, I use an HHI that includes the local Herfindahl index for industries that most likely compete locally and the national Herfindahl index for industries that are more likely to compete nationally. I measure electricity either using the average daily maximum market power or the average market power.

Table 4 displays the primary results of the estimation of equation 5. Estimations (1) and (2) use pooled OLS over the entire panel and therefore do not control for facility fixed-effects. Estimations (3) and (4) use a panel data estimation method with facility level fixed effects. The differences between the first two estimations and the second two indicate that unobservable facility characteristics do not seem to bias the results. (1) and (3) measure electricity market power using the monthly average

Table 4: Regression Results

	(1) Price	(2) Price	(3) Price	(4) Price	(5) Price
Elect. Avg. Daily Max. LI	0.0824***		0.0813***		1.000***
	(0.0223)		(0.0213)		(0.182)
Elect. Avg. LI		-0.286***		-0.298***	
		(0.0290)		(0.0297)	
Refinery LI	0.0230**	-0.00556	0.0227**	-0.00620	3.690***
	(0.0103)	(0.0106)	(0.00975)	(0.0100)	(0.0798)
Cement LI	0.487***	0.449***	0.482***	0.442***	282.8***
	(0.0411)	(0.0460)	(0.0404)	(0.0447)	(9.935)
HHI	-0.0167	-0.0101	-0.0296	-0.0174	0.0368
	(0.0297)	(0.0313)	(0.0431)	(0.0447)	(0.0894)
Revenue	-0.00223	-0.00258	-0.0879*	-0.103**	-0.0645*
	(0.00603)	(0.00607)	(0.0467)	(0.0507)	(0.0362)
Plant Fixed Effects	No	No	Yes	Yes	Yes
Z-Scores	Yes	Yes	Yes	Yes	No
N	5407	5407	5407	5407	5407
R-sq	0.617	0.619	0.581	0.584	0.655

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Lerner index, while (2) and (4) use the average daily maximum Lerner index.

As predicted by the theoretical model, market power in the electricity and cement production industries has a significant positive effect on the price of NOx permits in the RECLAIM market. When the Z-score of the monthly daily maximum average markup of the electricity price over marginal cost increases by one percentage point, the price of permits increases by 0.0824 percent. Similarly, when the Z-score of the refinery and cement Lerner indexes increase by one percentage point, the price of permits increases by 0.0227 percent and 0.482 percent, respectively. These results suggest that market power in the product market of high emitting industries can have significant impacts on prices in the permit market.

Differences exist between the effects of the two different measures of electricity market power. When electricity market power is measured in terms of the monthly average daily maximum Lerner index, electricity market power has a positive, significant effect on the price of permits, but when it is measured in terms of the average Lerner index, the it appears to have a significant negative effect of permit prices. Additionally, using the alternative market power measure changes the significance of the oil refinery results. The average Lerner index underestimates the significance of market power on a given day. At night, demand for electricity, and the potential to exercise market power, are low. In the average Lerner index, market power in all hours of the day are given equal weight. The average daily maximum Lerner index better captures the degree of market power on a given day than this average Lerner index. Thus, the average Lerner index clearly does not accurately measure electricity market power, leading to an omitted variable bias in estimations (2) and (4) in Table 4.

To determine the economic significance of these increases in terms of the actual permit price, I use the actual values of the Lerner index for all market power measures in column (5), rather than the Z-scores.[14] Given the effect size in column (5), the average price of permits \$1.88, and the fact that a one standard deviation increase in the degree of market power in the electricity industry represents a 24.4% increase in the Lerner Index (Table 3), a one standard deviation increase in the average daily maximum markup over marginal cost in the electricity industry translates to an increase in the price of permits by $(1.244)(1.88)(1.00) - 1.88 = \$0.45$, an economically significant change in the price.

Though electricity and cement market power have statistically and economically significant impacts on the price of RECLAIM permits, market power in the average industry, represented by the HHI, and in the oil refining industry do not appear to influence the price of permits. Table 4 indicates that neither the average industry

[14]Note that because the measures of market power in the oil refining and cement production industries are only proxies for the actual markup, I am unable to make conclusions about the magnitude of the price increase in response to a change in actual market power in those industries.

Table 5: Robustness Checks

	(1) Crisis	(2) Local	(3) National	(4) Price
Electricity LI	0.0165	0.184	0.0816***	0.147***
	(0.0187)	(0.117)	(0.0124)	(0.0242)
Refinery LI	0.0698***	-0.00721	0.0309***	0.0133
	(0.00857)	(0.0376)	(0.00669)	(0.0133)
Cement LI	2.230***	1.023***	0.465***	0.233***
	(0.0649)	(0.263)	(0.0277)	(0.0419)
HHI	0.0145	-0.596	0.0985	-0.000481
	(0.0278)	(0.384)	(0.136)	(0.0387)
Elec. LI*precrisis	0.0516***			
	(0.0430)			
Refinery LI*precrisis	0.434***			
	(0.0316)			
Cement LI*precrisis	-2.111***			
	(0.0622)			
Electricity LI*crisis	-0.316***			
	(0.0188)			
Refinery LI*crisis	-0.189***			
	(0.0109)			
Cement LI*crisis	-1.317***			
	(0.0631)			
N	5407	610	9591	4141
R-sq	0.633	0.636	0.584	0.548

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

HHI nor the oil refining Lerner index have statistically significant impacts on permit price. These results suggest that there may be some cross-industry heterogeneity in the effect of market power on the price. The current, single-sector theoretical model does not predict which characteristics of the industry may influence the ability of firms to create changes in the permit price. A multiple sector model should provide greater intuition into this result.

2.3.4 Robustness

Table 5 includes a number of checks of the robustness of the results in Table 4. First, I seperately estimate the effects of market power during the three time periods within the data set: the pre-crisis period (1998-1999), the crisis period (2000-2001), and the post-crisis period (2002-2003). Prior to the electricity crisis, the NOx emissions cap was not binding. The theoretical model predicts that when the supply of permits is large and firms have increasing marginal production costs, market power may have a negative effective on the price of permits. During the electricity crisis in the summer of 2000, the incentives of firms and, consequently, the ability of market power to impact the price in the permit market, may have changed. Specifically, there was a shortage of permits during the electricity crisis, while permits were relatively abundant during other periods (Israels, 2002) [14]. This change in incentives may have changed the ability of all regulated industries to influence prices in the permit market. During the post-crisis period, large electricity generators were removed from the primary emissions trading market and the emissions cap was binding. I expect that electricity generation will then no longer be able to influence the price of permits during this period and that the results from my theoretical model are more likely to hold.

To examine the effects of market power on the price during these three time periods, I interact each of the market power measures with an indicator variable for the electricity crisis and the pre-crisis period and reestimate equation 5 in column (1). Prior to the electricity crisis, both electricity market power and oil refining market power had a positive, significant effect on permit prices, while cement production had a significant negative effect on market power. These results are consistent with the theoretical model if the cement production industry has large, increasing marginal costs of production. During the electricity crisis, market power in all three industries had negative effects on permit prices, suggesting that the crisis created incentives for firms with market power to act to reduce the prices of permits. Finally, in the post-crisis period, when large generators no longer participated in the primary RECLAIM market, electricity market power has no significant effect on permit prices, as predicted. When the emissions cap becomes more binding during this period, market power in the hydraulic cement and oil refinery industries have much larger impacts on the permit price of 2.230% and 0.0698%, respectively.

Second, I constructed the "actual" HHI and "actual" revenue by assigning industries to categories based on whether they may be more "local" or "national" competitors. I also examine the extremes; that is, the case where all industries have local competition and the case where all industries have national competition. The results of these estimations are in columns (2) and (3) in Table 5. It appears that considering all industries to be nationally competitive does not significantly change the main results. However, considering all industries to be locally competitive significantly changes the results, reducing the significance of the electricity market power coefficient and eliminating the effect of cement market power. Many of the industries in the sample (for example, malt beverages) are clearly nationally competitive and this measure clearly underestimates market demand in these industries (i.e. total revenue). Therefore, I believe matching industries according to local vs. national competition markets is the correct method for constructing both the average industry concentration and total industry demand.

Finally, when constructing the quantity-weighted average price of pollution permits in the above estimations, I used the transaction prices in the trades of all permits, including those not intended to expire for multiple years. However, the theoretical model considers only the relevant permit price - the price of those permits traded for use in that year. To ensure that trades of permits that expire in the future do not influence the results, I also create another quantity-weighted average permit price using only those permits that expire within a year of the trade and reestimate equation 5 using this new dependent variable. Column (4) of Table 5. While the magnitudes of the effects change slightly, changing the measure of permit price impacts neither the significance nor the sign of the market power effect.

2.4 Conclusions

In a single-sector, Cournot competition model, I demonstrate that the price of permits decreases when the number of firms decrease. In Cournot models, the number of firms is, essentially, a proxy for the level of competition in the industry. Therefore, I conclude that the price of permits increases when the market becomes less competitive; that is, when firms have more market power. This result remains when assumptions about the marginal cost of production and the elasticity of product demand change.

To empirically examine the relationship between market power and permit prices, I use data from the RECLAIM program in Southern California, concentrating specifically on the electricity generation, oil refining, and cement production industries because they features a some inter-temporal variation in market power and because they are the largest participants in the market for RECLAIM permits. I find that an increase of one percentage point in the average daily maximum Lerner index increases the price of permits by about about 0.0813 percent, an increase in the markup of oil refinery prices over fuel costs increased the price of permits by 0.0227 percent, and an increase in the markup of cement prices over marginal fuel costs increases the price of permits by about 0.482 percent. This result is robust to various empirical specifications. Counter to the predictions of the theoretical model, the price of permits and market power in industries other than the electricity, oil refinery, and cement sectors are not related. This result suggests that different industries vary in their ability to influence the permit market. Further research will concentrate on the heterogeneity in this effect.

I also estimate the impact of market power before, during, and after the California electricity crisis to determine how the relationship changes when different market characteristics, like a shortage of permits or a non-binding emissions cap, exist. I find that firm incentives changed during the California electricity crisis, creating negative effects of market power on permits prices, and that firms were better able to influence prices in the period following the crisis when the emissions cap was binding.

These results have serious implications for the effectiveness of cap-and-trade programs over price-based mechanisms like pollution taxes. Creating a market for pollution creates cost-savings by allowing firms to trade permits and implicitly determine the market price. However, market failures from one industry may influence the market for permits, raising prices to all firms involved in the emissions trading scheme. The cost from this transmission of market failures through the permit market should be considered when determine the cost-savings of various cap-and-trade programs.

CHAPTER III

TEACHING AN OLD DOG NEW TRICKS: FIRM LEARNING FROM ENVIRONMENTAL REGULATION

Innovation[1] is the creation of knowledge. Learning is the transfer of knowledge across people or groups. Both innovation and learning are fundamental to growth and are thus of great importance to firm outcomes. Consequently, much empirical work has been dedicated to observing and measuring firm innovation.[2] However, it is difficult to empirically observe learning at the firm level.

To measure firm learning, one must first identify learning networks, those groups that share knowledge. Additionally, estimation of a learning effect requires some event that forces firms to create new knowledge and then allows these firms to share this knowledge through networks. The electric power industry, in which multiple distinct power plants are connected through firm ownership, and changes in environmental regulation, which require plants to adapt and potentially spark innovation, provide a framework in which we may measure how firms learn.

In this paper, we examine firm learning in response to regulation through the effects of regulation on technical efficiency in the electric power industry. We use county level variation in the stringency of environmental regulation of power plants caused by the National Ambient Air Quality Standards (NAAQS) to examine how firms respond to an increase in regulation at one plant and how efficiency enhancing knowledge is transferred within the firm. We concentrate our analysis on the electricity generation industry for a number of reasons. First, power plants are large

[1] Co-Author: Erik Johnson

[2] See Mairesse and Mohnen (2002) [23] for a detailed discussion of measurement of innovation.

stationary sources of emissions, and are major targets of environmental regulation, including the Clean Air Acts[3]. According to the National Emissions Inventory, the electricity sector is responsible for 67% of sulfur dioxide emissions and 23% of nitrogen oxide emissions. Second, electricity generation provides us with an objective measure of technical efficiency, the heat rate of a generator. The heat rate is the amount of fuel consumed to produce a single unit of electricity. It is affected by both environmental regulation and operational characteristics of the plant (Linn et al., 2013) [20], making it an ideal dependent variable for our empirical analysis. Third, both the EPA and the Energy Information Association (EIA) collect extensive, generator level data on the industry, allowing for a panel of data spanning more than 40 years.

While our results vary by fuel type, we find that non-attainment for pollutants most likely to cause additional regulation of power plants have positive effects on efficiency. For example, coal plants experience an average efficiency gain of 2.57% in response to non-attainment of the 1-hour ozone standard. We also find evidence that environmental regulations create efficiency spillovers to unregulated plants. Unregulated coal plants with connections to regulated plants receive positive average spillovers of 1.98%. Semiparametric estimates of these spillovers reveals that spillovers generally begin after 3 years, and grow to 2.48% after 6 years.

Moreover, we isolate the innovation effect in two ways. First, we include two sets of controls for abatement equipment in our primary estimation. Because our results are insensitive to the inclusion of abatement controls, we conclude that our regulatory and spillover effects cannot be explained by changes in abatement equipment, suggesting that the innovation effect drives our results. Second, we estimate the effects of changes in environmental regulation on both the generation and ramping behavior of regulated and spillover plants. We find that neither regulated nor spillover plants are utilized

[3]Other major air pollution programs that target the electricity sector include the Acid Rain Program and the NOx Budget Trading Program.

differently in response to environmental regulation. Therefore, we conclude that our primary results are also not driven by changes in plant utilization.

The first section below describes the variation in environmental regulation that we use to identify regulatory spillovers and the current literature about firm responses to environmental regulation. The second section discusses our model of firm behavior, the empirical methodology we employ. We then discuss the data in the following section. Next we present our primary results and tests of alternative explanations. Finally, we conclude.

3.1 Regulation and Firm Learning

There is a large body of literature examining the consequences of environmental regulation for firms, a response, in part, to increases in both the number and stringency of regulations in the U.S. Over the last half century, society has expressed growing preferences for the environmental goods. These changing preferences translate to the development of new regulations including the landmark Clean Air and Clean Water Acts. The Clean Air Act of 1963 began federal control of air pollution. A second Clean Air Act in 1970 established emissions standards for stationary sources of air pollution in the the National Ambient Air Quality Standards, which were amended in 1977 and 1990 in the Clean Air Act Amendments (CAAAs). These regulations have been successful at reducing pollution.

Much empirical work has found that the Clean Air Act increased innovation (Popp, 2003) [29]. However, very little research has examined how learning works in this context. Learning is difficult to observe, primarily because networks of knowledge are difficult to identify and because it happens over time. In this paper, we provide a unique lens to evaluate theinnovation and learning by taking advantage of the structure of the geographic variation created by the NAAQS and by estimating the dynamic effects of regulation.

The time component of learning also makes measuring learning difficult. Because learning takes time, its benefits may be slow to materialize. In a study of the cost effects of health information technology adoption, Dranove et al. (2012) [5] demonstrated the problem of measuring average effects when learning is involved. Fortunately, many counties remain in non-attainment status for many years. Thus, the NAAQS also provide a unique opportunity to examine the effects of learning over time.

The NAAQS are likely to have competing effects, potentially reducing efficiency of plants while simultaneously providing opportunities for firms to increase efficiency. There are at least two mechanisms through which environmental regulation reduces efficiency. The installation of abatement equipment, required by many regulatory schemes, decreases the technical efficiency of plants. Additionally, regulations create new constraints for the optimizing plant. If plants are minimizing their costs prior to a regulation, then these constraints cause a reallocation of resources away from the efficient, optimal allocation. Of course, the effects of regulation may not all be negative. Plants may innovate in response to the pressures of environmental regulation, as suggested by Popp (2003) [29]. For example, regulation may call attention to existing inefficiencies in plants. These innovations may be efficiency-enhancing, and can offset some of the negative effects of resource reallocation and abatement on efficiency.

If the same firm owns both regulated and unregulated plants, some of these unregulated plants may also be affected by environmental regulation. We define a *spillover eligible* plant as an unregulated plant that is owned by a firm with at least one regulated plant in its fleet; that is, these plants are eligible for within-firm regulatory spillovers. The innovations we are particularly interested in are process innovations, described by Hall et al. (1973) [9] as higher quality use of existing innovations. Such process innovations lend themselves to knowledge transfers between plants, and are ideal for the study of firm learning. We hypothesize that regulation may call attention to existing inefficiencies at one location of a firm, motivating the firm to innovate to reduce the inefficiencies at both regulated and eventually all locations.

There are two possible mechanisms for efficiency spillovers. First, if regulated plants develop efficiency-improving innovations in response to environmental regulation as described above, then firms should transfer these innovations to other plants in its fleet, creating positive efficiency spillovers. Second, regulation increases marginal costs at regulated plants, which may cause firms to change utilization of regulated and unregulated plants, shifting usage to more lightly regulated plants or changing usage patterns. As a result of some plants' greater utilization, firms may implement existing efficiency-improving technologies or processes at unregulated plants, creating positive spillovers. It is also possible that resource reallocation may negatively impact efficiency at unregulated plants. Firms may shift inputs, such as labor, between plants in order to cope with the additional pressures of the new regulation. The reallocation of these inputs away from the optimal allocation reduces efficiency at all plants within a firm, not just the regulated ones.

3.1.1 Environmental Regulation

As part of the CAAAs, the Environmental Protection Agency (EPA) measures the annual county-level emissions of sulfur dioxide (SO_2), ozone, lead, carbon monoxide (CO), particulate matter (both large and small), and nitrogen dioxide (NO_2)[4]. If a county exceeds the level of emissions set by the NAAQS, it is assigned "non-attainment" status and faces stricter environmental regulations. States with counties in non-attainment must submit a state implementation plan for the reduction of pollution in those counties. The implementation plan must include additional air pollution monitoring, an inventory of emissions and control strategies for all major emissions

[4]We do not include NO_2 in our analysis. Only four counties, all in the Los Angeles area of California, are ever in non-attainment status for the NO_2 standard. As a result, there is not a significant amount of variation in regulatory status.

sources, and the creation of enforceable measures aimed at reducing pollution to attainment levels.

Because non-attainment status is determined at the county-level, not the firm or plant level, the NAAQS creates heterogeneity in environmental regulation within firms. In the high-emitting industries regulated by the NAAQS, we define knowledge networks as networks of plants owned by the same firm. Some of these plants may be in non-attainment counties, while others are in attainment counties. Estimating the effect of environmental regulation on both attainment and non-attainment plants within a given firm allows us to observe the transfers of knowledge created by environmental regulation within a network.

The Clean Air Act requires state implementation plans for non-attainment counties to include abatement requirements. Plants in non-attainment counties must typically install high-cost abatement equipment to reduce their marginal emissions. For example, state implementation plans for the violation of the 8-hour ozone standard, facilities in a wide variety of emitting industries must usually install abatement equipment. The operation of abatement equipment is powered by electricity produced by the plant. This electricity consumption is called the abatement equipment's parasitic load.[5] While the parasitic load does not necessarily reduce the total amount of electricity generated at the plant, the amount of electricity available for sale falls.

In addition to parasitic load, environmental regulation may decrease efficiency through resource reallocation. The state implementation plans may include the imposition of taxes on or permits for emissions in additional to abatement requirements. Assuming that power plants behave optimally prior to the introduction of new regulation, minimizing their costs at their optimal resource allocation, the imposition of additional costs may force the firm to reallocate its resources away from the previous

[5]The EPA (2006) [7] finds that NOx control technologies for coal plants, used to meet ozone emissions standards, reduce the efficiency of power plants by 0.05% to 0.59%.

optimal allocation. To the extent that the optimal allocation maximizes technical efficiency, such resource reallocation causes plant efficiency to fall.

3.1.2 Effects of Regulation on Firms

Regulations may have benefits to firms by highlighting existing inefficiencies within the firm and creating a pressure for plant managers to develop process innovations, inducing an innovation effect. These innovations are likely previously ignored profitable investment opportunities (called low-hanging fruits by Ambec et al. (2013) [1]) or corrections of existing inefficiencies, highlighted by plant compliance. For example, in the installation of abatement equipment, plant operators may find that other equipment could operate more efficiently. These innovations may reduce the negative effects of parasitic load and resource reallocation, and possibly completely offset them, particularly if these process innovations are transferred to other plants in the firm.

However, our primary interest in this paper is the effect of regulation on unregulated plants. Note that for the purposes of brevity we refer to plants in non-attainment counties as "regulated" plants and plants in attainment counties as "unregulated" plants. However, the electricity generation industry is highly regulated, even in attainment counties. Instead, changes in non-attainment status represent changes in regulatory stringency. Specifically, we look at firms with both regulated and unregulated plants in their fleet and determine whether environmental regulation impacts the efficiency of their unregulated plants. Because these plants receive within-firm efficiency spillovers, we call them "spillover" plants.[6]

Environmental regulations do not necessarily change the incentives of these spillover

[6] The notion of regulatory spillovers is similar to the concept of green supply chains discussed by Lyon and van Hoof (2010) [22]. The Mexican green supply chain program uses large companies to encourage eco-friendly innovation in small- to medium-sized enterprises (SMEs). In this program, SMEs are linked, through a supply chain, to large, easily regulated companies, then educated about eco-efficiency. Lyon and van Hoof (2010) [22] found that though these SMEs are difficult to regulate, they innovate because of their ties to the larger "anchor" companies.

plants to adopt abatement technologies. Such technologies have high fixed costs and may also increase plant marginal cost, with minimal benefit to the plant. Plants are unlikely to install new abatement equipment unless required to by changes in environmental regulations. Because regulatory status does not change for spillover plants, their efficiency will not change as a result of parasitic load.

While environmental regulation may not directly reduce efficiency through abatement, the costs of regulation at one plant within a firm may have implications for all plants in the fleet. The negative resource reallocation effect impacts all plants within a firm, not just the regulated ones. An environmental regulation essentially imposes an additional constraint on the firm's overall cost minimization problem. For example, state implementation plans to reduce pollutants may limit the total emissions (and, in the absence of new abatement equipment, total output) at plants in regulated regions. A new binding constraint in the firm's optimization problem causes a change in the way resources are distributed among plants and a shift production along the firm's marginal cost curve. Assuming the firm optimally allocated its resources among its plants prior to regulation, any redistribution of resources away from this optimal allocation will negatively impact the efficiency of all of the plants at the firm. We may therefore observe negative efficiency effects at unregulated plants.

Resource reallocation provides only one mechanism for regulatory spillovers to unregulated plants. Spillovers may also occur as a results of changes in utilization among plants within a firm. Because of high ramping costs (i.e. the cost associated with starting up and increasing the load of a generator), electricity firms tend to concentrate their generation in their lowest cost plants and use their higher marginal cost plants to follow load or only during peak demand periods, rather than distributing generation across their fleet. Historically, the lowest marginal cost plants are coal plants, which have the highest emissions factors; consequently, they are more likely to be subject to stricter regulations. Depending on the specific mechanism used by the state to reduce emissions, environmental regulation may change the marginal costs of emitting plants and, consequently, the pattern of utilization across plants within a given firm. If the increases in plant marginal costs due to regulation are high enough that an unregulated plant replaces a regulated plant as the firm's lowest cost plant, the firm will then shift its production away from the regulated plant, toward the unregulated plant. The firm now has additional incentives to improve the efficiency of this unregulated plant to lower costs even further by installing existing technologies or developing new innovations. Thus, the unregulated plant will experience positive spillovers from regulation due to shifting of utilization.

This utilization effect will only occur if marginal regulatory costs are so high that a low-cost plant becomes a high-cost plant. We test for the presence of this effect by examining the impact of the Clean Air Act on generation and ramping hours at both regulated and unregulated plants. A positive effect of regulation on generation, ramping, and efficiency at unregulated plants and a negative effect on generation and ramping at regulated plants suggest that spillovers are driven by changes in patterns of utilization.

Our primary mechanism for efficiency spillovers is within-firm technology or process innovation transfers. Suppose a plant develops an efficiency-enhancing innovation in response to environmental regulation. Assume that, at plants of the same or similar type, the innovation is perfectly transferrable and that the benefits of implementing or installing this new technology outweigh the costs. These assumptions are particularly true of process innovations, rather than technological innovations. An optimizing firm will transfer this innovation to all of its plants, including the unregulated ones. That is, a spillover innovation effect may exist in addition to the regulatory innovation effect, driven by technology adoption rather than technology development. In this case, unregulated plants will experience gains in efficiency.

To illustrate this mechanism, consider the following example. A firm owns two identical power plants, P_1 and P_2, located in counties C_1 and C_2 respectively. In some period, C_1 falls into non-attainment status while C_2 stays in attainment and, as a result, P_1 is required to install abatement equipment. In the process of installing new equipment at P_1, the plant operator finds that a change in the existing equipment will produce efficiency gains. Because P_1 and P_2 are still identical except for the new abatement technology, any innovation that benefits the existing equipment at P_1 will also benefit P_2. Therefore, the cost-minimizing firm will transfer the innovation to P_2 and P_2 will experience gains in efficiency as a result of environmental regulation.

The observation of positive spillovers may also provide support for the innovation effect even in the absence of net positive regulatory effects. Plants may develop innovations that offset some of the negative efficiency effects of regulation, but not all of them. The magnitude of the efficiency gains relative to other efficiency losses should not impact of the incentives of firms to transfer these technologies to other plants, creating positive spillovers.

Thus, the effect of environmental regulation on power plant efficiency may therefore be positive or negative, depending on the magnitude of parasitic load and the innovation effect. Similarly, within-firm regulatory spillovers may exist. Positive regulatory spillovers suggest that regulated plants develop efficiency-enhancing innovations in response to regulation and that firms transfer these innovations to their unregulated plants. We rely on an empirical test to determine the magnitude and direction of the regulatory and spillover effects in order to test this hypothesis.

We have discussed four primary mechanisms through which environmental regulation may impact the efficiency of both regulated and "spillover" power plants:

1. Parasitic load from abatement equipment.

2. The innovation effect and technology transfer.

3. Resource reallocation at the plant or firm level.

4. Changes in utilization from regulated to unregulated plants.

These four mechanisms can be incorporated into a reduced form econometric model through the following equations.

$$\begin{aligned}\Delta \mathit{eff}_{it} = &\alpha_0 + \alpha_1 \cdot abatement_{it} + \alpha_2 \cdot innovation_{it} + \alpha_3 \cdot resource_{it} + \\ &\alpha_4 \cdot utilization_{it} + u_{0,it} \end{aligned} \tag{6}$$

$$abatement_{it} = \gamma_{1,0} + \gamma_{1,1} \cdot reg_{it} + \gamma_{1,2} \cdot spill_{it} + u_{1,it} \tag{7}$$

$$innovation_{it} = \gamma_{2,0} + \gamma_{2,1} \cdot reg_{it} + \gamma_{2,2} \cdot spill_{it} + u_{2,it} \tag{8}$$

$$reallocation_{it} = \gamma_{3,0} + \gamma_{3,1} \cdot reg_{it} + \gamma_{3,2} \cdot spill_{it} + u_{3,it} \tag{9}$$

$$utilization_{it} = \gamma_{4,0} + \gamma_{4,1} \cdot reg_{it} + \gamma_{4,2} \cdot spill_{it} + u_{4,it} \tag{10}$$

The variable eff_{it} is the technical efficiency of plant i in year t. For power plants, technical efficiency is measured using the heat rate, or the amount of energy required to produce 1 unit of electricity. Higher heat rates imply that plants require more fuel to generate electricity, therefore reducing the efficiency of the firm. The heat rate may be converted to a standard measure of efficiency as a percentage by comparing the heat rate of a plant to the heat rate for electricity.

The variables $abatement_{it}$, $innovation_{it}$, $reallocation_{it}$, and $utilization_{it}$ represent the hypothesized mechanisms above, reg_{it} indicates that a plant falls in a non-attainment county, $spill_{it}$ indicates that a plant is eligible for spillovers, and $u_{0,it}$-$u_{4,it}$ are the error terms. The term $spill_{it}$ equals 1, then the plant is "spillover eligible" because it is unregulated but owned by a regulated firm, i.e. a firm with at least one regulated plant.

Ideally, we would like to directly test the contribution of each of these mechanisms to the overall effect of regulation on plant efficiency by estimating equations 6-10. In this model, regulation impacts efficiency through the four possible mechanisms. Consider the abatement effect of regulation. (Assume, for discussion, that abatement may be measured according to some quantitative, continuous variable.) If a plant is regulated, its abatement changes by $\gamma_{1,1}$. Because changes in abatement impact efficiency according to α_1, the effect of regulation on efficiency through the abatement mechanism is $\gamma_{1,1} \cdot \alpha_1$.

Similarly, an unregulated plant may also be affected by changes in the regulatory status of other plants through regulatory spillovers. The term $spill_{it}$ indicates that plant i is unregulated, but it is owned by a firm that also owns at least one regulated plant. Like regulatory status, spillover eligibility may also affect abatement, innovation, resource allocations, and utilization according to $\gamma_{1,2}$-$\gamma_{4,2}$. Returning to the abatement effect example, a plant may receive efficiency spillovers of $\gamma_{1,2} \cdot \alpha_1$ through the abatement mechanism.

As a part of the state implementation plans for non-attainment counties, regulation increases the amount of abatement at regulated plants $\gamma_{1,1} > 0$, which reduces efficiency through by creating parasitic load $\alpha_1 < 0$. Because of the costs of abatement technology, firms are unlikely to increase their abatement without prompting via regulation ($\gamma_{1,2} = 0$). We therefore hypothesize that $\gamma_{1,1} \cdot \alpha_1 < 0$ and $\gamma_{1,2} \cdot \alpha_1 = 0$.

The innovation variable captures the idea that regulation can spark the discovery of efficiency enhancing ($\alpha_2 > 0$) innovations at regulated plants ($\gamma_{2,1} > 0$), and that the optimizing firm will transfer these innovations to its entire fleet of plants ($\gamma_{2,2} > 0$). Our hypothesized regulatory and spillover innovation effects are $\gamma_{2,1} \cdot \alpha_2 > 0$ and $\gamma_{2,2} \cdot \alpha_2 > 0$.

The resource reallocation hypothesis suggests that the imposition of a new constraint from regulation, either at the plant level (impacting only the regulated plant) or the firm level (impacting all of a firm's plants), will cause a reallocation of resources away from the optimal allocation. That is, regulation causes resource reallocation at both regulated and unregulated plants ($\gamma_{3,1} > 0$ and $\gamma_{3,2} > 0$), which reduces efficiency ($\alpha_3 < 0$). We therefore hypothesize that $\gamma_{3,1} \cdot \alpha_3 < 0$ and $\gamma_{3,2} \cdot \alpha_3 < 0$.

Table 6: Hypothesized Signs in the Idealized Model

	α_i	$\gamma_{i,1}$	$\gamma_{i,2}$	$\alpha_i \cdot \gamma_{i,1}$	$\alpha_i \cdot \gamma_{i,2}$
abatement	$-$	$+$	0	$-$	0
innovation	$+$	$+$	$+$	$+$	$+$
reallocation	$-$	$+$	$+$	$-$	$-$
utilization	$+$	0	$+$	0	$+$

Finally, changing utilization patterns suggests that unregulated plants may replace regulated plants as the lowest marginal cost sources of electricity and, consequently, firms change utilization of regulated to unregulated plants. Firms then have incentives to further increase the efficiency of unregulated plants using existing technologies. In this mechanism, the efficiency of regulated plants does not change, but spillover plants achieve efficiency gains. "Utilization," therefore, represents the installation of existing technologies (i.e. $\gamma_{4,1} = 0$ and $\gamma_{4,2} > 0$), which improve efficiency ($\alpha_4 > 0$). That is, $\gamma_{4,1} \cdot \alpha_4 = 0$ and $\gamma_{4,2} \cdot \alpha_4 > 0$. These hypothesized signs for the entire model described in equations 6-10 are summarized in Table 6.

We are unable to explicitly estimate the above model for a number of reasons. For example, innovation, particularly process innovation, is difficult to measure. Existing measures, like the number of patents filed, capture only innovation development, not innovation adoption and may miss important process innovations. Similarly, any measure of resource allocation, like measures of various inputs, will not capture the entire effect of some unquantifiable constraint on the plant or firm. Therefore we estimate a model whereby we only capture the net effects of the the NAAQS on the efficiency similar to

$$\Delta(\mathit{eff}_{it}) = \beta_0 + \beta_1 \cdot reg_{it} + \beta_2 \cdot spill_{it} + u_{it} \tag{11}$$

In this model $\beta_1 = \sum_{j=1}^{4} \gamma_{j,1} \cdot \alpha_j$ and $\beta_2 = \sum_{j=1}^{4} \gamma_{j,2} \cdot \alpha_j$ from equations (6)-(10). These coefficients will depend on the relative magnitudes of the individual effects of the various mechanisms. If the innovation effect is large enough to make up for the loss in efficiency due to the abatement and resource reallocation effects, then $\beta_1 > 0$.

If firms transfer innovations at their innovation plants, and these innovations make up for losses created by resource reallocations, then $\beta_2 > 0$.

3.1.3 Econometric Specification

First, note that emissions standards may have different impacts on plants with different fuel types. The emissions factor of an electricity generator depends largely on the type of fuel used. In general, coal plants have much higher emissions factors across major pollutants than oil and natural gas (Pulles and Appelman, 2008) [30]. For example, the emissions factor for particulate matter is much higher for coal plants ($\approx$ 1000 g/GJ) than for oil ($\approx$ 15 g/GJ) and gas ($\approx$ 0.1 g/GJ) plants. We expect that state implementation plans for PM non-attainment counties would focus more on lowering the emissions of coal plants. Therefore, the magnitude and significance of the effects should depend on fuel.

Additionally, the results depend on the specific emittant under consideration. The air pollution standards are not the only program regulating power plants emissions. The federal government's Acid Rain Program, implemented in 1995, specifically focuses on large sources of SO2 emissions, like power plants. If other programs already impose heavy regulations on power plants for specific pollutants, than the marginal effect of an additional regulatory measure may be small.

Because of the variation in emissions factors by fuel type and particular emittant, we estimate the effect of regulation and spillovers for a single standard, the one-hour ozone standard, and a given fuel type. To do this we first create three subsets of the data: the set of coal plants, the set of oil plants, and the set of natural gas plants. We define our regulatory and spillover variables and estimate a separate equation for each fuel type.

The NAAQS have eight separate emissions standards: sulfur dioxide (SO_2), one-hour ozone, eight-hour ozone, carbon monoxide, lead, particulate matter (both PM-2.5 and PM-10), and nitrous oxides (NOx). We concentrate our estimation on the one-hour ozone standard for a number of reasons. First, we expect the carbon monoxide, SO_2, and lead standards to have little effect on electricity generators. Electricity generators are not large emitters of carbon monoxide, accounting for only 0.9% of all emissions in 2008. While electricity generators are larger emitters of SO_2, with 75% of all emissions, the Acid Rain Program (ARP) specifically targeted and successfully reduced SO_2 emissions at electricity generators. While electricity generators (particularly at coal plants) are large emitters of lead and NOx, few counties fall into non-attainment for the lead standard and, consequently, we have little variation in lead regulatory status. However, the emission of NOx contributes significantly to the formation of ground level ozone, with 18.6% of all 2008 emissions. Particulate matter regulations are also likely to affect electricity generators since they are a concentrated source of emissions, though we also have little variation in the PM standards, particularly the PM-2.5 standard, which did not go into effect until 2005. Finally, we expect the estimation of the one-hour-ozone effect to have the greatest amount of power. Figure 7 ilustrates the number of plants that fall into the regulated and spillover categories for 6 of the regulatory standards.[7]. The one-hour ozone standard affects the largest number of plants and has the greatest potential for learning spillovers.

The EPA also provides historical data on the non-attainment status of counties from 1978 to 2010. We use this to create variables indicating whether a plant is subject to non-attainment regulations under the CAAAs. A plant is said to be "regulated" for a particular air standard if it was in non-attainment for the previous year. Regulation is lagged a year after non-attainment because non-attainment status is not determined until the end of the year. Therefore, the likely earliest response we may see is after

[7]We exclude lead and NOx from this figure because it affects only a small number of plants.

the county is officially in non-attainment, the following year.

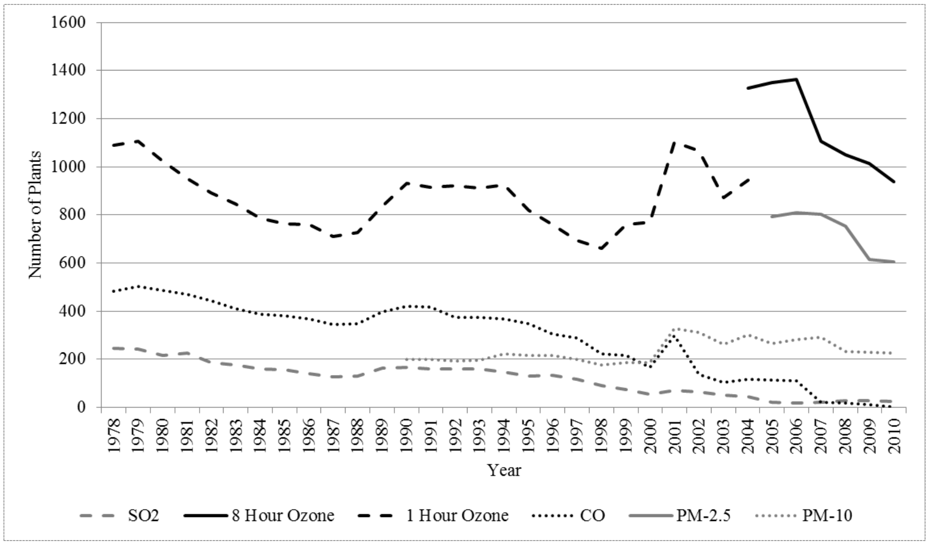
Many counties stay in non-attainment status for a long period of time. For example, if a county does not meet the one-hour ozone standard, it will, on average, stay in non-attainment for about 14 years. Therefore, in addition to finding the average effect of regulation over a long period of time in our primary estimations, we also look at the effect of being in the first through fifth years[8] of regulation to understand the dynamic effects of regulation on power plants. A plant is said to be in its n^{th} year of regulation in a given year if was in an attainment county $n+1$ years ago and in a non-attainment county n years ago.

A plant is eligible for spillovers if it is itself is unregulated and it is connected, through firm ownership, with a regulated plant. To identify spillover plants, we first designate firms as "regulated" if they own at least one plant in a non-attainment county. Then, a spillover plant is one which is owned by a regulated firm, but is not in a non-attainment county. We thus create three mutually exclusive categories of plants: regulated plants, spillover plants, and non-spillover plants.

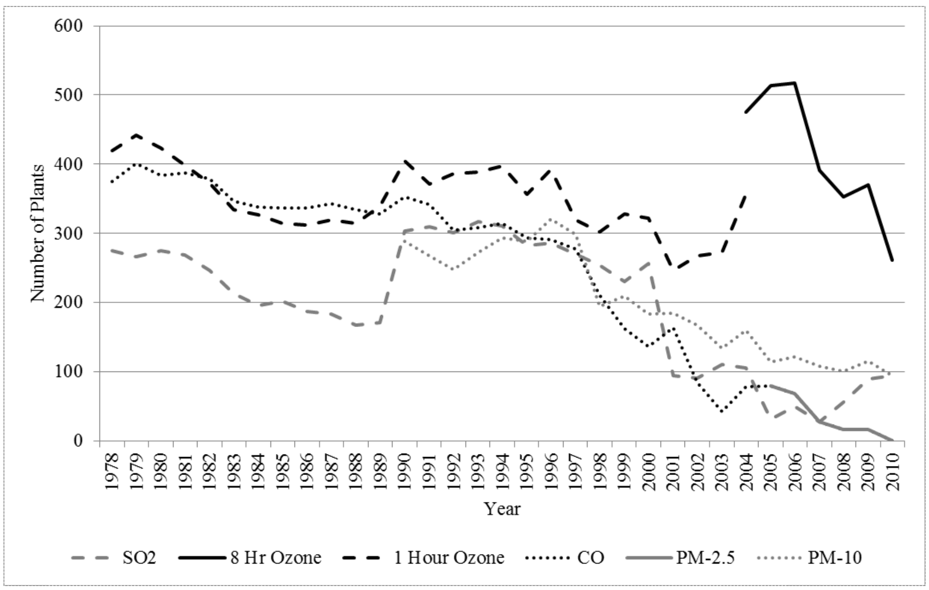
Rather than using plant fixed effects in our estimation, we use plant-epoch fixed effects. A plant-epoch changes every time the plant changes from one type of prime mover to another. An electricity plant's prime mover is the turbine which powers the generation of energy. When a plant moves from one type of prime mover to another, it changes the electricity generator significantly enough that we can consider it to be a new entity and could change a number of unobserved characteristics of that plant. Therefore, we differentiate between different plant-epochs, and control for plant-epoch fixed effects rather than plant fixed effects in our estimation.

Our estimating equation allows for different effects of being in non-attainment or spillovers for each of the seven different pollutants. We estimate the following

[8]We use ten years of regulation because ten years is a long enough period of time for plant learning to occur. In later years, fewer plants remain in the regulated or spillover categories. We therefore expect declines in significance over time from this reduction in the amount of variation.



(a) Regulated Plants



(b) Spillover Plants

Figure 7: Categorization of regulated and spillover plants by year.

equation

$$\log(\mathit{eff}_{it}) = \beta_0 + (\beta_1 \cdot \mathit{reg}_{it} + \beta_{2n} \cdot \mathit{spill}_{it}) + \mathbf{X_{it}} \cdot \delta + c_i + \delta_1 t + \delta_2 t^2 + \delta_3 t^3 + \alpha_t + u_{it} \quad (12)$$

where i indexes the plant-epoc and t indexes the year. $\mathbf{X_{it}}$ is a vector of control variables including nameplate, plant age, firm size, number of regulatory/spillover spells and indicator variables for restructured electricity markets, peaker status, co-generation, type of abatement equipment, and primemover type; c_i is a plant-epoch fixed effect; δ_1-δ_3 control for a cubic time trend; α_t is a year fixed effect, and u_{it} is the error term. We identify the regulatory and spillover effects using within-year variation in technical efficiency between plants in non-attainment counties and plants in attainment counties owned by firms that also own plants in non-attainment counties. Using within-year variation eliminates the efficiency effects of any technological advancements associated with changes in time rather than changes in regulatory or spillover status.

Our identification strategy is conditional on the assumption that regulatory and spillovers statis is orthogonal to plant characteristics. Plants are placed into non-attainment status on a county-by-county basis, not on a plant-by-plant basis, based on the level of air quality in that entire county. A single electricity generator's (recall that our unit of observation is a plant-epoch within a given fuel type, which amounts to the average generator of a given fuel type) emissions are unlikely to have a significant effect on the air quality measure of a county for a number of reasons. First, based on our definition of a generator as a plant-fuel combination, the average county in our data set contains 4 generators and the average non-attainment county in our data set has 5 generators. Therefore, each generator is unlikely to have a significant impact on the non-attainment status of the entire county. Second, the NAAQS are based upon geographic air quality and not emissions. The air quality in a given area is not only affected by the emissions within the county, but also but emissions in surrounding regions. Air pollution frequently moves across large geographic regions. In fact, the problem is so significant that the EPA established the Cross-State Air Pollution Rule in 2011 (Jones, 2011) [15][9] after a number of areas were unable to meet the NAAQS due to emissions in other regions. Therefore, the non-attainment status depends on the total emission within both a county and its surrounding areas, rather than the emissions of a single electricity plant, and we conclude that its assignment

[9]This rule replaced the 2005 Clean Air Interstate Rule.

to a particular plant is random.

Finally, we attempt to isolate the innovation effect by testing the significance of the abatement and utilization pathways. As previously discussed, environmental regulation may impact efficiency through changes in abatement controls. We test this hypothesis in our sample by comparing estimations with and without abatement control information. If our estimations without abatement controls are significantly different from our estimations with abatement controls, then there is evidence that regulatory status changes plant efficiency through abatement equipment installation. Additionally, we measure the effect of regulation on plant utilization by estimating the regulatory and spillover effects on generation and ramp hours. Changes in generation or ramping behavior in response to plant regulation or spillover status indicates that firms change plant utilization across their fleet in response to environmental regulation.

3.2 Data and Measures

We estimate equation 12 using data from the Energy Information Administration (EIA) and the Environmental Protection Agency (EPA)[10] on fossil fuel electricity generators in the United States from 1970-2010. The EIA collects annual information on generators and boilers, such as net generation and fuel consumption, from plants with a total nameplate (capacity), summed over all their generators, of more than 10 MW. The EPA contains information on additional plant and generator characteristics, such as abatement equipment, for the subset of plants with emissions monitors.

To build the complete dataset, we match multiple EIA forms with EPA data with observations at the generator level. Due to differences in the coding of individual generators, we are unable to distinguish between generators with the same fuel type at a given plant. We combine all generators of a specific fuel type at a given plant into

[10] Specifically, we use EIA-906/920/923, EIA-860, and the EPA's Air Markets Program Data set.

one aggregate generator and match data by year, plant, and fuel type. Therefore, our annual unit of observation is at the plant-fuel level. For the purposes of discussion, we refer to this unit as a coal, oil, or natural gas "plant."

Our dependent variable is the plant's efficiency, which is determined from the heat rate. The heat rate of a plant is the efficiency of the conversion of heat from fuel (Btu) into electricity (kWh)[11]. The heat rate of plant i is defined as:

$$\text{heat rate}_i = \frac{\text{fuel consumption}_i}{\text{net generation }_i} \tag{13}$$

Net generation is the total amount of electricity produced by a plant for sale, net the electricity required to run the equipment used in the generation process, like boilers and abatement controls. Our dependent variable, technical efficiency, is then calculated as the Btu content of electricity (3,412 Btu) divided by the heat rate.

We control for a variety of factors that affect the technical efficiency of power plants (Linn et al. (2013) [20] discusses these factors in detail). Both technical and operational characteristics impact heat rates. Regulations, environmental and otherwise, may also impact heat rates by affecting plant incentives. Specifically, Linn et al. (2013) [20] suggests that the installation of abatement controls in response to environmental regulation may increase the cost of efficiency improvements. Additionally, as we have previously discussed, abatement equipment may also reduce efficiency through its parasitic load. Referring to equation 13, abatement reduces the amount of electricity generated per unit of fuel consumed, increasing the heat rate and, consequently, decreasing technical efficiency.

We use two sets of abatement controls. The first comes from the EIA, which details the type of abatement technology within three categories: flue gas desulfurization units (i.e. scrubbers), flue gas particulate collectors, and NOx controls. The EPA

[11]From 2004-2008, the EIA used a different method for calculating fuel consumption for cogeneration units, which impacts the measured efficiency. We control for this with an interaction between the time period and the cogeneration fixed effect.

Table 7: Summary Statistics

		Coal	Oil	Natural Gas
Efficiency (%)	Mean	0.327	0.264	0.283
	Std. Dev.	0.129	0.093	0.123
Generation (GWh)	Mean	3,050	113	353
	Std. Dev.	4,060	539	927
Nameplate (MW)	Mean	631	281	255
	Std. Dev.	758	515	418
Age (years)	Mean	30.6	27.4	27.2
	Std. Dev.	19.3	19.6	19.2
Reg (all standards)	Mean	0.259	0.275	0.343
	Std. Dev.	0.438	0.446	0.475
Spill (all standards)	Mean	0.187	0.192	0.118
	Std. Dev.	0.390	0.394	0.322
N		22,408	54,822	42,918

data contains information on a wider variety of abatement controls for particulates, NOx, and SO_2. We use the information from these two data sets to create indicator variables for the presence of a specific type of technology. Using the EPA controls restricts the data to a subset of generators; therefore, we use each of the control sets in separate estimations and compare the results.

In addition to abatement equipment, we also control for a number of other characteristics of plants. We include fixed effects for year, cogeneration (i.e. whether a generator produces combined heat and power), and type of prime mover. We also control for the size of the generator (nameplate, measured in MW), plant age, and the firm (number of generators owned by each firm). Finally, plant-epoch fixed effects control for time-invariant plant characteristics.

Table 7 reports summary statistics for key variables by fuel type. Most notable are the differences between plants of different fuel types. Coal plants tend to be larger, more efficient, and older than oil and natural gas plants. The large differences across fuel types, in addition to differences in emissions factors, contribute to our decision to separately estimate the regulatory and spillover effects of regulation for different fuel types.

We also include an indicator variable for whether or not a plant is a peaker. Peaker plants only run when the demand for electricity is high. Because they are utilized less than other plants, peakers are, on average, less efficient and lower emitting than other plants. As a result, peakers are both less likely to be located in non-attainment counties and less likely to receive within-firm technology transfers. In peaker plants, we expect to see a substantial difference in generation in the summer months and the winter months since demand is higher in summer. Using monthly generation information, we find the difference between the percent of total generation in the months March-August, when demand is high, and the percent of total generation in September-February, when demand is low. We use a kernel density plot to examine the distribution of this variable and to determine the appropriate cutoff value for a peaker plant. A plant is designated a peaker if the difference between these two percents is more than 0.9, indicating that a plant operates significantly more during the summer than during the winter. That is, a peaker plant satisfies:

$$\frac{\text{summer gen}}{\text{total gen}} - \frac{\text{winter gen}}{\text{total gen}} > 0.9 \tag{14}$$

Using information from the EPA, we include fixed effects for participation in various other Air Markets Programs. Additionally, incentives may change in response to restructuring in electricity markets. We create two fixed effects for restructuring, for restructuring legislation and for restructuring action.

The impact of environmental regulation on efficiency may depend on how many times a county has been in a spell of non-attainment. The changes a plant can make during its second spell in non-attainment may be smaller, as may be the potential for innovation. Therefore, we control for the number of spells of non-attainment (or spillover eligibility) that a plant has faced. We define a ”spell” as a consecutive run of years in the non-attainment or spillover eligible categories.

To further examine the effects of non-attainment on plant utilization, we measure the number of hours that a plant is either substantially increasing or decreasing (ramping) output using the EPA's continuous emissions monitor data. We define an hour in which a plant is ramping production up or down as an hour in which the output changes by at least 25% from the previous hour. This measure will capture changes in output that are more substantial than responding small changes in system load or system congestion.[12]

Finally, though we are unable to directly measure process innovations and the reallocation pathway, we attempt to seperate the abatement and utilization pathways from innovation and reallocation by partially estimating equations 6-10. A single measure of the abatement quality of a particular plant does not exist. However, we are able to create a proxy for abatement intensity using the plant's emissions per unit of fuel consumed. When a plant installs a new piece of abatement equipment, this equipment reduces the plant's marginal emissions. However, marginal emissions (emissions per unit of electricity produced) depends on the efficiency of the plant, our dependent variable. Instead, we use emissions per unit of fuel consumed to measure emissions intensity independent of efficiency. We obtain power plant sulfur dioxide, NOx, and carbon dioxide emissions data from the EPA's Emissions and Generation Resource Integrated Database and use this to construct three different abatement proxy variables. As in our plant utilization test, we proxy for the utilization pathway using two different measures: plant ramping hours and total plant generation.

3.3 Results

Table 8 contains our primary estimation results, using a fixed-effect panel estimation strategy with standard errors clustered at the plant-epoch level, for all three fuel

[12] In addition to defining ramping in terms of a percentage change, we also construct a similar ramping measure that includes the restriction of an absolute change in output of at least 10 MW. This restriction does not change any of the results.

Table 8: Primary Results for the 1-hour Ozone Standard

	(1) Coal	(2) Oil	(3) NG
Regulatory Effect	0.0257**	0.0104	0.0231**
	(0.00782)	(0.00844)	(0.00814)
Spillover Effect	0.0198**	0.0210*	0.0157
	(0.00620)	(0.00954)	(0.00897)
N	18048	41874	34978
R-sq	0.071	0.038	0.061

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

types. Column (1) indicates that non-attainment has an effect of 2.57% on regulated coal plants. That is, in spite of any potential efficiency reductions associated with environmental regulation, coal plants experience efficiency gains in response to non-attainment. Additionally, we observe positive spillovers of 1.98% for coal plants. Taken together, these two results support our hypothesis; coal plants change their behavior in response to environmental regulation in ways that enhances their efficiency, and then transfer these efficiency gains to unregulated plants.

The 1-hour ozone standard may also create learning for oil plants and natural gas plants. According to Column (3), regulated natural gas plants are 2.31% more efficient than unregulated plants, though there are no significant spillovers. In Column (2), we see that, although 1-hour ozone non-attainment has no significant effect on regulated plants, unregulated plants receive positive spillovers of 2.10%. Despite the lack of a positive net regulatory effect, the presence of positive regulatory spillovers suggests that regulated plants do, in fact, change their behavior to improve their efficiency. Efficiency-enhacing changes offset any negative effects of regulation, creating a net zero effect for regulated plants. In this case, by examining regulatory spillovers we are able to detect evidence of firm learning even in the absence of significant effects for regulated plants.

The positive regulatory and spillover effects of 1-hour ozone non-attainment for coal and oil plants suggest that the positive channels through which regulation affects

Table 9: Testing the Abatement and Utilization Mechanisms

	(1) Efficiency Baseline	(2) Efficiency EIA	(3) Efficiency EPA	(4) Efficiency EPA Subsample	(5) Ramp Hours	(6) Generation
	Coal Plants					
Regulatory Effect	0.0257**	0.0257**	0.0233**	0.0234**	0.0663	0.101
	(0.00782)	(0.00776)	(0.00869)	(0.00859)	(0.0433)	(0.0588)
Spillover Effect	0.0198**	0.0207**	0.0218**	0.0216**	-0.0311	-0.0350
	(0.00620)	(0.00612)	(0.00701)	(0.00694)	(0.0358)	(0.0252)
Abatement	None	EIA	EPA	None	None	None
N	18048	18048	13717	13717	19122	10651
R-sq	0.071	0.076	0.085	0.081	0.113	0.167
	Oil Plants					
Regulatory Effect	0.0104	0.00935	0.00777	0.00600	-0.158*	0.210
	(0.00844)	(0.00846)	(0.0121)	(0.0122)	(0.0650)	(0.172)
Spillover Effect	0.0210*	0.0212*	0.0188	0.0195	-0.0465	-0.0574
	(0.00954)	(0.00959)	(0.0122)	(0.0122)	(0.0702)	(0.0998)
Abatement	None	EIA	EPA	None	None	None
N	41874	41874	15862	15862	43417	15768
R-sq	0.038	0.040	0.073	0.068	0.282	0.109

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

efficiency (that is, the innovation effect for regulated plants and technology transfer and generation shifting for spillover eligible plants) have larger effects than the negative channels (that is, abatement installation and resource reallocation). We attempt to isolate the innovation and technology transfer channels, estimate a number of different models presented in Table 9[13]. We first include variables indicating installation of abatement technology in order to remove the negative effect of parasitic load from our primary estimates. Column (1) in each table duplicates the results from Table 8 (for comparison). Columns (2) and (3) include the EIA and EPA abatement control variables, respectively. Including the EIA abatement controls do not change the results; the point estimates change only slightly for both coal and oil plants, indicating that the abatement effect is not large. However, including the EPA abatement controls in column (3) eliminates the significance of our results for oil and reduces the point estimates for both oil and coal. This change in the estimates is driven by sample selection, rather than abatement. Using the EPA variables limits the number of plants in the sample to those with continuous emission monitors. These are only power plants with a nameplate greater than 25 megawatts (MW). The larger plants also tend to be more efficient than plants in the complete dataset: the mean efficiency in the EPA subset is 31.0%, compared with a mean of 27.6% for all data. Therefore, plants in the EPA subsample are inherently different than plants in the full dataset and changes in regulatory and spillover status affect EPA plants differently than they do the average plant.

Column (4) shows the results without abatement controls for plants in the sample with EPA data. These results are not meaningfully different from those in Column (3) with the EPA abatement controls. The estimates in columns (3) and (4) are smaller than those in (1) and (2). This is intuitive since the baseline efficiency of these plants is

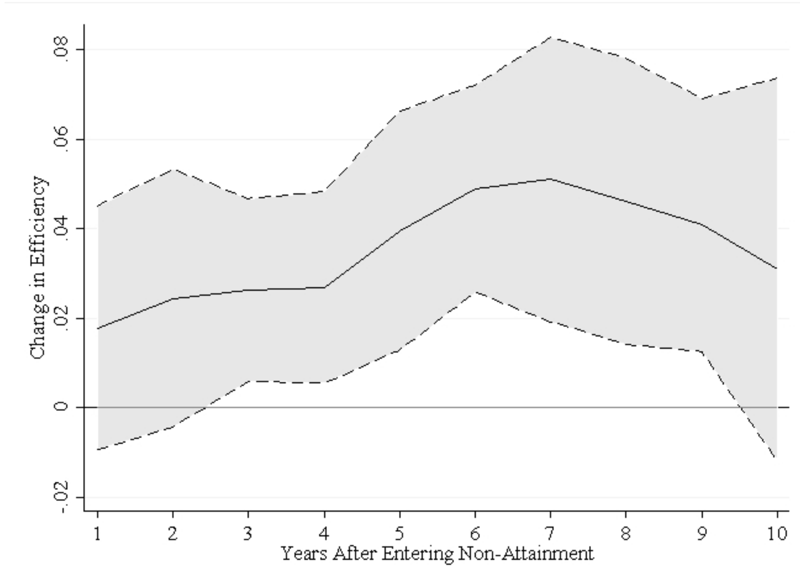
[13] Table 9 condenses the results to only those we discuss in detail. Results of the abatement and utilization estimations for all fuel types and all standards may be found in the Figure and Table Appendix

higher, they are less capable of making marginal efficiency improvements than plants in the full set. The robustness of the results to the inclusion of the abatement controls suggests that the efficiency gains due to regulation are independent of abatement.

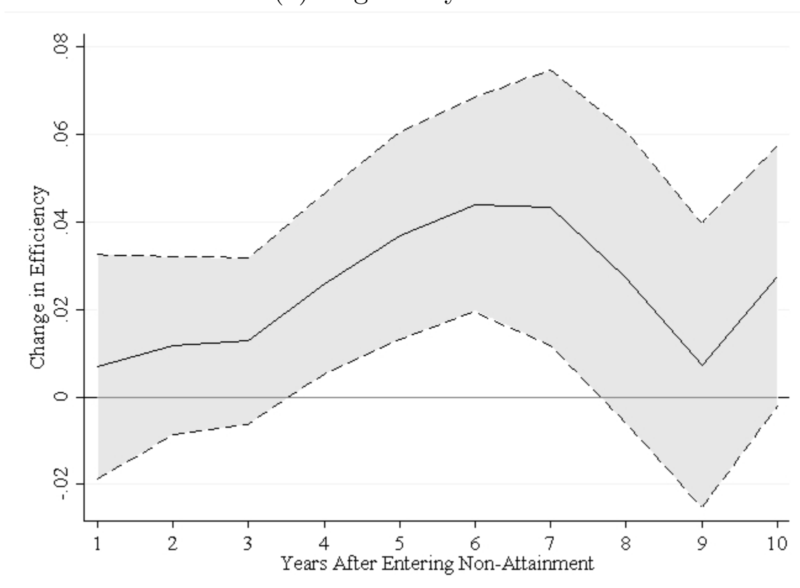
We additionally estimate the effect of regulation on generation and the number of hours that a plant significantly increases or decreases output on regulated and spillover eligible plants in an attempt to determine whether the primary channel through which regulation impacts efficiency changes in utilization, not innovation and technology transfer. These estimations include all the control variables from the primary estimation, as well as average annual fuel prices for the generation estimation. Column (5) and column (6) of Table 9 include the regulatory and spillover effects for ramp hours and generation, respectively. For coal plants suggest that firms do not change their utilization patterns among their coal plants. By combining these results with the abatement results from columns (2) and (3), we conclude that the positive regulatory and spillover effects of the 1-hour ozone standard are driven by innovation and learning in coal plants.

Column (5) in Table 9 suggests that non-attainment of the 1-hour ozone standards is associated with a 15.8% reduction in the ramp hours of regulated oil plants (with no associated change in generation). A reduction in ramping increases plant technical efficiency at regulated plants, though this increase is not large enough to overcome any negative effects of parasitic load and resource reallocation. However, positive spillovers combined with no changes in utilization among spillover plants suggests that learning creates the spillover effect.

To examine the dynamics of plant learning, we reestimate equation 12 using indicators for being in the 1st through 10th year of regulation or spillover eligibility and plot the point estimates and a 95% confidence interval (for the 1-hour ozone standard and coal plants) in Figure 8. This approach is similar to that of Lanoie et al. (2008) [19], who include lagged regulatory variables to measure the dynamic



(a) Regulatory Effect



(b) Spillover Effect

Figure 8: Regulatory and spillover effects of 1-hour ozone on coal plants

effects of regulation on total factor productivity and find some evidence of a negative initial regulatory effect but a positive long-term effect. The estimates in Figure 8 are the cumulative effects of regulation to date. We observe that both the regulatory and spillover effects grow over time, and that the effects are largest in years 6 and 7. In particular, we do not observe a significant spillover effect until year 2. Such

Table 10: Heterogeneous Effects of Regulation

	(1) Baseline	(2) Large	(3) Old
		Coal Plants	
Regulatory Effect	0.0257**	0.0150	0.0294**
	(0.00782)	(0.00773)	(0.00863)
Spillover Effect	0.0198**	0.0142*	0.0204**
	(0.00620)	(0.00615)	(0.00654)
N	18048	15621	15889
R-sq	0.071	0.077	0.071
		Oil Plants	
Regulatory Effect	0.0104	0.00529	0.0145
	(0.00844)	(0.0117)	(0.0104)
Spillover Effect	0.0210*	0.0117	0.0252*
	(0.00954)	(0.0112)	(0.0102)
N	41874	18830	33686
R-sq	0.038	0.059	0.034

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

increases in the effects of non-attainment is consistent with plant learning in response to regulation. The process of innovation and technology technology transfer takes time, and it takes a couple of years for the benefits to come into effect.

We also explore if there is a particular type of plant that is driving our results. There may be a non-linear effect of capacity or age on improvements in plant efficiency since large plants have a higher baseline efficiency or older plants may have a larger opportunity for efficiency gains. In column (2) of Table 10, we restrict the sample to only plants with a nameplate greater than 50 MW in order to determine whether the results are driven primarily by large or small plants. The regulatory effect on coal plants and the spillover effect on oil plants become insignificant and the point estimate for the spillover effect for coal plants falls when we restrict the sample to only small plants. It appears that small plants benefit more from innovation and technology transfer than large plants, an observation consistent with the EPA sample selection test from Table 9. Small plants tend to be less efficient initially and there

Table 11: 1-Hr Ozone Pathway Test (Coal)

		(1)	(2)	(3)	(4)	(5)	(6)
		Efficiency	CO2 Emissions	Nox Emissions	SO2 Emissions	Ramp Hours	Generation
1 Hr Ozone	Reg	0.0153*	-0.0226	-0.0151	0.0419*	0.146*	0.0663
		(0.00765)	(0.0549)	(0.0591)	(0.0185)	(0.0606)	(0.0434)
	Spill	0.0174**	0.0950	0.107*	0.0516**	-0.00742	-0.0311
		(0.00601)	(0.0487)	(0.0483)	(0.0143)	(0.0660)	(0.0361)
CO2 Emissions		-0.00945**					
		(0.00259)					
NOx Emissions		-0.0138*					
		(0.00571)					
SO2 Emissions		0.168**					
		(0.0230)					
Ramp Hours		0.00152					
		(0.00161)					
Generation		0.0635**					
		(0.00624)					
N		18048	19122	19122	19122	19122	19122
R-sq		0.162	0.817	0.831	0.788	0.710	0.113

Table 12: Pathway Test Coefficients (1-Hour Ozone, Coal)

	α_i	$\gamma_{i,1}$	$\gamma_{i,2}$	$\alpha_i \cdot \gamma_{i,1}$	$\alpha_i \cdot \gamma_{i,2}$
abatement (CO2)	-0.945%	0	0	0	0
abatement (NOx)	-1.38%	0	0	0	0
abatement (SO2)	16.8%	4.18%	5.16%	0.702%	0.867%
utilization (ramping)	0	14.6%	0	0	0
utilization (generation)	6.35%	0	0	0	0
innovation/reallocation				1.53%	1.74%

may, therefore, be a greater number of marginal efficiency improvements that may be made for these small plants, allowing for larger regulatory and spillover effects.

In Column (3) of Table 10 we include only plants with a plant age greater than 10 years since we expect the efficiency gains to be concentrated among older plant, potentially with more opportunity for gains. Restricting the sample to these plants does not significantly change the results, though the point estimates slightly increase.[14]

Finally, in equations 6-10, we introduced our idealized structural model. Ideally we would like to estimate the magnitudes and significance of all the various pathways using this model. Unfortunately, both process innovations, which we believe drive the innovation effect, and resource reallocations are difficult to measure. We can, however, partially estimate the structural model using proxies for abatement and utilization. We therefore estimate the following model:

$$\begin{aligned}\Delta \mathit{eff}_{it} =& \alpha_0 + \alpha_1 \cdot \mathit{so2emit}_{it} + \alpha_2 \cdot \mathit{noxemit}_{it} + \alpha_3 \cdot \mathit{co2emit}_{it} \\ & \alpha_4 \cdot \mathit{ramp}_{it} + \alpha_5 \cdot \mathit{gen}_{it} + \beta_1 \cdot \mathit{reg}_{it} + \beta_2 \cdot \mathit{spill}_{it} + u_{0,it}\end{aligned} \tag{15}$$

$$\mathit{so2emit}_{it} = \gamma_{1,0} + \gamma_{1,1} \cdot \mathit{reg}_{it} + \gamma_{1,2} \cdot \mathit{spill}_{it} + u_{1,it} \tag{16}$$

$$\mathit{noxemit}_{it} = \gamma_{2,0} + \gamma_{2,1} \cdot \mathit{reg}_{it} + \gamma_{2,2} \cdot \mathit{spill}_{it} + u_{2,it} \tag{17}$$

$$\mathit{co2emit}_{it} = \gamma_{3,0} + \gamma_{3,1} \cdot \mathit{reg}_{it} + \gamma_{3,2} \cdot \mathit{spill}_{it} + u_{3,it} \tag{18}$$

$$\mathit{ramp}_{it} = \gamma_{4,0} + \gamma_{4,1} \cdot \mathit{reg}_{it} + \gamma_{4,2} \cdot \mathit{spill}_{it} + u_{4,it} \tag{19}$$

[14]Varying our cutoff age to 20 years does not change the results in a meaningful way.

$$gen_{it} = \gamma_{5,0} + \gamma_{5,1} \cdot reg_{it} + \gamma_{5,2} \cdot spill_{it} + u_{5,it} \tag{20}$$

In this model, $\alpha_1 \cdot \gamma_{1,1}$, $\alpha_2 \cdot \gamma_{2,1}$, and $\alpha_3 \cdot \gamma_{3,1}$ represent the impact of a change in regulatory status on efficiency through changes in abatement, $\alpha_1 \cdot \gamma_{1,2}$, $\alpha_2 \cdot \gamma_{2,2}$, and $\alpha_3 \cdot \gamma_{3,2}$ represent the effect of spillover eligibility on efficiency through the abatement pathway, and $\alpha_4 \cdot \gamma_{4,1}$ and $\alpha_5 \cdot \gamma_{5,1}$, and $\alpha_4 \cdot \gamma_{4,2}$ and $\alpha_5 \cdot \gamma_{5,2}$ represent the regulatory and spillover effects, respectively, through the utilization channel. Finally, the remaining regulatory and spillover effects, β_1 and β_2, capture the combined effects of the innovation and resource reallocation pathways. Because we hypothesize that these two mechanisms will have opposite effects on efficiency - in Table 6 we predicted that resource reallocation would lead to negative regulatory and spillover effects while innovation would create positive regulatory and spillover effects - the signs of β_1 and β_2 will indicate which mechanism dominates.

We estimate equations 15-20 again using a fixed-effects panel estimation, with the same controls included in our primary estimations. The results of this estimation for coal plants and the 1-hour ozone standard are contained in Table 11 and the estimates are translated into the coefficients of the model in Table 12. Our estimation of the structural equation indicates that the primary mechanism through which changs in regulatory and spillover status impact efficiency is innovation. Contrary to our parasitic load hypothesis, a reduction in the rate of CO2 and NOx emissions per unit of fuel consumed (indicating an increase in the abatement intensity) lead to an increase in plant efficiency. However, neither CO2 nor NOx emissions were significantly changed by non-attainment or spillover status.

The results indicate that a 1% decrease in SO2 emissions intensity leads to a 16.8% decrease in plant efficiency and that regulated plants and spillover plants increased their SO2 emissions per unit of fuel consumed by 4.15% and 5.16%, respectively. Ground level ozone is unrelated to emissions of SO2 - it is created by reactions between nitrogen oxides and volatile organic compounds. Regulated and spillover plants may react to a change in ozone regulatory standards by reducing SO2 abatement activities or switching to higher SO2 emitting technologies in order to lower costs. The combined regulatory and spillover effects of this increase in SO2 emissions intensity are relatively small, at 0.702% and 0.867%, respectively.

Our utilization equations reveal similar results to those in Table 9. Though regulated plants significantly increase their ramping hours, this increase did not affect efficiency. As hypothesized, an increase in generation increased efficiency. However, generation did not change in response to changes in regulatory or spillover status. We therefore reject the utilization pathway as a mechanism through which regulatory and spillover status influence efficiency.

The coefficients on β_1 and β_2 reflect the remaining effect of 1-hour ozone non-attainment and spillover eligibility. Our results indicate that, after excluding the influences of the abatement and utilization pathways, increases in regulatory stringency lead to an increase in efficiency of 1.53% at regulated plants and 1.74% at spillover plants. Because these effects both have positive signs, we conclude that the innovation effect dominates the resource reallocation effect of regulation and that plants do indeed innovate in response to regulation and transfer these innovations to other, connected plants. Additionally, the point estimates in the structural model are slightly smaller than in the primary model (Table 8). It is possible that the increase in SO2 emissions intensity contributed to part of the positive effects shown in the primary model, and was not fully controlled by the inclusion of our abatement control variables in estimations shown in Table 9. However, the positive, significant effects remains even when we exclude this effect, supporting our hypothesized innovation mechanism.

Taken together, our results suggest that environmental regulation may actually increase efficiency at both regulated and unregulated plants. We determined that the abatement and generation shifting channels do not play a major role in the effect of regulation on efficiency; instead, efficiency changes are driven primarily by the innovation and resource reallocation effects. While we are unable to separate the positive innovation and technology shifting effect from the resource reallocation effect, the positive sign of our regulatory and spillover results suggests that the efficiency gains from innovation completely offset the losses from resource reallocation away from the optimal allocation.

3.4 Conclusions

In this paper, we tested the effects of non-attainment of the various air pollution standards set by the Clean Air Act Amendments on the efficiency of both regulated and unregulated "spillover" plants. Though the results depend on the particular fuel type and emissions standard under consideration, there is some evidence that plants may achieve efficiency gains in response to environmental regulation. Through our additional estimations, we find that these efficiency gains are likely to be caused by the development of efficiency-enhancing process innovations. Because these innovations reduced marginal fuel costs, firms transfer these innovations to similar plants in their fleet, both regulated and unregulated, allowing unregulated plants to achieve positive efficiency spillovers from regulation. The 1-hour ozone standard had positive regulatory of 2.57% and spillover effects of 1.98% for both coal plants; this result is consistent with our hypothesis of innovation and technology transfer. We also estimate these effects over time, after the initial change in regulatory status. Regulated plants experience efficiency gains almost immediately, and these effects grow over time. However, within-firm spillovers take time to take effect.

Our results have broader applicability beyond the electricity generation industry and environmental regulation. Many industries face regulations which may reduce inefficiency, increase costs, and decrease profits. However, the stress created by regulation on both firms and individuals creates an environment that is conducive to innovation and learning. If individuals develop efficiency-enhancing or cost-reducing process innovations in response to regulation and firm spread these innovations throughout the organization, then the firm may be able to reduce, or completely offset, the negative effects of regulation.

CHAPTER IV

RESERVE MARKET IMPACTS OF NEW INTERMITTENT GENERATING CAPACITY

On[1] February 2, 2011, a winter storm hit Texas, shutting down more than 200 power plants and causing rolling blackouts that affected over a million customers across the state. These blackouts sparked conversations about how to improve the reliability of the Texas electricity grid. Many attributed Texas' reliability problems to insufficient electric capacity. These regulators have pushed for the addition of "capacity markets" to the electricity market, called the Electricity Reliability Council of Texas, or ERCOT.

Capacity markets are payments made to power plants for the capacity they have installed. That is, in a capacity market, each year a power plant is paid per kilowatt of capacity that they have available. Theoretically, capacity markets create additional incentives for investment in new capacity, ensuring that enough electricity is available in periods of high demand. Opponents claim that the existing structure of electricity markets, particularly of the Texas market, is enough to generate sufficient capacity. In this case, capacity markets unnecessarily subsidize power plants (Kliet and Michaels, 2013) [18].

An existing mechanism for ensuring grid reliability within electricity markets is the use of ancillary services markets. In these markets, power plants sell portions of their capacity to be used as reserves. This reserve capacity must remain spinning so that the system operator can use them to account for short-term imbalances in the electricity grid. All electricity markets include some type of reserve market. If the

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composition of the electricity market is unchanging, then ancillary services markets do not affect investment incentives.

However, something is changing in the Texas electricity market: the growth of wind power. Wind capacity has grown tremendously in Texas in the past 15 years. The availability of wind power depends primarily on the amount of wind present on a given day. This unreliability of wind acts to change how power plants allocate their resources between retail production and reserve production. The entry of wind power has two primary effects on electricity markets. First, wind power has a marginal cost of near zero, so that it falls at the bottom of the supply curve and reduces the price of electricity. In this way, wind power supplants existing, high marginal cost power and forces remaining fossil fuel plants to accept lower electricity prices. Second, the potential for wind power to be unavailable affects the amount of reserves the electricity market must have available at any given time. Through the ancillary services market, power plants may sell a share of their spinning capacity to the electricity grid for quick load adjustments in order to prevent shortages and blackouts. Because of its unreliability, wind power is unable to sell its capacity in reserve markets and increases in wind capacity will increase the amount of reserves required to balance the grid. If the gains in profits from the reserve markets are significant enough to overcome the loss in spot profits, then new wind capacity may encourage investment.

In this paper, we examine the impact of increasing wind capacity on investment incentives through changes in the decision to enter reserve markets. We adapt a model developed by Just and Weber (2008) [17] of the decision of plants to participate in reserve markets to include plant entry and exit and the addition of wind power. Through simulation, we find the equilibrium set of reserve plants and the equilibrium set of operating plants in order to observe the changes in market outcomes.

We find that new wind power does indeed increase the profitability of plants in the reserve market through increased reserve demand. However, these profit increases are not enough to encourage investment. The effect of increased wind capacity on spot prices is large enough that the losses in spot profits are much larger than the gains in reserve profits, and total profits decrease with new wind. We observe that greater wind penetration results in fossil fuel divestment, reduces the total expected available capacity in the market. As a result, shortages in the electricity market will become more likely as more wind enters the market, suggesting that some form of intervention may be required to increase investment.

Capacity markets may provide one mechanism to increase the total expected capacity in the electricity market. However, our results suggest that changes in the requirements for reserve capacity may also foster investment. We estimate the relationship between the variability in reserve and spot market prices and profits as more wind enters the market. The standard deviation of reserve and spot profits decreases with the amount of wind capacity. Lower variability implies that the managers of the electricity grid have better market information when they make their decisions, which allows them to better manipulate markets. In this case, the existing policy mechanism in our model is the reserve requirement. As more wind enters the market and market outcomes become more predictable, the reservation requirement could be altered to increase the reserve demand in a way that increases reserve profits and encourages investment. Therefore, while we conclude that something must change in the Texas electricity market in order to stimulate investment in new capacity, alternatives to subsidies in capacity markets may exist.

This paper proceeds as follows: first, we introduce the Texas electricity market, focuses on the day-ahead spot and reserve markets; second, we adapt Just and Weber (2008) [17] to include wind power and entry and exit decisions; third, we described our simulation methodology and results to test the effect of wind on market outcomes; finally, we conclude and readdress the issue of capacity markets in Texas.

4.1 The Texas Electricity Market

We begin with an overview of the electricity market in Texas, run by the Electric Reliability Council of Texas (ERCOT). A large majority of the wholesale electricity sold in the Texas market is provided by "load serving entities" (LSE) who negotiate private forward contracts with retail customers. Woo et al. (2004) [37] provides an excellent description and model of the bidding process by LSEs. In this paper, we concentrate instead on the electricity sold in the day-ahead spot market by qualified scheduling entities or QSEs to meet demand not met by by LSEs.

The day-ahead market occurs the day before operating day. During this period, QSEs bid into the primary spot market used to meet demand and into ancillary services markets, which operate to ensure the reliability of the electricity grid. In the balancing services market, plants submit supply schedules to ERCOT. The market clearing price is found by "stacking" these bids and finding the marginal bid required to meet expected inelastic demand for the next day. The next day, actual load is determined and plants are paid the market clearing price for their services.

There are a number of different ancillary services markets that provide reserve capacity to the grid, including regulation reserves, responsive reserves, and non-spinning reserves. Regulation reserves, a form of spinning reserves, are used to maintain system frequency. In the day-ahead market, QSEs bid portions of their capacity into the regulation reserve market. These bids are binding commitments that the plants will reserve a portion of their capacity, which may be used to increase or decrease generation within 5 seconds in response to the needs of the grid. As in the spot market, ERCOT sets the market price equal to the bid of the marginal plant required to meet some reserve requirement, based upon historical reserve demand data.

A number of theoretical and empirical papers examine bidding behavior in Texas spot markets (Sioshani and Oren, 2007; Hortacsu and Puller, 2008) [33, 13], but little economic research has examined the relationship between spot market bids and ancillary services bids. Just and Weber (2008) [17] developed a theoretical model of bidding behavior between spot and reserve markets based on the German electricity market, which has a number of parallels to the Texas market; in particular, the German incremental capacity market operates like the Texas regulation reserves markets. We therefore use their methodology to model the plant investment decision.

Another important characteristic of the Texas electricity market is the prevalence of wind power. Wind capacity has grown at a very fast rate in Texas since 2000; according to ERCOT, in 2014 it made up more than 12,000 megawatts of installed wind capacity. Generation has been growing even faster, accounting for more than 10% of the annual electricity generation, compared to 6.2% in 2009.[2] However, this wind power is only intermittently available. The effective load carrying capacity (ELCC) measures what percentage of total wind capacity is readily available. The ELCC is 32.9% in the coastal region of Texas and only 14.2% in the west region. Due to the unreliability of wind power, the amount of reserves required to balance the grid increases (Morales and Conejo, 2009; Papvasiliou et al., 2009)[25, 27]. We therefore expect that the bidding decisions between the spot and reserve markets to change as more unreliable wind power enters the market. To this end, we adapt the Just and Weber (2008) [17]'s model to include wind power and analyze its effects on market outcomes, including prices, profits, and investment decisions.

4.2 Theoretical Model

The theoretical model is an adaptation of Just and Weber (2008)'s [17] model of the decision of German electricity plants to participate in secondary reserve power markets. In their model, electricity plants must decide whether or not to offer a share of their total capacity as spinning reserves, given the costs associated with having capacity readily available to balance the electricity grid. They find the conditions for

[2] This growth in wind generation is not a result of increase wind reliability, but of a removal of transmission constraints.

the equilibrium set of reserve plants and develop a methodology to find a numerical solution. We extend their model to include wind plants with a negligible marginal production cost and a high probability of being unable to provide generation to the grid, a value called the forced outage factor, which influences reserve demand. We then model the entry and exit decisions of firms to determine the impact of new wind capacity on the total installed capacity in the market.

4.2.1 Determining the Equilibrium Set of Reserve Plants

There exist a large number, x_{max}, of perfectly competitive power plants, where some small subset of these plants, x_{wind}, are wind plants and the remaining plants are fossil fuel plants. Each power plant has a capacity of 1. Wind plants have a marginal cost of 0, while fossil fuel plants have a marginal cost of $C_{ff}(x)$ where $C_{ff}(x) > 0$ and $C'_{ff}(x) > 0$. The marginal cost function is therefore given by:

$$C(x) = \begin{cases} 0 & \text{if } 0 \leq x_{wind} \\ C_{ff}(x) & \text{if } x_{wind} < x \leq x_{max} \end{cases} \tag{21}$$

The electricity grid draws upon capacity from plants in order of increasing marginal cost, so that at any point in time demand is met in the least cost way, using those plants that have the lowest marginal cost. Given our assumption that marginal costs are increasing the plant indexing variable x, x represents the position of the plant on the supply curve. We assume that each firm's marginal cost does not change over time or with the level of production of the plant.

We assume that both fossil fuel plants and wind plants occasionally suffer unexpected outages, in which their effective capacity is zero. Fossil fuel plants and wind plants suffer outages with a probability of p_{ff} and p_{wind}, respectively. Fossil fuel power is much more reliable than wind power due to the intermittent availability of wind to produce electricity. We therefore assume that $p_{ff} > p_{wind}$.

Fossil fuel plants may offer a share of their total capacity k for sale in the reserve market. The share that may be sold in the reserve market is limited by the ability of the plant to ramp up their generation in a short period of time to meet the grid's reserve needs. Assuming that all fossil fuel plants have the same load adjustment rate. The load adjustment rate measures how quickly a plant can ramp up its production to a given level. In the Texas regulation reserve market, reserve plants must be able to respond to grid requirements within 5 seconds; the load adjustment rate assumption implies that each plant can increase their production by the same capacity share within that period of time. That is, each plant may offer the same maximum capacity share $k^{res} > 0$ for sale in the reserve market.

By definition, any power plant participating in the spinning reserve market must have some minimum share of their capacity spinning so that the plant may be utilized quickly to balance the electricity grid. That is, reserve plants must be producing at least some share of their capacity $k^{min} > 0$ at all times. We call this requirement the "must-run" condition for the plant, which creates additional costs for the reserve plants.

Given a capacity of 1, the must-run condition, and the load adjustment constraint on the share of capacity that can be offered in the reserve market, each firm chooses k to maximize its expected profits:

$$\max_{k} \ (1-k)E(\pi_{spot}) + kE(\pi_{res}|\text{must-run}) \tag{22}$$

where $0 \leq k \leq k^{res}$, $E(\pi_{spot})$ is the plant's expected profits in the spot-market per unit of capacity, and $E(\pi_{res}|\text{must-run})$ is the expected per-unit profits in the reserve market, given the must-run condition.

In the spot electricity market, firms face perfectly inelastic demand y, which follows a probability density function $l(y)$ over some range $L_{min} \leq y \leq L_{max}$. The price in the spot market is set in an uniform price auction. Because all power plants are perfectly competitive and have complete information, in this auction each plant bids its marginal cost.

Unlike Just and Weber's model, our reserve demand is determined entirely by forced outages. In reality, demand shocks also make up a portion of the demand for reserve capacity, though for simplicity we assume that reserves are only required if a plant is offline. If any plant, wind or fossil fuel, suffers a forced outage, then reserve plants must be called upon to make up for the loss. The number of fossil fuel plants suffering outages may be approximated by a normal distribution $N(\mu_1, \sigma_1)$, where $\mu_1 = p_{ff}(x_{max} - x_{wind})$ and $\sigma_1 = p_{ff}(1 - p_{ff})(x_{max} - x_{wind})$. Similarly, the number of wind plants suffering outages is approximated by the normal distributed $N(\mu_2, \sigma_2)$, where $\mu_2 = p_{wind}x_{wind}$ and $\sigma_2 = p_{wind}(1 - p_{wind})x_{wind}$. Thus, the total number of outages follows a normal distribution $N(\mu_1 + \mu_2, \sqrt{\sigma_1^2 + \sigma_2^2})$. While this forced outage assumption has its limitations, it creates a clear distinction between wind and fossil fuel plants, simplifying our analysis of our results.

In the reserve market, regulators set a reserve requirement Q^{res} to ensure that there are enough plants spinning to meet any potential losses in generation due to outages. We assume that $Q^{res} = \mu_1 + \mu_2$, so that there are enough plants to meet the expected loss in load. This reserve rule is relatively conservative; it requires enough capacity for the expected number of plants suffering forced outages, regardless of whether these plants are required to meet expected demand. We will examine the impacts of choosing other reserve rules in extensions of this model. Given this reserve requirement, each fossil fuel plant makes a two-part bid into the reserve market including a reservation price $R(x)$ per unit of capacity committed as spinning reserves and the price of any capacity actually called upon to balance the grid given outages. Therefore, plants that participate in the reserve market receive a payment for simply having capacity reserved and are paid a market price for any capacity that is actually called upon for use. We call the equilibrium price of reserving capacity the "capacity price" and the price paid for actual use the "reserve price."

Plants will participate in the reserve market if their reservation price $R(x)$ is less than the equilibrium capacity price R^*. This equilibrium price is the reservation price of the marginal reserve plant required to meet the demand for reserve capacity. The function $S(x, R^*)$ indicates whether or not plant participate in the reserve market:

$$S(x, R^*) = \begin{cases} 1 & \text{if } R(x) \leq R^* \\ 0 & \text{if } R(x) > R^* \end{cases} \tag{23}$$

Following Just and Weber, we assume that each reserve plant sells the maximum amount of reserves possible, k^{res}, given their load adjustment rate. Then, the total supply of reserve capacity is:

$$s^{res}(R^*) = k^{res} \int_0^{x_{max}} S(y, R^*)dy \tag{24}$$

and market clearing implies that $s^{res}(R^*) = Q^{res}$.

In order to find the equilibrium set of reserve plants, we must first determine the residual supply function in the spot market. The requirements of participation in the reserve market modify the spot-market supply function in two ways. First, reserve plants are required to produce some minimum amount of electricity k^{min}. To minimize the loss of this must-run condition, reserve plants will offer the k^{min} for sale in the spot-market regardless of the spot price. The must-run capacity therefore forms the bottom of the supply curve. Second, the remaining capacity that a reserve plant may bid into the spot market, excluding the must-run and reserve capacities, is $1 - k^{min} - k^{res}$. Additionally, we assume that all forced outages are unexpected and occur after the bidding process. As a result of this assumption, each power plant bids its full capacity into the spot market, rather than its expected capacity. Then, the amount of capacity provided by a given plant x may be expressed as:

$$n(x, R^*) = \begin{cases} 0 & \text{if } S(x + x_{max}, R^*) = 0 \text{ and } -x_{max} \leq x \leq 0 \\ k^{min} & \text{if } S(x + x_{max}, R^*) = 1 \text{ and } -x_{max} \leq x \leq 0 \\ 1 & \text{if } S(x, R^*) = 0 \text{ and } 0 < x \leq x_{max} \\ 1 - k^{min} - k^{res} & \text{if } S(x, R^*) = 1 \text{ and } 0 < x \leq x_{max} \end{cases} \tag{25}$$

We denote the must-run capacity, electricity generated by reserve plants due to the must-run condition, sold by reserve plants with negative values of the position variable x to differentiate it from the capacity bid into the spot-market at marginal cost. Integrating $n(x, R^*)$ gives the cumulative capacity up to a plant x:

$$m(x, R^*) = \int_{-x_{max}}^{x} n(y, R^*)dy \tag{26}$$

Given that the reserve requirement is Q^{res} and that each reserve plant offers k^{res} into the reserve market, the total number of plants needed to meet the reserve requirement is $\frac{Q^{res}}{k^{res}}$. The total amount of must-run capacity at the bottom of the supply curve is then $m_1 = k^{min}\frac{Q^{res}}{k^{res}}$. The cumulative capacity $m(x, R^*)$ may then be expressed as:

$$m(x, R^*) = m_1 + \int_{0}^{x} n(y, R^*)dy \tag{27}$$

The function $n(x, R^*)$ is strictly positive in on the range $0 < x \leq x_{max}$ and the cumulative capacity function $m(x, R^*)$ is strictly increasing for all values of $m(x, R^*) > m_1$. As a result, $m(x, R^*)$ is invertible with respect to x on the range $m(x, R^*) > m_1$. Now, given some equilibrium capacity price R^* and the current demand in the spot-market y, we can determine the marginal plant required to meet that demand using the function $g(y, R^*) = m^{-1}(y, R^*)$. The spot-market price is the marginal cost of that marginal plant for all non-must-run capacity in the market, so the residual supply function is:

$$s^{spot}(y, R^*) = \begin{cases} 0 & \forall y \leq m_1 \\ C(g(y, R^*)) & \forall y > m_1 \end{cases} \tag{28}$$

Each fossil fuel plant must then decide whether to offer a share of their capacity k^{res} for sale in the reserve market. Any plant that chooses to enter the reserve market will earn profits of:

$$E[\Pi_{res}(x)|\text{must-run}] = k^{res}R(x) + E[\Pi_{actual}(x)] - E[C_{mustrun}(x)] \tag{29}$$

$E[\Pi_{actual}(x)$ is the expected profits the plant earns from its actual use; this is the electricity produced to make up for any losses in load due to forced outages. $E[C_{mustrun}(x)]$ is the expected cost to the plant of the must-run requirement. The must-run capacity is cost at the spot-market price, regardless of whether the spot-market price covers their marginal costs.

The reservation price for each plant is the price $R(x)$ that makes them indifferent between offering the capacity share k^{res} in the reserve market and offering it in the spot-market. We denote the expected profits that the fossil fuel plant can earn from that capacity share in the spot-market as $E[\Pi_{spot}^{k^{res}}(x)]$. The indifference condition yields each plant's reservation price:

$$R(x) = \frac{E[\Pi_{spot}^{k^{res}}(x)] + E[C_{mustrun}(x)] - E[\Pi_{actual}(x)]}{k^{res}} \tag{30}$$

To derive the equilibrium capacity price, we must first define the cumulative capacity available in the reserve market for each plant x. The function $p(x, R^*)$ gives the amount of reserve capacity offered by each plant:

$$p(x, R^*) = \begin{cases} 0 & \text{if } S(x, R^*) = 0 \\ k^{SRP} & \text{if } S(x, R^*) = 1 \end{cases} \tag{31}$$

The cumulative capacity is then found by integrating over x:

$$q(x, R^*) = \int_0^x p(y, R^*)dy \tag{32}$$

Finally, given equations 21-32, Just and Weber prove that the equilibrium capacity price for each fossil fuel plant is:

$$\begin{aligned} R(x, R^*) = & \int_x^{x_{max}} [C(y) - C(x)]l(m(y, R^*))n(y, R^*)dy \\ & + \frac{k^{min}}{k^{res}} \int_0^x [C(x) - C(y)]l(m(y, R^*))n(y, R^*)dy \\ & - \begin{cases} 0 & \text{if } S(x, R^*) = 0 \\ \int_x^{x_{max}} [C(y) - C(x)]f(q(y, R^*))p(y, R^*)dy & \text{if } S(x, R^*) = 1 \end{cases} \end{aligned} \tag{33}$$

The first term is the expected per-unit profit of sale in the spot market. The profit equals zero if the demand y is less than the cumulative capacity $m(x, R^*)$ If the load is greater than the cumulative capacity, then the expected equilibrium price is the marginal cost of the marginal plant used to meet that load. The second term is the expected per-unit cost of the must-run condition. Must-ran capacity is offered for sale at the equilibrium spot market price, even if that price is less than their marginal cost. The magnitude of the expected must-run cost is then based on the expected degree to which the spot market price is less than the market cost. The final term is the expected per-unit profit of actual use by the reserve market. As in the spot market, the plant will only make non-zero profit from actual use if the if the capacity called is greater than the cumulative capacity $q(x, R^*)$. The price is equal to the marginal cost of the marginal plant required to meet the the expected actual demand for reserves.

4.2.2 The Exit/Entry Decision

Having found the equilibrium set of reserve plants for a given set of existing plants, we now turn to entry and exit decisions in order to find the equilibrium set of plants in the market. Examining firm entry and exit will allow us to determine the impact of the introduction of new intermittent wind capacity on the total available capacity for use.

First, we assume that over the planning period, each fossil fuel plant incurs some fixed operating cost F_{op}. Then, we determine an equilibrium subset of reserve plants, given the current set of operational plants. The profits for operational plants are given by:

$$E[\Pi(x)] = \begin{cases} E[\pi_{spot}(x)] - F_{op} & \text{if } S(x) = 0 \\ (1 - k^{res})E[\pi_{spot}(x)] + k^{res}R^* + E[\Pi_{actual}(x)] - E[C_{mustrun}(x)] - F_{op} & \text{if } S(x) = 1 \end{cases} \tag{34}$$

Note that π denotes profits per-unit of capacity sold and Π denotes total profits. A plant will choose to exit the market if $E[\Pi(x, F_{op})] < 0$.

Additionally, other plants may decide to enter the market if it is profitable to do so. Plant entry requires some fixed start-up cost $F_{startup}$. A plant will decide to enter the market if:

$$E[\Pi(x)] - F_{startup} \geq 0 \tag{35}$$

The plant has three options for entry. The plant may decide not to enter, to enter the reserve market, or to enter the spot market only. It will choose the option that generates the highest expected profits. While fixed costs do not factor into existing plants' reservation prices, the fixed start-up and operating costs will impact the reservation prices of entering or existing plants. There are two different conditions to determine the reservation price. First, the reservation price of a potential entrant may be that price which makes the entrant indifferent between remaining out of the market and entering the reserve market:

$$\begin{aligned}(1 - k^{res})E[\pi_{spot}(x)] + k^{res}R_{enter}(x) + E[\Pi_{actual}(x)]\\ - E[C_{mustrun}(x)] - F_{op} - F_{startup} \geq 0\end{aligned} \tag{36}$$

Second, the plant has the option of entering the reserve market or entering the spot market only. The reservation price then must make the entrant indifferent between entering the reserve market and entering the spot market, determined by the indifference condition in equation 29 used by non-entrant plants.

The plant will bid its lowest possible reservation price into the reserve market. The entrant's reservation price is therefore given by:

$$\begin{aligned}R_{enter}(x) = \min \frac{(E[C_{mustrun}(x)] + F_{op} + F_{startup} - E[\Pi_{actual}(x)] - (1 - k^{res})E[\pi_{spot}(x)]}{k^{res}},\\ \frac{k^{res}E[\pi_{spot}(x)] + E[C_{mustrun}(x)] - E[\Pi_{actual}(x)]}{k^{res}}\end{aligned} \tag{37}$$

4.3 Simulation Methodology and Results

Having introduced the theoretical model with a continuous set of plants, we now find a numerical solution with a discrete set of plants. As in our theoretical model, we introduce wind plants and plant entry and exit in order to determine the equilibrium set of operational plants and to examine comparative statics involving the introduction of intermittent wind capacity. Our goal is to examine the effect of the entry of wind plants on incentives to participate in the reserve market and to invest in new capacity. If wind entry changes these incentives, the growth of wind power in Texas could impact the need for the implementation of capacity markets.

4.3.1 Structure of the Simulated Model

To determining the equilibrium set of reserve plants, we use the following methodology, used by Just and Weber (2008) [17]. Note that the subset of reserve plants will be continuous because we have ordered plants according to increasing marginal cost; every plant within some range $x_{min} \leq x \leq x_{min} + \frac{Q^{res}}{k^{res}}$ offers their capacity for sale in the reserve market.

1. Designate a random, continuous subset of $\frac{Q^{res}}{k^{res}}$ plants to be reserve plants, then determine the market capacity price as if this subset were the equilibrium set of reserve plants.

2. Calculate the reservation price of all non-reserve plants. Then determine the difference between the market capacity price and the reservation price for each plant.

3. If a non-reserve plant has a reservation price below the market capacity price, then it is profitable for that plant to offer their capacity in the reserve market. There is thus a profitable deviation from this set of reserve plants and the chosen subset is not an equilibrium. Repeat steps (a) and (b) for a new subset

of reserve plants.

4. If no existing non-reserve plant can profitably enter the reserve market, then the reserve subset of plants is an equilibrium.

As this process is repeated multiple times throughout the simulation, for expositional simplicity we will refer to this process of "determining the equilibrium set of reserve plants." The process to determine the equilibrium set of reserve plants is then combined with the following method for determining plant entry and exit decisions:

1. Determine the equilibrium set of reserve plants for some baseline set of plants with $x_{wind} = 0$.

2. Calculate expected profits according to equation 34 for all plants, reserve and otherwise.

3. If $E[\Pi(x)] < 0$ for any active plant x, then that plant exits the market.

4. If $E[\Pi(x)] \geq 0$ for any inactive plant x, with plant reservation prices given by $R_{enter}(x)$, then that plant enters the market.

5. Repeat steps 1-4 until no plants find it optimal to enter or exit the market.

6. Repeat steps 1-5 for $x_{wind} = x_{wind} + 1$.

The set of potential entrants for x_{wind} is determined from the equilibrium with $x_{wind} - 1$ wind plants. We begin at $x_{wind} = 0$ with some baseline set of plants. Any plant from this baseline set that was inactive in the equilibrium with $x_{wind} - 1$ wind plants is a potential entrant with x_{wind} wind plants. We calculate the expected profit of entry for each of these potential entrants, using the fact that all potential entrants believe that if they enter, all other potential entrants below them on the supply curve will also enter. This is true because (1) spot market profits are decreasing in x and (2) the profits of a plant x_0 depend only on the actions of plants lower in the supply

Table 13: Summary statistics and comparative statics with pwind=0.7.

	(1) Mean	(2) $\frac{\partial}{\partial x_{wind}}$	(3) $\frac{\partial^2}{\partial x_{wind} \partial x}$
Capacity Price	13.041	-0.001**	
Spot Price	45.762	-0.096**	
Reserve Price	39.905	0.099**	
Reserve Demand	41.901	0.658**	
Spot Profits	13.176	-0.057**	0.0002**
Reserve Profits	11.788	0.065**	0.0004**
Total Profits	17.820	-0.030**	0.0003**
Total Expected Capacity	800.460	-4.039%	

$^{*}p < 0.05$, $^{**}p < 0.01$

curve with $x < x_0$. If any of the potential entrants have positive expected profits from entry, they will enter the market. Otherwise, they will remain out of the market.

We assume that there are 1,000 fossil fuel plants, each with a marginal cost of $C(x) = 0.072042(x - x_{wind}) + -0.0000349(x - x_{wind})^2 + 7.690821$. To find this function, we use the data on marginal fuel costs and capacities of plants in Texas in 2010 to create the supply curve, and then compress the function for 1,000 plants. Each fossil fuel plant may bid a maximum capacity share of $k^{res} = 0.20$ into the reserve market and must run at least $k^{min} = 0.50$ to participate. The demand for electricity in the spot market follows a symmetric triangle distribution with a minimum demand of 500, mean demand of 650, and maximum demand of 800. Additionally, we add the assumption that fossil fuel and wind plants suffer forced outages 4% and 70% of the time, respectively. Finally, we assume that the cost of entry $F_{startup} = 0$ and the fixed cost of operations is $F_{op} = 5.28$, which is calibrated to the marginal cost to fixed cost ratio of power plants in Texas.

The equilibrium found represents the long-run decision of plants based on expected profits. To examine the impacts of these decisions in short-run, we randomized spot demand and forced outages and determine the spot prices, reserve demand, reserve prices, and profits. Examining profits with randomized load and outages allows us to analyze how profits vary for an individual plant. We use the following methodology over 300 runs for each value $x_{wind} = 0, 1, ..., 50$:

1. Spot demand is drawn from a triangle distribution. The spot price P^*_{spot} is the marginal cost of the marginal plant required to meet this demand.

2. A randomized vector of forced outages, based on p_{wind} and p_{ff}, is realized.

3. A plant x will supply electricity if they do not suffer an outage and if $C(x) \leq P^*_{spot}$. The demand for reserves is the difference between the spot demand and the total supply, given outages. The reserve price is then the marginal cost of the marginal reserve plant required to meet the reserve demand.

Table 13 contains the summary statistics and comparative statistics with respect to x_{wind} at the equilibrium. Column (1) gives the mean value of each key equilibrium value over all 51 equilibria with $x_{wind} = 0, 1, ...50$ to give a sense of the size of the effects in Column (2). Column (2) includes the results of the estimation of β for each variable. We use *var* as a placeholder for the different independent variables we include in these regressions.

$$var_{x,w} = \alpha + \beta \cdot xwind_w + \epsilon_{x,w} \tag{38}$$

Here x indexes the plant, so that β gives the expected value over all plants for profit variables[3], and w indexes the number of wind plants present in each equilibrium. While these effects are all significant, the effect sizes are small because a single wind plant accounts for a very small share of the overall capacity. Finally, to explore the

[3]Excluding reserve profits, which are averaged over all reserve plants only.

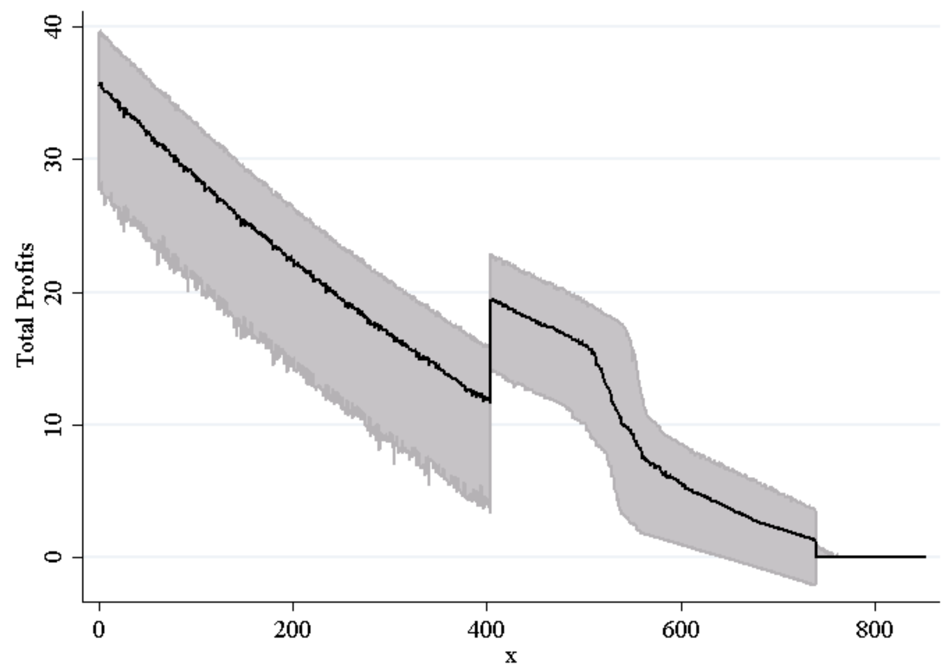
effect of new wind plants on profits along the supply curve, in Column (3) we include the estimates of the value $\frac{\partial^2}{\partial x_{wind} \partial x}$.

These comparative statics give us a sense of how the market changes when new, intermittent wind capacity is added to the bottom of the supply curve. The effect on the spot market is relatively straightforward. As predicted by the literature (Rathmann, 2007; Traber and Kemfert, 2009; Sensfuss et al., 2008) [31, 35, 32], new wind capacity drives down the expected spot market price in two ways. First, wind plants are able to underbid all fossil fuel plants due to their low marginal production cost; this shifts the supply of electricity outward and, with constant expected demand, causes the price to fall. Second, if the reserve requirement increases in the number of wind plants, then it ensures that more plants enter the reserve market when new wind plants enter the spot market. A larger number of reserve plants means that more plants are offering must-run capacity for a price of zero, shifting the supply curve even further out. Thus, the expected spot market price falls and this reduction in the price causes expected profits in the spot market to fall.

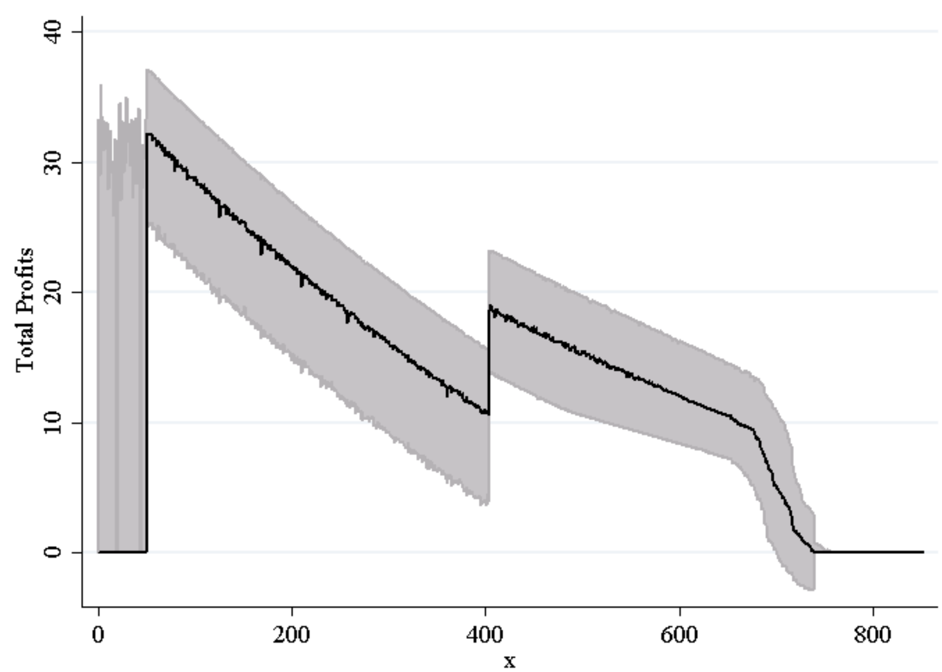
There are many factors at work in the effect of new wind capacity on the reserve market. First, the net effect of added wind on the equilibrium capacity price is negative, but small. Recall that the capacity price increases with the expected spot market profits and must-run cost and decreases with the expected profits from actual use. As previously discussed, the falling expected spot price reduces the profits to be had in the spot market, decreasing the opportunity cost of participating in the reserve market. Additionally, due to the high probability of outages in wind plants, the expected demand for reserves for actual use increases as wind enters the market. If the equilibrium set of reserve plants did not change as wind capacity increases, then this increase in demand would dramatically increase the expected reserve price. However, plants further and further down the supply curve enter the reserve market as wind increases. Much of this new demand is met by lower marginal cost plants, which act to reduce the reserve price. The net effect is a small, positive increase in the price of reserves. Therefore, the expected profits from actual use increase with increased wind capacity. The reduction in the opportunity cost of entering the reserve market and the increase in the potential profits from actual use both act to decrease the capacity price.

Finally, we turn to the effect of new wind capacity on plant entry and exit. Table 13 reveals that for each wind plant with a capacity of 1 that enters the market, the total expected capacity available decreases by 0.66. The prices in the market adjust so that approximately 851 plants are in the market; enough to ensure that, on average, there are no shortages of electricity. This result means that each wind plant in the market replaces a more reliable fossil fuel plant upon entry. The unreliability of wind means when wind replaces fossil fuel plants, the amount of expected capacity falls by the difference between the wind and fossil fuel forced outage factors (0.66). As a result, the probability of a shortage of electricity rises as the number of wind plants in the market increases, which has a significant impact on profits.

Figures 10a and 10b show the combined effect of the lower capacity price, the higher profits of actual use, and a lower must-run cost on reserve profits. The position of the reserve subset of plants does not change (with this particular reserve rule) as the number of wind plants increases. The marginal reserve plant is the 738th plant along the supply curve. When there are 50 wind plants in the market, the 738th plant has a lower marginal cost than the 738th plant with 0 wind plants in the market. Similarly, each plant along the supply curve has a lower marginal cost with $x_{wind} = 50$ than its corresponding counterpart when $x_{wind} = 0$. This shifting of the supply curve impacts the must-run cost. Though the spot price is falling, which increases the probability that reserve plants will suffer a loss from the must-run constraint, the reduction in the marginal cost of the reserve plants minimizes this loss and the must-run cost does not increase significantly. This low must-run cost, combined with the higher profits

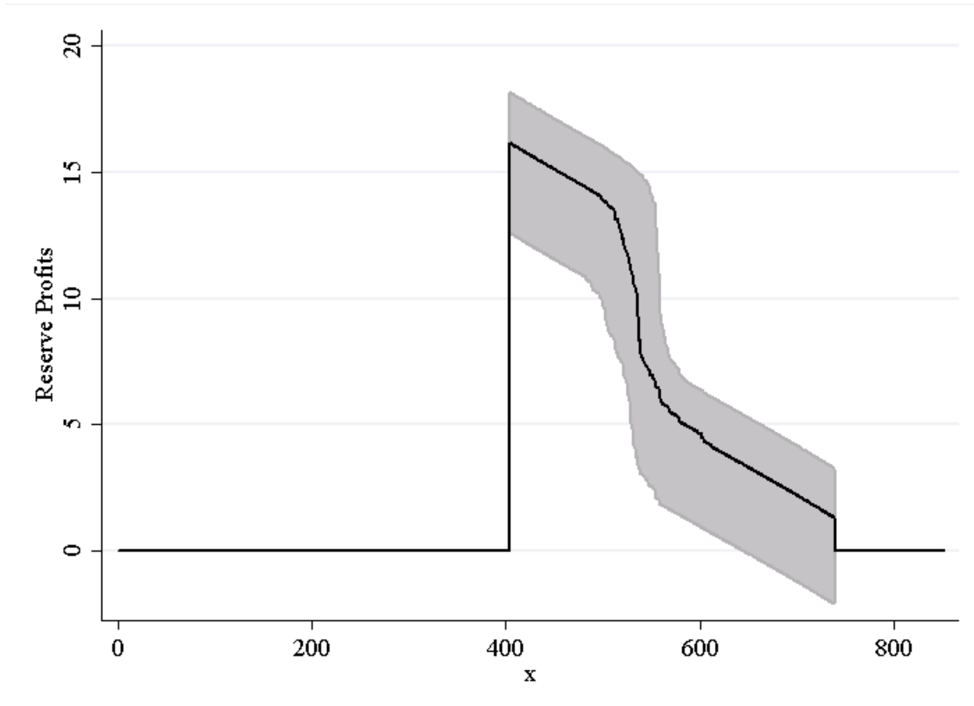


(a) 0 Wind Plants

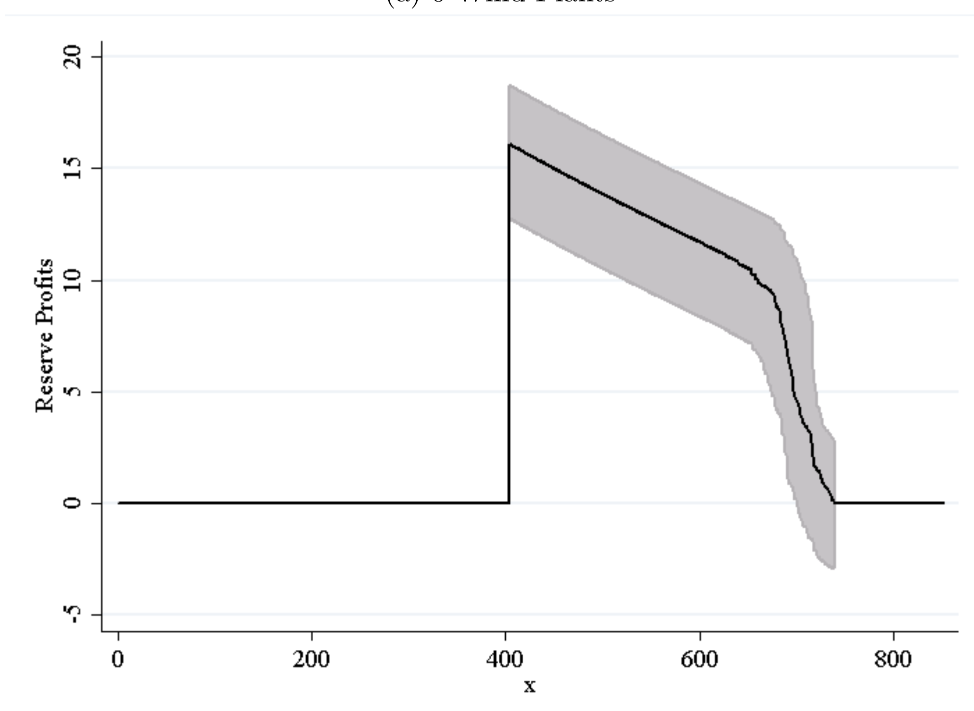


(b) 50 Wind Plants

Figure 9: Mean, 25 percentile, and 75 percentile of total profits.



(a) 0 Wind Plants



(b) 50 Wind Plants

Figure 10: Mean, 25 percentile, and 75 percentile of reserve profits.

of actual use driven by higher reserve demand, acts to increase the average profits in the reserve market when new wind capacity enters the market.

Figures 9a and 9b displays how total profits change for plants along the supply curve. While reserve profits increase, these account for only a small portion of the overall profits a plant can earn. Most of a plant's profits comes from the spot market, in which the price of electricity is falling with increased wind capacity. The significant reduction in the expected spot profits, which affects all plants, is much larger that the gain in expected profits from the reserve markets, and average total profits fall as wind capacity increases.

These figures also indicate that the effect of wind investment on plant profits depends on the location of the plant along the supply curve. Higher marginal cost plants are less affected by the entry of wind into the market than lower marginal cost plants. High marginal cost plants are only rarely called upon to provide generation to the grid, both with few wind plants and with many wind plants. Their profits are therefore less affected by the growth of wind than the profits of those who are much more active in the electricity market.

By simulating the short-run outcomes with realized electricity demand and power plant forced outages, we are also able to estiamte the effect of wind on the variability of outcomes in the market. Table 14 shows the results of the estimation of:

$$\sigma_{x,w}^{var} = \alpha + \beta_1 \cdot xwind_w + \epsilon_{x,w} \tag{39}$$

where σ^{var} is the standard deviation of the variable var for plant x with w wind plants over 300 simulations. Table 14 indicates that wind capacity increases variability in the demand for reserves, but decreases the variability in spot and reserve prices and profits.

Figures 9a and 9b also shows the 75 and 25 percentiles of total profits for all plants along the supply curve. The expected profits of wind plants is highly variable due to the high probability of forced outage, increasing the average degree of variation when

Table 14: Effect of wind on standard deviation of key variables with pwind=0.7.

	(1) $\frac{\partial}{\partial x_{wind}}$	(2) $\frac{\partial^2}{\partial x_{wind} \partial x}$
Spot Price	-0.481**	
Reserve Price	-0.008**	
Reserve Demand	0.026**	
Spot Profits	-0.360**	0.0004**
Reserve Profits	-0.210**	0.00004
Total Profits	-0.437**	0.0002**

$^{*}p < 0.05$, $^{**}p < 0.01$

$x_{wind} = 50$. However, fossil fuel plant profits fall within a smaller range when $x_{wind} = 50$ than when $x_{wind} = 0$, particularly for reserve plants. The negative relationship between wind capacity and spot profit variability contradicts the results of Woo et al. (2011) [38], who test the impact of new wind power on the spot price. Using Texas data, they found that the variance in the spot prices increases when the amount of wind in the market increases. Their results suggest that wind power has an alternative affect on the spot market variability to the mechanism described in the model.

Figures 10a and 10b shows the 75 and 25 percentiles of reserve profits along the supply curve as well. The variability in the profits of the marginal reserve plants depends partially on patterns in reserve demand, but primarily on the must-run cost. If spot demand is high, then the price in the spot market is high. The cost of selling the must-run capacity at the spot price in this case is small, and possibly even negative if spot demand is large enough. High prices in the spot market give reserve plants the opportunity to make big profits in the short-run. However the opposite is also true; if the spot price is low, then the must-run cost can be huge, causing the marginal reserve plants to suffer losses in the reserve market. As depicted in Figures 10a and 10b, the 25 percentile drops below zero for plants at the end of the reserve supply curve. This variation in the profits implies that entering the reserve market comes with a risk in the short-run; the plant could earn significant profits or suffer significant losses.

As the variation of the spot market price falls with the number of wind plants, the variation in the reserve market falls as well, in particular to those at the end of the supply curve. These plants are unlikely to earn profits from actual use and primarily rely on the capacity price to offset the must-run cost. The smaller varability in the spot price reduces the variation in the must-run cost and sigificantly impacts the variation in the reserve profits.

Wind entry also affects the potential gains and losses from participating in the reserve market. The maximum profits achieved by the first plant on the reserve supply curve increased by 0.24% as x_{wind} increased from 0 to 50 and the minimum profits achieved by the final plant on the surve supply curve decreased by 4.9%. Though the variability in the profits is smaller when there are more wind plants in the market, the potential losses by the marginal reserve plants are steeper. The possibility of these losses could prevent the entry of risk averse plants into the reserve market in reality.

4.3.2 Capacity Markets

The relationship between wind power, the reserve market, and profits suggests that capacity markets could make significant improvements to the reliability of the electricity grid by increasing the expected capacity in the market. We found that wind supplants fossil fuel power as it enters the market. Therefore, the growth of the wind industry in Texas causes reliable fossil fuel power to be replaced by unreliable wind power and the total expected capacity available in the market will fall. As result, the probability of an electricity shortage and blackouts will rise, revealing a role for capacity markets in Texas. Plants at the top end of the supply curve earn positive profits when the fixed operating cost is excluded. If capacity payments were tailored to offset enough of the fixed operating cost, some higher marginal cost plants would be less likely to leave the market as new wind enters the market, ensuring a greater total expected capacity in the electricity market.

On the other hand, the impact of wind power on the variability of plant outcomes reveals a different result. More information is better in this market. As prices and profits become more predictable, decision making by firms and policy makers become easier. Investment and policy decisions require relatively accurate information about market outcomes. As policy makers are better able to predict market outcomes, they are better able to make important decisions. The primary policy decision in our model is the reservation requirement. With greater predictive power, ERCOT could adjust the reserve requirement to the changing nature of the market in order to ensure greater reliability of the grid and perhaps to encourage greater investment. Given expected prices and profits, a reservation requirement may be able to achieve the optimal level of expected capacity in the market.

Combined, our results suggest that while the assumptions within our model lead to an outcome where expected capacity falls with the entry of wind plants, better manipulation of the reserve market due to less stochastic market outcomes could allow policy makers to counteract this effect using existing market mechanisms.

4.4 Conclusions

In this paper, we developed a theoretical model of power plant's decisions in the spot market and the reserve market, as well as plant entry and exit decisions, in order to determine how new, intermittent wind capacity will affect the Texas electricity market. We use this theoretical model to develop a simulation in which we can determine a numerical equilibrium and run comparative statics. We find that the low reliability and marginal cost of wind power increase the incentives of fossil fuel plants to participate in the reserve market by increasing the demand for reserves and the price of reserves when actually called. However, participating in the reserve market becomes more risky for those plants at the tail end of the reserve market, who become more likely to suffer losses in the reserve market when wind penetration is high. We also find that while the potential losses suffered in the reserve market increase for the marginal reserve plants, the variability in reserve profits as a whole falls, giving better powers of prediction to policy makers.

While wind increases profits in the reserve market, it decreases average profits in the market as a whole. Consistent with previous research, wind forces the spot market price downward, reducing potential profits in the spot market and causing fossil fuel plants to exit the market. These effects result in a reduction in the expected capacity available in the market, creating a greater potential for shortages.

The question then remains: should Texas implement capacity markets to increase investment and ensure the availability of enough reserve capacity in the market? The primary argument against capacity payments in Texas is that the market provides enough incentives to invest without subsidizing electricity production. Our results suggest that, given our reserve requirement, as wind power penetrates a greater portion of the Texas electricity market, the market itself will not be able to foster investment. However, an increased ability to predict market outcomes with greater wind capacity suggests that policy makers in Texas could act within the existing market structures to change this result. Therefore, capacity markets may in fact improve the operation of the Texas electricity market by increasing incentives to invest in new capacity and increasing incentives to provide that capacity in the reserve market, but ERCOT be able to improve reliability simply by manipulating the reserve requirement.

APPENDIX A

ADDITIONAL PROOFS

Proof of Proposition 3. Solving the for the equilibrium in this model follows the same process as for Proposition 2. Each firm chooses q_j and a_j to maximize its profits, according to:

$$\pi_j = (1 - bQ)q_j - r(Z)(q_j - a_j) - \frac{1}{2}a_j^2$$

The first order conditions of this choice are:

$$1 - bQ - bq_j - r'(Z)(q_j - a_j) - r(Z) = 0$$

$$r'(Z)(q_j - a_j) + Nr(Z) - a_j = 0$$

Each of the N firms has the same first order condition. Therefore, by summing the first order conditions over N:

$$N(1 - bQ - r(Z)) - bQ - r'(Z)(Q - A) = 0$$

$$r'(Z)(Q - A) + Nr(Z) - A = 0$$

These two equations define a system of equations. I can solve this system for the equilibrium total abatement and total output, as a function of the implicitly determined permit price:

$$Q(r) = \frac{N(1 + r'(Z) - r}{r'(Z) + b(1 + r'(Z))(N + 1)}$$

$$A(r) = \frac{N(r'(Z) + b(N + 1)r(Z))}{r'(Z) + b(1 + r'(Z)(N + 1}$$

The total demand for pollution is therefore:

$$Z(r) = Q(r) - A(r) = \frac{N(1 - (1 + b + bN)r(Z))}{r'(Z) + b(1 + r'(Z))(N + 1)}$$

I then solve for the inverse demand function for pollution:

$$r(Z) = \frac{-(b + r'(Z) + br'(Z))Z + N(1 - b(1 + r'(Z))Z)}{N(1 + b + bN)}$$

Assuming the demand for pollution is linear, so that $r''(Z) = 0$, I take the derivative of the inverse demand curve:

$$r'(Z) = -\frac{r'(Z) + b(1 + r'(Z))(1 + N)}{N(1 + b + bN}$$

Solving for the slope of the demand curve yields:

$$r'(Z) = -\frac{b}{1 + b + bN}$$

Therefore, the inverse demand for permits is:

$$r(Z) = \frac{1 - bZ}{1 + b + bN}$$

The supply of permits is $Z = S$. Therefore, the equilibrium permit price is $r(N, S) = \frac{1-bS}{1+b+bN}$, which will be positive for $S < \frac{1}{b}$. Now, the partial derivative of $r(N, S)$ with respect to N is:

$$\frac{\partial r(N, S)}{\partial N} = -\frac{b(1 - bZ)}{(1 + b + bN)^2} < 0$$

Therefore, for all $b > 0$, the price of permits is decreasing in N. □

Proof of Proposition 4. As in the previous proof, solving for the equilibrium once again follows the proof of Proposition 2. The firms choose their optimal output and quantity according to:

$$\pi_j = (1 - Q)q_j - r(Z)(q_j - a_j) - \frac{1}{2}a_j^2 - \frac{1}{2}q_j^2$$

This choice yields the first order conditions:

$$1 - Q - 2q_j - r'(Z)(q_j - a_j) - r(Z) = 0$$

$$r'(Z)(q_j - a_j) + r(Z) - a_j = 0$$

Summing these first order conditions over the N firms:

$$N(1 - Q - r(Z)) - 2Q - r'(Z)(Q - A) = 0$$

$$r'(Z)(Q - A) + Nr(Z) - A = 0$$

These two equations form a system of equations. Solving this system for the optimal levels of total output and abatement as a function of the implicitly determined permit price:

$$Q(r) = \frac{N(1 + r'(Z) - r(Z))}{2 + N + r'(Z)(N + 3)}$$
$$A(r) = \frac{N(r'(Z) + r(Z) + Nr(Z))}{2 + N + r'(Z)(N + 3)}$$

The demand for pollution permits is then:

$$Z = Q - A = \frac{N(1 - (N + 3)r(Z))}{2 + N + r'(Z)(N + 3)}$$

Therefore, the inverse demand for permits is:

$$r(Z) = \frac{N(1 - Z - r'(Z)Z) - (2 + 3r'(Z))Z}{N(N + 3)}$$

Assuming that the inverse demand for permits is linear (i.e., that $r''(Z) = 0$, then the derivative of the above is:

$$r'(Z) = -\frac{2 + 3r'(Z) + N + Nr'(Z)}{N(N + 3)}$$

The above equation allows me to solve for the slope of the demand curve:

$$r'(Z) = -\frac{N + 2}{3 + 4N + N^2}$$

Therefore, the demand for permits is:

$$r(Z) = \frac{1 + N - Z(N + 2)}{3 + 4N + N^2}$$

Also, the quantity-price and abatement-price curves are:

$$Q(r) = \frac{1 + 3N + N^2 - 3r + 3Nr - N^2 r}{6 + 5N + N^2}$$

$$A(r) = \frac{(3 + 4N + N^2)r - 1}{N + 3}$$

The supply of permits is $Z = S$. Therefore, the equilibrium permit price is $r(N, S) = \frac{1+N-Z(N+2)}{3+4N+N^2}$, which will be positive for $S < \frac{N+1}{N+2}$. Taking the partial derivative with respect to N yields:

$$\frac{\partial r(N, S)}{\partial N} = \frac{-1 - N^2(1 - S) + 5S - N(2 - 4S)}{(N + 1)^2(N + 3)^2}$$

Which will be negative for $S > \frac{(N+1)^2}{5+4N+N^2}$. Therefore, for the range $\frac{(N+1)^2}{5+4N+N^2} < S < \frac{N+1}{N+2}$, the price of permits is decreasing in N. $\square$

APPENDIX B

ADDITIONAL TABLES

Table 15: Controlling for Abatement (Natural Gas)

	(1) Baseline	(2) EIA	(3) EPA	(4) EPA Subsample
Regulatory Effect	0.0231**	0.0224**	0.0265*	0.0255*
	(0.00814)	(0.00810)	(0.0104)	(0.0104)
Spillover Effect	0.0157	0.0163	0.0227*	0.0236*
	(0.00897)	(0.00899)	(0.0109)	(0.0108)
Abatement	None	EIA	EPA	None
N	34978	34978	16291	16291
R-sq	0.061	0.062	0.080	0.077

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 16: Effects of Regulation on Utilization (NG)

	(1) Baseline	(2) Ramp Hours	(3) Generation
Regulatory Effect	0.0231**	0.518**	0.143
	(0.00814)	(0.0716)	(0.120)
Spillover Effect	0.0157	0.292**	-0.0590
	(0.00897)	(0.0830)	(0.104)
N	34978	36983	14864
R-sq	0.061	0.229	0.053

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

Table 17: Heterogeneous Effects of Regulation (NG)

	(1) Baseline	(2) Large	(3) Old
Regulatory Effect	0.0231**	0.0208*	0.0203*
	(0.00814)	(0.00951)	(0.00884)
Spillover Effect	0.0157	0.0240*	0.0248**
	(0.00897)	(0.00972)	(0.00924)
N	34978	20429	28119
R-sq	0.061	0.089	0.054

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$

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VITA

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