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Author
Novan, Kevin Michael

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Essays on Energy and Environmental Policy

A dissertation submitted in partial satisfaction of the
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by

Kevin Michael Novan

Committee in charge:

Professor Richard T. Carson, Chair
Professor Gordon B. Dahl
Professor Joshua Graff Zivin
Professor Mark Jacobsen
Professor Junjie Zhang

2012

The dissertation of Kevin Michael Novan is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

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DEDICATION

To my parents, sister, and Samie. I cannot thank you enough for your endless support.

EPIGRAPH

We believe that part of the answer lies in pricing energy on the basis of its full costs to society. One reason we use energy so lavishly today is that the price of energy does not include all of the social costs of producing it. The costs incurred in protecting the environment and the health and safety of workers, for example, are part of the real costs of producing energy-but they are not now all included in the price of the product.

—Richard Nixon

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Chapter 2, which has been co-authored with Richard Carson, is currently being prepared for submission for publication. The dissertation author was the primary investigator and author of this material.

Chapter 3, which has been co-authored with Michael Madowitz, is currently being prepared for submission for publication. The dissertation author was the primary investigator and author of this material.

VITA

2005	B.A. in Economics and Mathematics, Western Washington University
2012	Ph.D. in Economics, University of California, San Diego

ABSTRACT OF THE DISSERTATION

Essays on Energy and Environmental Policy

by

Kevin Michael Novan

Doctor of Philosophy in Economics

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Professor Richard T. Carson, Chair

This dissertation examines topics at the intersection of environmental and energy economics. The first two chapters explore how policies can induce more efficient use of the energy sources available for generating electricity. The electricity sector is a major source of a wide variety of harmful pollutants. To mitigate the environmental impacts of electricity production, a variety of policies are being implemented to increase the quantity of generation from clean, renewable energy sources. The first chapter identifies the short-run reductions in emissions caused by generation from a particular renewable technology; wind turbines. Using the estimates of the pollution offset by the renewable production, I explore the efficiency of the incentives created by the current set of renewable energy policies. The second chapter examines the impact adding bulk electricity storage capacity

will have on the full social costs of generating electricity. The third chapter explores the impact of various gasoline tax structures on both retail price volatility and state revenue volatility.

Chapter 1

Valuing the Wind: Renewable Energy Policies and Air Pollution Avoided

Abstract

This paper estimates the variation over time in the quantity of pollution avoided by renewable electricity. Taking advantage of the natural experiment presented by changes in hourly wind speeds, I identify the amount of CO_2, NO_X, and SO_2 reduced by electricity supplied from wind turbines in the Texas electricity market. The results provide clear evidence that renewable generation in the region offsets significant amounts of each of the pollutants examined. However, because different conventional generators are on the margin at different levels of demand, I find the amount of pollution avoided by a unit of renewable electricity varies substantially with the quantity of electricity demanded. As a result, renewable generators in separate locations, producing electricity at varying points in time, will provide very different reductions in pollution. By failing to account for these differences in the emissions avoided, policies equally subsidizing each unit of renewable electricity will not ensure efficient investment decisions are made.

1.1 Introduction

The combustion of fossil fuels in the electricity sector is responsible for a large share of a variety of harmful air pollutants. While the economic literature generally finds emissions prices to be the most efficient mechanism for reducing the level of pollution, policies designed to induce investment in renewable electricity capacity are receiving far greater use.[1] These policies are motivated by the belief that increasing production from renewable sources, such as wind and solar energy, has the potential to reduce emissions from generators reliant on fossil fuels. However, rather than subsidizing renewable generators based on the quantity of pollution avoided, the current mechanisms regularly provide payments or tax credits based on the quantity of renewable electricity generated. To determine if these flat generation payments create efficient incentives, it is crucial to know how much pollution is avoided by each unit of renewable electricity and how much the pollution avoided varies amongst renewable generators.

In this paper, I estimate the short-run emission reductions caused by wind turbines producing electricity at different points in time.[2] The analysis focuses on the Texas electricity market, which currently leads the nation in installed wind generation capacity. I combine data on the hourly production from wind turbines with the observed levels of CO_2, NO_X, and SO_2 emitted by fossil fuel generators in the region. Taking advantage of the natural experiment presented by changes in hourly wind speeds allows me to directly identify the impact of renewable generation on the quantity of pollution emitted.

The estimates reveal renewable electricity causes significant reductions in each of the pollutants examined. In addition, I demonstrate that the quantity of pollution offset by a unit of renewable electricity varies substantially with the

[1] For examples comparing the efficiency of emissions prices and renewable subsidies, see Fischer and Newell (2008) and Palmer and Burtraw (2005).

[2] Recent studies also examine the long-run impact increased renewable capacity may have on the composition of generation technologies. For example, see Lamont (2008) and Bushnell (2010). Starting from a clean slate with no existing capital, these studies find that the penetration of renewable capacity alters the cost minimizing mixture of technologies. However, given that renewable capacity is being added to markets with existing capital stocks that are typically quite long lived, it is also important to understand the impact renewable generation has in the short-run.

level of electricity demanded. Renewable generation replaces production from the marginal, non-renewable generating units. As the demand for electricity shifts, the generators on the margin change. Given that the emission rates differ across non-renewable generators, the quantity of pollution reduced by renewable electricity will vary based on when the generation occurs. I find that depending on the level of electricity demanded in Texas, a Megawatt-Hour (MWh) of wind generation will offset anywhere between 0.54 to 0.93 tons of CO_2, 0.88 to 1.92 pounds of NO_X, and 0.97 to 4.30 pounds of SO_2.

The temporal variation in the quantity of pollution avoided has important policy implications. During specific hours of the day, different renewable technologies tend to produce different amounts of electricity. Moreover, the same renewable technology installed in separate locations can produce electricity at different points in time. The current policies used to induce investment in renewable capacity often provide payments or tax credits based on the quantity of renewable electricity generated. Under these policies, two renewable generators that produce the same amount of electricity, but at different times, will receive equal subsidies. However, my results demonstrate that by generating at different times, the pollution reduced by the renewable generators will generally not be equal. As a result, the current policies will adversely favor certain technologies and locations over others.

The identification strategy I present in this paper contributes to the literature examining the environmental benefits of renewable electricity. Several strategies for quantifying the impact of renewable generation on pollution have been proposed (Broekhoff, 2007; Gil and Joos, 2007; Price, *et al.*, 2003; Connors,*et al.*, 2004; Callaway and Fowlie, 2009). However, rather than identifying the causal impact of renewable electricity on non-renewable generation, each method employs a variety of simplifying assumptions to predict which generators reduce output, and therefore emissions, in response to renewable supply. Cullen (2011) presents the first econometric estimates of the actual substitution pattern between renewable suppliers and non-renewable generators. Using short-run changes in the production from wind turbines as a natural experiment, Cullen estimates the average reduction in generation from each fossil fuel plant in the Texas market. Multiplying the generation avoided by the average emission rate of the respective plants, Cullen produces estimates of the pollution reduced by the renewable electricity. In contrast to the estimation strategy I present, Cullen's method imposes two assumptions which I find bias the estimates of the emission avoided.

The first assumption is that each fossil fuel plant has a constant marginal emission rate. In reality, a single plant often operates multiple generating units, each of which can have different average emission rates. In addition, the emission rate of a single generating unit varies over the range of its output, typically becoming less emission intensive when producing closer to maximum capacity.[3] Therefore, the marginal emission rate of a fossil fuel plant will vary based on which generating unit is on the margin and what the level of production is from the marginal unit.[4] The second assumption is that the short-run level of output from wind turbines is determined exogenously by wind energy (*e.g.* wind speed and direction). While the maximum generation from wind turbines is controlled by the available wind energy, the actual quantity of electricity produced is frequently curtailed when the transmission limits of the electric grid are reached.[5]

The identification strategy I use in this paper allows me to estimate the impact of renewable electricity on emissions without requiring these two untenable assumptions. Using wind speeds as an instrument for the observed wind generation, I am able to relax the assumption that output from wind turbines varies exogenously in the short-run. The use of actual emissions data allows me to relax the assumption that the marginal emission rates of fossil fuel plants are constant. My results demonstrate generation from wind turbines causes significant reductions in each of the pollutants. However, compared to Cullen's 2011 estimates, I find smaller average reductions; 16% less CO_2, 3% less NO_X, and 43% less SO_2. I

[3] This fact has been noted in both the engineering and economic literatures. For an example, see Bushnell and Wolfram (2005).

[4] The emission rates from fossil fuel generators can also increase significantly above their averages when ramping generation up or down. A frequent argument against producing electricity using volatile wind and solar energy is that fossil fuel generators will be forced to constantly ramp output up and down, and therefore, operate less efficiently.

[5] Fink, *et al.* (2009) provide several case studies of wind curtailment across markets. The authors state that between 2003 and 2009, the Texas system operator required the curtailment of a portion of wind generation capacity over 45% of the days.

show that assuming fossil fuel generators have a constant emission rate results in significant over-estimation of the CO_2 and SO_2 reductions. While I find evidence of endogeneity in the observed generation from wind turbines, ignoring this fact results in only small downward biases in the estimates of the emissions avoided.

In addition to presenting estimates of the causal impact of renewable generation on pollution, I provide a second contribution by exploring the policy implications of the variation in the emissions avoided by renewable electricity. Callaway and Fowlie (2009) as well as Metcalf (2009) highlight that the current renewable policies can potentially provide equal subsidies to renewable generators that reduce different amounts of pollution. However, given that prior studies have been unable to identify the actual impact of renewable electricity on emissions, the extent to which the effective payments per unit of pollution avoided vary amongst renewable generators has not been determined.

In this study, I simulate the pollution reductions that could be realized by installing additional renewable generators. I do this by combining the estimates of the emissions offset at different points in time with predicted hourly wind and solar generation at four locations in Texas. The results show that depending on which renewable technology and location is chosen, the average pollution offset by each additional MWh of renewable generation varies between 0.55 and 0.62 tons of CO_2, 1.02 and 1.16 pounds of NO_X, and 1 and 1.43 pounds of SO_2. Therefore, by providing a flat subsidy per MWh, different renewable generators will receive different payments per unit of pollution avoided. As a result, the current renewable policies do not ensure that efficient renewable capacity investments are made.

The remainder of the paper proceeds as follows. Section 1.2 briefly describes the key features of the electricity dispatch process. In addition, I present a simple model of a competitive electricity market to highlight which factors determine the quantity of pollution avoided by renewable electricity. Section 1.3 reviews the existing methods for estimating the emissions avoided by renewable generation and discusses the identification strategy in this study. Section 1.4 describes the Texas electricity market and the data used in the empirical estimation. Section 1.5 presents estimates of the average reduction in emissions. Section 1.6 presents estimates of the emissions avoided at different levels of demand. Section 1.7 uses the estimates of the emissions avoided to compare the external benefits of various renewable capacity investments. Section 1.8 concludes.

1.2 Electricity Market Model

This section presents a simple model of a competitive wholesale electricity market. The model provides intuition on how renewable electricity can reduce pollution from the electric sector. In addition, I highlight how the impact on emissions can vary in the short-run based on when the renewable generation occurs. Before describing the model, I provide a brief overview of the electricity dispatch process and discuss the current policies being used to support renewable electricity.

1.2.1 Background on Electricity Dispatch Process

To maintain the stability of an electric grid, the quantity of electricity supplied must always equal the quantity of electricity demanded. Balancing the real time supply and demand is a complex optimization problem in which a central system operator attempts to minimize the cost of meeting the level of electricity demanded. This cost minimization is subject to the production constraints of each interconnected generating unit and the transmission limits of the grid. Procedures to determine the level of production from each unit vary across markets. In regulated regions, a central planner directly schedules output from each unit while in deregulated regions, like the Texas market examined in this study, supply and demand are balanced through the operation of both centralized and decentralized markets.

As a result of the cost minimization problem, plants with the lowest variable costs regularly generate close to their maximum capacities at all hours. To meet the remaining demand, generation is dispatched from additional plants with the highest marginal cost generators supplying electricity at peak levels of demand. When not off-line for maintenance or repairs, these dispatchable sources are capable of supplying electricity at any time. In addition, the level of generation from each of these technologies can be increased or decreased at any time.[6]

While conventional, dispatchable sources account for the majority of generation, a small share of electricity is produced by intermittent renewable sources. In the United States, electricity form wind turbines accounts for the vast majority of intermittent generation.[7] A major difference between intermittent renewable generators and dispatchable generators is that once the fixed costs of building and installing a wind turbine or solar panel have been spent, only the regular maintenance and repair costs must be paid. Unlike combustion generators, however, there are no fuel costs and unlike hydroelectric plants, there are no opportunity costs to using the resource.

A temporary increase in generation from intermittent renewable sources effectively shifts the short-run electricity supply curve outwards. While this shift will reduce wholesale electricity prices, the quantity of electricity demanded will remain unchanged due to the fact that the short-run electricity demand is essentially perfectly inelastic.[8] As a result, an increase in the supply from renewable sources must result in a decrease in the quantity supplied by conventional generating sources. If any of the offset conventional generation comes from generating units burning fossil fuels, the aggregate level of pollution may be reduced.

[6]The ability to increase or decrease output from a conventional generating unit is subject to minimum/maximum operating levels, ramping constraints, and any minimum start-up or shut-down times.

[7]In 2009, 70,761 gigawatts of electricity was produced by wind turbines in the United States. The second largest source of intermittent renewable generation, solar, generated 808 gigawatts of electricity. Generation statistics are from the Energy Information Administration.

[8]The majority of consumers face a fixed short-run retail price. Real-time pricing is occasionally available to large industrial consumers, and in specific locations, residential consumers. In the Texas electricity market, which is examined in this work, consumers do not have real-time pricing options. A small number industrial consumers in the Texas market have real-time pricing options, however, estimates of the real-time price elasticity of industrial demand in Texas is zero (Zarnikau and Hallet, 2007). Therefore, the increase in supply from wind turbines will have no impact on short-run demand.

1.2.2 Renewable Energy Policies

Output from fossil fuel fired generators accounts for a substantial portion of dispatchable electricity generation.[9] As a result of the reliance on fossil fuels, the electricity sector is the single largest source of a variety of harmful pollutants. To reduce the level of pollution from the electric sector, the economic literature finds mechanisms which place a price on emissions, either a tax or a cap-and-trade system, to be the most efficient options (Palmer and Burtraw, 2005; Fischer and Newell, 2008).[10] Unlike other policies, emissions prices will equate the marginal cost of abatement across each available channel for reducing emissions; fuel-switching, end of pipe treatments, demand reduction, and increased use of renewable energy sources.

In practice however, emissions pricing has seen limited use. Currently, only a subset of the many pollutants created by fossil fuel fired generators are subject to an emissions tax or cap. In addition, most of these emissions prices only apply to emitters within certain regions.[11] Even in regions where a cap is placed on the total quantity of emissions, the market clearing price for the permits is often well below estimates of the social marginal cost of the pollutants.[12]

Policies designed to induce investment in renewable electricity capacity, as opposed to pricing emissions, are receiving substantial support. These policies are motivated in large part by the potential emissions reductions renewable electricity can cause. At the Federal level, the United States government offers the Renewable Electricity Production Tax Credit (PTC) which provides a tax credit of $22 per MWh produced by qualified renewable generators.[13] In addition to the

[9]In the United States, between 2001-2010, the annual share of electricity from fossil fuels was between 69% and 72% each year.

[10]In the presence of knowledge spillovers, previous work does highlight that a combination of emissions prices and small subsidies for renewable energy R&D and deployment may result in even lower cost emission reductions (Fischer and Newell, 2008; Jaffe, Newell, and Stavins, 2005).

[11]Some examples include the Regional Greenhouse Gas Initiative (RGGI), which provides a cap on CO_2 emissions from the electric sector in 10 northeastern states. Additionally, the Environmental Protection Agency has implemented a NO_X cap and trade program across much of the eastern United States.

[12]For example, in the tenth auction held in the RGGI market on December 3, 2010, the market clearing price for a permit was $1.86 per ton of CO_2, well below most estimates of the actual marginal external damage.

[13]The forms of eligible generation currently include wind turbines, geothermal units, and

Federal incentives, many states have adopted their own forms of support for renewable electricity. The most common state level policy is the Renewable Portfolio Standard (RPS). A RPS mandates a minimum share of electricity that must be purchased from a specified set of renewable sources.[14] For each MWh generated, renewable producers typically receive a renewable energy credit (REC) which can then be sold to the electricity providers who must fulfill their renewable electricity obligations.

The combination of these policies results in fairly substantial levels of support for renewable electricity producers. On top of the $22 PTC, the REC's in the Texas market are worth around $10 per MWh during the period studied in this paper, January 1, 2007-December 31, 2009. For comparison, the wholesale price of electricity in the region typically fluctuates between $30-$80 per MWh. The impact of these policies is nowhere more evident than in the recent growth in wind generation capacity.[15] Between 2001-2010, the average annual growth rate of wind generation in the United States was 33.5%.[16] With the recent extension of the PTC and the increasing numbers of RPS policies, total installed wind capacity is expected to continue to increase.[17]

With both the PTC and the RPS's, the level of support for a renewable producer is based on the quantity of electricity generated.[18] If each MWh of renewable electricity offsets the same amount of pollution, then these flat generation payments will provide each renewable generator the same payment per unit of

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closed-loop biomass generators. The tax credits can be claimed up to 10 years after the renewable generator is installed. The Federal government also offers an Investment Tax Credit (ITC) which is worth up to 30% of the fixed costs. The ITC is currently a much smaller program than the PTC. During 2011, the total tax expenditures on the PTC are expected to exceed $1.5 billion while the expenditures on the ITC are expected to be below $200 million. For information on tax expenditures, see Section 17 of, "*Fiscal Year 2012 Analytical Perspectives, Budget of the U.S. Government.*"

[14] Currently, 29 states, plus the District of Columbia and Puerto Rico, have binding renewable targets.

[15] The 2008 IEA report *Deploying Renewables: Principles for Effective Policies*, finds that the combination of the PTC and the state level RPS policies have contributed to the significant growth in wind capacity.

[16] Generation statistics from the U.S. Energy Information Administration.

[17] See Energy Information Administration (2010).

[18] This is also the case with Feed-in-Tariffs (FIT). While FIT's have received more limited use in the United States, they are widely used internationally.

pollution avoided. However, if the quantity of emissions offset by a MWh of renewable electricity varies, the effective payment per unit of pollution avoided will vary as well.[19] To demonstrate how the emissions avoided per MWh of renewable electricity can vary over time within a single market, the following section presents a simple analytical model of a competitive wholesale electricity market.

1.2.3 Simple Dispatch Model

Consider a perfectly competitive wholesale electricity market with two broad generation technologies: conventional generators which can be dispatched on command (coal, gas, nuclear, etc.) and intermittent renewable generators (wind, solar, etc.). This analysis focuses on the short-run, $t = 0, ..., T$, which is defined as the period of time over which the stock of conventional generators is fixed. In order to capture the daily variation in demand and renewable generation potential, t can be thought to represent individual hours. I examine the benefits that accrue during periods $t = 1, \ldots, T$ from a marginal increase in renewable generation capacity during the initial period, $t = 0$.

The aggregate generation at time t from conventional sources is given by G_t. Conventional generating units are dispatched in increasing order of their private generation costs.[20] In addition to the private generation costs, conventional generators can produce an external cost in the form of unpriced pollution. The aggregate pollution emitted during period t is given by $e_t = e(G_t)$, where $e(\cdot)$ is a weakly increasing function with no restrictions placed on $e''(\cdot)$. The conventional generators on the margin for low levels of G_t can have higher or lower marginal emission rates than the conventional generators on the margin at higher levels of

[19] Past work highlights, that due to the fact that the mix of conventional generation varies across regions, the emissions reductions from renewable generation can vary across regional markets (Connors,*et al.*, 2004; Callaway and Fowlie, 2009). However, given that individual states have adopted their own renewable policies, the actual subsidy per MWh of renewable electricity can vary across regions as well.

[20] In addition to the contemporaneous generation costs, conventional units typically face dynamic costs (*e.g.* start up and shutdown costs) as well as dynamic operating constraints (ramp rate constraints, minimum stable generation levels, etc.). Analytically examining the impact of marginal changes in renewable generation, I abstract from these dynamic costs and constraints. In the empirical analysis, the reduced form strategy used to identify the impact on aggregate emissions does not impose any assumptions on the dynamic costs and constraints.

G_t.

There are N potential sites where intermittent renewable generation can be produced. Each individual site represents a specific generation technology at a specific location. Therefore, a wind turbine and a solar panel at the same location are two unique sites. Unlike conventional generation, intermittent generation is not dispatchable. The level of production at site i, for $i = 1, ..., N$, randomly varies between 0 and $K_i \geq 0$, the level of installed capacity at site i. For each unit of renewable capacity installed at site i, the share of potential generation that is realized at time t is represented by the capacity factor, $x_{i,t} \in [0, 1]$.[21] Therefore, the level of intermittent renewable generation at site i at time t is given by Eq. (2.1) below:

$$R_{i,t} = x_{i,t} \cdot K_i. \tag{1.1}$$

To produce electricity from renewable sources, there is an upfront fixed cost which I assume includes the regular maintenance expenditures. However, the marginal cost of the renewable generation is equal to zero and the renewable sources do not create any emissions.[22]

Not all of the electricity generated reaches the final consumers. During the transmission and distribution process, a portion of the generation is lost. I assume the fraction of generation lost from a specific generator is constant and determined by the location of the generator.[23] The share of generation lost from

[21] In reality, the best locations at a specific site may be exhausted first. If this is the case, the capacity factor may be decreasing in total installed capacity at a specific site. In addition, past work has demonstrated that upwind turbines can negatively impact the efficiency of nearby, downwind turbines (Kaffine and Worley, 2010). Both of these cases can be captured by specifying $x_{i,t}$ as a function of K_i. However, the general results are unchanged by assuming $\partial x_{i,t}/\partial K_i = 0$.

[22] While intermittent generation does not produce emissions during generation, there are potentially negative externalities that may arise. These externalities, such as the life-cycle emissions from production and scrapping (Lenzen and Munksgaard, 2002) or the visual impact (Hoen, *et al.*, 2009), can be proportional to the installed capacity. Alternatively, the externalities may be related directly to renewable generation. For example, spinning wind turbine blades can create a noise externality and also have been found to result in bird and bat mortality (Boyles, *et al.*, 2011). This work abstracts from these potential externalities, however the model can be adapted to deal with either. The external costs proportional to K can be represented as an additional fixed cost and the externalities proportional to $x_{i,t} \cdot K_i$ can be represented as an external variable cost.

[23] A complete representation of the factors that determine the quantity of generation lost is beyond the scope of this study. For an overview of the electricity transmission and distribution process, see Brown and Sedano (2004).

intermittent site i is given by the constant $l_i \in (0,1)$ while the share of generation lost from the marginal conventional generator is given by $l_g(G_t) \in (0,1)$. The loss rate from the marginal conventional generator is a function of G_t due to the fact that the marginal generator will vary based on the level of conventional generation. Therefore, the quantity of electricity supplied, generation less losses, by intermittent sources (S_{R_t}) and conventional sources (S_{G_t}) are given by Eq. (2.2) and Eq. (2.3) respectively:

$$S_{R_t} = \sum_{i=1}^{N} (1 - l_i) \cdot x_{i,t} \cdot K_i \tag{1.2}$$

$$S_{G_t} = \int_0^{G_t} \big(1 - l_g(z)\big) dz. \tag{1.3}$$

Demand for electricity at time t, D_t, is perfectly inelastic and varies exogenously across periods. To rule out the case where the quantity demanded cannot be met, demand is assumed to never exceed the maximum potential supply available from conventional sources. Additionally, I assume the quantity of electricity demanded always exceeds the maximum potential supply from intermittent sources, which avoids the case where excess renewable generation must be curtailed:

$$D_t > \sum_{i=1}^{N} (1 - l_i) \cdot K_i \quad \forall\ t. \tag{1.4}$$

To ensure the stability of the grid, the quantity of electricity demanded must equal the quantity of electricity supplied at all times:

$$D_t = \int_0^{G_t} \big(1 - l_g(z)\big) dz + \sum_{i=1}^{N} (1 - l_i) \cdot x_{i,t} \cdot K_i. \tag{1.5}$$

Combining the assumption in Eq. (2.4) with the fact that the marginal cost of intermittent generation is zero, when electricity is available from an intermittent source, it will be supplied to the grid. Given the marginal conventional loss function $l_g(\cdot)$, the set of constant loss rates $\{l_i\}_1^N$, and the installed intermittent capacities $\{K_i\}_1^N$, Eq. (2.5) implicitly defines the level of conventional generation in each period as a function of the exogenous quantity demanded and the exogenous intermittent capacity factors.

1.2.4 Short-Run Emission Reductions

This section examines the impact an increase in renewable capacity will have on emissions over the short-run, $t = 1, \ldots, T$. A marginal increase in K_i during the the initial period, $t = 0$, will weakly reduce the residual demand that must be met by G_t during each subsequent period. As a result, the quantity of pollution emitted in any single period will be reduced by $\left|\frac{\partial e(G_t)}{\partial G_t} \cdot \frac{\partial G_t}{\partial K_i}\right|$, where G_t is implicitly defined by Eq. (2.5). Solving for the reduction in emissions during period t caused by a marginal increase in K_i yields the following expression:

$$\text{Marginal Emissions Avoided}_{i,t} = e'\big(G_t\big) \cdot \frac{1 - l_i}{1 - l_g(G_t)} \cdot x_{i,t}. \tag{1.6}$$

The marginal emissions avoided is the product of two margins. The first is $e'(G_t)$, the emission rate of the marginal conventional generation at time t. The second is the reduction in conventional generation at time t caused by the marginal increase in K_i. The quantity of conventional generation avoided at time t is equal to the product of the additional intermittent generation, $x_{i,t}$, and the ratio of the marginal loss rates, $\frac{1-l_i}{1-l_g(G_t)}$. If the share of generation lost from renewable site i is less than the loss rate from the marginal conventional generator, an additional unit of intermittent generation at site i will offset more than one unit of conventional generation. Alternatively, if the loss factor for site i is greater than the marginal conventional loss factor, an additional unit of intermittent generation will offset less than one unit of conventional generation.

The quantity of emissions avoided by an additional unit of intermittent generation from site i can vary over time if either the marginal emission rate, $e'(G_t)$, or the offset conventional output, $\frac{1-l_i}{1-l_g(G_t)}$, varies with the level of G_t. Additionally, the quantity of emissions avoided by an additional unit of intermittent generation at time t can vary across sites if $l_i \neq l_j$ for sites i and j.

For subsidies to fail at achieving the lowest cost emission reductions from renewable electricity, the payment per unit of pollution avoided must vary across potential renewable investments. In practice, the policies currently used to reward renewable sources effectively provide a flat subsidy for each unit of electricity generated. Therefore, if the average quantity of pollution avoided by a unit of renewable generation varies across sites, the current policies can induce inefficient investments. The average emissions avoided by each unit of renewable electricity produced by a capacity addition at site i is given by the following expression:

$$\text{Average Emissions Avoided}_i = \frac{\sum_{t=1}^{T} e'(G_t) \cdot \frac{1-l_i}{1-l_{g,t}(G_t)} \cdot x_{i,t}}{\sum_{t=1}^{T} x_{i,t}}, \tag{1.7}$$

where G_t is defined by Equation Eq. (2.5).

If two conditions are satisfied, the average emissions avoided can vary across sites. First, the marginal emissions avoided by a unit of renewable generation must vary across time:

$$e'(G_t) \cdot \frac{1-l_i}{1-l_{g,t}(G_t)} \neq \text{constant} \quad \forall\ t. \tag{1.8}$$

Second, the timing of renewable potential must vary across sites:

$$\frac{x_{i,t}}{x_{i,t'}} \neq \frac{x_{j,t}}{x_{j,t'}}, \tag{1.9}$$

for two sites i and j during periods $t \neq t'$. If both of these conditions hold, then the uniform generation subsidies may induce inefficient siting decisions. In this situation, larger emissions reductions for the same cost, or the same reduction for a lower cost, could potentially be realized by allowing the subsidy payments to vary with the emissions avoided.

1.3 Estimation Strategy

The remainder of this paper examines whether uniform renewable generation subsidies provide inefficient incentives for firms investing in a particular market, the Texas electricity market. Texas currently leads the nation in installed wind generation capacity. In addition, the market is very isolated from the surrounding regions. As a result, the set of generators that potentially serve as substitutes to the wind turbines are easily identified. These characteristics make the Texas grid an ideal market for this study.

Using information on the observed generation from wind turbines and the aggregate emissions from fossil fuel fired generators, I identify the pollution avoided at different points in time by intermittent renewable generation. Combining the estimates of the emissions avoided with information on the potential wind and solar generation from sites across Texas, I predict the quantity of pollution that would be avoided by adding a renewable generator at any one of the sites. The results demonstrate that the average emissions avoided by a unit of renewable generation will vary among locations and technologies. As a result, uniform subsidies for renewable generation do not ensure efficient siting of renewable capacity additions in the Texas market.

This section introduces the identification strategy used to estimate the emissions avoided by intermittent electricity generators. First, I provide a brief overview of the existing estimation methods and the assumptions imposed by each strategy. Next, I discuss the natural experiment I take advantage of to identify the pollution avoided by renewable generation.

1.3.1 Existing Estimation Strategies

For a variety of reasons, there has been a surge of interest in developing methods to estimate the emissions avoided by renewable electricity. The estimates are needed to evaluate the efficiency of policies supporting renewable generation (NAS, 2007). In many cap and trade programs, renewable generators are being awarded valuable permits based on the estimated amount of emissions avoided (EPA, 2004). Additionally, estimates of the emissions avoided are used in the siting of renewable generators.

To estimate the impact of renewable electricity on pollution, one common method is the use of system dispatch models. These models simulate the cost minimizing level of production from each generating unit in a regional grid using information on the generation costs (*e.g.* fuel costs, operating costs, start-up costs) and operating limitations (*e.g.* ramp rates, minimum and maximum generation levels, and times) of each generating unit, as well as detailed information on the transmission constraints of the regional grid. One of the main advantages of the dispatch simulations is the ability to predict the impact of large scale changes in renewable generation capacity. For example, the GE Energy (2008) study of the Texas electricity market examines the impact tripling the installed wind generation capacity will have on the interconnected conventional units.

The structural simulations, however, have several drawbacks. First, the data required is often proprietary and very expensive. In addition, the results can be quite sensitive to the simplifying assumptions imposed. For example, Denny and O'Malley (2006) demonstrate the predicted quantity of pollution avoided by generation from wind turbines depends heavily on how wind generation forecasts are assumed to be incorporated in the dispatch decision.

Given the drawbacks of the simulation methods, there is significant interest in providing more transparent, reduced form estimates of the emission reductions that can be achieved by renewable generation. The most simplistic reduced form strategy is the use of average emission rates. Estimates based on average emission rates fall into two categories: 1) system average emission rates, or 2) technology average emission rates. The system average method estimates the emissions avoided as the product of the aggregate level of renewable generation and the average emission intensity of electricity generation on the regional grid. To find the average emission rate, the total emissions are divided by the aggregate generation. This method assumes that an equal percentage of output from each conventional technology will be offset by the renewable generation. In reality, certain technologies are more likely to be on the margin than others. For example, low marginal cost nuclear generators are unlikely to serve as the marginal source of electricity.

Instead of using the system average emission rate, the technology average emission rate method assumes the renewable generation offsets output from a specific technology. Examples of this approach are commonly seen in state level NO_X Set-Aside programs. States operating cap and trade markets for NO_X emissions often hold back a set number of emissions permits during the initial allocation.

These set aside permits are distributed to renewable electricity producers based on the quantity of pollution avoided by the renewable output, and can in turn, be sold to the highest bidder. To estimate the NO_X avoided by renewable generation for compliance with NO_X Set-Aside programs, several states multiply the quantity of renewable generation by 1.5 lbs NO_X/MWh, the average NO_X emission intensity of coal fired generators.[24] While the technology average emission rate estimates acknowledge that not all generating technologies will be the marginal source of electricity, they are still overly simplistic. First, the emission intensities can vary significantly across generators using the same fuel source. Additionally, the marginal technology and fuel can vary over time.

To accurately identify the impact of renewable generation on emissions, an estimation strategy must identify the pollution created by the marginal generators that actually reduce output in response to the renewable generation. Several reduced form strategies have been developed to estimate this "marginal emission rate". One method utilizes a Load Duration Curve (LDC) framework in order to predict the marginal generating plant for a specific level of demand (Broekhoff, 2007; Gil and Joos, 2007; Price, *et al.*, 2003). Electricity plants are arranged in descending order based on their respective capacity factors, total generation over some period of time divided by the total capacity. A given plant is assumed to be on the margin if the quantity demanded just exceeds the cumulative capacity of all plants with higher capacity factors. Plants with the highest capacity factors will never be on the margin while plants with the lowest capacity factors will only be operating and on the margin when the quantity demanded is large. For any given level of demand, the marginal emission rate is estimated to be the average emission intensity of the marginal plant. To predict the emissions avoided, the quantity of renewable output is multiplied by the marginal emission rate at the time the renewable generation is supplied.

Connors, *et al.* (2004) propose a different method for estimating the marginal emission rate. The authors first determine the set of "load following" plants; the

[24] For example, see Connecticut's and Missouri's Clean Air Interstate Rule set-aside program rules; ($www.ct.gov/dep/lib/dep/air/permits/eeresa_app.pdf$) and ($www.dnr.mo.gov/ENERGY/financial/docs/CAIR-appendix-E.pdf$).

generators that increase and decrease output in response to changes in load. To identify the load following generators, the hourly changes in output from each generator are compared to the hourly change in the quantity demanded. If the output and quantity demand changes have the same sign, the plant is assumed to be on the margin. The weighted average of the emission intensities of the load following generators is the predicted marginal emission rate.

In contrast to the LDC and load following methods, Callaway and Fowlie (2009) propose a method for directly estimating the hourly marginal emission rate. Using hourly fossil fuel generation and emissions data, the authors regress changes in aggregate emissions on changes in aggregate generation.[25] The rate at which emissions change when generation changes is described as the "Marginal Operating Emission Rate". Using this method, the average marginal emission rate can be estimated for different times during the day and for different seasons.

Similar to the LDC and the load following method, Callaway and Fowlie must assume that an increase in renewable generation has the same impact on conventional generation, and therefore aggregate emissions, as an equal decrease in demand. In the case of intermittent renewable generation, this assumption may not be valid. Output from wind turbines and solar panels is considerably more volatile than aggregate demand. As a result, changes in renewable generation are not forecasted as accurately as changes in demand. Given that conventional generating technologies are often constrained in terms of how rapidly output levels can be adjusted, the response from conventional units to an increase in renewable generation may in fact differ from the response to an equal decrease in demand.

Relaxing the assumption that increases in renewable supply have the same impact as decreases in demand, Cullen(2011) presents the first econometric estimates of the actual substitution pattern between wind generation and conventional generators. Using short-run changes in the aggregate generation from wind turbines as a natural experiment, Cullen estimates the average reduction in generation

[25] The authors point out that load is correlated with hydroelectric output in the New England and New York markets, the focus of their study. Given that the hydroelectric output is unlikely to be the marginal fuel source, the authors regress emission changes on fossil fuel generation changes.

from each conventional plant in the Texas electricity market caused by a MWh of wind generation. To predict the resulting average reduction in emissions, the individual plant level average emission intensities are multiplied by the average output avoided from each plant.

To estimate the average emissions avoided by wind generation, Cullen must impose two strong assumptions. First, short-run changes in the output from wind turbines are assumed to be caused entirely by exogenous factors (*e.g.* variation in wind speed and direction). This would certainly be the case if generation from wind turbines is always supplied when it is available. However, due to the fact that the installed wind capacity exceeds the transmission capacity of the electric grid in Texas, output from wind turbines is intentionally curtailed quite frequently.[26] When and how much wind generation is curtailed is endogenously determined by market supply and demand conditions. For example, if the short-run demand for electricity in a region with wind turbines falls, exports of electricity out of the region into the surrounding areas may have to increase. If the volume of the electricity to be exported exceeds the transmission limits of the electric grid, then generation from wind turbines may be reduced.[27]

The second assumption imposed in Cullen's strategy is that each fossil fuel plant has a constant emission rate. In reality, the marginal emission rate of a fossil fuel plant will vary for a variety of reasons. First, a single plant can operate

[26]While data on how much, and when, wind generation is curtailed is not readily available, Fink, *et al.* (2009) provide several case studies of wind curtailment across markets. The authors note that during several months between 2003-2009, the Texas system operator required curtailment of a portion of wind generation capacity over 45% of the days.

[27]In addition, the decision to curtail available wind generation can be driven by a wind farm operator's profit maximization motive. For example, wind turbines require regular maintenance and repairs. Potentially, wind farm operators may have the flexibility to schedule the times turbines will be off-line based on the expected forgone profits. Additionally, newer wind turbines with the ability to rapidly come on-line or go off-line are allowed to participate in the balancing energy market. If the current market price is below the marginal cost of generation, the owners may choose to curtail generation. Recall the marginal cost of production from a wind turbine is essentially zero. In addition, ERCOT turbines receive subsidies of $22/MWh through the PTC as well as valuable renewable energy credits for compliance with the state's renewable portfolio standard. Therefore, the market price must be well below zero for the wind turbine operators to find it optimal to curtail production. Over the three year sample studied, the market clearing price in the Western Congestion Zone, the region with the overwhelming majority of installed wind capacity, was negative 7.9% of the time. Market clearing prices below -$22/MWh in the Western Zone were observed during 6.2% of the time.

several generating units, each with a different average emission rate. In addition, the emission intensity of a single generating unit varies over its range of generation. Therefore, the emission intensity of each plant will differ based on which unit is on the margin and what the level of generation is from the marginal unit. Finally, fossil fuel fired generators can produce large spikes in emissions when they are forced to alter their level of production in short time frames. Given that generation from wind turbines can fluctuate rapidly, fossil fuel generators may be forced to frequently increase and decrease production, and therefore, operate at a higher average emission intensity. Within the engineering literature, simulation studies commonly find that abstracting from the impact of wind generation intermittency will lead to overestimation of the quantity of pollution avoided. In fact, previous studies even find that the addition of wind generation can increase the short-run level of emissions (Denny and O'Malley (2006); Katzenstein and Apt, 2009).

Following the strategy used in a previous version of this paper, Kaffine, *et al.* (2010) directly estimate the impact of wind generation on the observed emissions from fossil fuel generators. However, Kaffine, *et al.* continue to impose the assumption that generation from wind turbines is exogenously determined in the short-run. In addition, the authors explore the impact of wind generation on a subset of the fossil fuel generating units supplying electricity to the Texas market, not the full set of units that serve as substitutes to wind turbines in the region. Therefore, the full impact on emissions is not estimated.

1.3.2 Identification Strategy

This work reexamines the impact of wind generation on emissions in the Texas electricity market. The strategy I use to identify the reduction in emissions caused by generation from wind turbines allows me to relax the previously imposed assumptions. Extending the analysis of the previous studies, I estimate not only the average emissions avoided, but also how the emissions avoided by a unit of renewable generation varies over time. As the theoretical model in Section 2 demonstrates, understanding how the emissions avoided changes over time is crucial in determining whether the current policies induce efficient investment decisions.

I combine data on the hourly emissions from fossil fuel generating units in the Texas market and the surrounding regions with data on the hourly generation from wind turbines in the Texas market. Rather than first estimating the generation avoided and then indirectly predicting the emissions avoided through the use of average emission rates, this combined dataset allows me to directly identify the impact of wind generation on the actual emissions. Therefore, no restrictions are placed on how the emission intensities of fossil fuel plants vary over the range of output.

To ensure the full impact of wind generation on aggregate emissions is estimated, I identify how fossil fuel units in the Texas market, as well as in the surrounding regions, respond to generation from Texas wind turbines. While limited trading occurs between the Texas market and the surrounding regions, the inclusion of fossil generation outside of Texas turns out to be important due to the fact that several generators, located inside and outside of Texas, are directly connected to multiple markets. If these units transfer supply from the Texas market to the surrounding markets in response to additional wind generation, then studying the impact on the units in Texas will not identify the full impact on emissions.

Finally, in my analysis, I do not impose the assumption that the generation from wind turbines is exogenously determined. To control for the potential endogeneity that arises due to curtailments, I use the wind speed in the region with the majority of installed wind turbines as an instrument for the observed wind generation. While the output from a set of wind turbines can be directly affected by shifts in short-run market supply and demand, variation in the wind speeds cannot be caused by changes in market supply and demand.

1.4 ERCOT Market and Data

This work utilizes data from several sources. The Electric Reliability Council of Texas (ERCOT) provides data on the hourly net generation by fuel source as well as the hourly load on the regional grid. Included with the ERCOT data is the combined hourly generation from wind turbines. From the Environmental Protection Agency (EPA), I gather data on the hourly gross electricity generation and emissions of CO_2, NO_X, and SO_2 from fossil fuel fired generating units located in the ERCOT region as well as in the surrounding markets. From the National Climatic Data Center (NCDC), I obtain data on the hourly average temperature and wind speeds at several locations throughout Texas. Finally, from the Alternative Energy Institute (AEI), I collect data from several wind speed monitors throughout Texas. The data spans the three years from January 1, 2007-December 31, 2009. This section describes the ERCOT market and the individual datasets.

1.4.1 ERCOT Supply and Demand

Over 85% of electricity consumed in Texas is bought and sold through a deregulated market.[28] ERCOT is the independent system operator responsible for managing the scheduling, transmission, and financial settlement in the market. Over 90% of the electricity supplied to the ERCOT region is purchased through bilateral contracts.[29] Each day, qualified scheduling entities (QSE) representing portfolios of generators and retail electricity providers submit schedules of the generation and demand obligations for each hour of the upcoming day. ERCOT reviews the schedules to ensure that the transmission and distribution constraints will not be exceeded over any of the 40,000 miles of wires on the regional grid.

The remainder of electricity is purchased in a real-time balancing market. In addition to submitting generation schedules, each QSE representing electricity producers also submits a balancing supply curve for each 15 minute interval of the upcoming day. The balancing supply curve defines the amount of increased or decreased electricity the QSE will provide at different prices. ERCOT aggregates the bids to produce a market-wide balancing supply curve for each interval of the upcoming day. In real-time, ERCOT equates actual electricity supply and demand

[28] A small portion of the eastern border with Louisiana is part of the SERC Reliability Corporation (SERC). Part of the northern panhandle is served by the Southwest Power Pool (SPP) and the region immediately surrounding El Paso is part of the Western Electricity Coordinating Council (WECC).

[29] In 2010, ERCOT transitioned to a Nodal market in which a large portion of the electricity is bought and sold in a centralized day-ahead market rather than through bilateral contracts.

by purchasing the required amount of up or down balancing energy at a single, market clearing price. If congestion occurs on the grid, then a separate market price is established for each of the four Congestion Zones: North, South, Houston, and West Congestion Zones.

By the end of 2009, there was over 84,000 megawatts (MW) of generation capacity in the ERCOT region. A summary of the average hourly net generation from ERCOT plants, separated by fuel source, between 2007 and 2009 is shown in Table 1.1.[30] Production from natural gas, coal, and nuclear generators account for 43.2%, 37.0%, and 13.4% respectively, of the total electricity. The next largest source of generation comes from wind turbines. During this period, wind generation accounts for 4.7% of the total ERCOT output. The remaining generation comes from hydroelectric plants and 'other' fuels.[31]

Table 1.1: 2007-2009 Hourly ERCOT Generation by Fuel (MWh)

	Natural Gas	Coal	Nuclear	Wind	Hydroelectric	Other
N	26,117	26,117	26,117	26,117	26,117	26,117
Mean	15,128	12,956	4,681	1,626	105	491
Std. Dev.	7,166	1,523	763	1,205	96	227
Min.	2,900	6,601	2,415	0	1	45
Max.	41,480	16,722	5,181	5,984	446	1,210
Share	43.2%	37.0%	13.4%	4.7%	0.3%	1.4%

"Other" production is from biomass, landfill gas, oil, diesel, and solar units. Shares are equal to the total supply from each fuel source during the sample period divided by the aggregate supply.

Between 2007 and 2009, the total installed wind generation capacity in the ERCOT region grew from 2631 MW to 8908 MW.[32] Almost all of this capacity is

[30]Net generation is a measure of the actual electricity supplied to the regional grid. It does not include the electricity that is used during the generation process.

[31]ERCOT aggregates generation from the burning of biomass, landfill gases, petroleum, and diesel, as well as production from solar units into 'other' generation. Combined, these units account for only 1.4% of the total ERCOT generation during the sample. From *ERCOT's 2009 Annual Report on the Texas Renewable Energy Credit Trading Program*, which can be found at https://www.texasrenewables.com/reports.asp, generation from solar units accounted for only 0.1% of the 'other' generation.

[32]The Public Utility Commission of Texas provides data on the capacity and month new wind farms come on-line (http://www.puc.state.tx.us/electric/maps/index.cfm).

located in the Western Congestion Zone in the northwest portion of Texas. Figure 1.1 plots the average daily profile of wind generation during each quarter of the year. Across all four quarters, average wind generation peaks in the early morning hours and falls to the lowest point in the middle of the afternoon. Additionally, the average wind generation is the highest between October and December and the lowest during the summer months of July through September. Figure 1.1 also plots the average daily adjusted load profile in the ERCOT region. The adjusted load is equal to the quantity of electricity demanded by end-use consumers plus the total electricity lost during the transmission and distribution process.[33] The average adjusted load follows the opposite daily and seasonal patterns displayed by wind generation, peaking in the afternoon hours and during summer months.

The Texas region has several characteristics that make it an ideal market for this study. First, there is a relatively large amount of wind capacity connected to the ERCOT grid. As a result, there is substantial variability in the amount of wind generation which makes it possible to clearly identify the impact of wind generation on the emissions from interconnected plants. Second, the region has very little hydroelectric generation potential. This fact makes identifying the impact of wind generation on emissions much less difficult. If electricity from wind turbines replaces supply from pumped hydroelectric plants or hydroelectric dams, the renewable generation would effectively be stored as potential energy. As a result, the avoided emissions would occur at a different point in time. Finally, the ERCOT grid is quite isolated from the surrounding markets.[34] Therefore, the primary set of units that serve as substitutes for wind generation, and the main factors that affect the consumers they are supplying, are easily identified.

[33]ERCOT charges retail suppliers for electricity losses. Therefore, the losses are added to the electricity consumed for the purpose of settling financial obligations. During 2007, transmission and distribution losses on the Texas grid were equal to 6.42% of the total generation. For statistics on transmission and distribution losses, see the eGRID "State Import-Export, U.S. Generation and Consumption Data Files".

[34]The entire United States is separated into three interconnections: the Eastern Interconnection, the Western Interconnection, and the Texas Regional Entity which is overseen by ERCOT. Within each interconnection, electricity is produced and transmitted at a synchronized frequency. Electricity traded between interconnections must first be converted from alternating current to direct current and flow through a limited number of DC transmission lines. The DC lines between ERCOT and the surrounding regions have an aggregate limit of 1090 MW.

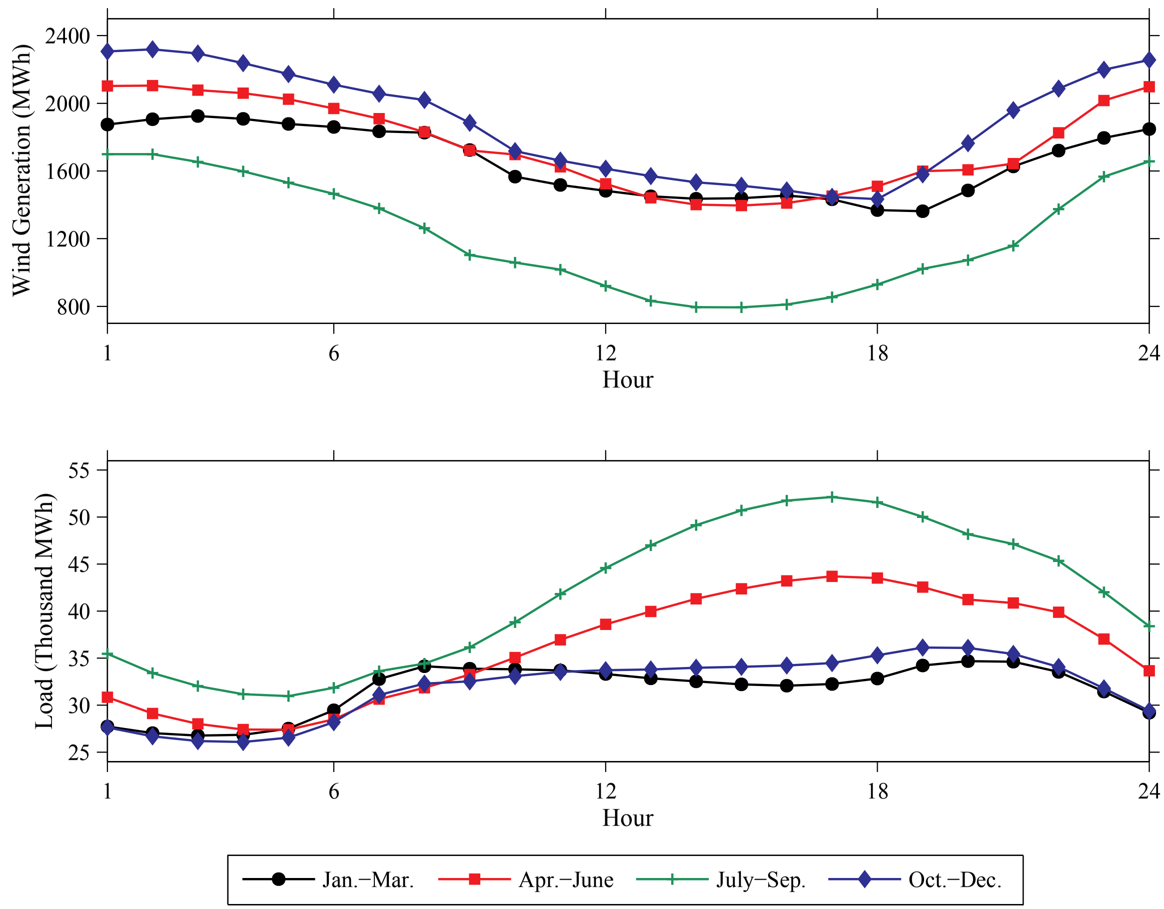

Figure 1.1: Average Hourly Wind Generation and Load by Quarter

1.4.2 EPA Emissions Data

For compliance with various regulations and emission trading programs, the EPA collects and maintains data on the hourly emissions of CO_2, NO_X, and SO_2, as well as the gross electricity generation from every unit that burns fossil fuels with a capacity greater than 25 MW.[35] For the period between 2007-2009, the EPA data provides information from 140 fossil fuel plants which operate over 400 units in Texas. Of these, 102 plants directly supply electricity to the ERCOT grid. These plants account for almost all of the fossil fuel generation capacity in the ERCOT region.[36]

While the Texas market is relatively isolated, electricity can still flow back and forth between neighboring grids. Any excess generation from the ERCOT grid can be exported across the DC ties connecting ERCOT to the Southwest Power Pool to the north.[37] In addition, three plants connected to the ERCOT grid can also directly supply electricity to the Eastern Interconnection.[38] To accurately identify the emissions avoided by wind generation, the potential impact on surrounding markets must also be considered.[39] In addition to the units in Texas, I obtain hourly data on the emissions and gross electricity generation from fossil

[35]See the EPA (2009) for a description of the Constant Emission Monitoring Systems. For coal units, the emissions are directly measured. For gas units, the emissions can be directly measured or calculated using the measured heat input and a measured correlation curve of the heat input and emission rate for the unit. In rare cases, a natural gas fired unit would have positive levels of generation during a given hour, but the CO_2 emissions would be missing. In this case, I calculate the average CO_2/MMBtu for the specific unit and infer the emissions using the observed hourly heat input.

[36]Only 10 plants from the ERCOT region, each with a capacity below 25 MW, are not included in the EPA dataset.

[37]The Eagle Pass, Laredo, and Railroad DC ties connect the ERCOT grid to the *Comision Federal de Electricidad* (CFE) grid serving northern Mexico. Although I do not have data on the output and emissions from fossil fuel plants outside of the United States, the requirements for trading between the ERCOT market and the CFE region are stricter than the requirements for trading across the other DC ties. As a result, it is likely more difficult to adjust the level of trading between ERCOT and the CFE in response to changes in wind generation.

[38]These three plants are the Kiamichi Energy Facility (Oklahoma), Tenaska Frontier, and Tenaska Gateway plants. The electricity supplied to the surrounding markets by these three plants does not flow through the DC ties controlled by ERCOT.

[39]In Cullen's analysis, the author finds that imports and exports through the DC ties are unaffected by wind generation. The author, however, only observes supply to the ERCOT grid and flows across the DC ties. If wind generation added to the grid causes any of the three plants connected to multiple markets to shift supply away from the ERCOT market and into one of the surrounding grids, Cullen's method will not identify the true substitution pattern.

fuel fired units serving the Southwest Power Pool in Oklahoma. As a result, I am able to identify the impact of wind generation on the production and emissions from fossil fuel units inside and outside of the ERCOT region.

Table 1.2 presents summary statistics for the coal and natural gas generating units in the EPA dataset. There are many more natural gas units than coal units, however, the coal units tend to be much larger on average.[40] The coal fired units also have significantly larger average emission intensities than the natural gas fired units. Even across units using the same fuel, there is substantial variation in the average emission rates. These differences highlight why it is crucial to accurately identify the set of units that reduce output in response to added wind generation.

Table 1.2: CEMS Unit Summary Statistics

	Units by Fuel	
	Coal	**Natural Gas**
Number of Units	47	397
Average Capacity (MWh)	579	197
	(172)	*(145)*
Average Heat Rate (MMBtu/MWh)	10.09	10.31
	(0.62)	*(2.27)*
Average CO_2 Intensity (tons/MWh)	1.05	0.62
	(0.09)	*(0.18)*
Average NO_x Intensity (lbs/MWh)	1.99	1.21
	(0.96)	*(1.48)*
Average SO_2 Intensity (lbs/MWh)	5.86	0.03
	(3.11)	*(0.20)*

Average Heat Rates and Emission Intensities are calculated by taking the average across the individual unit level means. Standard deviations of the unit level means are in parentheses.

Table 1.3 presents the average hourly generation and emissions from fossil fuel units located within each of the four ERCOT Congestion Zones as well as in

[40]The unit level capacities were obtained from the EIA-860 Generator Database.

Oklahoma. While the West Congestion Zone has the majority of wind capacity, the region has the smallest share of fossil fuel generation. This is due to the fact that the major population centers are not located in the western portion of Texas.

Table 1.3: CEMS Aggregate Summary Statistics

	Average Hourly Generation (MWh)					
Fuel Source	**North (TX)**	**South (TX)**	**Houston (TX)**	**West (TX)**	**Oklahoma**	**Total**
Natural Gas	10,423	2,657	5,105	663	3,576	**22,425**
	(4,576)	*(1,213)*	*(1,524)*	*(481)*	*(1,880)*	***(9,204)***
Coal	10,901	3,964	2,290	455	3,952	**21,562**
	(1,247)	*(680)*	*(392)*	*(259)*	*(651)*	***(2,423)***
Petroleum	-	-	119	-	-	**119**
	-	-	*(66)*	-	-	***(66)***
Total	**21,324**	**6,621**	**7,514**	**1,118**	**7,528**	**44,105**
	(5,242)	***(1,576)***	***(1,703)***	***(613)***	***(2,221)***	***(10,780)***

	Average Hourly Emissions					
Pollutant	**North (TX)**	**South (TX)**	**Houston (TX)**	**West (TX)**	**Oklahoma**	**Total**
CO_2 (tons)	17,781	5,780	4,896	911	6,050	**35,424**
	(3,4505)	*(1,182)*	*(1,007)*	*(457)*	*(1,348)*	***(6,860)***
NO_x (lbs)	23,518	7,498	2,208	2,069	17,497	**53,072**
	(4,335)	*(1,976)*	*(1,040)*	*(1,238)*	*(3,983)*	***(10,936)***
SO_2 (lbs)	71,904	23,952	12,706	881	22,585	**132,029**
	(10,374)	*(4,539)*	*(3,374)*	*(534)*	*(4,188)*	***(16,690)***

Note: Hourly averages of aggregate generation and emissions calculated over 26,117 hourly observations between 2007-2009. Standard deviations listed in parentheses.

1.4.3 Wind Speed Instrument

To identify the impact of wind generation on emissions, I must account for potential endogeneity in the observed generation from wind turbines that arises due to the frequent curtailments. Ideally, I would be able to instrument for the aggregate hourly wind generation using the wind speeds at the face of each wind turbine. While data is available from weather stations scattered throughout the state, the wind speeds from these stations are not representative of the potential wind generation for two reasons. First, the weather stations are located in or near population centers while the wind farms are sited outside of population centers. Second, the weather stations record the ground level wind speed while the wind turbines are installed on towers that are typically 80 meters or taller to take advantage of the fact that wind speeds increase with height.[41] If the relationship between the ground level wind speeds and the wind speeds 80 meters above the ground is constant, the height would not present a problem. However, the pattern between upper and lower level wind speeds varies substantially (Schwartz and Elliot, 2006). In some cases, ground level wind speeds can increase while the wind speed at higher altitudes decreases.

I collect wind speed information available from the Alternative Energy Institute (AEI) of West-Texas A&M University. The AEI provides data on the average hourly wind speed from wind monitoring towers at a variety of locations. Three of the test towers are located in the region of Nolan County (Sweetwater, TX) and the bordering Runnels County (Miles, TX and Olfen, TX). Observations from each of the individual towers are not available for the entire sample. Instead, a single time series of the average hourly wind speed at a height of 80 meters is created by combining readings from each site.[42]

At the beginning of the sample in 2007, there is 2,631 MW of installed wind generation capacity in the ERCOT region. Of this, 1,877 MW is in the 10 counties surrounding the AEI test sites.[43] At the end of the sample, 6,533 MW of the total

[41]During 2009, 2,067 MW of wind capacity was added to the ERCOT grid. Of this, 1,870 MW came from turbines built on towers measuring 80 meters.

[42]For January 1, 2007-September 30, 2008, data is available from the Sweetwater site. From October 1, 2008-March 31, 2009, hourly readings from Miles are used. From April 1, 2009-December 31, 2009, data from the Olfen site are used. For each site, the average hourly wind speed at a height of 80 meters is calculated by using the implied wind shears from two heights. For a full description of the power law estimation method, refer to the Appendix.

[43]The ten counties include Borden, Howard, Martin, Mitchell, Nolan, Scurry, Shackleford, Sterling, Taylor, and Tom Green.

8,908 MW are installed in the surrounding region. Nolan County, the location of the Sweetwater test site, led all other counties with 1,788 MW of installed capacity by the end of the sample. Therefore, wind speeds at the test sites serve as a good measure of the wind energy in the region containing the majority of the installed wind capacity.

To control for potential endogeneity in the short-run level of wind generation, I instrument for hourly production from wind turbines using a measure of the potential wind generation. Recall from the analytical model, the potential hourly wind generation is determined by the product of two factors: the installed wind generation capacity and the hourly capacity factor. The average hourly wind speed at a height of 80 meters in northwest Texas serves as a good proxy for the capacity factor. Due to the fact that the installed capacity in the region steadily grows over the sample period, the impact of the wind speed on the potential level of generation will not be constant. An increase in the AEI wind speed likely has a larger impact on aggregate wind generation at the end of the sample, when the number of wind turbines in the region is larger. To capture this fact, I interact the the wind speed with the installed capacity in the 10 counties surrounding the test sties.[44]

1.4.4 Weather Data

A major determinant of the demand for electricity is temperature (Engle, *et al.*, 1992; Li and Sailor, 1995; Yan, 1998). To control for potential correlation between changes in the generation from wind turbines in ERCOT and temperature driven demand changes in Texas and Oklahoma, I gather temperature data from the National Climatic Data Center. ERCOT divides the region served by the deregulated market into eight weather zones.[45] In addition, I treat the northern Texas panhandle and the state of Oklahoma, which are both served by the

[44]The Public Utility Council of Texas maintains a database providing the year and month of generating capacity additions; http://www.puc.state.tx.us/electric/maps/index.cfm. To attribute the capacity additions to a date within the given months, I gather information from local newspaper articles.

[45]The weather zones are as follows: Coast, East, Far West, North Central, North, South, South Central, West.

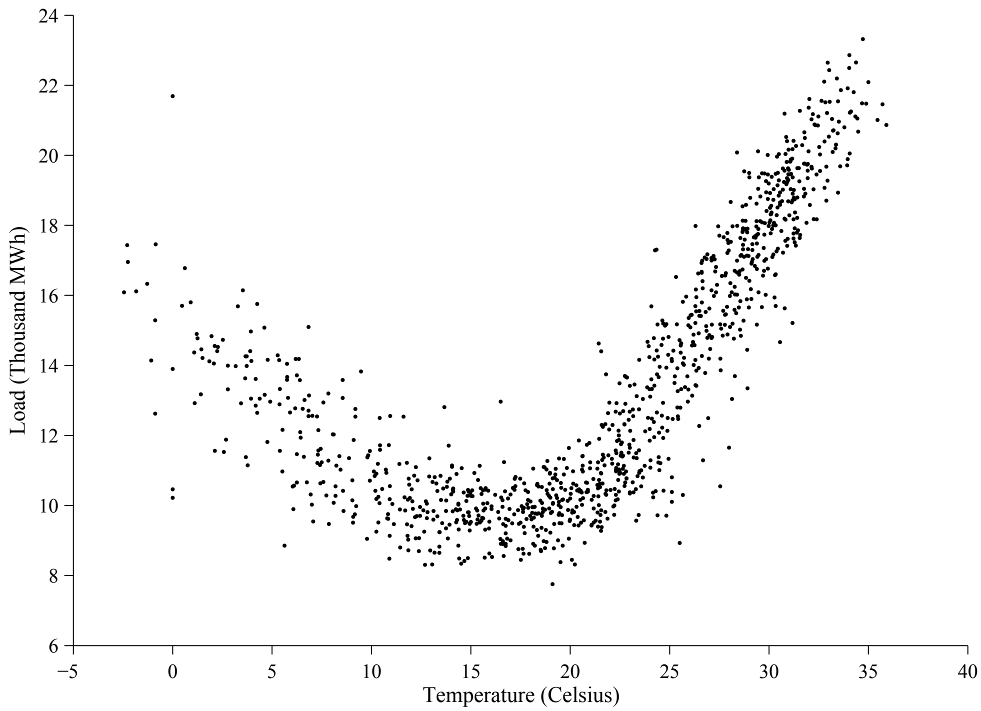

Figure 1.2: North Central Load vs. Temperature (Hour=6pm)

Southwest Power Pool, as two additional weather zones. For each weather zone, I calculate the hourly temperature by averaging the temperature readings across the two most populated metropolitan areas within each region.[46] Figure 1.2 plots the adjusted load in the the North-Central Weather Zone of ERCOT during the 6 p.m. hour versus the hourly average temperature in the region. The plot demonstrates the strong, nonlinear relationship between temperature and demand that must be controlled for in the empirical analysis.

While temperature is the major weather related driver of electricity demand,

[46]The ten zones, and the two metropolitan areas used for each zone, are as follows: Coast (Houston-Sugarland-Baytown, Beaumont-Port Arthur); East (College Station-Bryan, Tyler); Far West (El Paso, Odessa); North Central (Dallas-Fort Worth-Arlington, Killeen-Temple-Fort Hood); North (Wichita Falls, Sherman-Denison); South Central (San Antonio, Austin-Round Rock); South (McAllen-Edinburg-Mission, Corpus Christi); West (Abilene, San Angelo); non-ERCOT Panhandle (Lubbock, Amarillo); Oklahoma (Oklahoma City, Tulsa).

there is evidence that wind itself can have small impacts on electricity demand. For example, wind blowing across the exterior of buildings can have a cooling effect (Hor, *et al.*, 2005). If variation in the AEI wind speeds are correlated with changes in both wind generation and electricity demand, then I must control for this fact in the empirical estimation. This is unlikely to pose a problem in this study for the same reasons that the weather station wind speeds do not serve as good measures of the potential generation from wind turbines; the installed wind capacity is located far from demand centers and the wind speed at the height of the wind towers is not highly correlated with ground level wind speeds. Regardless, to control for any potential correlation between AEI wind speeds and the ground level wind speeds in the population centers, I gather ground level wind speed data from the National Climatic Data Center. I divide the Texas counties with wind turbines into 13 regions.[47] For each region, I calculate the hourly ground level wind speed (meters/second) by averaging across each wind speed station in the region.

1.5 Average Emissions Avoided

This section presents estimates of the average impact each MWh of wind generation has on the aggregate emissions CO_2, NO_X, and SO_2. To find the aggregate hourly emissions, I sum the hourly pollution across each electricity generating unit in the EPA dataset. To estimate the quantity of pollution offset by wind generation, I identify how hourly production from wind turbines alters the concurrent level of aggregate emissions.

[47]The counties included in the 13 wind speed regions are Kenedy, San Patricio, Pecos/Upton, Ector, Hale/Lubbock, Jack, Cooke, Erath, Borden/Scurry, Howard/Martin, Mitchell/Nolan, Shackleford/Taylor, and Sterling/Tom Green.

1.5.1 Econometric Specification

The following general model is used to identify the average reduction in aggregate emissions caused by each MWh of wind generation:

$$E_{h,d} = \beta \cdot W_{h,d} + \phi \cdot \overline{Z}_{h,d} + \mu_{h,d}, \tag{1.10}$$

where index $h = [1, \ldots, 24]$ represents the individual hours from each day, $d = [1, \ldots, 1096]$, during the the three year sample and

$E_{h,d}$ = aggregate hourly generation of CO_2 (tons), NO_X (lbs), or SO_2 (lbs),

$W_{h,d}$ = ERCOT wind generation (MWh) during hour h of day d, and

$Z_{h,d}$ = vector of controls.

The coefficient of interest, β, represents the average change in emissions caused by a MWh of wind generation.

To identify the impact of wind generation, I must control for a variety of factors that affect the level of emissions and are potentially correlated with wind generation. First, in the ERCOT region, wind generation follows hourly and seasonal patterns which are negatively correlated with the demand for electricity. Ignoring this correlation and directly regressing the level of emissions on the level of wind generation will result in biased estimates of the impact of wind generation; the decrease in emissions caused by lower demand will be incorrectly attributed to the increase in wind generation. Ideally, the demand for electricity could be included in the vector of controls. However, only data on the adjusted ERCOT load is available. The adjusted load is equal to the sum of the quantity of electricity demanded and the transmission and distribution losses on the ERCOT grid. As discussed, the short-run elasticity of demand in ERCOT is estimated to be essentially zero. Therefore, changes in the supply from wind turbines will not directly impact the quantity of electricity demanded. However, as the theoretical model demonstrates, the aggregate losses on a grid can be impacted by generation from wind turbines. In order to identify the net impact of wind generation on aggregate emissions, I cannot include the adjusted load in the vector of controls.

To control for correlation between hourly and seasonal patterns in electricity demand and wind generation, I difference the observed levels of hourly emissions and generation across days; $\Delta E_{h,d} = E_{h,d} - E_{h,d-1}$ and $\Delta W_{h,d} = W_{h,d} - W_{h,d-1}$.[48] For example, I take the difference between the total emissions during the 4 a.m. hour and the 4 a.m. hour during the preceding day. Differencing across 24 hours removes the negatively correlated hourly fixed effects, which are effectively allowed to vary across seasons, in the aggregate emissions and wind generation.[49]

In addition to the negative correlation between daily and seasonal patterns, short-run fluctuations in weather variables may also cause a link between wind generation and demand. For example, if changes in the wind speed at locations with wind turbines are correlated with changes in temperature across the state, this could result in a relationship between changes in wind generation and demand. To account for this possibility, the vector of controls, $\overline{Z}$, includes a non-linear function of the changes in hourly average temperatures in the ten weather zones throughout Texas and Oklahoma. Consistent with prior studies examining electricity demand, the impact of temperature is allowed to be non-linear around a base temperature set equal to 18 degrees Celsius (65 degrees Fahrenheit).[50] For each region ($i = 1, ..., 10$), Heating Degree (H) and a Cooling Degree (C) variables are created:

$$H_{i,h,d} = \begin{cases} 18 - T_{i,h,d} & \text{if } T_{i,h,d} \leq 18 \\ 0 & \text{if } T_{i,h,d} > 18 \end{cases}$$

[48] A logical alternative is to difference the data across weeks (168 hours); subtracting the aggregate emissions during hour h of day $d-7$ from the aggregate emissions during hour h of day d. As a robustness check, I estimated the model differencing across 168 hours and the results are essentially unchanged. I choose to provide the results from the 24 hour difference approach because the estimates are more precise. Even after controlling for weather related demand shifts, the load during period $t-24$, and not period $t-168$, predicts more of the variation in the load during period t.

[49] Both Cullen (2011) and Kaffine, *et al.* (2010) estimate the impact of wind generation in levels, using hourly and monthly fixed effects to control for the daily and seasonal patterns. Monthly fixed effects will control for the negative correlation in the monthly average emissions and wind generation. However, from Figures 1a and 1b, it is apparent that the daily demand and wind generation patterns do not simply shift across seasons. The shape of the entire profiles change. To properly control for the variation in the daily profiles, the set of hourly fixed effects must be allowed to flexibly vary across months and years.

[50] For study of heating and cooling degree impacts, see Valor, *et al.* (2001).

$$C_{i,h,d} = \begin{cases} T_{i,h,d} - 18 & \text{if } T_{i,h,d} \geq 18 \\ 0 & \text{if } T_{i,h,d} < 18, \end{cases}$$

where $T_{i,h,d}$ is the average temperature, in degrees Celsius, during hour h on day d in weather zone i. $H_{i,h,d}$ increases as the temperature falls below 18 degrees, capturing the increased use of electricity for heating purposes. $C_{i,h,d}$ increases as the temperature in region i increases above 18 degrees, capturing the increased use of electricity for cooling.[51] To control for differences in demand driven by temperature changes, $\overline{Z}$ includes the differences in both the levels and the squares of heating and cooling degrees between hour h of days d and $d-1$ for each of the nine weather regions. In addition, I allow the demand response to a change in temperature to differ across hours of the day by interacting $\Delta H_{i,h,d}$, $\Delta C_{i,h,d}$, $\Delta H^2_{i,h,d}$, and $\Delta C^2_{i,h,d}$ with a set of dummy variables, $\{b_1, b_2, b_3, b_4\}$, which separate the observations into six hour periods (10 p.m.-3 a.m., 4 a.m.-9 a.m., 10 a.m.-3 p.m., 4 p.m.-9 p.m.).[52]

In addition to controlling for temperature driven demand changes, I also account for potential wind speed driven demand changes. In the set of controls, I include the change in the hourly average ground level wind speeds for each of the 13 regions with wind turbines. Recall wind speeds have been found to have a cooling impact. Therefore, higher wind speeds will reduce electricity demand when temperatures are high and increase electricity demand when temperatures are low. Therefore, I also include the change in the interaction between the ground level wind speeds with the heating cooling degrees variables from the respective weather zones.

A variety of unobserved factors can alter the level of emissions during each hour of a day. For example, if a baseload coal plant is taken off-line for maintenance, cleaner gas fired generation may replace the missing output. As a result,

[51] Using separate heating and cooling degree variables allows the demand response to be asymmetric around the base temperature. Alternative base temperatures ranging between 15-21 degrees Celsius were examined and the results remained unchanged.

[52] Regressing the changes in adjusted loads in each weather zone on the corresponding $\Delta H_{i,h,d}$, $\Delta C_{i,h,d}$, $\Delta H^2_{i,h,d}$, and $\Delta C^2_{i,h,d}$ for the region, I find R^2 values of 0.28 (Coast), 0.10 (East), 0.35 (Far West), 0.38 (North Central), 0.37 (North), 0.40 (South Central), 0.36 (South), and 0.45 (West).

the emissions will fall during each hour. If the timing of the coal plant being taken off-line is correlated with the level of generation, the estimate of the impact of wind generation can be biased. To control for the possibility that the unobserved fixed effects are correlated with the included regressors, I estimate the model using fixed effects for each day in the sample. Fixed effects estimation will also control for any long run trends that may result in spurious correlation between the changes in wind generation and the changes in conventional generation.

Finally, to control for potential endogeneity in the short-run level of wind generation, I instrument for hourly production from wind turbines using a measure of the potential wind generation. Recall from the analytical model, the potential hourly wind generation is determined by the product of two factors: the installed wind generation capacity and the hourly capacity factor. From the AEI test towers, I have the average hourly wind speed during hour h of day d in the northwest region of Texas, $S_{h,d}$. These wind speeds predict the potential capacity factors of the northwest wind turbines. The installed wind generation capacity in the northwest region, which steadily grows over the sample, is given by $K_{h,d}$. The product of the two, $S_{h,d} \cdot K_{h,d}$, serves as a good proxy for the potential hourly wind generation from the northwest wind turbines. To account for potential endogeneity in the changes in wind generation, $(W_{h,d} - W_{h,d-1})$, I use $(S_{h,d} \cdot K_{h,d} - S_{h,d-1} \cdot K_{h,d-1})$ as an instrument.[53]

The full specification is shown below:

$$\Delta E_{h,d} = \beta \cdot \Delta W_{h,d} + m(H, C, G) + \alpha_d + \varepsilon_{h,d} \tag{1.11}$$

[53]Estimates are also made using $\Delta S_{h,d}$, $\Delta K_{h,d}$, and $\Delta S_{h,d} \cdot K_{h,d}$ as instruments with the results remaining unchanged. In this case, the coefficients on the change in wind speed and the change in capacity are both insignificant in the first stage. The changes in the levels explain no additional variation in $\Delta W_{h,d}$ above and beyond what is explained by the interaction.

where

$$\begin{aligned} m(\cdot) &= \sum_{i=1}^{10}\left(\delta_{1,i,b}\Delta H_{i,h,d} + \delta_{2,i,b}\Delta H_{i,h,d}^2 + \delta_{3,i,b}\Delta C_{i,h,d} + \delta_{4,i,b}\Delta C_{i,h,d}^2\right) \\ &\quad + \sum_{k=1}^{13}\left(\phi_{1,k}\Delta G_{k,h,d} + \phi_{2,k}\Delta(G_{k,h,d}\cdot H_{k,h,d}) + \phi_{3,k}\Delta(G_{k,h,d}\cdot C_{k,h,d})\right), \end{aligned}$$

and

$$\begin{aligned} \Delta &= \text{change between hour } h \text{ of day } d \text{ and } d-1, \\ \Delta E_{h,d} &= \text{Change in CO}_2 \text{ (tons), NO}_x \text{ (lbs), or SO}_2 \text{ (lbs)}, \\ \Delta W_{h,d} &= \text{Change in ERCOT wind generation (MWh)}, \\ \Delta H_{i,h,d} &= \text{Change in heating degrees in zone } i \text{ (Celsius)}, \\ \Delta C_{i,h,d} &= \text{Change in cooling degrees in zone } i \text{ (Celsius), and} \\ \Delta G_{k,h,d} &= \text{Change in ground wind speed in region } k \text{ (meters/second).} \end{aligned}$$

In the specification of $m(\cdot)$, the coefficients on $(\Delta H_{i,h,d}, \Delta H_{i,h,d}^2, \Delta C_{i,h,d}, \Delta C_{i,h,d}^2)$ are allowed to vary across the four 6-hour blocks of the day, (b_1, b_2, b_3, b_4). The interaction terms, $G_{k,h,d}\cdot H_{k,h,d}$ and $G_{k,h,d}\cdot C_{k,h,d}$, represent the ground level wind speed in region k, one of the thirteen regions with installed wind turbines, multiplied by the hourly heating and cooling degrees in the respective region.

To identify the exogenous variation in aggregate wind generation, the following first stage equation is estimated:

$$\Delta W_{h,d} = \gamma\cdot\Delta(S_{h,d}\cdot K_d) + \tilde{m}(H,C,G) + \tilde{\alpha}_d + \nu_{h,d}, \tag{1.12}$$

where

$$\begin{aligned} \tilde{m}(\cdot) &= \sum_{i=1}^{10}\left(\tilde{\delta}_{1,i,b}\Delta H_{i,h,d} + \tilde{\delta}_{2,i,b}\Delta H_{i,h,d}^2 + \tilde{\delta}_{3,i,b}\Delta C_{i,h,d} + \tilde{\delta}_{4,i,b}\Delta C_{i,h,d}^2\right) \\ &\quad + \sum_{k=1}^{13}\left(\tilde{\phi}_{1,k}\Delta G_{k,h,d} + \tilde{\phi}_{2,k}\Delta(G_{k,h,d}\cdot H_{k,h,d}) + \tilde{\phi}_{3,k}\Delta(G_{k,h,d}\cdot C_{k,h,d})\right), \end{aligned}$$

and

$$S_{h,d} = \text{wind speed (meters/second) at AEI test site, and}$$
$$K_d = \text{installed wind generation capacity (MW) in AEI region.}$$

To account for arbitrary serial correlation and heteroskedasticity, the errors $\epsilon_{h,d}$ are clustered across each day, d, in the sample.[54]

1.5.2 Average Emissions Offset

Results from the first stage estimation of Eq. (2.16) are presented in Table 1.4. The coefficient on the excluded instrument, the change in the AEI test site wind speed interacted with the installed wind generation capacity, is positive and statistically significant at the 1% level. The partial-R^2 value for the single excluded instrument is 0.27 and the F-statistic testing the instrument significance is 785.116, which well exceeds the Stock-Yogo weak identification test critical values. Therefore, I can conclude that the instrument is relevant and does not suffer from weak instrument issues.

Fixed effect estimates of Eq. (2.15) are presented in Table 1.5.[55] For each of the three pollutants, two estimates of the average impact of wind generation are shown. The first estimates are based on the assumption that changes in wind generation are exogenous. The second estimates are found using Eq. (2.16) to instrument for wind generation changes. Under the assumption that wind generation is exogenous, a MWh of production from wind turbines offsets an average of 0.630 tons of CO_2, 1.015 lbs of NO_X, and 1.615 lbs of SO_2. Instrumenting for the changes in wind generation, I find a MWh of wind generation on average offsets 0.658 tons of CO_2, 1.023 lbs of NO_X, and 1.816 lbs of SO_2. For each pollutant,

[54] The error term is likely correlated across hours of a single day due to the unique institutional features. At the close of the day ahead balancing market, the supply bids for each 15 minute interval of the next day must be submitted. Therefore, the dispatch order for the next day is determined largely in advance using a single information set. This introduces potential correlation between the within day errors. This is a common assumption in studies of electricity markets. For example, see Guthrie and Videbeck (2007).

[55] For each of the six models, I use a Hausman test to examine the random effects assumption. In each case, I reject the null hypothesis that the daily fixed effects are random.

Table 1.4: First Stage Regression Results

	Δ Wind Generation (MWh)
Δ (Wind Speed · Capacity)	0.032**
	(0.001)
N	20,886
Partial-R^2	0.27
Kleibergen-Paap rk Wald F-stat	785
Stock-Yogo weak ID test critical Value 10%	16.4

Model includes changes in the level and square of heating and cooling degrees by weather zone, changes in ground wind speeds, and the interaction between ground wind speed and heating and cooling degree changes. Estimates are made using daily fixed effects. Errors clustered by day. Standard error presented in parentheses. Partial-R^2 value for excluded instrument presented. * significant at 5%, ** significant at 1%.

the IV estimates are larger, but not statistically different from the estimates made assuming exogeneity. Table 5 also presents the Chi-square statistics from Durbin-Wu-Hausman tests of wind generation exogeneity. In each case, I fail to reject the null hypothesis that changes in wind generation are exogenous.

For perfectly mixing pollutants such as CO_2, it is not important where the emission reductions occur. However, with local or regional pollutants, where the pollution is emitted is an important determinant of the social cost. To identify where the emissions reductions caused by wind generation take place, I re-estimate Eq. (2.15) using the change in emissions by sub-region as the dependent variables. ERCOT has split the service territory into four separate Congestion Zones; the North, South, Houston, and West zones.[56] I sum the hourly emissions from the generating units located in each zone to find the aggregate regional emissions. Oklahoma is treated as the fifth region.

Fixed effects estimates of Eq. (2.15) using the wind speed changes as an instrument are presented in Table 1.6. The results show that wind generation

[56] I include non-ERCOT generating units in the northern pan-handle of Texas in the North Congestion Zone.

Table 1.5: Average Emissions Offset

	Δ CO_2 (tons)		Δ NO_x (lbs)		Δ SO_2 (lbs)	
	Exogenous	**IV**	**Exogenous**	**IV**	**Exogenous**	**IV**
Δ Wind Gen.	-0.630**	-0.658**	-1.015**	-1.023**	-1.615**	-1.816**
	(0.025)	*(0.043)*	*(0.055)*	*(0.097)*	*(0.165)*	*(0.286)*
N	20,886	20,886	20,886	20,886	20,886	20,886
R^2	0.45	0.45	0.29	0.29	0.15	0.15
Chi-sq(1)	-	0.63	-	0.01	-	0.76
P-value	-	0.43	-	0.91	-	0.38

Models include changes in the level and square of heating and cooling degrees by weather zone, changes in ground wind speeds, and the interaction between ground wind speed and heating and cooling degree changes. Estimates are made using daily fixed effects. Errors are clustered by day. Standard errors reported in parentheses. Explained within day variation given by R^2. Chi-square statistic and p-value from Durbin-Wu-Hausman test of endogeneity are reported.
* significant at 5%, ** significant at 1%.

results in significant reductions in CO_2, NO_X, and SO_2 within each region in Texas. In addition, significant reductions in CO_2 and NO_X from Oklahoma based generating units occur as well. SO_2 emissions in Oklahoma are not significantly impacted by ERCOT wind generation. This is explained by subsequent results which demonstrate that coal fired units, the primary source of SO_2 emissions, within Oklahoma, do not alter production in response to ERCOT wind generation.

Table 1.6 also reports the Chi-squared test statistics and p-values from Durbin-Wu-Hausman tests examining whether changes in wind generation are exogenous. The null hypothesis that wind generation changes are exogenous can be rejected at the 5% level for the West Congestion Zone in two of the three models and the South region in one of the three models. Re-estimating Eq. (2.15) for the West Congestion Zone under the assumption that wind generation changes are exogenous, I find on average, a MWh of wind generation offsets 0.063 tons of CO_2, 0.216 lbs of NO_X, and 0.079 lbs of SO_2. The instrumental variable estimates of the average reductions in West CO_2, NO_X, and SO_2 are 0.072 tons, 0.245 lbs, and 0.096 lbs respectively. The estimates of the reductions are slightly larger in the IV models, with the differences in the reductions of CO_2 and SO_2 significant at the

Table 1.6: IV Average Emissions Offset by Zone

	Δ CO_2 Emissions (tons)				
	North	**South**	**Houston**	**West**	**Oklahoma**
Δ Wind Gen.	-0.299**	-0.135**	-0.086**	-0.072**	-0.056**
	(0.026)	*(0.010)*	*(0.010)*	*(0.005)*	*(0.012)*
N	20,886	20,886	20,886	20,886	20,886
R^2	0.37	0.36	0.23	0.23	0.18
Chi-sq(1)	0.01	0.01	0.12	5.70	3.62
P-value	0.94	0.91	0.73	0.02	0.06

	Δ NO_x Emissions (lbs)				
	North	**South**	**Houston**	**West**	**Oklahoma**
Δ Wind Gen.	-0.397**	-0.143**	-0.083**	-0.245**	-0.155**
	(0.044)	*(0.027)*	*(0.017)*	*(0.023)*	*(0.051)*
N	20,886	20,886	20,886	20,886	20,886
R^2	0.21	0.17	0.08	0.18	0.13
Chi-sq(1)	0.35	3.81	2.68	3.57	2.27
P-value	0.56	0.05	0.10	0.06	0.13

	Δ SO_2 Emissions (lbs)				
	North	**South**	**Houston**	**West**	**Oklahoma**
Δ Wind Gen.	-1.096**	-0.473**	-0.256**	-0.096**	0.105
	(0.238)	*(0.072)*	*(0.060)*	*(0.009)*	*0.057*
N	20,886	20,886	20,886	20,886	20,886
R^2	0.11	0.12	0.05	0.16	0.06
Chi-sq(1)	0.20	0.21	2.76	6.24	0.04
P-value	0.66	0.65	0.10	0.01	0.84

Models include changes in the level and square of heating and cooling degrees by weather zone, changes in ground wind speeds, and the interaction between ground wind speed and heating and cooling degree changes. Estimates are made using daily fixed effects. Errors clustered by day. Standard errors reported in parentheses. Explained within day variation given by R^2 values. Chi-square statistic and p-value from Durbin-Wu-Hausman test of endogeneity are reported. * significant at 5%, ** significant at 1%.

5% level. These results suggest that imposing the assumption of wind generation exogeneity will result in biased estimates of the average emission reductions across regions. At the current levels of curtailment, the induced bias is not large. However, future applications of this identification strategy will likely need to address the endogeneity of wind generation as the quantity, and frequency, of curtailments increases on regional grids.

1.5.3 Average Generation Avoided

The results in the previous section identify the average reduction in emissions from fossil fuel units in the EPA dataset. If fossil fuel fired units serving as substitutes to ERCOT wind turbines are not included in the EPA dataset, then the estimates of the emissions offset will be below the actual reductions.[57] This section tests if the full set of fossil fuel generating units that respond to wind generation are included in the dataset. Recall, the quantity of electricity generated must always equal the quantity demanded plus total losses:

$$\text{(Wind Gen.)} + \text{(Non-Wind Gen.)} = \text{(Quantity Demanded)} + \text{(Losses)}. \tag{1.13}$$

Therefore, controlling for changes in the quantity demanded, an increase in wind generation must result in an equal and opposite decrease in non-wind generation plus any change in total losses:

$$\frac{\partial\text{(Non-Wind Gen.)}}{\partial\text{(Wind Gen.)}} - \frac{\partial\text{(Losses)}}{\partial\text{(Wind Gen.)}} = -1. \tag{1.14}$$

To test if the identity in Eq. (2.11) holds, I identify the average impact of a MWh of wind generation on electricity generation from conventional sources and on aggregate losses on the ERCOT grid. Data on the hourly aggregate generation

[57] There are two potential reasons fossil fuel units that adjust output in response to wind generation could be missing. First, the EPA does not require natural gas fired units with capacities below 25 MW to report the hourly emissions. However, the units excluded from the EPA dataset represent less than 1% of the generating capacity in the region. A second reason fossil fuel substitutes could be missing is that generators outside of Texas and Oklahoma adjust output in response to ERCOT wind generation.

(MWh) from coal and natural gas fired units is available from the EPA dataset and hourly generation from nuclear, hydroelectric, and 'other' generation sources is provided by ERCOT. In addition, ERCOT reports the hourly adjusted load (MWh), which is the sum of the quantity of electricity demanded plus transmission and distribution losses. To identify the average impact on non-wind generation, I re-estimate Eq. (2.15) using the changes in generation from conventional fuel sources and the change in adjusted load as the dependent variables. The full specification is shown below:

$$\Delta G_{j,h,d} = \beta_j \cdot \Delta W_{h,d} + m_j(H, C, G) + \alpha_{j,d} + \varepsilon_{j,h,d} \tag{1.15}$$

where

$$\begin{aligned} m_j(\cdot) \;\; = \;\; & \sum_{i=1}^{10} \left(\delta_{1,j,i,b} \Delta H_{i,h,d} + \delta_{2,j,i,b} \Delta H_{i,h,d}^2 + \delta_{3,j,i,b} \Delta C_{i,h,d} + \delta_{4,j,i,b} \Delta C_{i,h,d}^2 \right) \\ & + \sum_{k=1}^{13} \left(\phi_{1,j,k} \Delta G_{k,h,d} + \phi_{2,j,k} \Delta (G_{k,h,d} \cdot H_{k,h,d}) + \phi_{3,j,k} \Delta (G_{k,h,d} \cdot C_{k,h,d}) \right), \end{aligned}$$

and

$$\begin{aligned} \Delta \;\; &= \;\; \text{change between hour } h \text{ of day } d \text{ and } d-1, \\ \Delta G_{j,h,d} \;\; &= \;\; \text{change in generation from fuel source } j \text{ (MWh)}, \\ \Delta W_{h,d} \;\; &= \;\; \text{change in ERCOT wind generation (MWh)}, \\ \Delta H_{i,h,d} \;\; &= \;\; \text{change in heating degrees in zone } i \text{ (Celsius)}, \\ \Delta C_{i,h,d} \;\; &= \;\; \text{change in cooling degrees in zone } i \text{ (Celsius), and} \\ \Delta G_{k,h,d} \;\; &= \;\; \text{change in ground wind speed in region } k \text{ (meters/second).} \end{aligned}$$

Fixed effects estimates of Eq. (1.15) are made for j = (Natural Gas, Coal, Nuclear, Hydro, 'Other', Adjusted Load).[58] To allow for arbitrary heteroskedasticity

[58] To test whether unobserved daily fixed effects are correlated with the included regressors, I use a Hausman test comparing the fixed effects estimates of Eq. (1.15) to the random effects estimates. The null hypothesis that the FE coefficients are equivalent to the RE coefficients is

and serial correlation, I again cluster the errors at the daily level. Estimating Eq. (1.15) using the change in the adjusted load as the dependent variable results in a predicted value of β_{Load}. Due to the fact that the short-run demand is perfectly inelastic, β_{Load} represents the average impact of wind generation on the total losses on the ERCOT grid.

Table 1.7 reports the estimates of Eq. (1.15). For each conventional fuel, as well as adjusted load, two models are estimated. The first assumes changes in wind generation are exogenous. The second controls for curtailments by instrumenting for $\Delta W_{h,d}$ using the first stage specified by Eq. (2.16). Assuming that wind generation is exogenous in the short-run, I find that a MWh of wind generation offsets an average of 0.686 MWh of natural gas generation and 0.282 MWh of coal generation. Estimates from the IV model find that on average, 0.685 MWh of natural gas generation and 0.308 MWh of coal generation is offset by each MWh of wind generation.[59] In both the exogenous and IV models, small, but statistically significant reductions in output from hydroelectric units and 'other' sources occur in response to an additional MWh of wind generation. No significant reduction in nuclear generation occurs. Finally, both the exogenous and IV models estimate that wind generation has a positive, but statistically insignificant, impact on the total ERCOT adjusted load. Table 1.7 also reports the Chi-square statistics and p-values from Durbin-Wu-Hausman tests examining whether short-run changes in wind generation are exogenous. The null hypothesis that $\Delta W_{h,d}$ is exogenous is rejected in only the 'other' generation model.

To test whether Eq. (2.11) holds, I sum the average generation avoided by fuel source and subtract the average increase in adjusted load from the IV models,

$$\beta^{IV}_{Gas} + \beta^{IV}_{Coal} + \beta^{IV}_{Nuclear} + \beta^{IV}_{Hydro} + \beta^{IV}_{Other} - \beta^{IV}_{Load} = -1.03.$$

rejected at the 1% confidence level for four of the models (coal generation, gas generation, 'other' generation, and adjusted load).

[59]In addition, an average of 0.002 MWh of generation from the petroleum fired plant in the Houston region is reduced for each 1 MWh of wind generation. This result is significant at the 1% level. However, the ERCOT measure of 'other' generation includes the non-coal and non-natural gas fossil fuel generation. Therefore, to avoid double counting of the offset petroleum generation, I exclude the petroleum fired plant from the generation by fuel source regressions. When estimating the total fossil generation avoided and the total emissions avoided, the petroleum fired plant, and its resulting emissions, are included in the dataset.

Table 1.7: Average Generation Avoided by Fuel

	Δ Gas (MWh)		Δ Coal (MWh)		Δ Nuclear (MWh)	
	Exogenous	**IV**	**Exogenous**	**IV**	**Exogenous**	**IV**
Δ Wind Gen.	-0.686**	-0.685**	-0.282**	-0.308**	-0.002	-0.001
	(0.035)	*(0.057)*	*(0.018)*	*(0.030)*	*(0.002)*	*(0.003)*
N	20,886	20,886	20,886	20,886	20,886	20,886
R^2	0.38	0.38	0.26	0.26	0.04	0.04
Chi-sq(1)	-	0.01	-	1.02	-	0.16
P-value	-	0.97	-	0.31	-	0.69
	Δ Hydro (MWh)		**Δ Other (MWh)**		**Δ Load (MWh)**	
	Exogenous	**IV**	**Exogenous**	**IV**	**Exogenous**	**IV**
Δ Wind Gen.	-0.002**	-0.002*	-0.010**	-0.015**	0.004	0.021
	(0.0005)	*(0.001)*	*(0.002)*	*(0.003)*	*(0.029)*	*(0.049)*
N	20,886	20,886	20,886	20,886	20,886	20,886
R^2	0.06	0.06	0.12	0.12	0.39	0.39
Chi-sq(1)	-	0.01	-	5.07	-	0.20
P-value	-	0.91	-	0.02	-	0.65

Models include changes in the level and square of heating and cooling degrees by weather zone, changes in ground wind speeds, and the interaction between ground wind speed and heating and cooling degree changes. Estimates are made using daily fixed effects. Errors are clustered by day. Standard errors reported in parentheses. Explained within day variation given by R^2. Chi-square statistic and p-value from Durbin-Wu-Hausman test of endogeneity are reported.

* significant at 5%, ** significant at 1%.

From the models imposing the assumption of wind generation exogeneity, the sum of the average generation levels avoided plus the increase in adjusted load is equal to -0.99. Both values are statistically indistinguishable from -1. These results provide strong evidence that the full set of generating units that adjust output in response to changes in wind generation are included in the sample. Therefore, identifying the impact of wind generation on the emissions from the included fossil fuel units will capture the full impact of ERCOT wind generation on aggregate emissions.

In addition to examining the substitution pattern across different technologies, I estimate the spatial substitution pattern between wind generation and fossil fuel fired generation. Using the change in natural gas and coal fired generation by region as the dependent variables, I re-estimate Eq. (1.15) using the instrumental variable approach with the first-stage specified by Eq. (2.16). Results from the fixed effects estimates are presented in Table 1.8. The North Congestion Zone, which accounts for the largest share of ERCOT generation, experiences the largest reductions in fossil generation. Significant reductions in natural gas fired generation occur in each region. In addition, significant reductions in coal fired generation occur within each Congestion Zone in Texas. Consistent with the earlier findings that SO_2 emissions in Oklahoma are unaffected, the generation from Oklahoma coal fired units are not significantly impacted.

Repeating the Durbin-Wu-Hausman test on the disaggregated fossil generation data, I reject the null hypothesis that wind generation is exogenous for the West coal generation model. The IV estimate of the average reduction in coal generation is significantly larger than the estimate made assuming wind generation is exogenous. This result supports the earlier finding that the estimates of the aggregate emissions avoided by wind generation suffer from a small downward bias due to the assumption of wind generation exogeneity.

1.5.4 Comparing Estimation Strategies

The estimation results identify the average emissions offset per MWh of wind generation. Over the three year sample examined, Table 1.1 shows the average

Table 1.8: IV Average Fossil Generation Avoided by Zone

	Δ Gas Generation (MWh)				
	North	**South**	**Houston**	**West**	**Oklahoma**
Δ Wind Gen.	-0.314**	-0.099**	-0.124**	-0.039**	-0.109**
	(0.029)	*(0.011)*	*(0.014)*	*(0.005)*	*(0.018)*
N	20,886	20,886	20,886	20,886	20,886
R^2	0.36	0.26	0.22	0.15	0.20
Chi-sq(1)	0.17	0.90	0.30	0.08	3.27
P-value	0.68	0.34	0.59	0.78	0.07
	Δ Coal Generation (MWh)				
	North	**South**	**Houston**	**West**	**Oklahoma**
Δ Wind Gen.	-0.120**	-0.092**	-0.044**	-0.048**	-0.005
	(0.019)	*(0.009)*	*(0.007)*	*(0.004)*	*(0.008)*
N	20,886	20,886	20,886	20,886	20,886
R^2	0.18	0.23	0.10	0.17	0.08
Chi-sq(1)	0.13	1.82	0.68	9.40	0.78
P-value	0.72	0.18	0.41	0.00	0.38

Models include changes in the level and square of heating and cooling degrees by weather zone, changes in ground wind speeds, and the interaction between ground wind speed and heating and cooling degree changes. Estimates are made using daily fixed effects. Errors clustered by day. Standard errors are reported in parentheses. Explained within day variation given by R^2 values. Chi-square statistic and p-value from Durbin-Wu-Hausman test of endogeneity are reported. * significant at 5%, ** significant at 1%.

hourly generation from ERCOT wind turbines was 1,626 MWh (4.7% of total ERCOT generation). Therefore, the IV estimates of the average emissions avoided per MWh from Table 1.5 imply that over the sample period, ERCOT wind turbines reduce an average of 1,070 tons of CO_2, 1,663 pounds of NO_X, and 2,953 pounds of SO_2 per hour. Comparing these values to the aggregate hourly emissions from Table 1.3, I can conclude that between 2007-2009, ERCOT wind turbines offset the equivalent of 3.51% of ERCOT CO_2 emissions, 4.45% of NO_X emissions, and 2.63% of SO_2 emissions.

The estimates of the actual emission reductions can be compared to predictions from alternative estimation methods. For example, assuming the emissions reduced per MWh of wind generation is equal to the average ERCOT emission intensity, I would conclude that the equivalent of 4.7% of the total ERCOT CO_2, NO_X, and SO_2 emissions were reduced. The average emission intensity estimates will overestimate the emissions avoided due to the fact that coal generation accounts for 37% of the total ERCOT generation but only 31% of the generation avoided by wind turbines. This highlights the importance of identifying the technologies and fuel sources that serve as substitutes for renewable generators.[60]

Comparing the estimates of the average impact of wind generation on aggregate emissions (Table 1.5) and emissions by zone (Table 1.6), there is evidence that imposing the assumption of wind generation exogeneity results in a slight downward effect on the predicted pollution avoided. To examine the impact of assuming each fossil fuel plant has a constant emission rate, I re-estimate Eq. (1.15) using the change in generation from each individual plant in the EPA dataset as the new dependent variables. The resulting IV estimates of β represent the average change in generation from each plant caused by a MWh of wind generation.[61] Results for

[60] An alternative strategy would be to multiply the quantity of coal and natural gas fired generation avoided by the average emission intensity of each coal and gas fired units. Combining the IV estimates of the average reduction in coal and natural gas fired generation per MWh of wind (Table 1.7) with the average emission intensities of coal and gas fired units (Table 1.2), I would predict an average reduction of 0.75 tons of CO_2, 1.48 pounds of NO_X, and 1.83 pounds of SO_2 per MWh of wind generation. These values are 14%, 45%, and 1% larger than the actual IV estimates (Table 1.5).

[61] Not every plant is in the EPA sample over the entire time period. Therefore, the estimates $\hat{\beta}$ represent the average change in generation during the subset of hours the plant is in the dataset. To estimate the average generation offset at each plant by a MWh of wind generation over the

the top 20 plants with the largest average reductions in output are presented in Table 1.13 in the Appendix. Recall, on average, a MWh of wind generation offsets 0.99 MWh of generation from fossil fuel plants. Of this reduced output, on average 0.54 MWh of generation is reduced from the top 20 substitutes.

For each plant, I calculate the average CO_2, NO_X, and SO_2 rates by aggregating the total plant level pollution during the sample period and dividing by the total plant level generation. Multiplying the average generation avoided over that time from each plant by the plant's average emission rates results in estimates of the average reduction in pollution from each plant. Aggregating across each plant, I predict that each MWh of wind generation offsets an average of 0.72 tons of CO_2, 0.95 lbs of NO_X, and 1.96 lbs of SO_2. These predicted reductions in CO_2 and SO_2 are 10% and 8% larger than the respective IV estimates from Table 1.5. In contrast, assuming the plants have a constant emission rate results in predictions 7% below the IV estimates of the average NO_X reduction.

To summarize the results of the various estimates of the average emissions offset by wind generation, Table 1.9 lists the IV estimates of the aggregate emissions avoided per MWh. In addition, the estimates made assuming wind generation varies exogenously, as well as assuming each plant has a constant emission rate, are shown. Finally, I include the range of the estimates presented by Cullen (2011). Comparing the preferred IV estimates to the lower range of Cullen's estimates, I find Cullen's predictions of the average CO_2, NO_X, and SO_2 reductions are 20%, 3%, and 74% larger than my estimates. The larger CO_2 and SO_2 estimates appear to be, in part, explained by imposing the assumption that fossil fuel plants have a constant average emission rate.

1.6 Variation in Emissions Avoided

The previous results identify the average reduction in pollution caused by each MWh of wind generation. In this section, I estimate how the quantity of pollution avoided varies over time.

full sample, the estimates $\hat{\beta}$ must be multiplied by the fraction of the total hours each individual plant is in the EPA dataset.

Table 1.9: Comparing Estimates of Average Emissions Offset

	Average Emissions Avoided per MWh		
Estimation Strategy	**CO_2 tons**	**NO_x lbs**	**SO_2 lbs**
IV Approach	-0.66	-1.02	-1.81
Exogenous Generation	*-0.63*	*-1.02*	*-1.62*
Constant Emission Rates	*-0.72*	*-0.95*	*-1.96*
Cullen (2011)	*(-0.79 , -0.85)*	*(-1.05 , -1.16)*	*(-3.15 , -3.29)*

"IV Approach" and "Exogenous Generation" estimates from Table 5. "Constant Emission Rates" estimates from Table A2. Low and high range of average emissions avoided from Table 6 and Table A5 in Cullen (2011).

1.6.1 Econometric Specification

To identify whether the emissions avoided varies over time, one option is to simply allow the estimates of the emissions offset by a MWh of wind generation to vary across the 24 hours of day. Recall however, from the simple model, the quantity of emissions avoided by a marginal increase in intermittent generation will vary with the marginal dispatchable generator. Therefore, the impact of a MWh of wind generation during hour h on a day with high demand may differ from the impact during hour h on a day with low demand.

To capture this fact, ideally the impact of wind generation on emissions can be modeled as a function of the unobserved quantity of electricity demanded, $D^*_{h,d}$:

$$E_{h,d} = \tilde{\beta}_0 \cdot W_{h,d} + \tilde{f}(D^*_{h,d}) \cdot W_{h,d} + \tilde{\gamma} \cdot \tilde{f}(D^*_{h,d}) + \tilde{\theta} \cdot \overline{Z}_{h,d} + \tilde{\varepsilon}_{h,d}. \tag{1.16}$$

In the above equation, $E_{h,d}$ and $W_{h,d}$ are the aggregate hourly emissions and wind generation while $\overline{Z}_{h,d}$ is a vector of controls. Taking the partial derivative of Eq. (1.16) with respect to $W_{h,d}$ yields the following expression for the impact of wind generation on emissions:

$$\frac{\partial E_{h,d}}{\partial W_{h,d}} = \tilde{\beta}_0 + \tilde{f}(D^*_{h,d}).$$

However, the actual demand is not observed by itself. Instead, I observe the adjusted ERCOT load, $L_{h,d}$, which is equal to the sum of the quantity demanded plus the unobserved losses, $l^*_{h,d}$. Recall from the analytical model, the aggregate losses can be affected by the level of wind generation. Using the adjusted load to proxy for the unobserved demand, Eq. (1.16) can be written as:

$$E_{h,d} = \beta_0 \cdot W_{h,d} + f\big(D^*_{h,d} + l^*_{h,d}\big) \cdot W_{h,d} + \gamma \cdot f\big(D^*_{h,d} + l^*_{h,d}\big) + \theta \cdot \overline{Z}_{h,d} + \varepsilon_{h,d}. \quad (1.17)$$

Taking the partial derivative of Eq. (1.16) with respect to $W_{h,d}$, again yields the following expression:

$$\frac{\partial E_{h,d}}{\partial W_{h,d}} = \beta_0 + f(D^*_{h,d} + l^*_{h,d}).$$

The above partial derivative represents the impact of a change in wind generation on emissions, holding other variables constant. If wind generation affects the level of losses, then the partial derivative does not equal the net impact of a change in wind generation on emissions. Instead, the full impact on emissions is represented by the total derivative:

$$\frac{dE_{h,d}}{dW_{h,d}} = \beta_0 + f\big(D^*_{h,d} + l^*_{h,d}\big) + \big(W_{h,d} + \gamma\big) \cdot f'\big(D^*_{h,d} + l^*_{h,d}\big) \cdot \frac{\partial l^*_{h,d}}{\partial W_{h,d}}.$$

Therefore, if $f'(\cdot) \neq 0$ and if $\frac{\partial l^*_{h,d}}{\partial W_{h,d}} \neq 0$, then $\frac{\partial E_{h,d}}{\partial W_{h,d}} \neq \beta_0 + f(\cdot)$.

To ensure that the net impact of wind generation on emissions is identified, I first estimate fitted values for the ERCOT load using the hourly load from the prior week. I regress the adjusted load during hour h of day d on the load during hour h of day $d - 7$. The model used to estimate the fitted load values is shown below:

$$L_{h,d} = \alpha_0 + \alpha_1 \cdot L_{h,d-7} + \mu_{h,d}. \quad (1.18)$$

The lagged load explains 76% of the variation in the hourly load over the sample period. Figure 1.3 provides the distributions of the actual and the fitted load values.

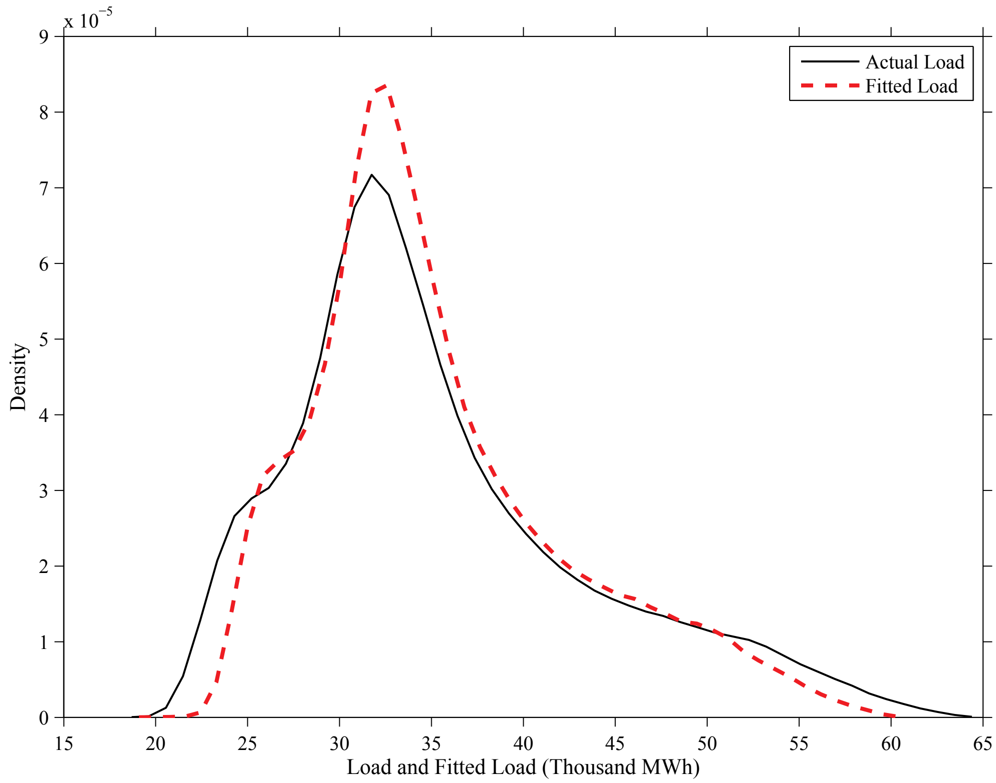

Figure 1.3: Distribution of Actual and Fitted Load

Using the fitted values of the adjusted load, $\hat{L}_{h,d}$, I can estimate the following general model:

$$E_{h,d} = \beta_0 \cdot W_{h,d} + f\left(\hat{L}_{h,d}\right) \cdot W_{h,d} + \gamma \cdot f\left(\hat{L}_{h,d}\right) + \theta \cdot \overline{Z}_{h,d} + \varepsilon_{h,d}. \tag{1.19}$$

Given that $\frac{\partial \hat{L}_{h,d}}{\partial W_{h,d}} = 0$, the net impact of a change in wind generation, conditional on the fitted level of load, is given by the following expression:

$$\frac{dE_{h,d}}{dW_{h,d}} = \beta_0 + f(\hat{L}_{h,d}).$$

Recall, wind generation displays strong hourly and seasonal patterns which are negatively correlated with the regular pattern of demand in the region. While the fitted loads control for potential correlation with the hourly and seasonal patterns of ERCOT demand, the measure of aggregate emissions includes generation from units that serve demand outside of ERCOT as well. To account for arbitrary seasonal and hourly patterns in demand, I again difference the data across the same hour h of consecutive days, d and $d-1$.

To control for potential correlation between changes in wind generation and weather driven demand changes, I include changes in the level and squares of the heating and cooling degrees in the ten weather zones. In addition, the changes in ground level wind speeds in the thirteen regions with wind turbines, and their interactions with heating and cooling degrees, are used as controls. The full specification is shown below:

$$\Delta E_{h,d} = \beta_0 \cdot \Delta W_{h,d} + \Delta\big(f(\hat{L}_{h,d}) \cdot W_{h,d}\big) + \gamma \cdot \Delta f(\hat{L}_{h,d}) + m(H, C, G) + \alpha_d + \tilde{\varepsilon}_{h,d} \quad (1.20)$$

where

$$\begin{aligned} m(\cdot) \;&=\; \sum_{i=1}^{10} \left(\delta_{1,i,b} \Delta H_{i,h,d} + \delta_{2,i,b} \Delta H_{i,h,d}^2 + \delta_{3,i,b} \Delta C_{i,h,d} + \delta_{4,i,b} \Delta C_{i,h,d}^2 \right) \\ &\quad + \sum_{k=1}^{13} \left(\phi_{1,k} \Delta G_{k,h,d} + \phi_{2,k} \Delta (G_{k,h,d} \cdot H_{k,h,d}) + \phi_{3,k} \Delta (G_{k,h,d} \cdot C_{k,h,d}) \right), \end{aligned}$$

and

$$\begin{aligned} \Delta E_{h,d} &= \text{change in } CO_2 \text{ (tons), } NO_X \text{ (lbs), or } SO_2 \text{ (lbs),} \\ \Delta W_{h,d} &= \text{change in ERCOT wind generation (MWh),} \\ f(\hat{L}_{h,d}) &= f(\cdot) \text{ evaluated at fitted ERCOT adjusted load,} \\ \Delta H_{i,h,d} &= \text{change in heating degrees in zone } i \text{, and} \\ \Delta C_{i,h,d} &= \text{change in cooling degrees in zone } i. \end{aligned}$$

Eq. (1.20) is estimated using fixed effects and the errors are clustered at the daily level.

In the full specification, $\beta_0 + f(\hat{L}_{h,d})$ represents the marginal impact of wind generation on the aggregate emissions, conditional on the level of the fitted ERCOT load. I model $f(\cdot)$ as a cubic polynomial of the fitted load. Therefore, the net impact of a change in wind generation on aggregate emissions is equal to the following expression:

$$\frac{\partial E_{h,d}}{\partial W_{h,d}} = \beta_0 + \beta_1 \cdot \hat{L}_{h,d} + \beta_2 \cdot \hat{L}_{h,d}^2 + \beta_3 \cdot \hat{L}_{h,d}^3. \tag{1.21}$$

In this specification, there are now four potentially endogenous regressors: ΔW, $\Delta\big(W \cdot \hat{L}\big)$, $\Delta\big(W \cdot \hat{L}^2\big)$, and $\Delta\big(W \cdot \hat{L}^3\big)$. To control for potential endogeneity in these regressors, I use the following set of excluded instruments: $\Delta\big(S_{h,d} \cdot K_d\big)$, $\Delta\big(S_{h,d} \cdot K_d \cdot \hat{L}_{h,d}\big)$, $\Delta\big(S_{h,d} \cdot K_d \cdot \hat{L}_{h,d}^2\big)$, $\Delta\big(S_{h,d} \cdot K_d \cdot \hat{L}_{h,d}^3\big)$.

1.6.2 Emissions Offset at Different Loads

IV estimates of Eq. (1.20) are made for each of the three pollutants. In the first-stage, ΔW, $\Delta\big(W \cdot \hat{L}\big)$, $\Delta\big(W \cdot \hat{L}^2\big)$, and $\Delta\big(W \cdot \hat{L}^3\big)$ are regressed on remaining explanatory variables in Eq. (1.20) and the four excluded instruments. The Shea Partial-R^2 values are 0.30, 0.36, 0.43, and 0.30 respectively. The resulting parameter estimates of $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ define the quantity of emissions avoided by a MWh of wind generation as a function of the fitted ERCOT load.

Figure 1.4 presents the estimates of Eq. (1.21), the emissions offset as a function of the fitted load, as well as the corresponding 95% confidence intervals. The results are shown for values of fitted loads between 24,000 MWh and 51,000 MWh, approximately the 5^{th} and 95^{th} percentiles. The results reveal significant variation in the quantity of emissions avoided per MWh of wind generation. Estimates of the pollution offset per MWh of wind generation range between 0.54 to 0.93 tons of CO_2, 0.88 to 1.92 pounds of NO_X, and 0.97 to 4.30 pounds of SO_2.

For both CO_2 and SO_2, the quantity of emissions avoided by an additional unit of wind generation are estimated to be significantly larger during hours with the lowest loads. For each of the pollutants, a MWh of wind generation reduces the lowest levels of emissions during hours when the fitted load is between 30,000 and 40,000 MWh. The quantity of NO_X reduced by a MWh of wind generation reaches its maximum levels during hours with the highest levels of load.

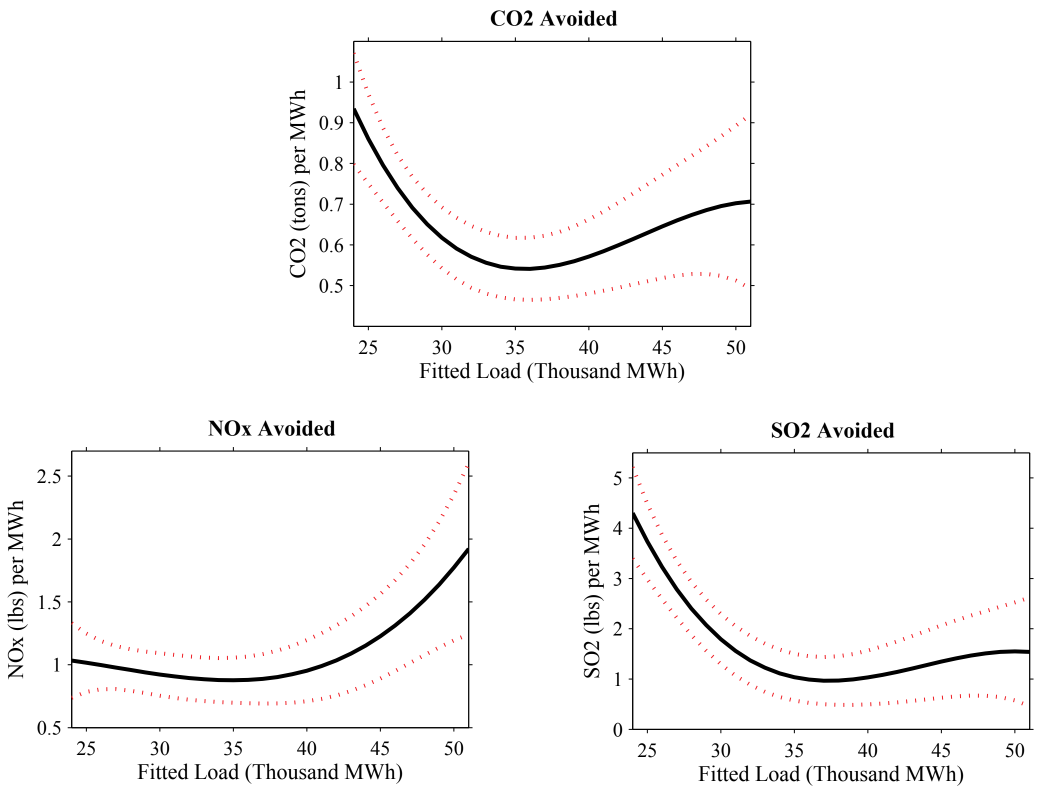

Figure 1.4: Emissions Avoided Across Load

1.6.3 Generation Offset at Different Loads

Recall from the simple model presented in Section 1.2, variation in the emissions avoided per MWh can stem from two sources. First, the quantity of conventional generation avoided per MWh of renewable output can vary as demand shifts. Second, the emission intensity of the offset generation can vary as the marginal generators changes. To identify what is driving the variation in the emissions avoided at different levels of load, I examine how the level and composition of conventional generation offset by wind generation varies with the ERCOT load.

To identify the total conventional generation avoided by each MWh of wind generation, I estimate the specification defined in Eq. (1.20) using the combined change in the aggregate generation from coal, natural gas, nuclear, hydroelectric, and 'other' generators as the dependent variable. Figure 1.5 presents the estimates of the aggregate generation avoided per MWh at different levels of fitted load. The point estimates of the conventional generation offset per MWh varies slightly around 1 MWh, however the values are not significantly different than 1 MWh for any level of fitted loads.[62] These results demonstrate that the primary driver of the variation in the emissions avoided stems from changes in the composition of generation avoided.

To identify how the substitution pattern between wind generation and conventional generation varies, I re-estimate the specification defined in Eq. (1.20) using the change in the aggregate generation by each individual fuel source as the dependent variables. In addition to exploring how the shares of coal and natural gas fired units on the margin varies, I also explore how the type of natural gas units on the margin varies. There are two broad types of natural gas generators: efficient combined-cycle units and less efficient open-cycle units. To divide the set of natural gas units in my sample, I separate the units into two categories based on the observed generation efficiencies. The efficient units are the 'Low Heat-Rate' units and the less efficient generators are the 'High Heat-Rate' units. The method I use for dividing the units is described in Appendix B.

Figure 1.6 presents the share of avoided generation by fuel source. At the lowest levels of fitted load, coal fired generators, which have the lowest private marginal costs, serve as the main substitute for wind generation. As the level of fitted load increases, the share of coal generation avoided by each MWh of wind generation falls and the share of output avoided from gas fired units, which have higher private marginal costs, rises. Given that the CO_2 and SO_2 intensity of coal

[62]Given that the generation from the coal and natural gas units is measured as gross generation, and not net generation, the total output offset will exceed the actual offset supply. Therefore, values of generation offset slightly above 1 MWh per MWh of wind generation are to be expected.

fired units are significantly larger than the emission intensities of gas fired units, this is consistent with the findings that the CO_2 and SO_2 avoided by an additional unit of wind generation fall as load increases.

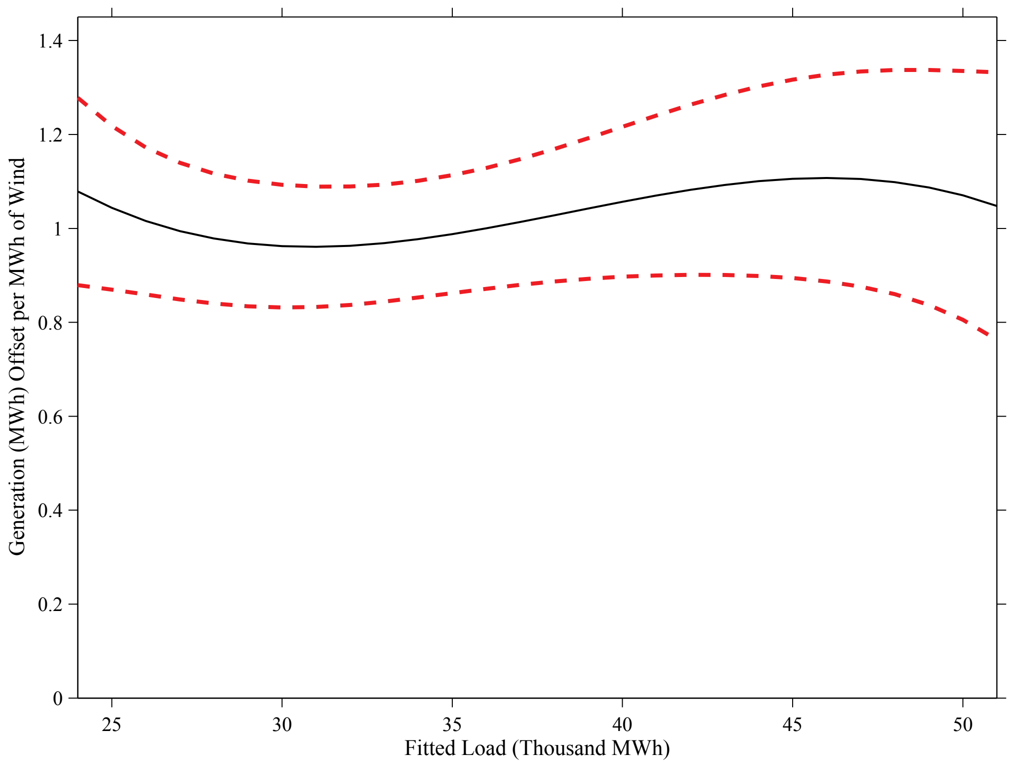

Figure 1.5: Total Generation Avoided

As the load increases, the composition of natural gas generation avoided changes as well. As the level of load increases, the share of higher polluting, high heat-rate gas units increases while the share of cleaner, low heat rate gas generation avoided begins to fall. These results are consistent with the finding that the largest reductions in NO_X occur when wind generation is supplied at high levels of load.

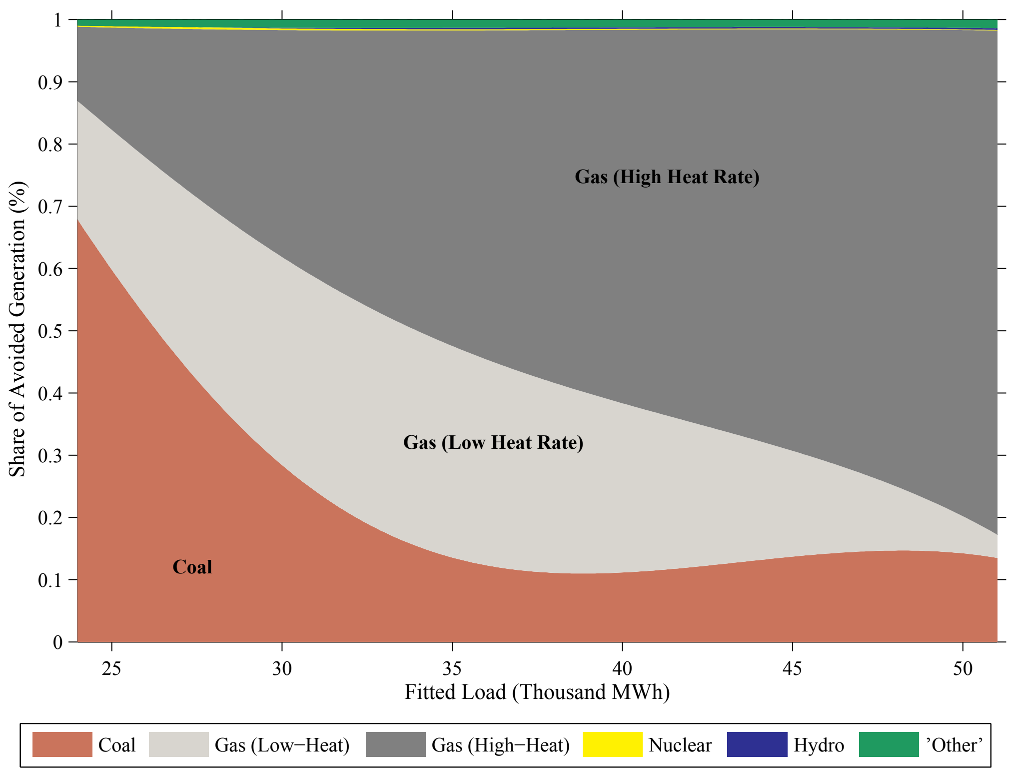

Figure 1.6: Share of Generation Avoided

1.7 Potential Renewable Generation Investments

The empirical analysis in this paper demonstrates that the emissions avoided by a MWh of renewable generation supplied to the ERCOT market varies substantially with the demand for electricity. By itself, this variation does not imply generation subsidies create inefficient incentives for siting renewable generators. In order for the mechanisms to fail at coordinating efficient investment decisions, there must also be temporal variation in the renewable generation potential across sites and technologies. In this section, I demonstrate that there is in fact substantial variation in the renewable energy profiles across potential sites and across technologies. Using the estimates from the empirical analysis, I explore how much resulting variation there may be in the pollution avoided per MWh of of generation from potential renewable investments.

1.7.1 Renewable Generation Potential

To examine how renewable generation potential varies across sites, I estimate the hourly generation that would have been realized by installing a hypothetical wind turbine in three locations.[63] The sites are located in Sweetwater (in west Texas), Washburn (northern Texas panhandle) and Corpus Cristi (on Padre Island in the Gulf). A description of how the estimates of the hourly generation are produced is provided in the Appendix. In addition, to compare the potential generation across renewable technologies, I collect data on the hourly solar generation from a photovoltaic panel in Tulia, TX (northern Texas Panhandle).[64]

For the Sweetwater, Washburn, and Corpus Cristi test sites, the predicted

[63]Each of the sites chosen are located within one of the designated Competitive Renewable Energy Zones (CREZ). To ensure that the necessary transmission capacity exists for Texas to meet the renewable generation goals, the Public Utility Commission of Texas established several CREZ's throughout the state. The CREZ's are located in regions with substantial renewable energy potential. The majority of the CREZ's are located in the northwest region of the state, where nearly all of the current wind generation capacity is installed. In addition, several locations along the Gulf Coast of Texas were established as CREZ's.

[64]Texas Tech University maintains the West Texas Mesonet, a set of weather stations throughout northern Texas that collect a variety of weather readings. The equipment at each site is powered by a solar photovoltaic panel. Data on the hourly realized generation from the solar panel is collected.

average hourly capacity factor that could be realized by installing a wind turbine at each site are 38.3%, 40.3%, and 38.4% respectively.[65] The solar panel in Tulia has an average hourly capacity factor of 14.0%. Figure 1.7 plots the average capacity factor by hour for each of the three AEI wind test sites as well as the Tulia solar panel. The two wind sites in northwest Texas, the Sweetwater and Washburn sites, have similar capacity factor profiles, both peaking in the late evening and early morning. The capacity factors from the Corpus Cristi wind site have a different daily pattern, peaking in the early afternoon when the coastal winds are higher. The solar panel in Tulia produces at its peak capacity factor between noon and 2pm and falls to zero during the nighttime.

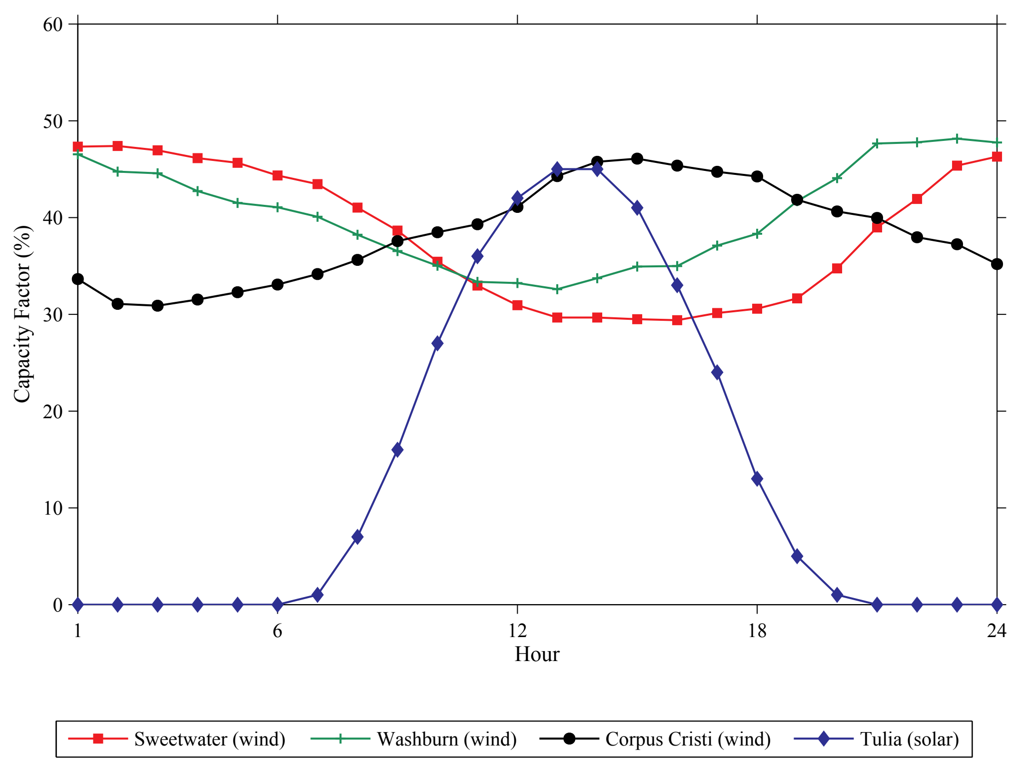

Figure 1.7: Average Capacity Factor by Hour

[65]These values likely overstate the potential capacity factors due to the fact that the variability in the direction of the wind is not considered. For a turbine to realize the predicted capacity factors, the turbine must at all times be perpendicular to the wind. If the wind direction is volatile, then the turbine cannot constantly be orthogonal to the direction of the wind.

1.7.2 Average Emissions Avoided

The predicted capacity factors demonstrate substantial variation in the timing of potential generation across CREZ's as well as across technologies. In this section, I explore the impact this variation has on the average emissions avoided by each potential MWh of electricity produced from each site. I define AEA_i to be the average emissions avoided by each MWh of renewable generation that would be produced at site i. Additionally, I define $MEA_{h,d}$ to be the marginal emissions avoided by a MWh of renewable generation from site i during hour h of day d. To estimate the average emissions avoided, I assume the marginal emissions avoided are specified by Eq. (1.21), $MEA_{i,h,d} = \hat{\beta}_0 + \hat{\beta}_1 \cdot \hat{L}_{h,d} + \hat{\beta}_2 \cdot \hat{L}^2_{h,d} + \hat{\beta}_3 \cdot \hat{L}^3_{h,d}$. I must assume that the impact of renewable generation on losses does not vary across sites or across technologies.[66] For each of the four test sites, I calculate the average CO_2, NO_X, and SO_2 avoided using the following equation:

$$AEA_i = \frac{\sum_d \sum_h \left(MEA_{h,d} \cdot x_{i,h,d} \right)}{\sum_d \sum_h x_{i,h,d}}, \tag{1.22}$$

where $x_{i,h,d}$ is the hourly capacity factor at site i during hour h of day d. I calculate the average emissions that could have been avoided between January 1, 2007 and September 30, 2008.[67]

Table 1.10 presents the average emissions avoided by each potential MWh of renewable generation across the sites. A wind turbine installed at the Sweetwater site or the Washburn site would provide nearly identical emission reductions for each MWh produced.[68] A wind turbine at Corpus Cristi offsets less CO_2 and SO_2 per MWh compared to the other two wind sites. Compared to a wind turbine

[66]Without renewable generation data disaggregated by region and technology, this assumption cannot be tested.

[67]September 30, 2008 is the last date in the sample for the Sweetwater site. To produce comparable estimates of $AEA_{i,t}$, with similar load distributions, I focus on the period when both Washburn and Sweetwater wind speeds are available.

[68]The average emissions avoided per MWh from the simulated northwest wind turbines differs slightly from the estimates of the actual average emissions avoided per MWh, despite the fact that the simulated wind turbines are located in the region where the majority of wind capacity is installed. The differences are due to the fact that the simulation spans a subset of the three years used to estimate the actual average emissions avoided.

in Sweetwater, the region with the largest current installed wind capacity, a solar panel in Tulia would avoid 11% less CO_2, 14% more NO_X, and 31% less SO_2 per MWh produced.

Table 1.10: Average Emissions Avoided by Site

	Average Emissions Avoided per MWh		
Site	**CO_2 (tons)**	**NO_x (lbs)**	**SO_2 (lbs)**
Wind - Northwest (*Sweetwater, TX*):	0.62	1.02	1.43
Wind - Northwest (*Washburn, TX*):	0.61	1.05	1.42
Wind - Gulf Coast (*Corpus Cristi, TX*):	0.57	1.04	1.29
Solar - Northwest (*Tulia, TX*):	0.55	1.16	1.00

The variation in the average emissions avoided per MWh can be explained by the correlation between the capacity factors and the ERCOT load. The capacity factors from the two wind sites in northwest Texas (Sweetwater and Washburn) have a correlation with load of -0.15 and -0.09 respectively. Therefore, these wind turbines tend to produce electricity more heavily when the demand on the grid is lower and the marginal CO_2 and SO_2 rates tend to be larger. The capacity factor for the Corpus Cristi wind turbine would have a correlation with load of -0.01, and therefore, would produce electricity more heavily during periods with larger loads than the northwest wind turbines. Finally, the solar panel has a correlation with ERCOT load of 0.37. Compared to the northwest wind turbines, the solar panel would offset generation when the marginal producers have higher NO_X rates but lower CO_2 and SO_2 rates.

1.7.3 Average Avoided External Costs

The previous results demonstrate that the average quantity of pollution offset by each MWh of renewable generation varies across the sample sites. To translate the offset emissions into avoided costs, estimates of the external cost of the actual pollution reduced are needed.

In the Texas region, CO_2 is the only pollutant of the three studied that is not subject to an emission cap. Therefore, offset emissions of CO_2 represent real reductions in aggregate pollution. In contrast to CO_2 emissions, SO_2 emissions are capped nationwide under the Clean Air Act. In addition, NO_X emissions from large electricity generators in Texas are subject to regional emission caps.[69] Therefore, rather than representing real reductions in pollution, offset NO_X and SO_2 emissions can free up pollution permits to be used at a later point in time or in a different location. While shifting when and where the NO_X and SO_2 emission occur can alter the costs of the pollution emitted, placing a value on the cost savings provided is beyond the scope of this study.[70]

To evaluate the benefits of CO_2 reductions, I use cost estimates from the Interagency Working Group (2010) report. The report provides lower (\$5/ton), middle (\$21/ton), and upper (\$35/ton) estimates of the external cost of CO_2 using discount rates of 5%, 3.5%, and 2%, respectively. Additionally, under the assumption of larger than expected external damages, a high estimate of \$65/ton is presented. These are the range of values used in government cost-benefit analysis of environmental policies. I estimate the average external benefit provided by a MWh of renewable generation from each site by multiplying the cost of a ton of CO_2 by the average reduction in CO_2 per MWh.

Table 1.11 provides the average external benefit per MWh of renewable generation at the low, middle, upper, and high values of CO_2 cost estimates. Recall, the current Federal PTC provides a tax credit worth \$22/MWh to wind turbine owners. Using the lower and middle cost estimates, the PTC cannot be justified solely on the basis of CO_2 cost savings. However, assuming CO_2 has an external cost of \$35/ton, the external benefits provided by wind generation from Northwest

[69] Additionally, local caps on NO_X emissions within Non-attainment regions of Texas, such as the Houston-Galveston-Brazoria area, are in place.

[70] The cost of non-perfectly mixing pollutants such as NO_X and SO_2 can vary across seasons with the prevailing wind patterns. In addition, the interaction of NO_X with other environmental factors such as sunlight and temperature, which vary with time of day and season, alter the external costs of the pollution.

Texas wind turbines ($21.70/MWh and $21.35/MWh) are almost equal to the tax expenditures of the PTC. In contrast, at an assumed cost of $35/ton of CO_2, the external benefits provided by Gulf Coast wind turbines and northwest solar panels are $1.75 and $2.45 less than the benefit provided by the northwest turbines.

Table 1.11: Average External Benefit by Site

	Avoided CO_2 Cost ($/MWh)			
Site	**Lower** *($5/ton)*	**Middle** *($21/ton)*	**Upper** *($35/ton)*	**High Cost** *($65/ton)*
Wind - Northwest (*Sweetwater, TX*):	$3.10	$13.02	$21.70	$40.30
Wind - Northwest (*Washburn, TX*):	$3.05	$12.81	$21.35	$39.65
Wind - Gulf Coast (*Corpus Cristi, TX*):	$2.85	$11.97	$19.95	$37.05
Solar - Northwest (*Tulia, TX*):	$2.75	$11.55	$19.25	$35.75

While the gaps between the external benefit per MWh across renewable investments are not large, the resulting impact on the aggregate benefits are in fact substantial once the size and lifespans of modern wind and solar farms are considered. Recall the predicted capacity factors from the wind turbines in Northwest Texas and the Gulf Coast were roughly 38%. Therefore, a single MW of wind capacity installed in either location will produce around 3,329 MWh during a single year. Assuming 200 MW of wind generation capacity are installed, a 200 MW wind farm in either location will produce 665,760 MWh per year. Assuming the external cost of CO_2 is $35/ton, a 200 MW wind farm in Northwest Texas will provide a $1.63 million/year larger external benefit than a similar Gulf Coast wind farm. Aggregating over the expected lifespan of modern wind farms, upwards of 15 years, the differences in the external benefits provided by various renewable investments becomes substantial.

1.8 Conclusion

This paper makes two key contributions to the literature examining the environmental benefits of renewable electricity. First, using an identification strategy that allows me to relax the assumptions required in previous studies, I directly estimate the emissions avoided by wind turbines in the Texas electricity market. The estimates reveal generation from wind turbines in the region offsets significant amounts of pollution. Second, I use the estimates of the emissions avoided to show the current policies being used to subsidize renewable generation create inefficient incentives.

Between January 1, 2007 and December 31, 2009, wind turbines accounted for 4.7% of the total generation in the Texas electricity market. During this time period, I estimate the production from wind turbines offset 3.5% of the CO_2 emissions, 4.5% of the NO_X emissions, and 2.6% of the SO_2 emissions. These values highlight the importance of identifying the actual set of generators which serve as substitutes to renewable output. While Texas coal fired units supply 37% of the total electricity, they only account for 31% of the generation offset by wind turbines. On the other hand, lower polluting natural gas fired units, which provide 43% of the Texas generation, account for 68% of the output offset by wind turbines. In this case, assuming the pollution offset by a unit of renewable electricity is equal to the average emission rate in the market will lead to substantial overestimation of the emissions avoided.

In addition to identifying the average pollution offset per MWh, I estimate the emissions reduced by renewable electricity supplied at different points in time. Given that the conventional units on the margin will change as demand shifts, the impact of renewable electricity will vary based on the quantity of electricity demanded. Estimating the impact of wind generation supplied at different levels of load on the Texas market, I find the average pollution offset by a MWh of renewable electricity fluctuates between 0.54 to 0.93 tons of CO_2, 0.88 to 1.92 pounds of NO_X, and 0.97 to 4.30 pounds of SO_2.

These temporal variations in the pollution avoided by renewable electricity have significant policy implications. Current efforts to reduce emissions from the electric sector focus largely on increasing generation from renewable sources. The policies in place regularly provide payments or tax credits to renewable producers based on the quantity of electricity generated. However, the results in this paper demonstrate that renewable generators producing electricity at different points in time will reduce different amounts of pollution per MWh. Therefore, the current policies will adversely favor certain renewable technologies or locations over others. As a result, the mechanisms do not ensure efficient investment decisions will be made.

This work provides several directions for future research. The results suggest potential efficiency gains can be realized by allowing renewable subsidies to vary with the quantity of pollution avoided. In future work, a more comprehensive dataset of renewable potential across space and time will allow for a thorough examination of the impact of alternative renewable policies on investment decisions. In addition, the analysis can be extended to consider the interactions between renewable subsidies and emission prices. In many cases, both policy tools are being employed in unison to achieve pollution reductions. The inclusion of emission prices alters the dispatch order of conventional generating units. As a result, the marginal units or technology at a specific time can change. This will effectively alter the private and external benefits of renewable generation. Exploring these interactions, future work can examine the extent to which emission prices and renewable subsidies serve as complements or substitutes in achieving pollution reductions. Finally, this paper focuses on the short-run impact of renewable investments. As the share of intermittent renewable capacity continues to grow, future work can begin to explore the impact of renewables on the retirement of existing conventional capacity and the investment in new conventional capacity.

1.9 Appendix

1.9.1 Average Impact on Daily Emissions

The estimates of the average impact of wind generation on emissions presented in this paper are made by identifying the impact wind generation on the concurrent emissions. The results demonstrate that, all else equal, if the level of wind generation increases from hour h of day $d-1$ to hour h of day d, the level of emissions will be significantly lower during hour h of day d. However, if the increase in wind generation alters the level of emissions in between the two hours being compared, the estimates of the impact of wind generation on emissions will not identify the net impact. For example, if wind generation decreases during hour $h-1$, fossil fuel generating units may be required to ramp up output. Forcing the fossil fuel generators to increase output may cause a spike in the emission rates of the generating units during hour $h-1$. By comparing the change in emissions across hour h of day d and $d-1$, I will not be identifying the impact on emissions from the spike during hour $h-1$ of day d.

To test whether the estimation strategy identifies the full impact of wind generation on emissions, I estimate the average impact of the daily level of wind generation, $W_d = \sum_{h=1}^{h=24} W_{h,d}$, on the daily level of aggregate emissions, $E_d = \sum_{h=1}^{h=24} E_{h,d}$. The full specification is shown below:

$$\Delta E_d = \beta_0 + \beta_1 \cdot \Delta W_d + \theta \cdot \Delta L_d + \varepsilon_d \tag{1.23}$$

where

$$\begin{aligned}
\Delta &= \text{change between day } d \text{ and } d-1, \\
\Delta E_d &= \text{daily change in CO}_2 \text{ (tons), NO}_X \text{ (lbs), or SO}_2 \text{ (lbs),} \\
\Delta W_d &= \text{daily change in ERCOT wind generation (MWh), and} \\
\Delta L_d &= \text{daily change in ERCOT adjsuted load (MWh).}
\end{aligned}$$

In this specification, β_1 represents the average change in the daily emissions caused by a change in the level of wind generation, controling for changes in the quantity demand and losses. The load is included as an explanatory variable to control for weather driven changes in demand that may be correlated with wind generation.[71] As a result, β_1 represents the partial impact of wind generation on emissions. The

[71] Due to the fact that the sample size has been divided by 24, the original set of weather controls becomes quite large relative to the numbe of observations.

results from Section 5 demonstrate that wind generation may have a small upward impact on aggregate losses. If this is the case, the estimates of β_1 will be slightly larger than the average net impact of wind generation on emissions.

To control for potential endogeneity in wind generation that arises due to curtailments, I use the following first stage to instrument for changes in wind generation:

$$\Delta W_d = \alpha_0 + \sum_{h=1}^{h=24} \alpha_h \cdot \Delta\big(K_d \cdot S_{h,d}\big) + \gamma \cdot \Delta L_d + \mu_d \tag{1.24}$$

where

$$\begin{aligned} \Delta S_{h,d} &= \text{hourly average AEI wind speed (meter/sec), and} \\ \Delta K_d &= \text{installed northwest wind capacity (MW).} \end{aligned}$$

Estimates of Eq. (1.23) are presented in Table 1.12. In the first stage, the Shea Partial-R^2 for the 24 excluded instruments is 0.66. Testing the overidentification restrictions, I cannot reject the null hypothesis that the instruments are valid in any of the models. The results show that controlling for changes in load, an additional MWh of wind generation will on average offset 0.73 tons of CO_2, 1.15 pounds of NO_x, and 1.97 pounds of SO_2. Each of these estimates is slightly larger than the point estimates presented in Table 5. Given that the results presented in Table 1.12 represent the partial impact on emissions, not including the indirect affect of losses, the slight increase is expected. However, each of the estimates of β_1 presented in Table 1.12 fall within the 95% confidence interval of the original point estimates presented in Table 1.5.

These results suggest that the full impact of wind generation on aggregate emissions largely occurs within the same hour. As the quantity of intermittent capacity in the market continues to grow, dynamic impacts of wind generation on conventional generation will likely arise. At the current levels, however, there is no evidence of a dynamic impact of wind generation on emissions.

Table 1.12: Average Impact on Daily Emissions

	Δ CO_2 (tons)	**Δ NO_x (lbs)**	**Δ SO_2 (lbs)**
Δ Wind Gen.	-0.729**	-1.154**	-1.974**
	(0.030)	*(0.104)*	*(0.345)*
Δ Load	0.755**	1.132**	0.861**
	(0.009)	*(0.032)*	*(0.091)*
N	1,038	1,038	1,038
R^2	0.89	0.65	0.14
First Stage:			
Shea Partial-R^2	0.66	0.66	0.66
Hansen J-Statistic	12.05	19.81	16.25
P-Value	0.97	0.65	0.84

Models regress the change in daily aggregate emissions on the change in aggregate wind generation. First stage includes the change in daily wind generation on the 24 hourly changes in wind speed interacted with the installed capacity in the northwest region. Errors are clustered at the weekly level with the standard errors reported in parentheses. * significant at 5%, ** significant at 1%.

1.9.2 Natural Gas Units by Heat-Rate

In addition to exploring how the share of coal and natural gas generation offset varies, I explore the substitution pattern between wind generation and different types of natural gas units. There are two broad types of natural gas generating units; combined cycle units and open cycle gas turbines. Combined cycle units have lower heat rates (MMBtu/MWh) and emission intensities than open cycle turbines. As a result, output avoided from the more efficient combined cycle units, compared to open cycle turbines, will result in a smaller emissions reductions.

I divide the gas units in the CEMS sample into two groups; low heat rate units and high heat rate units. To identify the heat rate at which to divide the units, I examine the distribution of hourly heat rates of the ERCOT gas units. During 2009, there were 1,249,249 hourly observations across the 376 units in which a positive level of generation occurred. For each of these hourly observations, I calculate the heat rate by dividing the hourly heat input by the hourly generation for each unit.

Figure 1.8 provides the frequency distribution of the hourly heat rates divided into 100 equally sized bins. The distribution has a clear local minimum at a heat rate of 9 MMBtu/MWh. Natural gas units with average heat rates below 9 MMBtu/MWh have average emissions intensities for CO_2, NO_x, and SO_2 of 0.51 tons/MWh, 0.32 lbs/MWh, and 0.005 lbs/MWh, while units with average heat rates above 9 MMBtu/MWH had corresponding average emission intensities of 0.64 tons/MWh, 1.58 lbs/MWh, and 0.04 lbs/MWh. Therefore, I define low heat rate gas units as being those with average heat rates below 9 MMBtu and high heat rate gas units as units with average heat rates greater than 9 MMBtu.[72]

1.9.3 Renewable Generation Potential

The AEI provides data on the average hourly wind speed from wind monitoring towers at several locations. I examine the potential wind generation from three sites that are representative of three different CREZ's: 1) Sweetwater (in

[72]To calculate the average heat rate, I divide the total heat input by the total generation across all hours in the sample for each unit.

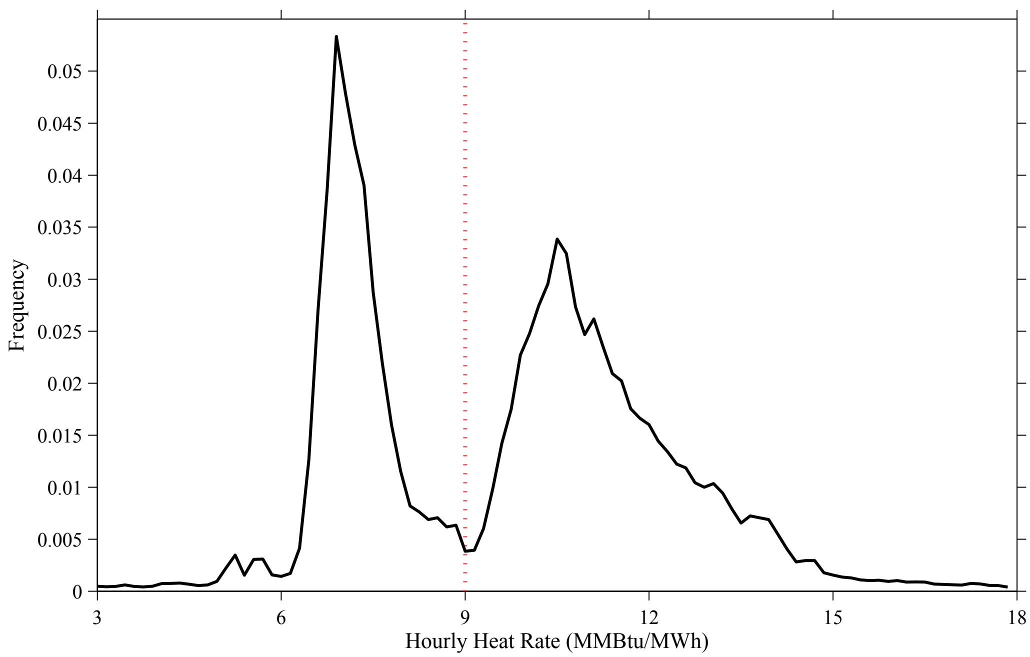

Figure 1.8: Distribution of Hourly Heat Rates for Natural Gas Units

west Texas), 2) Washburn (northern Texas panhandle), and 3) Corpus Cristi (on Padre Island in the Gulf). In the analysis, I study the hypothetical performance of a wind turbine 80 meters off the ground.[73] The test sites at Sweetwater and Washburn report the average hourly wind speed at heights of 75 meters and 100 meters. The Corpus Cristi test site reports average hourly speeds at heights of 25 meters and 40 meters. To estimate the hourly potential wind generation from each site, I must first predict the hourly wind speed at a height of 80 meters.[74] A commonly used method for predicting wind speeds at different heights involves the use of the Power Law. The Power Law states that S_x, the wind speed at a height of x, is related to S_y, the speed at a height of y, based on the following formula:

$$S_x = \big(x/y\big)^{\alpha} \cdot S_y, \tag{1.25}$$

where α represents the wind shear factor. Wind shear factors vary across locations. Additionally, the shear factors display regular diurnal patterns which vary across seasons.

To predict the wind speed at 80 meters for each site, I first calculate the hourly shear factor implied by the pair of average hourly speed readings:

$$\alpha_{i,t} = \frac{ln(Speed^h_{i,t}/Speed^l_{i,t})}{ln(h_i/l_i)}, \tag{1.26}$$

where $Speed^h_{i,t}$ and $Speed^l_{i,t}$ are the average hourly speeds at the tall height, h_i, and the low height, l_i, for site i during hour t. To account for the regular daily and seasonal patterns in site specific shear factors, I calculate $\overline{\alpha}_{i,h,m}$, the average across all shear factors at site i during hour h and month m. Using the estimates of the hourly shear factors and the Power Law specified by Eq. (1.25), I predict the hourly wind speeds at a height of 80 meters. Across all hourly observations, the average speed at the Sweetwater, Washburn, and Corpus Cristi test sites are 7.93 m/s, 8.13 m/s, and 7.83 m/s, respectively.

The actual energy passing through the region swept by the blades of a

[73] During 2009, 2067 MW of wind capacity was added to the ERCOT grid. Of this, 1870 MW came from turbines built on towers measuring 80 meters.

[74] Wind speeds tend to increase with the distance above ground level.

turbine increases non-linearly with the wind speed.[75] How much of the available energy is converted to useable electricity depends on the efficiency of the specific turbine. To convert the hourly wind speeds at 80 meters to an hourly turbine capacity factor, I use NREL test performance results from a 1.65 MW Vestas V66 turbine.[76] The turbine begins to produce electricity at speeds greater than 4 m/s and cuts out at speeds beyond 20 m/s. The capacity factor increases non-linearly between 4 m/s and 20 m/s. I use a fifth degree polynomial, fitted to the observed performance at different wind speeds, to model the capacity factor as a function of the speed.

1.9.4 Plant Level Generation Avoided

To identify the average plant-level generation offset by wind turbines, I estimate the following specification:

$$\Delta G_{j,h,d} = \beta_j \cdot \Delta W_{h,d} + m_j(H, C, G) + \alpha_{j,d} + \varepsilon_{j,h,d} \tag{1.27}$$

where

$$\begin{aligned} m_j(\cdot) \quad = \quad & \sum_{i=1}^{10} \left(\delta_{1,j,i,b} \Delta H_{i,h,d} + \delta_{2,j,i,b} \Delta H_{i,h,d}^2 + \delta_{3,j,i,b} \Delta C_{i,h,d} + \delta_{4,j,i,b} \Delta C_{i,h,d}^2 \right) \\ & + \sum_{k=1}^{13} \left(\phi_{1,j,k} \Delta G_{k,h,d} + \phi_{2,j,k} \Delta (G_{k,h,d} \cdot H_{k,h,d}) + \phi_{3,j,k} \Delta (G_{k,h,d} \cdot C_{k,h,d}) \right), \end{aligned}$$

[75] In addition, the wind energy passing through the area swept by the blades increases linearly with the density of the air. In this examination, I assume the density of the air is constant.

[76] For the test performance results, see Smith, *et al.* (2001), *Power Performance Testing Progress in the DOE/EPRI Turbine Verification Program.*

and

$$
\begin{aligned}
\Delta &= \text{change between hour } h \text{ of day } d \text{ and } d-1, \\
\Delta G_{j,h,d} &= \text{change in generation from plant } j \text{ (MWh)}, \\
\Delta W_{h,d} &= \text{change in ERCOT wind generation (MWh)}, \\
\Delta H_{i,h,d} &= \text{change in heating degrees in zone } i \text{ (Celsius)}, \\
\Delta C_{i,h,d} &= \text{change in cooling degrees in zone } i \text{ (Celsius), and} \\
\Delta G_{k,h,d} &= \text{change in ground wind speed in region } k \text{ (meters/second)}.
\end{aligned}
$$

Fixed effects estimates of Eq. (1.27) are made for plants $j = 1, \ldots, 153$. To allow for arbitrary heteroskedasticity and serial correlation, I cluster the errors at the daily level. To control for curtailments in wind generation, I instrument for the change in wind generation using the first stage specified by Eq. (2.16).

The coefficient of interest, β_j, represents the average change in generation at plant j caused by a MWh of wind generation during the period the plant is in the dataset. Not every fossil fuel plant is in the EPA dataset over the full sample period. To account for this, I weight the estimates of β_j by the fraction of the sample observations are available for plant j. Table 1.13 reports the weighted estimates of β_j for the 20 plants with the largest average reductions in output. The results highlight that significant reductions in output occur across technologies and within each region. Multiplying the estimates of the average generation avoided by the plant-level average emission rates, I produce predictions of the average reduction in pollution from each of the plants.

Table 1.13: Average Plant-Level Generation Avoided

						Average Emission Intensity			Predicted Emissions Avoided		
Plant ID	Fuel	Congestion Zone	β	Std. Error	R^2	CO_2 tons/MWH	NO_X lbs/MWh	SO_2 lbs/MWh	CO_2 tons/MWH	NO_X lbs/MWh	SO_2 lbs/MWh
3470	Coal	Houston	-0.052**	*0.004*	0.10	0.971	0.475	4.958	-0.050	-0.025	-0.256
127	Coal	West	-0.048**	*0.002*	0.17	1.028	3.498	1.923	-0.049	-0.167	-0.092
6179	Coal	South	-0.047**	*0.002*	0.21	1.024	1.061	4.832	-0.048	-0.050	-0.228
55501	Gas	OK	-0.044**	*0.003*	0.17	0.414	0.214	0.004	-0.018	-0.010	0.000
3497	Coal	North	-0.032**	*0.003*	0.11	1.081	1.430	14.765	-0.034	-0.045	-0.466
55480	Gas	North	-0.030**	*0.003*	0.12	0.648	0.355	0.007	-0.019	-0.011	0.000
55464	Gas	Houston	-0.030**	*0.002*	0.15	0.405	0.053	0.004	-0.012	-0.002	0.000
6147	Coal	North	-0.025**	*0.002*	0.12	1.086	1.623	8.289	-0.027	-0.040	-0.203
55230	Gas	North	-0.024**	*0.001*	0.22	0.412	0.111	0.004	-0.010	-0.003	0.000
6181	Coal	South	-0.024**	*0.002*	0.11	1.219	1.580	7.836	-0.029	-0.038	-0.186
55463	Gas	OK	-0.022**	*0.002*	0.08	0.447	0.107	0.005	-0.010	-0.002	0.000
7900	Gas	South	-0.022**	*0.001*	0.17	0.436	0.135	0.004	-0.010	-0.003	0.000
6146	Coal	North	-0.020**	*0.004*	0.06	1.095	1.663	8.052	-0.022	-0.034	-0.164
55132	Gas	North	-0.019**	*0.002*	0.17	0.428	0.215	0.006	-0.008	-0.004	0.000
55062	Gas	North	-0.017**	*0.002*	0.08	0.416	0.266	0.004	-0.007	-0.005	0.000
55137	Gas	South	-0.017**	*0.002*	0.06	0.431	0.221	0.004	-0.007	-0.004	0.000
55226	Gas	North	-0.016**	*0.002*	0.08	0.580	0.428	0.006	-0.010	-0.007	0.000
3490	Gas	North	-0.016**	*0.001*	0.08	0.654	2.387	0.014	-0.010	-0.038	0.000
55047	Gas	Houston	-0.015**	*0.002*	0.04	0.362	0.183	0.004	-0.006	-0.003	0.000
55215	Gas	West	-0.015**	*0.001*	0.11	0.719	0.475	0.007	-0.011	-0.007	0.000
Total (Top 20)			-0.54	-	-	-	-	-	-0.40	-0.50	-1.60
Total (All Plants)			**-0.99**	-	-	-	-	-	**-0.72**	**-0.95**	**-1.96**

Models include changes in the level and square of the heating and cooling degrees by weather zone, changes in the ground wind speeds, and the interaction between the ground wind speed and heating and cooling degree changes. Estimates are made using daily fixed effects. Errors clustered by day. Standard errors reported in column 5. Explained within day variation given by R^2. Average emissions avoided per MWh calcluated as the product of the plant level reduction in output and the plant level average emission rates. Totals equal sum across 153 plants. For each of the Top 20 plants, N=20,886. ** Significant at the 1% level.

Chapter 2

The Economics of Bulk Electricity Storage with Intermittent Renewables

Abstract

Efforts to reduce emissions from the electricity sector are driving a shift towards greater use of intermittent, renewable sources such as wind and solar energy. Motivated largely by the belief that electricity storage technologies are a vital complement to these intermittent renewables, states have begun implementing requirements that will dramatically increase the amount of bulk storage capacity (*e.g.* batteries, compressed air energy storage, pumped hydroelectric storage). This paper analytically and empirically demonstrates that, in contrast to the environmental objectives of expanding renewable generation, adding bulk storage capacity will generally increase the short-run level of emissions. Only after renewable capacity becomes large enough that the renewable sources are frequently on the margin does the introduction of bulk storage reduce the level of emissions. In addition, contrary to the view that bulk storage and renewables are necessarily complements, increased storage is shown to make solar less attractive and typical wind sites more attractive. As a result, in regions with substantial solar potential, and minimal wind generation potential, bulk storage expansions may in fact reduce

the optimal renewable capacity.

2.1 Introduction

Maintaining the stability of an electric grid requires continuously equating the quantity of electricity supplied with the quantity of electricity demanded. Accomplishing this task is complicated because the short-run demand for electricity is essentially perfectly inelastic and constantly shifting over time. To meet the level of electricity demanded, suppliers have typically depended on fossil fuels. However, concerns over the environmental impacts of fossil fuel combustion are driving a shift towards greater use of renewable energy sources (*e.g.* wind, solar), which, unlike fossil fuels, are often available only intermittently. To overcome the grid stability issues posed by the intermittency of renewable generation, many policy-makers and industry participants are advocating for sizable increases in electricity storage capacity. To determine if storage additions are justified, it is important to understand the impact of electricity storage on the total costs of the electric sector.

This paper explores the social benefits provided by a specific use of electricity storage; arbitraging electricity across time. Contrary to the environmental objectives of expanding renewable generation, we demonstrate that electricity arbitrage will generally increase the aggregate level of pollution and, in some cases, reduce the social value of renewable capacity. In a simple, two-period model of a competitive electricity market, short-run renewable output is shown to be unaffected by electricity arbitrage in regions with low to moderate levels of renewable capacity.[1] Instead, arbitrage will increase the production from the conventional generators on the margin during the low demand (off-peak) periods and decrease generation from the marginal conventional units during the high demand (peak) periods. If the emission rates of the off-peak marginal generators are not less than the peak period marginal emission rates, aggregate pollution will increase as the quantity of electricity arbitraged grows.[2]

[1]This result formalizes the argument put forth by Swift-Hook (2010).

[2]How far the off-peak marginal emission rate must be below the peak marginal emission rate

In addition, we use the simple model to explore how increased arbitrage alters the benefits provided by expanding renewable capacity. By replacing a portion of peak period electricity generation with increased off-peak production, electricity arbitrage will push off-peak wholesale prices up and peak prices down. Across regional electricity markets, off-peak periods typically occur during the late night or early morning, while the peak demand occurs during the daytime or early evening. Therefore, output from renewable generators which produce most heavily overnight (*e.g.* onshore wind turbines) will typically become more valuable with increased arbitrage. Conversely, the value of electricity from renewable sources that produce mainly during the daytime (*e.g.* solar) will fall with increased arbitrage. In contrast to the general belief that storage and renewables are necessarily complements, these results imply that in regions with substantial solar potential and little off-peak wind potential, increased bulk storage capacity may in fact decrease the optimal amount of renewable capacity.

To examine the magnitude of the potential impact of arbitrage on emissions, we simulate the effect a marginal increase in arbitrage will have on electricity production in the Texas electricity market. The Texas region serves as an ideal market for this study because the regional grid is very isolated. Therefore, we can easily identify the conventional generators which will be impacted by storage. Building on the estimation strategy proposed by Callaway and Fowlie (2009), we present reduced form estimates of the marginal emission rates during the daily off-peak, and peak, demand periods. The results reveal the marginal CO_2 and SO_2 rates are consistently higher during the off-peak hours, when arbitrage will increase electricity generation. In contrast, the marginal NO_X rates are frequently higher during the peak hours, when arbitrage will decrease electricity generation.[3] As a result, at the current levels of renewable capacity in the Texas market, arbitraging

in order to not increase pollution is determined by the loss rate of the specific storage unit.

[3]The results are similar to a study by Holland and Mansur (2007) which explores the impact of real time pricing (RTP) on the aggregate level of pollution in the electric sector. The authors present reduced form estimates of how reductions in the variance of electricity demand alters the level of emissions. Unlike RTP, arbitrage will increase and decrease generation in specific periods of the day. In addition, the magnitudes of the increases and decreases in generation caused by arbitrage are linked by the loss rates of the storage units being used, not the demand elasticities, as would be the case with RTP.

electricity between off-peak and peak hours will increase the daily emissions of CO_2 and SO_2 while the aggregate NO_X emissions will decrease during most months.

This paper builds on previous studies, in both the engineering and economics literature, exploring the benefits of electricity storage. Several engineer-oriented studies consider the external impact of storage on pollution. For example, Tuohy and O'Malley (2009) use a system dispatch model to simulate the impact of large scale storage on the Irish power grid. The authors demonstrate that carbon emissions can increase with the addition of storage, however, the conditions under which emissions increase or decrease are not explored. Denholm and Kulcinski (2004) examine the life-cycle emissions from alternative types of storage units. However, when considering the impact of storage on the emissions from interconnected generating units, Denholm and Kulcinski only focus on the pollution created during the generation of the stored electricity. The authors do not consider the emissions avoided from the marginal generation that is offset when the stored electricity is supplied.

In contrast to the engineering studies, little attention has been paid to electricity storage in the economic literature. Previous work focuses exclusively on examining the private benefits of storage (Graves, *et al.*, 1999; Walawalker, *et al.*, 2007; Sioshansi, *et al.*, 2009; Denholm and Sioshansi, 2009). Using historical wholesale electricity prices, these studies estimate the profit that can be earned by storing electricity when the price is low and supplying the stored energy when the price is high. However, given that emissions from the electricity sector are not efficiently priced, the observed wholesale prices do not reflect the full social marginal cost of electricity generation. As a result, the social benefits provided by arbitrage may in fact differ from the private benefits being estimated.

Extending these previous studies, this paper explores the full social value of electricity arbitrage by specifically examining the impact of electricity arbitrage on pollution. We demonstrate that, in the absence of efficient emissions prices, the social benefits of electricity arbitrage will generally differ from the private benefits previously identified. The empirical estimates of the potential impact of arbitrage on emissions in the Texas electricity market reveal that the marginal social benefits are substantially lower than the marginal private benefits. These findings highlight that, given the current levels of renewable capacity, increases in bulk storage capacity will not necessarily augment the social benefits provided by renewable electricity expansions.

The remainder of the paper proceeds as follows. Section 2.2 briefly reviews the various storage technologies and discusses the potential for growth in bulk electricity storage capacity. Section 2.3 presents a two-period model of a competitive electricity market to demonstrate how electricity arbitrage can affect aggregate pollution levels as well as the value of renewable capacity. Section 2.4 describes the regional electricity market studied in the empirical application. Section 2.5 presents the estimates of the marginal emission rates during the off-peak and peak periods. Section 2.6 uses the empirical results to simulate the impact of marginal increases in electricity arbitrage on aggregate pollution. Section 2.7 concludes.

2.2 Electricity Storage Technologies

This section provides a brief overview of the different types of electricity storage systems and the functions they can serve when embedded within an electricity market. We then discuss the potential for growth in bulk electricity storage, the primary technology used for arbitraging electricity.

2.2.1 Categorization of Storage Technologies

Electricity is typically stored in three broad ways: as potential energy, kinetic energy, or chemical energy.[4] An example of a technology that stores electricity as potential energy is pumped hydroelectric storage (PHS). Electricity from a grid can be used to pump water from a low reservoir to a higher reservoir. At a later point in time, the water can be released back downhill through a turbine,

[4]Additionally, electricity can be stored as thermal energy. For example, some cooling systems will absorb electricity from the grid to create ice. The ice can then be used for cooling at a later point in time. Another example is using solar energy to heat a material that holds the heat for extended periods of time. For reviews of current storage technologies available, see Denholm, *et al.* (2010) and EPRI (2010).

generating electricity. Another technology that stores electricity in the form of potential energy is compressed air energy storage (CAES). CAES units use electricity from a grid to compress air, typically in underground caverns, which can then be released at a later point in time and used to co-power a turbine. Different from potential energy, electricity can be stored in the form of kinetic energy. For example, electricity from a grid can be used to rotate a flywheel that continues to spin with very little friction. When electricity is needed, the spinning flywheel can be used to generate electricity. Finally, electricity can be converted to chemical energy and stored in batteries.[5]

Regardless of whether a storage unit stores electricity as potential, kinetic, or chemical energy, the storage technologies can be coarsely divided along two dimensions. The first is the power the storage unit can provide. Power is measured in terms of Watts (*e.g.* Kilowatts, Megawatts). PHS and CAES generally have the largest power ratings, often up to 100 Megawatts or more.[6] Batteries, flywheels, and capacitors generally have lower power capacities, typically no more than a few Megawatts.

The second dimension is the duration the storage unit can supply electricity at the rated power. Many capacitors and flywheels are only capable of supplying short bursts of stored energy, on the order of seconds to minutes. Batteries can supply electricity anywhere from minutes up to multiple hours. Depending on the size of the reservoir or cavern, PHS and CAES units are capable of supplying electricity for hours at a time.

Where a storage unit lies along the power and duration dimensions plays a large role in determining the specific services the storage device can provide. Units capable of supplying small amounts of power (*i.e.* less than one Megawatt) for short periods of time (*i.e.* seconds to minutes) are well suited for providing ancillary services, such as voltage or frequency regulation. However, these storage units are not capable of providing electricity for a duration long enough to participate in

[5] A wide range of battery technologies are available. However, the majority are not yet at the point of being cost-competitive with the other storage technologies.

[6] For comparison, average sized natural gas fired generating plants have capacities in the range of 300 Megawatts.

wholesale electricity markets. Therefore, they are not well suited for electricity arbitrage.

On the other hand, storage units capable of supplying large amounts of power (*i.e.* multiple Megawatts or more) for long periods of time (*i.e.* an hour or longer) are capable of arbitraging electricity across time. These storage technologies are referred to as bulk storage units. This paper focuses on the social benefits provided by arbitraging electricity in wholesale markets using bulk storage technologies. Our goal is not to estimate the full social value of bulk storage units, which could potentially provide a number of services to an electricity market. Rather, our objective is to carefully examine the relationship between the private and social benefits of arbitrage, one of the primary uses of bulk electricity storage.[7]

2.2.2 Potential Growth in Bulk Electricity Storage

Currently, PHS and CAES are the most cost competitive forms of electricity storage. With 127,000 Megawatts of capacity worldwide, PHS systems account for almost all of the grid connected storage capacity, followed by CAES units. However, storage capacity is currently very small relative to the total generation in electricity markets. For example, in the United States, only 2.5% of the electricity consumed is supplied by storage units.[8]

Despite the small levels of existing bulk storage capacity, increasing support for both renewable electricity and electricity storage are making it increasingly important to understand the social value provided by both technologies. Currently, 29 states have adopted binding Renewable Portfolio Standards (RPS) which set targets for renewable electricity shares as high as 40%. In addition, a variety of federal subsidies and tax credits are available to renewable producers.[9] Combined,

[7]EPRI (2010) compares the private returns to a variety of services that can be provided by electricity storage. Our analysis focuses on arbitrage, which is one of the primary sources of revenue for bulk storage units. In addition, Sioshansi and Denholm (2010) highlight that unlike the private returns to arbitrage, the private value of participating in ancillary service markets declines rapidly as storage capacity increases.

[8]For information on storage capacity, see EPRI (2003).

[9]For information on federal subsidies and state RPS policies, see www.dsireusa.org.

these policies are expected to significantly increase the share of electricity produced from intermittent renewable sources.[10]

Increases in electricity storage capacity are seen as a vital way to augment the benefits provided by the expansion of renewable generation. As a result, efforts to induce investment in storage are gaining momentum as well. For example, California recently passed Assembly Bill 2514, the "Energy Storage Portfolio", which will require utilities in the state to procure a minimum level of storage capacity.[11] In addition, five states directly include electricity storage units in the list of qualified technologies which can be used to satisfy the RPS targets.[12] Combined with sizable federal subsidies, these energy storage policies have electricity storage capacity poised for significant growth.

Where future electricity bulk storage units are located will have a large impact on the value they provide.[13] Graves, *et al.* (1999), Walawalker, *et al.* (2007), and Sioshansi, *et al.* (2009) highlight that the private returns to arbitrage will vary across markets based on regional variation in the differences between off-peak and peak prices. In addition, if transmission constraints exist within a regional market, where the storage unit is embedded will affect which services the storage unit can provide. For example, several studies explore the cost effectiveness of combining bulk storage units with intermittent generators located in regions with transmission constraints (Cavallo, 1995; DeCarolis and Keith, 2006; Greenblatt, *et al.*, 2007). These studies find that the storage units will reduce the investments in transmission capacity that are required to transport renewable generation to demand centers.

The remainder of this paper examines the value of bulk storage in the case

[10]The Energy Information Administration's *"Annual Energy Outlook 2010"* predicts renewable generation will account for 45-65% of the increase in total U.S. generation between 2008 and 2035.

[11]Similar policies have received support at the federal level as well. For examples, see the proposed STORAGE Act of 2009 as well as the STORAGE 2010 Act.

[12]These states include California, Hawaii, Montana, Ohio, and Utah. For a complete list of the technologies that can be used to satisfy the RPS targets, see www.dsireusa.org/.

[13]While batteries can be installed in any location, both PHS and CAES units require specific geological characteristics. PHS requires access to water and elevation differences. While many of the ideal locations have PHS systems already in place, there is still room for growth in PHS capacity. For example, a PHS unit is being installed by San Diego Gas & Electric in Southern California. The storage unit will provide 40 MW for up to 10 hours. In addition, Succar and Williams (2008) find that 75% of the U.S. has ground formations suitable for CAES units.

where transmission constraints do not exist. Denholm and Sioshansi (2009) point out that there is a tradeoff between installing bulk storage units near demand centers versus locating them near transmission constrained renewable sources. While siting the storage with intermittent renewables will reduce the amount of curtailed output, the private arbitrage value of storage units is maximized by siting them near demand centers where transmission constraints will not limit access to wholesale markets. In order to determine where bulk storage units provide the greatest social value, it is crucial to first understand what the value of electricity arbitrage is. The remainder of this paper focuses on exploring the social and private returns of using electricity storage units specifically for electricity arbitrage.

2.3 Two-Period Model

In this section, we present a simple two-period model of a competitive, wholesale electricity market. The model highlights which factors determine the magnitudes of the marginal private benefits and marginal social benefits of electricity arbitrage. We demonstrate that, in the presence of unpriced emissions, there is generally a gap between the private and social benefits of arbitrage. Additionally, we use the model to demonstrate the conditions under which arbitrage will increase or decrease the returns to renewable capacity investments.

2.3.1 Competitive Electricity Market

Consider a competitive wholesale electricity market in which electricity is supplied in two distinct periods. Period one is the "off-peak" period and period two is the "peak" period. Demand in each period is perfectly inelastic and the off-peak demand, D_o, is strictly less than the peak demand, D_p. Electricity is generated using two broad technologies: conventional generators, which can be dispatched on command (*e.g.* coal, natural gas, nuclear, hydroelectric), and intermittent renewable generators (*e.g.* wind, solar).

The aggregate generation from conventional sources during period $t = \{\text{Off-peak, Peak}\}$ is given by G_t. The private costs of producing G_t is given by the cost function $c(G_t)$, which is assumed to be strictly increasing and convex. These assumptions imply that the conventional generators are dispatched in order of increasing marginal private costs.

In addition to the private generation costs, conventional generators produce a negative externality; unpriced pollution. The aggregate level of pollution emitted by conventional generators in a single period is given by $e(G_t)$, which is assumed to be weakly increasing, however, no restrictions are placed on the second derivative of the pollution function.[14] Therefore, the emission rates of the conventional generating units on the margin at low levels of G_t can be greater than, or less than, the emission rates of the units on the margin at higher levels of G_t. The marginal external cost of pollution is assumed to be constant and equal to τ.[15]

The aggregate level of generation from renewable sources, during period t, is given by R_t. Unlike production from conventional sources, renewable generation cannot be dispatched on command. The output in period t is equal to the product of the installed renewable capacity, K, and the capacity factor, x_t, which can vary between 0 and 1. Initially, we explore the impact of storage in markets where the level of renewable penetration is not large enough to force renewable output to be curtailed. Therefore, we begin with the assumption that demand exceeds the maximum renewable generation in each period, $D_t > K$. Without loss of generality, we additionally assume that $D_p - K \cdot x_p > D_o - K \cdot x_o$. This ensures the profit maximizing storage owners will optimally purchase electricity during the off-peak period and supply electricity during the peak period.[16] To produce electricity from intermittent renewables, only a fixed cost, which includes the regular required

[14]The level of emissions is not strictly increasing in G_t due to the fact that non-polluting dispatchable sources (*e.g.* nuclear, hydroelectric) can potentially be the marginal source of electricity.

[15]While a variety of pollutants are emitted during the combustion of fossil fuels, this model uses a single aggregate measure of pollution. To the extent that the marginal damage varies across pollutants, and varies based on where the pollutants are emitted, the measure e can be thought of as the weighted sum of the various pollutants, where the weights are determined by marginal external damage of each pollutant. For a pollutant with a higher marginal social cost, each unit of pollution emitted will contribute a larger amount to the overall level of e. In the discussion section following the empirical application, we consider the impact of allowing the marginal external damage of pollution to vary across periods ($\tau_o \neq \tau_p$).

[16]If we instead assume, $D_p - K \cdot x_p < D_o - K \cdot x_o$, then we can simply reverse the order of period's one and two and the conclusions will remain unchanged.

maintenance expenditures, must be paid. The marginal generation cost is zero and no emissions are created from the renewable generation.

In addition to the conventional and intermittent renewable generators, we introduce a third technology; an electricity storage sector. Storage owners can arbitrage electricity across periods by demanding electricity during the initial off-peak period and supplying the stored electricity during the peak period. The quantity of electricity stored off-peak is given by S_o. During the process of charging and discharging, a portion, $\alpha \in [0,1]$, of the electricity is lost. The remaining electricity supplied during the peak period is equal to $(1-\alpha) \cdot S_o$.

To maintain the stability of the electric grid, the quantity of electricity demanded must exactly equal the quantity of electricity supplied during each period. Therefore, the following two conditions must hold:

$$D_o + S_o = G_o + K \cdot x_o \tag{2.1}$$

$$D_p = G_p + K \cdot x_p + (1-\alpha) \cdot S_o. \tag{2.2}$$

Given the installed renewable capacity, K, and the storage loss rate, α, Eq. (2.1) and Eq. (2.2) define the level of conventional generation in each period as a function of the exogenous demands, exogenous capacity factors, and the quantity of electricity stored during the off-peak period.

2.3.2 Marginal Social Benefits of Arbitrage

To determine the social benefit of electricity arbitrage, we examine the impact a marginal increase in storage has on the total cost of generating electricity. Over the two periods, the social cost of supplying electricity is given by the following expression:

$$TC = c(G_o) + c(G_p) + \tau \cdot \left[e(G_o) + e(G_p)\right], \tag{2.3}$$

where G_o and G_p are defined by Eq. (2.1) and Eq. (2.2), respectively.

The social benefit of a marginal increase in storage is equal to the reduction in total costs; $MSB(S_o) = -\partial TC/\partial S_o$. Taking the derivative of Eq. (2.3), with respect to S_o, yields the following expression for the marginal social benefit of storing off-peak electricity:

$$MSB(S_o) = (1-\alpha)\cdot c'(G_p) - c'(G_o) + \tau \cdot \big[(1-\alpha)\cdot e'(G_p) - e'(G_o)\big], \qquad (2.4)$$

where G_o and G_p are defined by Eq. (2.1) and Eq. (2.2).

Under the assumption that the market is perfectly competitive, the market clearing price in each period will equal the private marginal cost of supplying electricity: $P_o = c'(G_o)$ and $P_p = c'(G_p)$. Substituting the prices into Eq. (2.4), the marginal social benefit of storage can be expressed as the sum of the marginal private benefit and the marginal external benefit:

$$MSB(S_o) = \underbrace{(1-\alpha)\cdot P_p - P_o}_{\text{Marginal Private Benefit}} + \underbrace{\tau \cdot \big[(1-\alpha)\cdot e'(G_p) - e'(G_o)\big]}_{\text{Marginal External Benefit}}. \qquad (2.5)$$

The first term in Eq. (2.5) is the marginal private benefit from storing an additional unit of off-peak electricity. If $(1-\alpha)\cdot P_p > P_o$, storage owners will earn positive marginal profits.

The second term in Eq. (2.5) represents the external benefit from a marginal increase in storage. This term is equal to the product of the marginal external cost of pollution, τ, and the decrease in pollution from a marginal increase in S_o. If $\frac{e'(G_o)}{e'(G_p)} > (1-\alpha)$, then the aggregate emissions will increase with additional storage. In this case, the marginal social benefit of arbitrage will be less than the marginal private benefit.

2.3.3 Impact on the Value of Renewable Electricity

In addition to identifying the direct social value of arbitraging electricity across periods, we use the simple model to examine the impact of arbitrage on the value of intermittent renewable capacity. In the short-run, the social benefit of a marginal increase in renewable capacity is equal to the avoided costs, $MSB(K) = -\partial TC/\partial K$, where the total costs are given by Eq. (2.3). Taking the derivative of the total cost with respect to K yields the following expression for the marginal social benefit of renewable capacity:

$$MSB(K) = c'(G_p) \cdot x_p + c'(G_o) \cdot x_o + \tau \cdot \left[e'(G_p) \cdot x_p + e'(G_o) \cdot x_o\right] \tag{2.6}$$

where G_o and G_p are defined by Eq. (2.1) and Eq. (2.2). The marginal social benefit of renewable capacity can again be split into the marginal private and marginal external benefits. The marginal private benefit is equal to the prices weighted by the additional generation in each period; $MPB = P_p \cdot x_p + P_o \cdot x_o$. The marginal external benefit is equal to the cost of the avoided pollution; $MEB = \tau \cdot \left[e'(G_p) \cdot x_p + e'(G_o) \cdot x_o\right]$.

To determine how electricity arbitrage affects the value of renewable capacity, we examine the impact a marginal increase in off-peak storage has on the marginal social benefit of renewable capacity. Taking the derivative of Eq. (2.6) with respect to S_o results in the following expression:

$$\begin{aligned} \frac{\partial MSB(K)}{\partial S_o} &= \overbrace{c''(G_o) \cdot x_o - (1-\alpha) \cdot c''(G_p) \cdot x_p}^{\partial MPB(K)/\partial S_o} + \\ &+ \underbrace{\tau \cdot \left[e''(G_o) \cdot x_o - (1-\alpha) \cdot e''(G_p) \cdot x_p\right]}_{\partial MEB(K)/\partial S_o} \end{aligned} \tag{2.7}$$

where G_o and G_p are defined by Eq. (2.1) and Eq. (2.2).

Eq. (2.7) highlights that an increase in arbitrage can increase or decrease the private benefit of renewable capacity. A marginal increase in electricity arbitrage will increase the off-peak price by $\frac{\partial P_o}{\partial S_o} = c''(G_o)$ and decrease the peak price by $\frac{\partial P_p}{\partial S_o} = (1-\alpha) \cdot c''(G_p)$. If the following inequality is satisfied,

$$\frac{x_o}{x_p} > \frac{(1-\alpha) \cdot c''(G_p)}{c''(G_o)}, \tag{2.8}$$

then a marginal increase in arbitrage will increase the private returns to renewable capacity. Therefore, the private returns to a renewable generator that has larger capacity factors during the off-peak period are more likely to increase. Alternatively, the ratio of $\frac{x_o}{x_p}$ will be closer to zero for a renewable technology that produces electricity more heavily during the peak, daytime hours as opposed to the off-peak hours (*e.g.* solar). As a result, the inequality in Eq. (2.8) is less likely to be satisfied. Therefore, by decreasing the peak electricity prices, arbitrage will reduce the value of renewables that produce more heavily during the peak period.

In addition, Eq. (2.7) demonstrates that arbitrage has an ambiguous impact on the external benefits provided by renewable electricity. Storing electricity off-peak, and supplying the stored energy during the peak period, will alter which generating units are on the margin in each period. If $e''(G_o) < 0$, then storing electricity during the off-peak period will move a cleaner conventional generating unit onto the margin. As a result, renewable electricity supplied during the off-peak period will avoid less pollution than it would without storage. Similarly, if $e''(G_p) > 0$, supplying additional stored electricity during the peak period will again move a cleaner producer onto the margin.

The results from this simple model highlight several key points. First, in situations where the full social cost of emissions are not internalized in the market prices, the marginal social benefit of electricity arbitrage will generally differ from the marginal private benefits. Whether the social benefits are larger or smaller than the private benefits depends heavily on the off-peak and peak marginal emission rates: $e'(G_o)$ and $e'(G_p)$. Additionally, the results demonstrate that electricity arbitrage can increase or decrease the private and external benefits of renewable capacity additions. The impact on the private returns to renewables depends on the pattern of renewable generation $(\frac{x_o}{x_p})$ and the price elasticity at the off-peak and peak levels of conventional generation. Similarly, the impact on the external returns to renewable capacity depends on the pattern of renewable production and the shape of the marginal emission rate profile.

2.4 Application to Texas Electricity Market

The two-period model provides the intuition for how the social benefits of electricity arbitrage can differ from the private benefits. To determine the magnitude of the difference between the private and social benefits, it is crucial to know the marginal emission rate when bulk storage units demand electricity, $e'(G_o)$, and the marginal emission rate when storage units supply electricity, $e'(G_p)$. The remainder of this paper explores the potential impact of electricity arbitrage in a specific market; the Texas electricity market.

The objective of the study is not to model the optimal demand and supply decisions for a bulk storage unit. Graves, *et al.* (1999) and Sioshansi, *et al.* (2009) both model the operations of a profit maximizing storage unit. These previous studies highlight that the profit maximizing charge and discharge behavior is very stable across days. Electricity is consistently stored during the minimum price, off-peak period of the day. The stored energy is then discharged during the maximum price, peak period of each day. While the timing of charging and discharging is affected slightly by factors such as weekdays versus weekends, the results demonstrate that the patterns are quite steady.

Instead of modeling a dynamically optimized storage unit, we instead predict the impact of a bulk storage unit that stores electricity during the off-peak period each day and supplies the electricity during the peak period of each day. To estimate the effect on pollution, we first need to know when the off-peak and peak periods occur. Second, we need estimates of the marginal emission rates during the off-peak and peak periods.

The Texas region serves as an ideal market for this analysis because the regional electric grid is very isolated. As a result, the conventional generating units which would be impacted by a storage sector, and the pollution those units emit, are easily identified. Using the intuition from the two-period model, combined with reduced form estimates of the marginal emission rates, we compare the potential marginal social benefits and marginal private benefits of electricity arbitrage in the Texas market. This section briefly describes the generation and emissions data used to estimate the marginal emission rates. In addition, we discuss the demand and price data used to determine when the off-peak and peak periods occur.

2.4.1 Generation and Emissions Data

The majority of the state of Texas is served by a deregulated electricity market.[17] The Electric Reliability Council of Texas (ERCOT) is the independent system operator charged with maintaining the stability of the regional transmission grid. To estimate the marginal emission rates, we use data on the hourly electricity generation and emissions in the EROCT region between January 1, 2007 and December 31, 2009. Table 2.1 presents the mean and standard deviation of the hourly ERCOT generation, separated by fuel source, over the three year period. Natural gas and coal fired generators account for 80% of the total electricity generated while nuclear plants produce 13% of the electricity. Intermittent output from wind turbines accounts for 5% of the total generation. Hydroelectric units and 'Other' sources, which include biomass, landfill gas, other fossil fuels, and solar, provide the remaining generation.

Table 2.1: 2007-2009 Hourly Net Generation by Fuel (MWh)

	Natural Gas	**Coal**	**Nuclear**	**Wind**	**Hydroelectric**	**Other**
N	26,117	26,117	26,117	26,117	26,117	26,117
Mean	15,128	12,956	4,681	1,626	105	491
Std. Dev.	7,166	1,523	763	1,205	96	227
Share	43.2%	37.0%	13.4%	4.7%	0.3%	1.4%

"Other" production is from biomass, landfill gas, oil, diesel, and solar units. Shares are equal to the total supply from each fuel source during the sample period divided by the aggregate supply.

A unique feature of the Texas market is that the region serves as its own "Interconnection". The electric transmission grid in the United States is split into three separate Interconnections: the Eastern Interconnection, the Western Interconnection, and the Texas Regional Entity. Within each Interconnection, electricity is transmitted at a synchronized frequency. To trade electricity between Interconnections, however, electricity must be converted from alternating current to direct current (DC) and transmitted across a limited number of DC transmission

[17] Over 85% of the electricity consumed in Texas is supplied by the deregulated market.

lines.[18] To simulate the impact of arbitrage in the ERCOT region, we assume storage will not alter the flow of electricity across the DC connections.

The Environmental Protection Agency (EPA) collects data on the hourly emissions of CO_2, NO_X, and SO_2 from 276 fossil fuel fired generating units that directly supply electricity to the ERCOT market.[19] Only 10 small natural gas fired units in the region, each with a capacity below 25 MW, are not included in the EPA dataset. Therefore, the observed emissions effectively represent the total hourly pollution from the ERCOT market. Table 2.2 presents summary statistics for the coal and natural gas units in the EPA dataset.[20] In addition to separating the units by fuel, we further divide the natural gas fired units into 'low' and 'high' heat-rate subgroups.[21] This division is motivated by the fact that there are two broad natural gas generating technologies: cleaner combined-cycle units, which have lower heat-rates, and dirtier open-cycle units, which have higher heat-rates. We classify natural gas units with average heat-rates below 9 MMBtu/MWh as low heat-rate units and the rest as high heat-rate units.

The coal units on average have the largest capacities while the high heat-rate gas units tend to be the smallest.[22] Comparing the average heat-rates, the efficient gas fired units have lower average heat-rates than the coal units. However, the private cost of fuel required to generate a MWh of electricity is typically smaller for coal units because coal is the cheaper fuel.[23] Table 2.2 also highlights the variation in the emission rates across generators using different fuels and technologies. Coal fired units have the highest CO_2 and SO_2 rates. Low heat-rate natural gas units

[18]During the period studied in this analysis, the maximum amount of electricity that could be traded between ERCOT and the surrounding Interconnections totaled 1,090 MW.

[19]This includes each fossil fuel unit in the ERCOT service region plus the Kiamichi Energy Facility in Oklahoma which is connected to the Texas grid.

[20]One petroleum unit in the ERCOT market is included in the EPA dataset. The emissions from this unit are included in the measure of the aggregate hourly emissions used in the empirical analysis.

[21]Heat-rate is a measure of generation efficiency. It is equal to the fuel input (in MMBtu's) divided by the level of generation (MWh's). Higher heat-rates imply less efficient generation.

[22]Unit level capacities are from the EIA-860 Generator Database.

[23]The average monthly price of coal delivered to Texas utilities is \$1.82/MMBtu over the sample period. The average monthly price of natural gas delivered to Texas utilities during the same time period is \$6.42. Information on the fuel prices is available from the Energy Information Adminstration.

Table 2.2: Fossil Fuel Unit Summary Statistics

	Coal	**Natural Gas** *(Heat-Rate<9)*	**Natural Gas** *(Heat-Rate>9)*
Number of Units	27	80	168
Average Capacity (MWh)	677	320	154
	(173)	*(153)*	*(185)*
Average Heat Rate (MMBtu/MWh)	10.00	7.38	11.46
	(0.66)	*(1.10)*	*(2.06)*
Average CO_2 Rate (tons/MWh)	1.06	0.44	0.69
	(0.07)	*(0.07)*	*(0.22)*
Average NO_x Rate (lbs/MWh)	1.44	0.31	1.67
	(0.63)	*(0.55)*	*(1.72)*
Average SO_2 Rate (lbs/MWh)	6.51	0.00	0.01
	(3.67)	*(0.00)*	*(0.05)*

Average Heat Rates and Emission Intensities are calculated by taking the average across the individual unit level means. Standard deviations of the unit level means are in parentheses.

have the lowest emission intensities and high heat-rate natural gas units have the highest NO_X emission rates.

2.4.2 Demand and Market Prices

Recall, in the two-period model, conventional generation is dispatched to meet the residual demand not served by intermittent renewable producers. The wholesale price of electricity is determined by the marginal cost of the conventional generator on the margin at any given time. Therefore, within a single day, the minimum price, off-peak period, and the maximum price, peak period, will occur when the residual demand is at its lowest and highest points, respectively.

To determine when the off-peak and peak hours occur in the Texas market, we use two different sources of information: hourly residual demand in the region and hourly average wholesale electricity prices. The residual demand is equal to the hourly quantity of electricity demanded (load) less the hourly generation from wind turbines. Figure 2.1 plots the average load and wind generation by hour. The figure demonstrates that the load tends to fall to its lowest levels during the early morning hours and rises to its peak during the early evening. In addition, the figure plots the average residual load by hour. Given that intermittent renewable generation represents a small share of generation, the residual load follows the same pattern as the load.

While the majority of electricity generated in the Texas market is purchased through bilateral contracts, a centralized balancing market is operated to balance the quantity of electricity supplied with the quantity demanded. Each day, Qualified Scheduling Entities (QSE), representing portfolios of electricity generators, submit balancing supply curves for each fifteen minute interval of the following day.[24] These balancing supply curves list the increase or decrease in generation each QSE will provide at different prices. To equate supply and demand, ERCOT purchases the necessary amount of up or down balancing energy at a single market clearing price.[25] Figure 2.1 plots the average market clearing price by hour over

[24]These balancing supply bids can be adjusted up to one hour before real-time.

[25]If transmission limits between regions are binding, then four separate prices are set in each of the four ERCOT congestion zones (North, South, Houston, and West).

the three year sample.[26] Following the pattern displayed by the residual load, the minimum average price occurs during the 4 a.m. hour while the maximum average price occurs between 4 p.m. and 5 p.m.

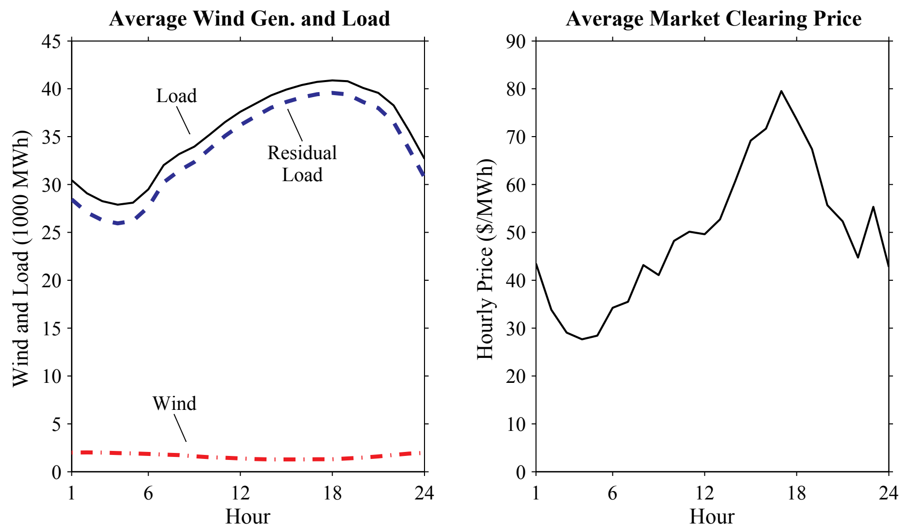

Figure 2.1: Average Hourly Wind Generation, Load, and Market Price

2.5 Marginal Emission Rates

To predict the impact of arbitraging electricity between the off-peak and peak periods, we estimate the marginal emission rate in the Texas market at different points in time. We use a strategy similar to Callaway and Fowlie (2009) to first estimate the average marginal emission rate for each individual hour over the full three year sample. To examine why the marginal emission rates vary across hours, we next explore the composition of the generators on the margin during different hours of the day. Finally, to allow for seasonal variation in the marginal emission rates, we present estimates of the hourly marginal emission rates across each individual month.

[26]If the market clearing price varies across congestion zones, a simple average of the four prices is taken.

2.5.1 Average Hourly Marginal Emission Rates

The general specification we estimate is shown below:

$$\Delta E_{h,d} = \beta_h \cdot \Delta G_{h,d} + \varepsilon_{h,d} \tag{2.9}$$

where subscript $h = 1, \ldots, 24$ represents the individual hours of each day $d = 1, \ldots, 1095$. $E_{h,d}$ is the aggregate hourly emissions of CO_2 (tons), NO_X (lbs), or SO_2 (lbs). $G_{h,d}$ represents the hourly aggregate generation (MWh) from dispatchable sources. To calculate $G_{h,d}$, we sum the hourly net generation from coal, natural gas, nuclear, hydroelectric, and 'other' sources in the ERCOT market. In Eq. (2.9), Δ represents the difference across 168 hours. Therefore, we are taking the differences between hour h of day d and hour h of day $d-7$, the the same hour and day of the preceding week. The coefficient β_h represents the average change in emissions caused by a change in dispatchable generation during hour h. Allowing β_h to vary across hours allows for the estimation of the average hourly marginal emission rate.

Estimates of Eq. (2.9), using the change in CO_2, NO_X, and SO_2 as the dependent variables, are estimated simultaneously. To control for arbitrary serial correlation and heteroskedasticity, the errors are clustered at the daily level. Table 2.3 reports the estimates of β_h for $h = 1, \ldots, 24$ and for each pollutant where each of the point estimates is positive and significant at the 1% level. An additional MWh of dispatchable generation during any hour will, on average, increase the hourly level of each of the three pollutants. The results also reveal that a marginal increase in generation will, on average, increase the aggregate emissions by different amounts during different hours. Figure 2.2 plot the hourly estimates of $\hat{\beta}_h$, along with the corresponding 95% confidence intervals, for each of the three pollutants. Average marginal CO_2 and SO_2 rates peak between 3 a.m. and 4 a.m. and fall to their lowest average levels between 6 p.m. and 7 p.m. In contrast, the average marginal NO_X rates peak at 5 p.m. and fall to their lowest average levels around 11 a.m. and midnight.

Table 2.3: Average Hourly Marginal Emission Rates

	ΔCO_2 tons / MWh		ΔNO_X lbs. / MWh		ΔSO_2 lbs. / MWh	
Hour	**β**	**Std. Err.**	**β**	**Std. Err.**	**β**	**Std. Err.**
1	0.62*	*(0.006)*	0.63*	*(0.01)*	1.44*	(0.09)
2	0.63*	*(0.007)*	0.63*	*(0.02)*	1.67*	(0.10)
3	0.65*	*(0.008)*	0.66*	*(0.02)*	2.07*	(0.13)
4	0.65*	*(0.007)*	0.68*	*(0.02)*	2.00*	(0.10)
5	0.64*	*(0.007)*	0.68*	*(0.02)*	1.91*	(0.10)
6	0.62*	*(0.007)*	0.68*	*(0.02)*	1.68*	(0.10)
7	0.60*	*(0.006)*	0.73*	*(0.02)*	1.52*	(0.09)
8	0.58*	*(0.006)*	0.74*	*(0.02)*	1.19*	(0.09)
9	0.57*	*(0.006)*	0.66*	*(0.02)*	0.96*	(0.09)
10	0.57*	*(0.006)*	0.62*	*(0.02)*	0.80*	(0.09)
11	0.56*	*(0.006)*	0.59*	*(0.02)*	0.69*	(0.09)
12	0.56*	*(0.006)*	0.63*	*(0.02)*	0.64*	(0.09)
13	0.56*	*(0.005)*	0.69*	*(0.02)*	0.57*	(0.08)
14	0.57*	*(0.005)*	0.82*	*(0.02)*	0.50*	(0.07)
15	0.57*	*(0.005)*	0.94*	*(0.03)*	0.44*	(0.07)
16	0.57*	*(0.004)*	1.04*	*(0.03)*	0.44*	(0.07)
17	0.57*	*(0.004)*	1.06*	*(0.03)*	0.41*	(0.07)
18	0.56*	*(0.004)*	1.04*	*(0.03)*	0.35*	(0.06)
19	0.56*	*(0.004)*	0.94*	*(0.03)*	0.30*	(0.07)
20	0.56*	*(0.004)*	0.81*	*(0.02)*	0.34*	(0.07)
21	0.56*	*(0.005)*	0.74*	*(0.02)*	0.36*	(0.07)
22	0.56*	*(0.005)*	0.66*	*(0.02)*	0.50*	(0.08)
23	0.56*	*(0.006)*	0.62*	*(0.02)*	0.62*	(0.09)
24	0.59*	*(0.006)*	0.59*	*(0.02)*	0.99*	(0.09)
N	25,920		25,920		25,920	
R^2	0.91		0.65		0.14	

Models estimated simultaneously. Clustered standard errors in parentheses.
* = Significant at 1% level.

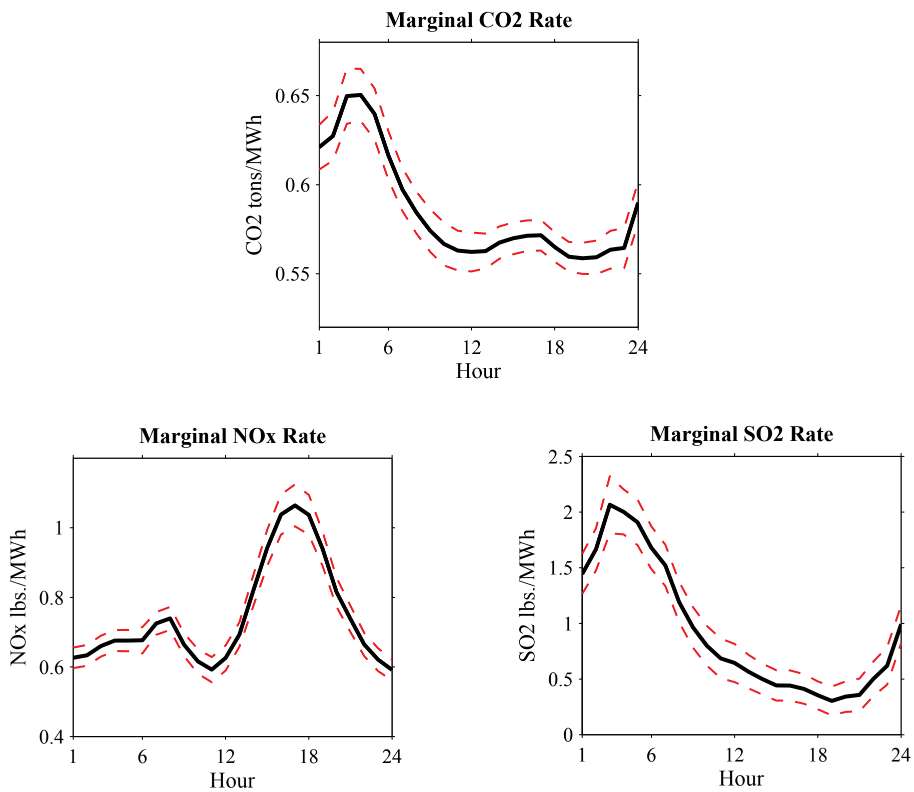

Figure 2.2: Average Hourly Marginal Emission Rates

2.5.2 Marginal Generation by Fuel Source

To examine what is driving the variation in the marginal emission rates, we estimate the following specification:

$$\Delta G_{j,h,d} = \beta_{j,h} \cdot \Delta G_{h,d} + \varepsilon_{j,h,d} \tag{2.10}$$

where $G_{j,h,d}$ is the aggregate hourly generation from fuel source $j = \{$Low Heat-Rate Gas, High Heat-Rate Gas, Coal, Nuclear, Hydroelectric, 'Other'$\}$. Given that $\Delta G_{h,d}$ equals the aggregate hourly change in generation from natural gas, coal, nuclear, hydroelectric, and 'other' generating units, the following identity will necessarily be true:

$$\beta_{low,h} + \beta_{high,h} + \beta_{coal,h} + \beta_{nuclear,h} + \beta_{hydro,h} + \beta_{other,h} = 1. \tag{2.11}$$

The coefficients of interest, $\beta_{j,h}$, represents fuel source j's average share of the marginal dispatchable generation during hour h.

Figure 2.3 plots the average hourly marginal generation by fuel source. The results demonstrate the composition of the marginal dispatchable generation varies substantially across hours. On average, coal fired generation accounts for almost one third of the marginal dispatchable output at 3 a.m. The average share of coal generation on the margin steadily falls to its lowest point between 5 p.m. and 6 p.m. Given that coal generation has the highest CO_2 and SO_2 intensities, these results explain why the average marginal CO_2 and SO_2 rates peak in the early morning and fall to their lowest points in the afternoon.

Figure 2.3 also demonstrates that on average, high heat-rate natural gas generation accounts for the largest share of the marginal output during 5 p.m. to 6 p.m. Recall from Table 2.2, these high heat-rate gas units tend to have the highest NO_X emission intensities. This explains why, on average, the marginal NO_X rate peaks in the early evening hours.

2.5.3 Marginal Emission Rates by Month

The previous estimates represent the average marginal emission rates, for each hour, over the course of the entire sample. However, the marginal emission rate for a specific hour will likely change over the course of a year. Figure 2.4 shows the average daily minimum and maximum residual loads, separated by month, on the Texas grid. The plot reveals large variations in the minimum and maximum daily residual loads across seasons. The maximum average residual load during the spring and fall months (March, April, October, November) is very similar to the minimum average residual load during the summer months (June, July, August). Therefore, the set of units on the margin during the off-peak hours will be different across months.[27]

In addition, when the off-peak and peak hours occur also varies across the course of a year. For each day in the three year sample, we identify which hour had the lowest residual load and which hour had the highest residual load. Figure 2.5 displays the frequency distributions of the minimum load hours and the maximum load hours for each month. During May through November, the minimum load hours are concentrated during the early morning hours (3 a.m. to 5 a.m.) and the maximum load hours are concentrated during the late afternoon (5 p.m. to 7 p.m.). During December through April, the distribution of the minimum and maximum load hours are more dispersed. In several of the months, the distribution of the minimum and maximum hourly loads are often bimodal. This is due to the fact that the daily load profiles reach local maximums during the mid-morning and during the afternoons.

Combined, Figure 2.4 and Figure 2.5 demonstrate that the residual demand during the off-peak and peak hours, as well as the timing of the off-peak and the peak hours, will change across months. To accurately estimate the impact of arbitrage on aggregate emissions, separate estimates of the off-peak and peak

[27]On top of the variation in the residual load, the quantity of base-load nuclear output varies systematically across months. During the low demand spring and fall months, the nuclear units are often taken off-line for maintenance and re-fueling. Therefore, at the same level of residual demand, more fossil fuel generation will be dispatched during the spring and fall to replace the missing nuclear output.

marginal emission rates are needed for different months. To predict these values, we re-estimate Eq. (2.9), allowing the coefficients to vary across both hours and months. The specification is shown here:

$$\Delta E_{h,d} = \beta_{h,m} \cdot \Delta G_{h,d} + \varepsilon_{h,d}. \tag{2.12}$$

The errors are again clustered across each individual day. The coefficient of interest, $\beta_{h,m}$, represents the average change in emissions from an additional MWh of dispatchable generation during hour h of month m.

Figure 2.6 displays the point estimates of average hourly marginal CO_2 rates, $\hat{\beta}_{h,m}$, for each month. The plots demonstrate there is substantial variation in the marginal emission rates across the hours of a single day, as well as across the same hour in different months. During most of the months, the average hourly marginal CO_2 rate peaks in the early morning hours and falls to its lowest levels in the afternoon hours. This is most pronounced during March, April, May, June, and October. During May for example, the average hourly marginal CO_2 rate peaks at a value of 0.79 tons of CO_2 per MWh at 4 a.m. and falls to around 0.54 tons of CO_2 per MWh during the late afternoon.

Figure 2.7 displays the average hourly marginal emission rates across each month for NO_X. In contrast to the marginal CO_2 rates, the average marginal NO_X rates tend to peak during the afternoon. This stems from the fact that the highest private cost generators, the high-heat rate natural gas units, represent the largest share of the marginal generation during the peak demand hours of the afternoon. Given that these less efficient natural gas units have the highest NO_X emission intensities, the marginal NO_X rates peak during the afternoon. This fact is most pronounced during the high demand summer months of May through September.

Figure 2.8 plots the average hourly marginal SO_2 rates for each month. Similar to the marginal CO_2 rates, the marginal SO_2 rates tend to peak during the early morning hours and reach their lowest points during the afternoon. Recall from Table 2.2, coal fired units are responsible for essentially all of the SO_2 emitted by the electric sector. Therefore, the variation in the marginal SO_2 rates is determined almost entirely by the variation in the share of coal generation on the margin.

2.6 Simulation

This section simulates the impact of a hypothetical electricity storage unit on the short-run emissions of CO_2, NO_X, and SO_2. Rather than modeling the dynamically optimized charging and discharging decisions of a profit maximizing storage owner, we assume the storage unit demands electricity from the grid during the off-peak period and supplies the electricity in the subsequent peak period. We examine the impact of a storage unit which charges at a rate of 1 MW and a storage capacity of 1 MWh.[28] Therefore, the storage unit will charge fully during a single hour. To explore the effect of different storage efficiencies, we allow the loss rate to vary.

2.6.1 Off-peak and Peak Marginal Emission Rates

The estimates of $\beta_{h,m}$ from Eq. (2.12) represent the average marginal emission rate during hour h of month m. To calculate the the average off-peak and peak marginal emission rates, we weight the values of $\hat{\beta}_{h,m}$ by the fraction of the time the off-peak period, or the peak period, occurs during hour h of month m. For example, assume the daily peak hour occurred at 5 p.m. ($h = 17$) half the time and 6 p.m. ($h = 18$) the other half during month m. Our measure of the the average peak marginal emission rate would be equal to $\hat{e}'_{p,m} = \frac{\hat{\beta}_{17,m}+\hat{\beta}_{18,m}}{2}$.

To determine the distribution of the daily off-peak and peak hours, we use two different strategies. The first method uses the frequency distribution of the hours with the minimum and maximum daily residual loads. These distributions are displayed in Figure 2.5. For month m, $\underline{f}_{h,m}$ represents the frequency the minimum daily residual load occurs during hour h, for $h = 1, \ldots, 24$. Similarly, $\bar{f}_{h,m}$ represents the frequency the maximum daily residual load occurs at hour h during month m. The second method uses the frequency distribution of the hours

[28]Future work will extend the analysis to consider a storage unit with a charge rate less than 1 MW and a storage capacity of 1 MWh. Therefore, the storage unit will demand electricity over multiple off-peak hours.

with the minimum and maximum daily market clearing prices, instead of residual loads. Both distributions are very similar, and as a result, produce very similar estimates of the monthly average off-peak and peak marginal emission rates.

To predict the off-peak and peak marginal emission rates for month m, we calculate the weighted average of the 24 hourly estimates of $\beta_{h,m}$. The weights used to calculate the average off-peak marginal emission rate for month m are the hourly values for $\underline{f}_{h,m}$. The weights used to calculate the average peak marginal emission rate for month m are the hourly values for $\bar{f}_{h,m}$. For each month, the off-peak and the peak marginal emission rates, $\hat{e}'_{o,m}$ and $\hat{e}'_{p,m}$, respectively, are given by the following expressions:

$$\hat{e}'_{o,m} = \sum_{h=1}^{24} \underline{f}_{h,m} \cdot \hat{\beta}_{h,m} \tag{2.13}$$

$$\hat{e}'_{p,m} = \sum_{h=1}^{24} \bar{f}_{h,m} \cdot \hat{\beta}_{h,m}. \tag{2.14}$$

Figure 2.9 plots the average off-peak and peak marginal emission rates for each of the three pollutants. The solid lines represent the estimates made using the frequency distributions of the minimum and maximum residual load hours. The dashed lines represent the estimates made using the frequency distributions of the minimum and maximum price hours.

With the exception of the peak demand summer months of July and August, the marginal off-peak CO_2 rates are greater than the marginal peak CO_2 rates. During the spring and fall months (April, May, June, October, and November), the off-peak marginal CO_2 rates are larger than the peak marginal CO_2 rates by 0.14-0.24 tons per MWh. These results are largely driven by the fact that coal generation accounts for a larger share of the off-peak marginal generation. During the peak demand summer months, the share of coal generation on the margin off-peak falls and the share of inefficient, high heat-rate gas units on the margin during the peak periods rise. As a result, the peak marginal CO_2 rate exceeds the off-peak marginal CO_2 rate during these months.

In contrast to CO_2, the marginal NO_X rates are consistently higher during the peak hours. This is most pronounced between May and August when the peak demand tends to be quite large. Again, during these summer months, inefficient gas units, with high NO_X emission rates, account for a large share of the marginal peak generation.

Finally, the off-peak marginal SO_2 rate exceeds the peak marginal SO_2 rate in each month. Recall from Table 2.2, the combustion of coal is responsible for essentially all of the SO_2 emitted. Therefore, the off-peak and peak marginal SO_2 rates are primarily driven by the share of coal generation on the margin during the respective periods. Coal fired units, which have low marginal generation costs, typically operate at full capacity during the peak hours. As a result, the marginal peak SO_2 rate during the summer months is essentially zero.

2.6.2 Impact of Arbitrage on Emissions

This section uses the estimates of the average monthly off-peak and peak marginal emission rates to simulate the impact a marginal increase in arbitrage would have on aggregate pollution. We do not simulate the optimal charge and discharge pattern of a storage unit. Instead, we model a storage unit that stores a MWh of electricity during each off-peak period and supplies the stored energy during the subsequent peak period.

Recall from the analytical model, a marginal increase in arbitrage will result in the following change in emissions:

$$\frac{\partial e_m}{\partial s_o} = e'_{o,m} - (1 - \alpha) \cdot e'_{p,m}, \tag{2.15}$$

where e_m is the daily aggregate emissions, during month m, and α is the loss rate of the hypothetical storage unit. Using the average monthly off-peak and peak marginal emission rates presented in the previous section, we predict the value of $\frac{\partial e_m}{\partial s_o}$ for a hypothetical storage device with loss rates of $\alpha = \{0.3, 0.2, 0.1, 0\}$. PHS and CAES units in operation have loss factors typically between 0.2 and 0.3. Therefore, the hypothetical storage units modeled represent the current technology, as well as the impact of potentially more efficient, future storage technologies.

Table 2.4 presents the estimates of the impact arbitraging a MWh of off-peak electricity will have on the daily level of CO_2, NO_X, and SO_2 emitted. Consistent with the results presented in Figure 2.9, arbitraging electricity will generally increase the daily emissions of CO_2. The only exception is during July and August when the peak marginal CO_2 rate exceeds the off-peak marginal emission rate. Even during these months, a storage unit will need to have a loss rate near $\alpha = 0$ in order to achieve any emission reductions. With loss rates of 0.3 or 0.2, storing off-peak electricity, and re-supplying the energy during the daily peak hour, will increase the daily CO_2 by an average of 0.26 or 0.20 tons per MWh stored, respectively.

Similar to the predicted impact on CO_2, arbitraging electricity will uniformly increase the daily emissions of SO_2. In most cases, increasing the efficiency of the hypothetical storage unit does not substantially alter the estimated impact on SO_2. This is due to the fact that the peak marginal SO_2 rates tend to be quite small. Therefore, even if none of the energy is lost during the storage process, the quantity of SO_2 being offset during the peak period is trivial compared to the increase in off-peak SO_2 emissions.[29]

In contrast to CO_2 and SO_2, the results in Table 2.4 demonstrate that, on average, NO_X emissions will fall when electricity is arbitraged across periods. The predicted reductions in NO_X are the largest during the summer months when the peak marginal NO_X rates are the greatest. As opposed to the predicted impact on SO_2, increasing the efficiency of the storage unit has large impacts on the quantity of NO_X avoided. This is due to the fact that the peak marginal NO_X rates become quite large over the high demand months.

2.6.3 External and Private Benefits of Arbitrage

The two-period model in Section 2.3 demonstrates that the marginal private benefit and the marginal social benefit of electricity arbitrage can differ if the wholesale prices do not accurately reflect the social cost of pollution. This section

[29]Although the point estimate is not statistically different than zero, during August, the estimate of the peak marginal SO_2 rate is slightly negative. As a result, increasing the efficiency of the storage unit results in a slight increase in the predicted level of SO_2 emissions.

Table 2.4: Impact of Arbitrage on Emissions

		Month												
		Jan.	**Feb.**	**Mar.**	**Apr.**	**May**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**	***Average***
	$\alpha = 0.3$	0.22	0.20	0.22	0.32	0.40	0.29	0.14	0.13	0.19	0.36	0.34	0.26	***0.26***
ΔCO_2	$\alpha = 0.2$	0.16	0.14	0.16	0.26	0.35	0.24	0.08	0.06	0.13	0.31	0.28	0.20	***0.20***
(tons/MWh)	$\alpha = 0.1$	0.11	0.08	0.11	0.20	0.30	0.18	0.02	0.00	0.08	0.25	0.22	0.15	***0.14***
	$\alpha = 0$	0.05	0.02	0.05	0.14	0.24	0.12	-0.04	-0.06	0.02	0.20	0.16	0.09	***0.08***
	$\alpha = 0.3$	0.15	0.16	-0.01	0.17	-0.15	-0.40	-0.90	-0.74	-0.10	0.31	0.45	0.18	***-0.07***
ΔNO_X	$\alpha = 0.2$	0.08	0.08	-0.10	0.09	-0.25	-0.54	-1.07	-0.92	-0.19	0.24	0.38	0.10	***-0.18***
(lbs/MWh)	$\alpha = 0.1$	0.00	0.01	-0.19	0.02	-0.35	-0.69	-1.25	-1.11	-0.29	0.17	0.31	0.02	***-0.28***
	$\alpha = 0$	-0.07	-0.06	-0.28	-0.06	-0.45	-0.83	-1.43	-1.30	-0.38	0.11	0.24	-0.05	***-0.38***
	$\alpha = 0.3$	0.85	1.00	1.23	2.37	2.01	2.58	1.33	1.45	2.27	2.60	3.12	1.27	***1.84***
ΔSO_2	$\alpha = 0.2$	0.83	0.89	1.20	2.33	1.99	2.52	1.32	1.46	2.23	2.57	2.98	1.20	***1.79***
(lbs/MWh)	$\alpha = 0.1$	0.80	0.78	1.17	2.28	1.97	2.47	1.31	1.48	2.20	2.54	2.85	1.13	***1.75***
	$\alpha = 0$	0.77	0.67	1.14	2.24	1.95	2.41	1.31	1.49	2.17	2.50	2.71	1.06	***1.70***

Change in emissions represent average change caused by storing one MWh of off-peak electricity each day. Loss rate of hypothetical storage unit represented by α. Averages are equal to the simple average of the predicted impact on emissions over the twelve months for the given pollutant and loss rate.

examines the extent to which the marginal private and marginal social benefits of electricity arbitrage differ in the Texas electricity market. Combining the estimates of the average impact on emissions with information on the average off-peak and peak wholesale electricity prices, we demonstrate that the marginal private benefits of arbitrage exceed the marginal social benefits by a sizable amount.

The results in Table 2.4 demonstrate electricity arbitrage will affect the short-run level of pollution emitted by fossil fuel generators. In the Texas market, the daily aggregate emissions of CO_2 and SO_2 will increase with arbitrage while the quantity of NO_X will generally decrease. Within the region, CO_2 emissions are not subject to any form of regulation. Therefore, the social cost of CO_2 is not reflected in the wholesale electricity prices. In addition, short-run increases in the emissions of CO_2 represent real increases in the level of pollution.

In contrast to CO_2, the emissions of SO_2 and NO_X are subject to national and regional caps.[30] For each pound of SO_2 and NO_X emitted, fossil fuel generators incur a private cost equal to the market price of the pollution permits. As a result, the social cost of SO_2 and NO_X are at least partly reflected in the wholesale electricity prices. In addition, if the SO_2 and NO_X caps are binding, short-run changes in SO_2 or NO_X emissions will not represent long-run changes in the aggregate level of pollution. Instead, changes in the short-run level of SO_2 and NO_X will result in more, or less, permits that can be used to pollute at a different time or in a different location.

Despite the fact that the aggregate level of SO_2 and NO_X emissions will not change over the long-run with increased arbitrage, the social cost of these emissions can change. Unlike CO_2, both SO_2 and NO_X are not perfectly mixing pollutants. Where and when the emissions occur can alter the the social costs. For example, arbitrage may reduce the level of NO_X from natural gas units located near population centers. If the freed up NO_X permits are used by fossil fuel units located farther from demand centers, the social cost of the pollution may in fact be reduced. Additionally, if the pollution occurs during the off-peak, nighttime

[30] SO_2 emissions are capped nationally under the Clean Air Act. Additionally, regional and local caps on NO_X emissions across states and within Non-attainment regions of Texas, such as the Houston-Galveston-Brazoria area, are in place.

hours instead of the peak daytime hours, the costs incurred by the non-perfectly mixing pollutants may differ.

Future work on this topic will explore the implications of arbitrage on the social costs of both regulated and unregulated non-perfectly mixing pollutants. In this study, we focus instead on the impact of arbitrage on the external costs of CO_2 emissions. To determine the external costs from changes in the quantity of CO_2 emitted, we use values for the social cost of carbon from the Interagency Working Group (2010) report. The report provides lower (\$5/ton), middle (\$21/ton), and upper (\$35/ton) estimates of the external cost of CO_2 using discount rates of 5%, 3.5%, and 2%, respectively. A high cost estimate of \$65/ton of CO_2 is also provided, representing the case where the external damages are assumed to be at the upper end of the distribution.

Table 2.5 presents the estimates of the average external benefit, by month, of arbitraging one MWh of off-peak electricity for different levels of α. Given that arbitrage will generally increase the daily emissions of CO_2, the external benefits are consistently negative. As the storage unit become more efficient, the average external costs uniformly approach zero. For higher estimates of the social cost of CO_2, the external costs of arbitrage are larger.

Recall from the two-period model, the private returns to arbitrage are given by the following expression:

$$\frac{\partial \pi_m}{\partial s_o} = (1-\alpha) \cdot P_{p,m} - P_{o,m} \tag{2.16}$$

where $P_{p,m}$ and $P_{o,m}$ are the peak and off-peak wholesale electricity prices during month m. Table 2.5 provides predictions of the marginal profit a storage owner will earn by arbitraging one MWh of electricity between off-peak and peak hours each day. Given that we do not simulate the optimal charge and discharge decisions of a profit maximizing storage owner, these values can be thought of as representing reasonable lower bounds on the private returns to arbitrage. The results demonstrate that depending on the efficiency of the storage unit, the owner will earn between \$20.70 and \$42.24 per MWh of off-peak electricity stored. The largest monthly profits occur during the peak demand summer months when the

Table 2.5: External and Private Benefits of Arbitrage

Benefit ($/MWh)		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	*Average*
		Month												
External Benefit (CO_2= $5/ton)	$\alpha = 0.3$	-1.08	-1.01	-1.08	-1.58	-2.01	-1.47	-0.71	-0.63	-0.95	-1.82	-1.69	-1.30	***-1.28***
	$\alpha = 0.2$	-0.80	-0.72	-0.81	-1.28	-1.75	-1.18	-0.41	-0.32	-0.67	-1.54	-1.39	-1.02	***-0.99***
	$\alpha = 0.1$	-0.53	-0.42	-0.53	-0.99	-1.48	-0.88	-0.11	-0.02	-0.39	-1.27	-1.09	-0.73	***-0.70***
	$\alpha = 0$	-0.26	-0.12	-0.25	-0.69	-1.21	-0.58	0.18	0.29	-0.11	-0.99	-0.80	-0.45	***-0.42***
External Benefit (CO_2= $21/ton)	$\alpha = 0.3$	-4.52	-4.25	-4.54	-6.62	-8.46	-6.18	-2.96	-2.65	-3.99	-7.64	-7.08	-5.45	***-5.36***
	$\alpha = 0.2$	-3.38	-3.00	-3.38	-5.38	-7.33	-4.94	-1.72	-1.36	-2.81	-6.48	-5.84	-4.27	***-4.16***
	$\alpha = 0.1$	-2.24	-1.76	-2.22	-4.14	-6.20	-3.69	-0.48	-0.08	-1.64	-5.31	-4.60	-3.08	***-2.95***
	$\alpha = 0$	-1.10	-0.51	-1.06	-2.90	-5.07	-2.45	0.77	1.20	-0.46	-4.15	-3.36	-1.89	***-1.75***
External Benefit (CO_2= $35/ton)	$\alpha = 0.3$	-7.54	-7.08	-7.57	-11.04	-14.10	-10.30	-4.94	-4.41	-6.64	-12.73	-11.80	-9.09	***-8.94***
	$\alpha = 0.2$	-5.63	-5.01	-5.64	-8.97	-12.22	-8.23	-2.87	-2.27	-4.69	-10.79	-9.73	-7.11	***-6.93***
	$\alpha = 0.1$	-3.73	-2.93	-3.71	-6.91	-10.34	-6.16	-0.79	-0.14	-2.73	-8.86	-7.66	-5.14	***-4.92***
	$\alpha = 0$	-1.83	-0.86	-1.77	-4.84	-8.45	-4.09	1.28	2.00	-0.77	-6.92	-5.59	-3.16	***-2.92***
External Benefit (CO_2= $65/ton)	$\alpha = 0.3$	-13.99	-13.15	-14.06	-20.50	-26.18	-19.12	-9.18	-8.19	-12.34	-23.64	-21.92	-16.88	***-16.60***
	$\alpha = 0.2$	-10.46	-9.30	-10.47	-16.66	-22.69	-15.28	-5.33	-4.22	-8.70	-20.04	-18.07	-13.21	***-12.87***
	$\alpha = 0.1$	-6.93	-5.44	-6.88	-12.82	-19.19	-11.44	-1.48	-0.26	-5.07	-16.45	-14.23	-9.54	***-9.14***
	$\alpha = 0$	-3.40	-1.59	-3.29	-8.99	-15.70	-7.59	2.37	3.71	-1.43	-12.85	-10.39	-5.86	***-5.42***
Private Benefit (Profit/MWh)	$\alpha = 0.3$	4.89	8.19	4.81	16.98	24.88	25.67	34.69	38.50	35.58	23.23	20.76	10.17	***20.70***
	$\alpha = 0.2$	11.04	13.94	10.23	23.59	32.59	34.31	43.88	48.46	43.56	29.52	26.93	16.46	***27.88***
	$\alpha = 0.1$	17.18	19.69	15.65	30.20	40.31	42.95	53.07	58.42	51.53	35.81	33.11	22.75	***35.06***
	$\alpha = 0$	23.32	25.44	21.07	36.81	48.02	51.59	62.26	68.38	59.51	42.10	39.29	29.04	***42.24***

Loss rate of hypothetical storage unit represented by α. Monthly average external benefit is equal to the product of the average change in CO_2 per MWh stored off-peak and the external cost of CO_2. Profits are calculated by multiplying the average daily peak prices across each month by the loss rate and substracting the average daily off-peak price. Total averages are equal to the simple average external or private benefit across each month.

peak wholesale prices on average exceed \$100/MWh.

The marginal social benefit of storage is equal to the sum of the marginal external benefit and the marginal private benefit. For $\alpha = \{0.3, 0.2, 0.1\}$, and for each value of the social cost of CO_2, the marginal social benefit of storing a MWh of off-peak electricity falls below the marginal private benefit. Even with a perfectly efficient storage unit ($\alpha = 0$), the marginal private benefit exceeds the marginal social benefit of arbitrage during ten of the twelve months. In the case where $\alpha = 0.3$, and the marginal social cost of CO_2 is \$65/ton, the external cost of arbitraging one MWh of off-peak electricity is larger than the average private benefit during eight of the twelve months. While electricity arbitrage will earn positive profits for the storage owner during these months, the social benefit is actually below zero.

2.7 Conclusion

States have begun implementing policies which will spur dramatic increases in electricity storage capacity. These storage additions are seen as a vital complement to the growing share of intermittent, renewable generation. Despite the widely held belief that bulk electricity storage will augment the benefits provided by expanding renewable capacity, this paper demonstrates that electricity arbitrage, a major role of bulk storage, can in fact lead to greater levels of pollution and, in some cases, lower optimal levels of renewable capacity.

Given the small penetrations of renewable capacity currently in place, low marginal cost renewables are generally not the marginal sources of electricity. As a result, arbitraging electricity across time will not alter the short-run level of renewable generation. Instead, arbitrage will lead to increased off-peak conventional generation and decreased peak conventional generation. If the emission rates of the units on the margin during the peak periods are not sufficiently below the emission rates of the units on the margin during the off-peak periods, then arbitraging electricity will increase the aggregate daily level of pollution.

In addition to altering the level of pollution from conventional sources, electricity arbitrage will also affect the value of renewable capacity investments. Arbitraging electricity will increase the demand for off-peak electricity and increase the supply of electricity during peak demand periods. As a result, the off-peak prices will increase while the peak prices will decrease. Renewable technologies which produce more heavily during the off-peak periods, such as on-shore wind turbines, will benefit from arbitrage. However, the returns to renewable sources which produce more heavily during the peak demand periods, such as solar, decrease with greater amounts of arbitrage. Depending on the type of renewable energy available in a specific region, greater levels of arbitrage can increase or decrease the optimal amount of renewable capacity.

The empirical estimates of the external impact of arbitrage focus on the social cost of CO_2. Future work will explore how electricity arbitrage affects the costs of non-perfectly mixing pollutants such as NO_X. This will include an examination of how arbitrage not only affects the temporal distribution of emissions, but also the spatial distribution of pollution. In addition, extensions of this analysis can examine the dynamic interactions between electricity storage capacity and renewable generation. We demonstrate that storage will alter the value of renewable investments. The opposite is true as well; some renewable sources will increase the value of bulk storage (*e.g.* on-shore wind), while other renewable sources will decrease the value of storage (*e.g.* solar).

Chapter 2, which has been co-authored with Richard Carson, is currently being prepared for submission for publication. The dissertation author was the primary investigator and author of this material.

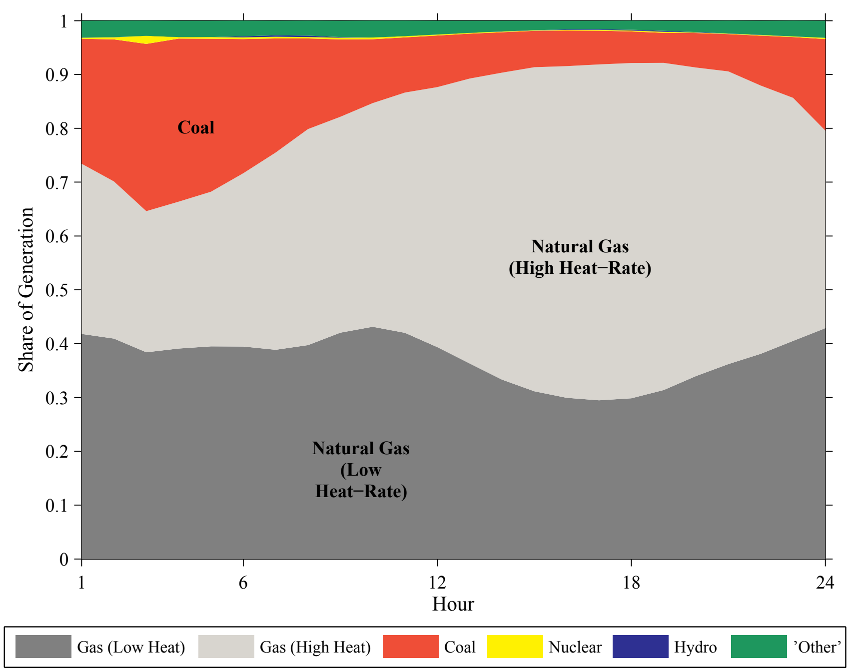

Figure 2.3: Hourly Marginal Generation by Fuel

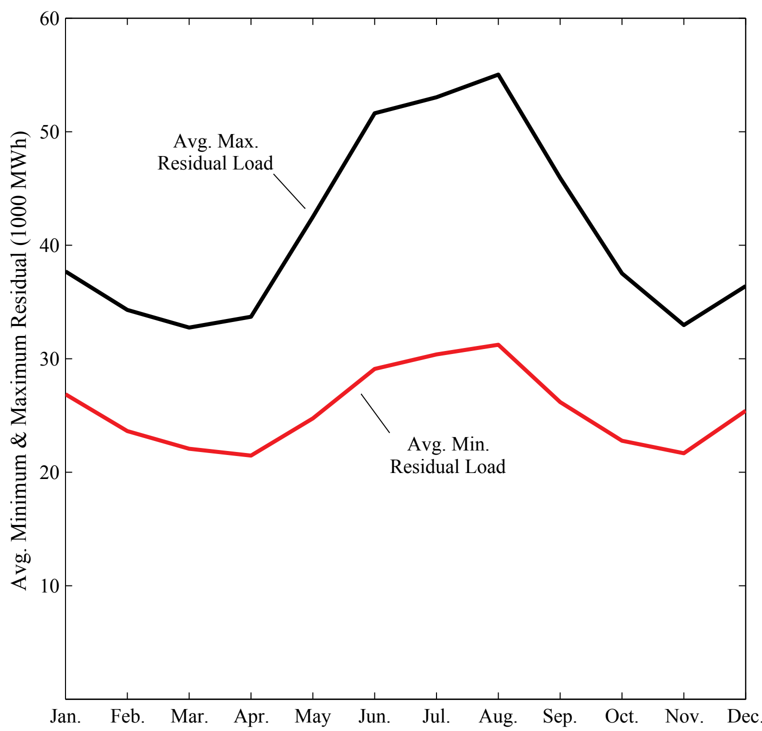

Figure 2.4: Average Daily Minimum and Maximum Residual Load

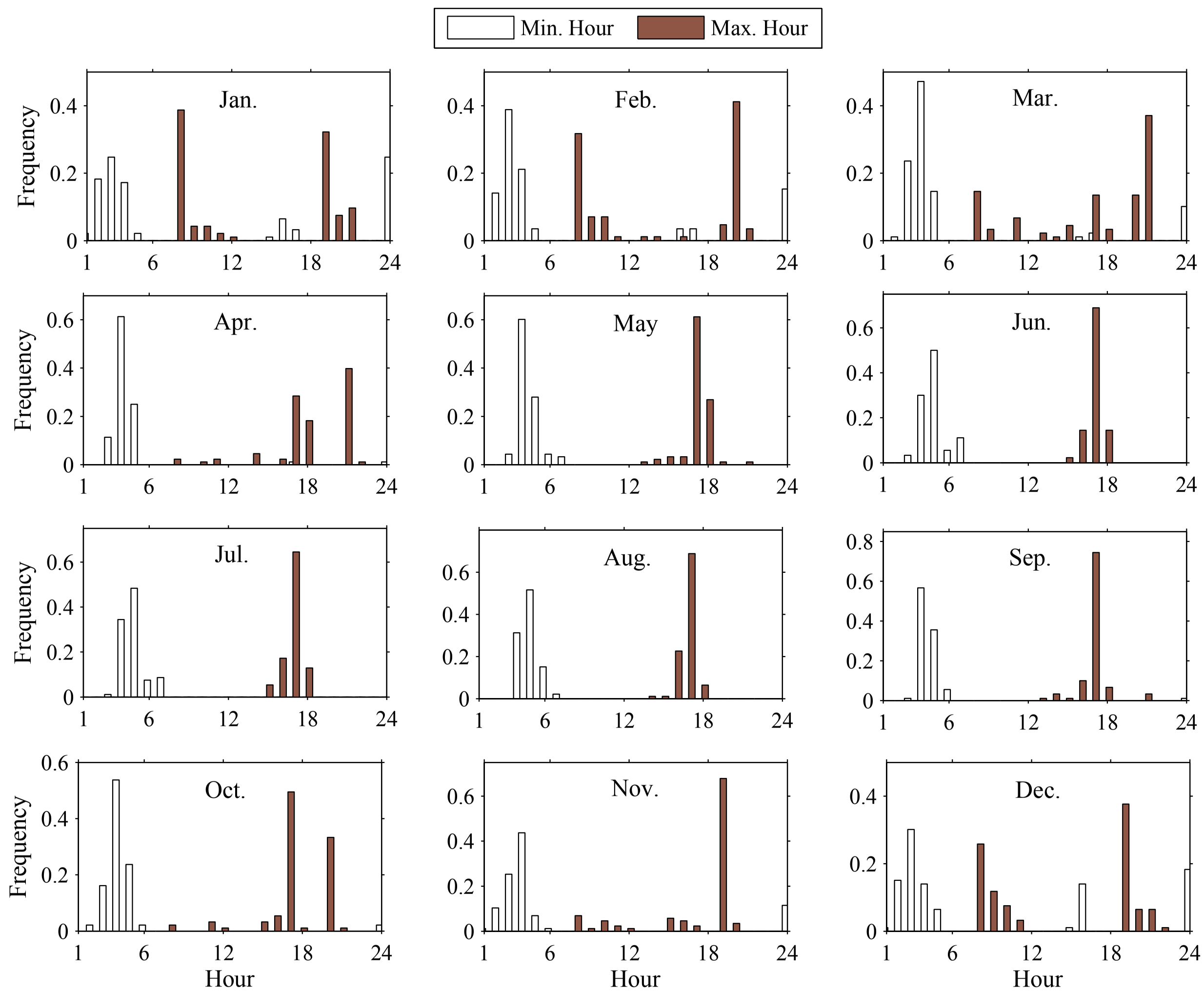

Figure 2.5: Distribution of Minimum and Maximum Residual Load Hours

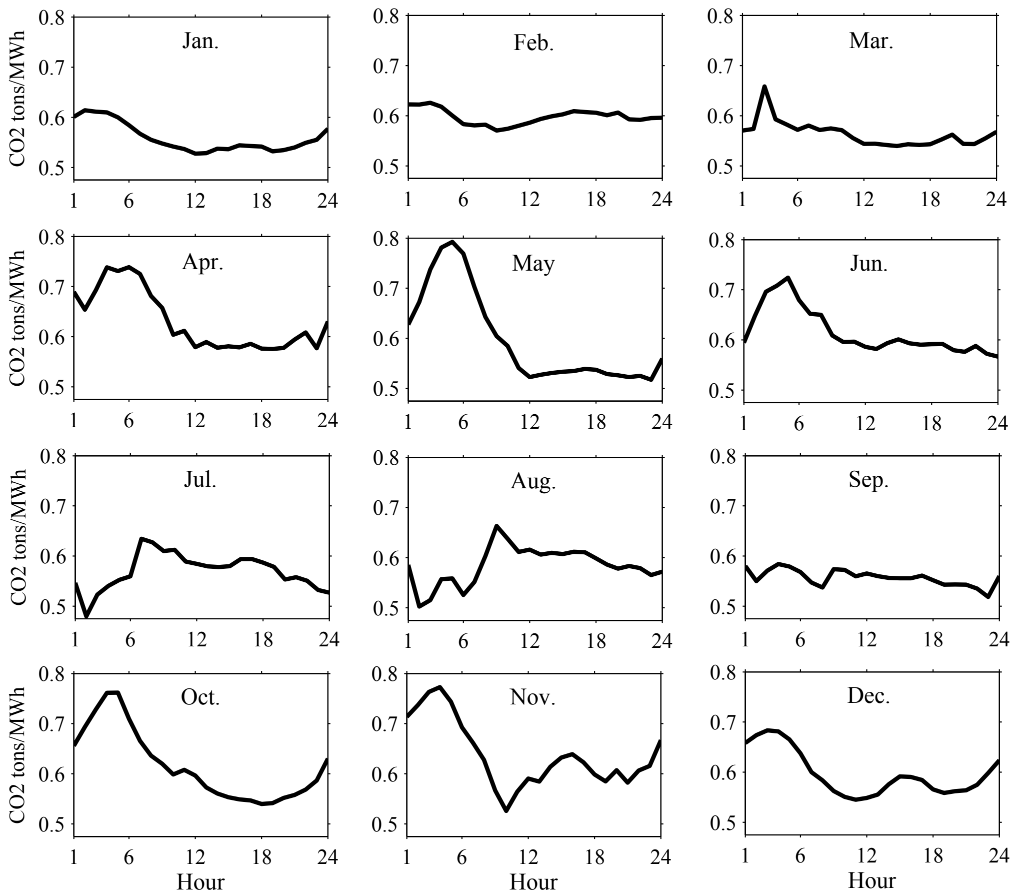

Figure 2.6: Average Hourly Marginal CO_2 Rate

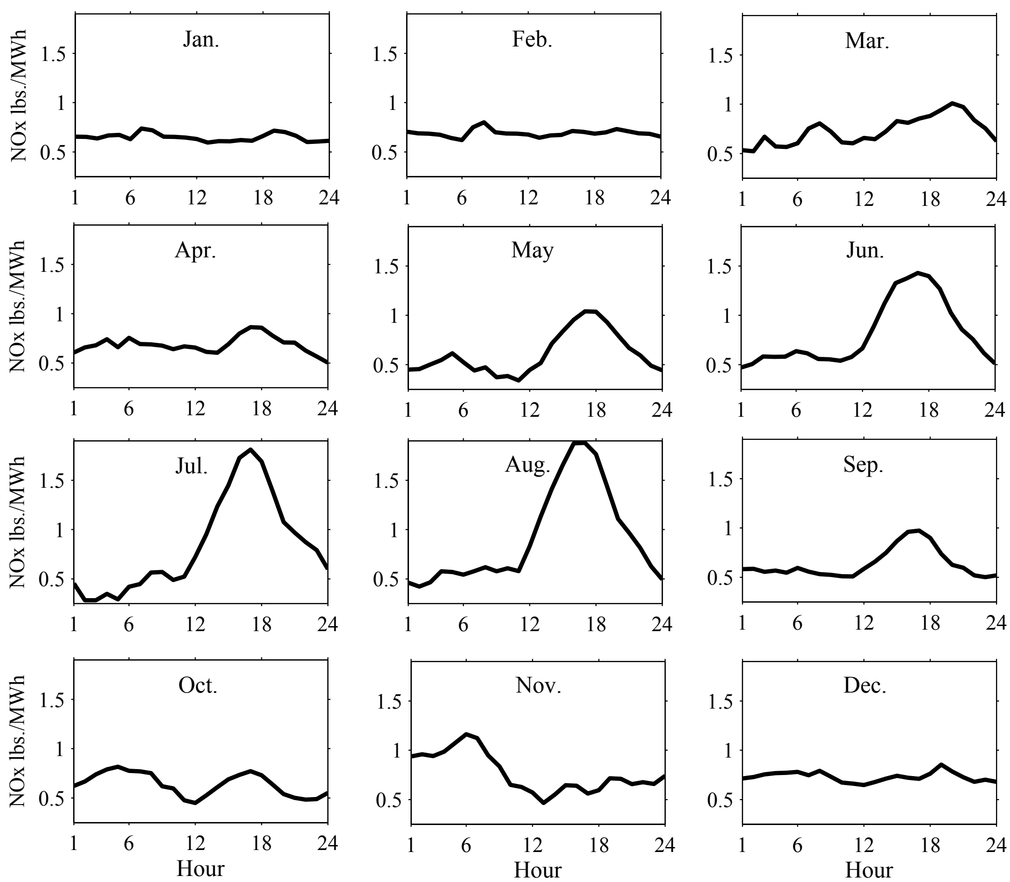

Figure 2.7: Average Hourly Marginal NO_X Rate

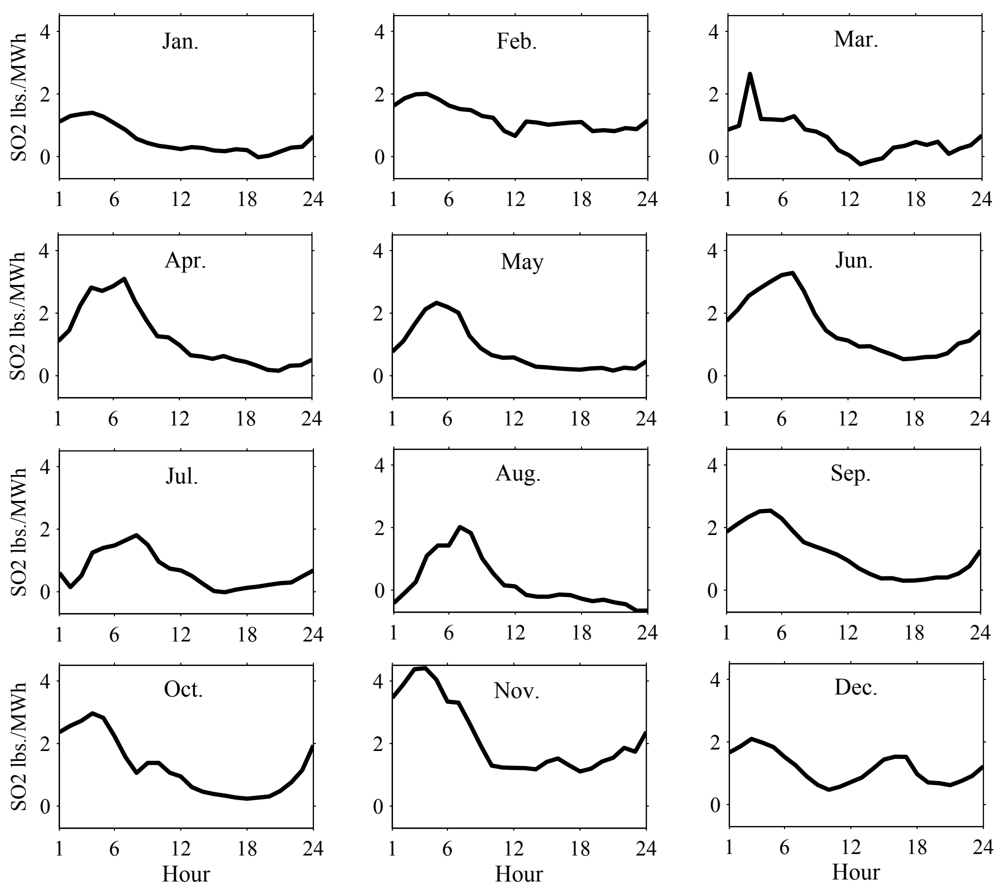

Figure 2.8: Average Hourly Marginal SO_2 Rate

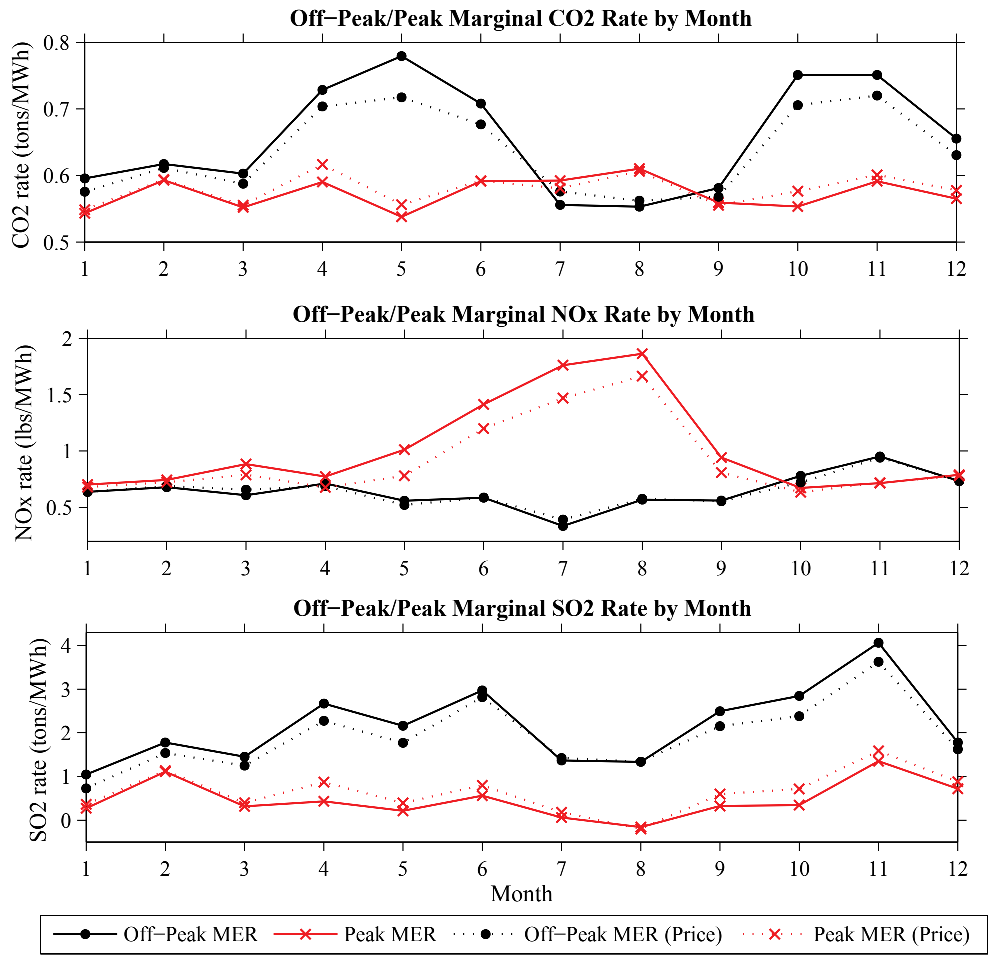

Figure 2.9: Off-Peak vs. Peak Marginal Emission Rates by Month

Chapter 3

Gasoline Taxes and Revenue Volatility: An Application to California

Abstract

This paper examines how different combinations of gasoline excise and sales taxes impact the volatility of state tax revenues. Unlike many commodities which have sales taxes levied on them, gasoline has a unique combination of two key features. First, prices are very volatile. Second, demand for gasoline is extremely inelastic. As a result, there is substantial variation in the total expenditures on gasoline over time. Tying state revenue to these variable fuel expenditures, as is the case with a sales tax, results in a volatile stream of revenue which imposes real costs on agents in an economy. On July 1, 2010, California enacted Assembly Bill 6, the "Gas Tax Swap", which increased the excise tax and decreased the sales tax on fuel purchases. While the initial motivation behind the revenue neutral tax swap was to provide the state with greater flexibility within its budget, we point out that this temporary change has had an overlooked benefit; it reduces tax revenue volatility. Simulating the monthly fuel prices and tax revenues under alternative tax policies, we quantify the potential reductions in revenue volatility. The results reveal that greater benefits can be achieved by going beyond the tax

swap and eliminating the gasoline sales tax entirely.

3.1 Introduction

An extensive literature examines the optimal long-run level of fuel taxation, however, very little attention has been paid to the type of tax mechanism that should be used to achieve this target.[1] In practice, many US states levy both per unit (excise) taxes as well as ad valorem (sales) taxes on the purchases of gasoline and diesel. This analysis compares the performance of different combinations of excise and sales taxes. We demonstrate that the structure of fuel taxes affects the volatility of both retail fuel prices and resulting tax revenues. The analysis focuses on California, where the fiscal environment makes the costs of volatility in both series clear, although our conclusions hold more generally for any government with borrowing constraints.

The combination of two features of the market for gasoline and diesel makes fuel unlike other commodities which have sales taxes levied on them. First, prices for the fuels are very volatile. Second, demand for gasoline and diesel is extremely inelastic. As a result, there is substantial variation in the total expenditures on gasoline and diesel over time. Tying state revenue to these variable fuel expenditures, as is the case with a sales tax, results in a volatile stream of revenue which imposes real costs on agents in an economy. In contrast, a fixed per unit tax on gasoline results in less volatile prices and generates government revenues that are decoupled from volatile gas prices.

On July 1, 2010, California enacted Assembly Bill x8-6, the "Gas Tax Swap". This tax change increased the state excise tax on gasoline purchases from 18 to 35.3 cents per gallon and decreased the state sales tax on gasoline from 8.25% to 2.25%.[2] The initial motivation behind the policy change was to provide the state with greater flexibility within its budget, by reducing the amount of

[1] For an examination of the optimal long-run tax level, see for example Parry and Small (2005), Harrington *et al.* (2007), and Lin and Prince (2009).

[2] The Gas Tax Swap will achieve revenue neutrality if gas prices average $2.79 per gallon over the life of the program. The Tax Swap was reenacted for the period from July 1, 2011 through June 30, 2012 with an excise tax rate of 35.7 cents per gallon.

revenues earmarked for transportation spending, while remaining revenue neutral in the long run.[3] We point out that this policy change has had two potentially overlooked benefits; it reduces retail fuel price volatility as well as tax revenue volatility in the state of California. The objective of this paper is twofold. First, we quantify the reductions in both retail price volatility and state fuel revenue volatility stemming from the Gas Tax Swap. Second, we estimate the additional reductions in volatility that can be achieved by going beyond the tax swap and eliminating the sales tax on fuel expenditures entirely.

The remainder of this paper proceeds as follows. Section 2 discusses the sources of retail gasoline price volatility and the resulting impact on total gasoline expenditures. Section 3 describes the structure of California's gasoline tax policy. Specific attention is paid to the revenue generated by fuel taxes and the resulting impact on revenue volatility. Section 4 explains the methodology we use to simulate the alternative gasoline tax policies and Section 5 presents the results. Section 6 concludes by discussing further considerations.

3.2 Fuel Prices and Consumer Gasoline Expenditures

Gasoline and diesel price volatility stems from multiple sources. Shifts in supply and demand at the state and local level account for a portion of the variation in these prices. For example, seasonal shifts in driving patterns and stricter environmental regulations tend to increase prices during the summer (Chouinard, 2004). Further research uncovers price cycles driven my monopolistic competition at the local level (Noel, 2009). However, the majority of retail gasoline and diesel price volatility stems from fluctuations in the price of their primary input, crude oil. A simple regression of the monthly average gasoline price on the monthly average oil price over the last 15 years reveals that 95% of the variation in gasoline

[3] Proposition 42, passed March 5, 2002 by a 69-31% margin, requires sales taxes collected on motor fuel to be spent exclusively on transportation projects. Although one goal of the swap was budget flexibility, voters approved two ballot initiatives during the November 2010 election which reestablished the link between fuel revenues and transportation spending.

prices is explained by changes in the spot oil price.[4]

Oil prices are both notoriously volatile and prone to large and persistent swings. The price of crude oil, which is determined on a world market, is essentially unaffected by changes in fuel demand within a single state.[5] As a result, unlike regular, expected cycles in regional gasoline supply and demand, fluctuations in world oil prices are much less forecastable.[6]

While fuel prices are prone to large and persistent fluctuations, fuel demand is not. An individual consumer's demand for gasoline is largely driven by major life decisions: choice of vehicle, location of residence, and location of employment. As a result, consumers are often unable to respond significantly to price swings in the short and medium-run. Hughes *et al.* (2008) estimate the short-run elasticity of demand using monthly, aggregate US data and find values ranging between -0.034 to -0.077. Following their estimation, in an appendix we present separate estimates of the monthly price elasticities of demand for both gasoline and diesel in California. The point estimates from our sample period, 2001-2010, are elasticities of -0.056 for gasoline and -0.034 for diesel.

Combining consumer's very inelastic demand for fuel with volatile fuel prices results in large swings in the share of household expenditures allocated to fuel purchases.[7] These large swings in total fuel expenditures can have two negative impacts.

First, when fuel prices abruptly change, consumers are faced with random shocks to their purchasing power. These unpredictable shocks impose real costs on households, with larger shocks imposing larger costs. Ideally, consumers could hedge this financial risk however, no simple options exist. Past work highlights that fuel taxes can be used to mitigate retail price volatility. For example, LeClair

[4]The Energy Information Administration provides data on the average retail gasoline price at the state level as well as the daily spot price for oil delivered to Cushings, TX. The general finding that oil prices drive gasoline prices has been shown to hold more broadly by many authors (for example, see Chouinard and Perloff, 2007).

[5]California accounts for about 1% of world oil consumption. Marginal changes within California alone would have a trivial impact on world oil markets.

[6]Hamilton (2008) highlights that historically, oil price changes have been both permanent and difficult to predict.

[7]During 2008, expenditures on gasoline and diesel accounted for 5.4% of total consumer spending in the US. Expenditure information is available from the 2008 Consumer Expenditure Survey.

(2006) proposes a variable excise tax on gasoline which moves inversely with the actual retail price.

In contrast, a fuel tax policy that includes a sales tax results in a per gallon tax that increases with prices. The positive correlation between per gallon prices and per gallon taxes amplifies volatility in retail gasoline prices, making consumers worse off.[8]

The second potential negative impact of fuel expenditure volatility is its effect on government revenues. A government can tax the quantity of a good consumed–by imposing an excise tax–or the expenditure on consumption of the good–by imposing a sales tax. When consumption of a good is unresponsive to price, as it is in the case of gasoline and diesel, an excise tax will completely insulate tax revenues from price fluctuations. Under the same conditions, a sales tax will pass price variation through to government revenues. Previous research has paid very little attention to the impact of fuel tax structure on the volatility of resulting revenues.[9] In the proceeding section, we examine the structure of California fuel taxes before and after the Gas Tax Swap. Specific attention is paid to the revenue resulting from these taxes as well as the costs of volatility in these revenue streams.

3.3 Fuel Taxes and Revenue Volatility

During 2009, the combination of all federal and state taxes accounted for 17.55% of the average US retail price of gasoline paid at the pump.[10] Every gallon of gasoline is subject to an 18.4 cent federal excise tax–a flat fee per gallon purchased.[11] In addition, all states in the US charge an excise tax on gasoline, with values ranging from 2 to 35.7 cents per gallon (Tax Foundation, 2011). Seven states

[8]There many reasons why increased volatility has increased costs for households. A few of the more prominent examples include risk aversion, liquidity constraints, borrowing costs.

[9]Borenstein (2009) suggests a variable gasoline surcharge for California explicitly taking into consideration the effect of fuel price declines on state revenue. However, the surcharge, which functions as a price floor, represents an overall increase in the tax rate rather than a revenue neutral change in the tax structure.

[10]See Energy Information Administration's Gasoline Components History.

[11]The federal excise tax on diesel fuel is 24.4 cents per gallon. Other taxes apply to crude oil, and are presumably at least partially passed through to make up some portion of the price at the pump.

also impose some form of sales tax on gasoline–ranging from 2% to 9.25%–with taxes paid by consumers varying across local jurisdictions as well.

California is one of the states that applies a sales tax in addition to an excise tax on gasoline and diesel. The recently imposed Gas Tax Swap increased the state excise tax on gasoline purchases from 18 to 35.3, and finally 35.7, cents per gallon and decreased the state sales tax on gasoline expenditures from 8.25% to 2.25%. As originally enacted, the policy represented a temporary change, with the new rates in place through the end of the 2012 fiscal year.

During the 2009-2010 fiscal year, the last fiscal year before the Gas Tax Swap, the total state revenue for California was 112.1 billion dollars. The two largest sources of revenue were the personal income tax (40.4% of total revenue) and the retail sales tax (29.7% of total revenue). Combined, revenue from gasoline and diesel taxation accounted for 6.5% of total state revenue. Though not as large as the share of revenues derived from other sources, such as income, sales or capital gains taxes, fuel taxes are nonetheless a sizable share of state revenues.

Of the 7.3 billion dollars of Fiscal Year 2009 revenue linked to fuel taxes, 44% came from sales taxes and 56% came from excise taxes. Over time however, these two revenue streams behave very differently. The bottom panel of Figure (3.1) plots the monthly revenue from fuel excise taxes, on both gasoline and diesel purchases, as well as the monthly sales tax revenue from fuel expenditures between January, 2005 and June, 2010. The excise tax revenues, which are linked to fuel consumption, are very smooth. In contrast, the sales tax revenues, which are linked to fuel expenditures, are not. Comparing the monthly sales tax revenue to the monthly average gasoline price demonstrates how these swings in revenue generated by taxing fuel expenditures are driven by the fluctuations in the retail price.

Over this time period, California raised revenue from a combination of two taxes on fuel, and it is clear from Figure (3.1) that relying more heavily on an excise tax would have produced a much more stable revenue stream than the hybrid approach. For a government with low borrowing costs and no borrowing constraints, there will be no real benefits from increased revenue stability in the

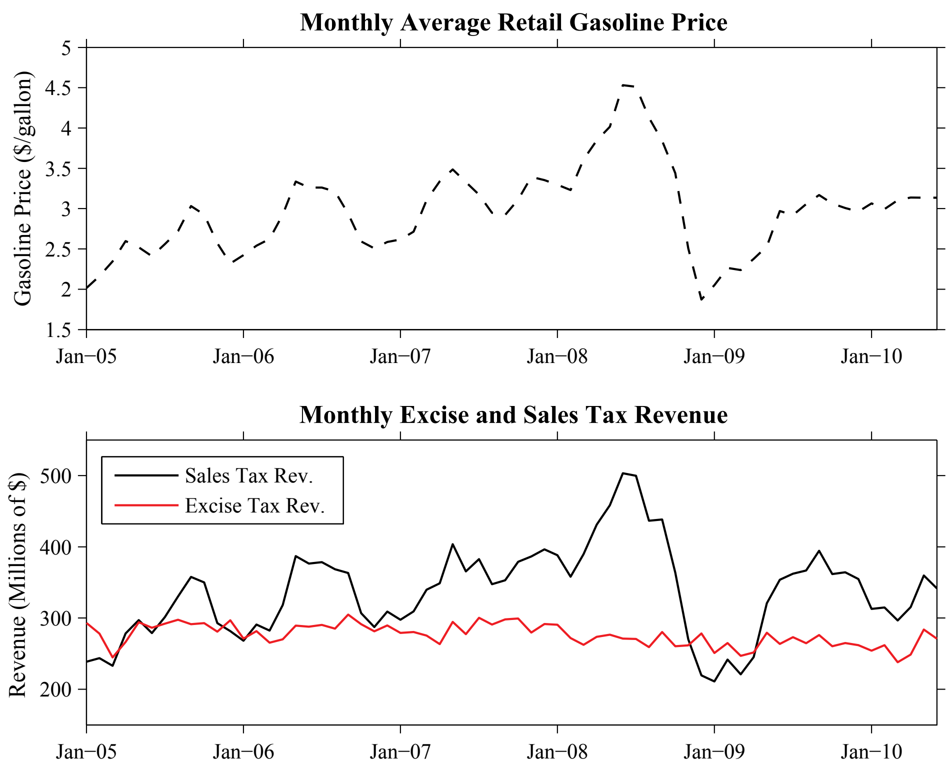

Figure 3.1: Monthly Gasoline Price and Fuel Tax Revenue

short-run. The short-run volatility of federal tax revenues in the US has no direct effect on the provision of government services. So long as federal borrowing costs are low, and the long-run debt to GDP ratio remains reasonable, policies can be altered in a way that changes public good provision along a smoother path.

However, at the state level, the existence of budget rules can make short-term revenue volatility affect more than just balance sheets.[12] Under these constraints both revenue shortfalls and windfalls can be problematic. Budget rules can force a state experiencing a temporary shortfall to abruptly cut spending or raise taxes in current, as well as future, years.

It is less intuitive, and not widely noted, that revenue windfalls can be problematic for governments as well. The California example is rather transparent, because the State's constitution requires that gains in general fund revenues are accompanied by permanent increases in spending across certain state programs. For example, in California, the State constitution requires that public education funding grow at the same rate as either personal income per capita or general fund revenues (whichever is higher).[13] Therefore, a short-run windfall leads directly to long-run increases in legislatively mandated spending obligations. However if the revenue is truly a short-run windfall, then sufficient funds to meet the required level of future spending will not exist.

While California's unique legal structure makes the cost of revenue windfalls transparent, the point that short-term revenue gains can result in increased long-term liabilities holds much more generally. The majority of elected officials do not require a constitutional restriction to compel windfalls to be spent (or rebated as tax cuts), the need to be reelected is generally sufficiently compelling to ensure governments do not maintain a large budget surplus.[14] The implicit threat of the ballot box can cause revenue volatility to impose costs by putting politicians in

[12] With the exception of Vermont, all US states have some form of balanced budget requirement. Poterba (1995) provides an overview of issues created by state budgeting rules.

[13] In practice a 2/3 majority of the legislature can prevent the increase, but supermajorities are rare in California's budgeting process, and the formula binds in almost all years.

[14] Many states, and some cities, recognize this problem explicitly and maintain 'rainy-day funds', to allow governments to operate in surplus more often. In practice these funds are quite small and only allow governments to engage in less-severe austerity in the first budget year of a recession.

politically uncomfortable positions.

Additionally, revenue volatility can be costly because identifying the difference between a short or medium-term windfall and a permanent shift in the economy frequently outstrips the technical abilities of not just elected officials, but professional economic forecasters. For example, at the federal level, the US currently has a large structural deficit. Current federal tax rates were chosen in the late 1990's and early 2000's, when economic forecasts suggested they would generate significantly more revenue than they have. In spite of a decade of revenue shortfalls and a significant weakening of federal balances, the political difficulties of altering federal income and outlays have prevented adjustments to either side of the ledger.

At the federal level, the gasoline excise tax has remained steady at 18.4 cents per gallon with no sales tax since 1993. Although the value of the revenue it generates has fallen over time–because the tax is not indexed to inflation–the federal excise tax has generated a steady stream of revenue, with all fluctuations coming from changes in gasoline consumption. Most states have followed suit, with a large fraction imposing only excise taxes on gasoline. These states have generated a reliable stream of revenue from taxing gasoline. Several states, such as California, have gone further and imposed an additional sales tax on gasoline, creating another revenue stream that is a more volatile and comes at a cost of more volatile retail prices. In the next section, we quantify the reduction in revenue and price volatility that California can achieve by substituting increased excise taxes for sales taxes levied on gasoline and diesel.

3.4 Policy Evaluation

In this section, we compare California's observed monthly fuel prices and fuel tax revenues to the counterfactual prices and revenues that would have occurred under alternative, fuel tax policies. The baseline tax policy is the mix of sales and excise taxes in place prior to the Gasoline Tax Swap. The first alternative policy is the 2010 Gasoline Tax Swap which lowered the fuel sales tax rate and increased the gasoline excise tax. The second policy we simulate goes one step further, entirely eliminating the sales tax levied on fuel expenditures and only using a flat excise tax.

We compare the effects of the two alternative policies to the baseline policy over fiscal years 2007-2009 (July, 2007-June, 2010). One of the major difficulties in comparing the effects of gas tax structures over a given time frame is that the timing of a tax reform significantly affects the aggregate revenue raised by a policy. Though long-run studies of gasoline prices suggest they follow a unit root, there is a clear upward trend over the last decade, which has significant effects on the aggregate revenue generated by each policy. One result of eliminating sales taxes on fuel is that a government may be left with less revenue if prices increase. Conversely, if prices decrease, the resulting revenue will be larger under the policy not taxing expenditures.

Because our focus is on the volatility of tax revenues, we normalize all policies to generate approximately the same average revenue across the simulated period. To accomplish this, we first calculate the actual average tax rate per gallon of fuel purchased between July, 2007 and June, 2010. We use data on the monthly tax receipts provided by the state of California's Franchise Tax Board as well as data on the monthly average fuel prices and consumption from the Energy Information Administration. Over this period, an average state revenue of 42 cents per gallon was generated by the baseline California tax policy.

In order to determine alternative policies that would both be approximately revenue neutral relative to the observed baseline, we abstract from any changes in the fuel consumption that would result from changes to the tax rates. This enables us to choose an excise rate for the simulated Gasoline Tax Swap policy that, when combined with a state sales tax of 2.25% on gasoline expenditures, would achieve an average tax of 42 cents per gallon over the same time period. This results in an excise tax rate in the Swap policy that is slightly smaller than the enacted policy. Finally, for the excise tax only policy, we simply peg the excise rate equal to 42 cents per gallon and set the sales tax on fuel expenditures equal to zero.

For each time period, the simulation consists of four steps. First we establish the baseline monthly gasoline and diesel prices, exclusive of taxes. Similar to Borenstein and LeClair, we assume the full amount of a state tax on gasoline is passed through to consumers. In a rigorous evaluation of state gas tax incidence, Chouinard and Perloff (2004, 2007) find empirical support for this prediction. Maintaining this assumption, we construct a monthly series of gasoline prices that would have prevailed in California by deflating retail prices appropriately. The structure of California's fuel taxes over the time period examined implies:

$$P_{\text{retail}} = (P_{\text{untaxed}} + \tau_{\text{US excise}} + \tau_{\text{CA excise}}) \cdot (1 + \tau_{\text{CA sales}})$$

where $\tau_{\text{US excise}} = 0.184$, $\tau_{\text{CA excise}} = 0.18$ and $\tau_{\text{CA sales}}$ varies over the sample. All parameters except P_{untaxed} are observable and we assume that local changes in fuel consumption do not affect world oil markets, making the changes in consumption implied by alternative fuel tax structures minimal enough to alleviate the need to model secondary price effects. As long as this assumption holds, simple algebra allows us to deflate retail prices to simulate a series of untaxed gasoline and diesel prices.

$$P_{\text{untaxed}} = \frac{P_{\text{retail}}}{(1 + \tau_{\text{CA sales}})} - \tau_{\text{US excise}} - \tau_{\text{CA excise}}$$

Second, we use this price series to simulate the monthly average retail gasoline and diesel prices in California using any tax mechanism we wish to consider over our sample period. Third, we use the simulated counterfactual prices and our estimates of the short-run elasticity of demand for gasoline and diesel, discussed in the appendix, to determine the monthly consumption of gasoline and diesel that would have prevailed under the simulated alternative tax polices. Combining the simulated retail gasoline and diesel prices with the simulated fuel consumption, we can finally back out estimates of the fuel tax revenue each policy would have generated in each month.

3.5 Results

The simulation, which covers July 2007-July 2010, clearly demonstrates the effects of each policy on gasoline price and tax revenue volatility. The effects on retail prices are minimal, but noticeable, at the extremes of observed prices. Gasoline prices from all three series fell within a range of \$ 0.03 75% of the time, and within a range of \$0.06 89% of the time. Even in the most extreme cases, the total price differential between any of the series never exceeded 5% of the price of gasoline, with the peak statewide average gasoline price of July 2008 dropping from \$4.48 in the base case to \$4.38 under the swap and \$4.28 under the fixed tax. Over the simulated period, the policy would have cost the consumer the most in December of 2008, when gas prices fell to their trough of \$1.823 under business as usual, but would have been \$1.898 under the swap and \$1.900 under a fixed excise tax.

the total tax revenue per gallon falling from the range of \$0.32 to \$0.52 per gallon in the base case, to between \$0.39 and \$0.48 per gallon in the swap case, and remaining fixed at \$0.42 per gallon under the pure excise tax.

The single most salient effect of the simulated policies is the clear reduction in revenue volatility directly attributable to the structure of the fuel tax. The top panel of Figure 3.2 compares the average monthly tax rate per gallon of gasoline under the three policies. The effective tax per gallon of gasoline under the observed baseline policy fluctuates between 32 cents per gallon and 52 cents per gallon. In contrast, the monthly tax rate of the Swap policy ranges between 39 cents per gallon and 48 cents per gallon while the Excise policy generates a constant 42 cents per gallon.

As a result, both the Swap and Excise tax polices result in much smoother tax revenue collection across the time periods we examine. While some volatility remains, it is largely the result of volatility in consumption. Perhaps the clearest illustration of the extent to which moving away from ad valorem taxes reduces revenue volatility comes from the bottom panel of Figure 3.2, which displays the aggregate monthly revenue collected from fuel consumption.

The actual fiscal year fuel tax revenue under the baseline policy is given in

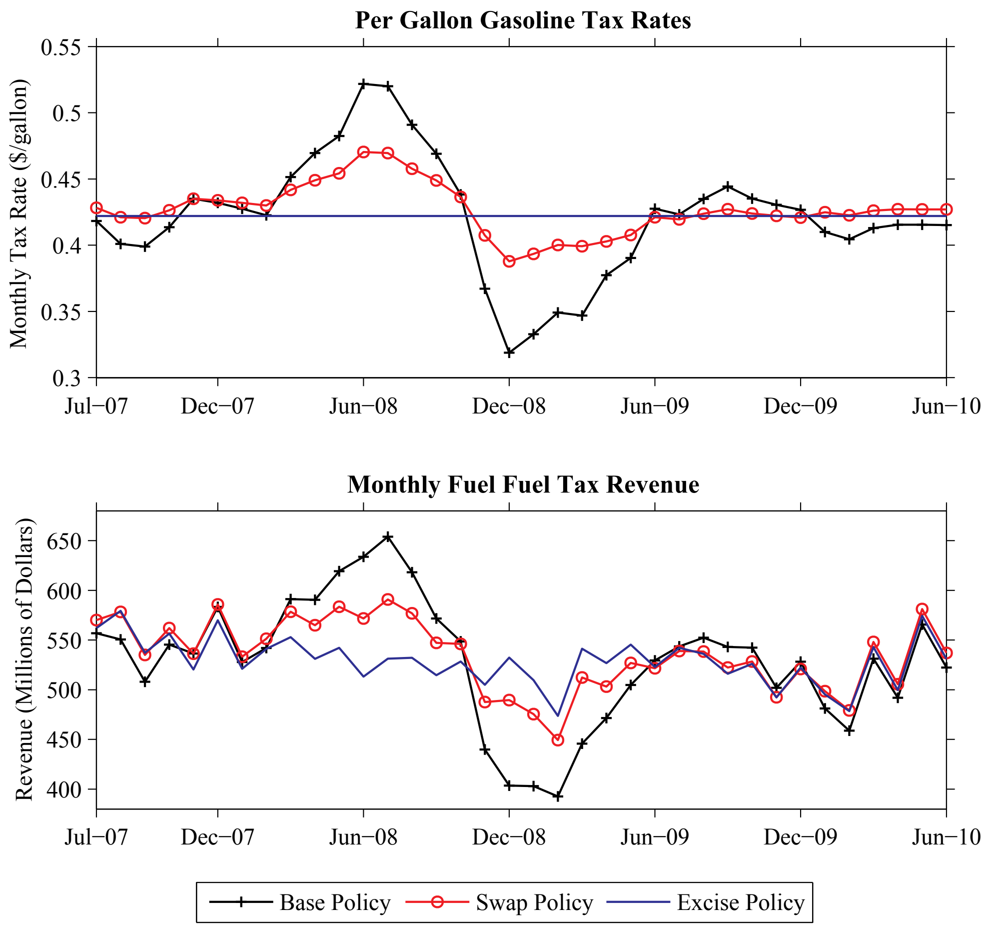

Figure 3.2: Simulated Monthly Tax Rates and Tax Revenue

Table 3.1. During fiscal years 2007, 2008, and 2009, the baseline policy generated \$6.36 billion, \$6.79 billion, and \$5.98 billion, respectively. In contrast, the simulated Swap and Excise policies generate fiscal year revenues with less variation, ranging from \$6.23-\$6.75 billion and \$6.26-\$6.66 billion, respectively.

Table 3.1: Comparison of Fuel Tax Revenue by Fiscal Year

	Baseline	Swap	Excise
July 2007 - June 2008	6.36	6.66	6.66
July 2008 - June 2009	6.79	6.75	6.53
July 2009 - June 2010	5.98	6.23	6.26
Total	19.13	19.64	19.45

Note: Fiscal year revenues in billions of 2010 dollars.

3.6 Conclusion

The results of our simulations are clear. When the government raises revenue by taxing a good that is inelastically demanded and has a volatile price, ad valorem taxes translate this price volatility into revenue volatility. Governments which can borrow at little cost have little incentive to pay attention to this volatility, but governments with high borrowing costs–either due to high interest rates on public debt or legislative constraints–can provide public services more consistently by structuring taxes to reduce revenue volatility. On this count, California's 2010 gas tax swap is a considerable improvement relative to the policy it replaced. The implications are that California's government will have a more reliable stream of revenue, and California's consumers will face marginally more stable prices for a good with very inelastic demand.

In comparing the performance of alternative tax structures, there are several long-run issues that deserve consideration. First, our this analysis does not model changes in consumer behavior which affect the long-run demand for gasoline. If consumers are risk averse over fuel consumption, the present lack of insurance mechanisms for oil price risk would imply that the best way for consumers to ensure against oil price swings is through vehicle choice (or potentially home choice). If this is true, and the current automotive fleet reflects both consumer preferences over vehicle attributes and over oil price risks, then this policy could lead to a decline in the fuel efficiency of an equilibrium vehicle fleet, and possibly less energy efficiency in other durable goods as well.

An additional factor that must be considered is the impact of the tax policy on the long-run tax, real tax rate. One potential benefit of an ad valorem fuel tax relative to a fixed excise tax is that, in the presence of long-run growth in price levels, the real tax rate will continually decrease with a constant per unit tax. However, levying a sales tax on fuel expenditures is not the only way to avoid long-run decreases in the real tax rate. A simple alternative would be to peg a per unit excise tax to an alternative price index which is not prone to large, unpredictable swings; for example, the Consumer Price Index.

The gas tax swap of 2010 is not a permanent policy change, and is up for renewal soon. While our analysis suggests possible benefits to moving to a excise tax, there should be no question that reverting to the old fuel tax would be less desirable than maintaining the gas tax swap. Recent court rulings have also suggested the state's greenhouse gas initiative, AB32, may need to consider further options before implementing a carbon cap and trade program. Should carbon taxes on vehicle fuels be considered as a part of a new program, our research suggests significant benefits to structuring any increase in the tax paid on gasoline as an excise tax. Indeed, with a larger excise tax, the state would have a significantly larger revenue stream with little volatility.

Chapter 3, which has been co-authored with Michael Madowitz, is currently being prepared for submission for publication. The dissertation author was the primary investigator and author of this material.

3.7 Appendix: Fuel Demand Elasticity

To simulate the impact of the variable tax policy on gasoline and diesel consumption, estimates of the short-run (monthly) price elasticity of demand are made for California. While a vast number of estimates of the elasticity of demand have been presented in previous studies, for a variety of reasons it is important to identify the recent response of California consumers to fuel price changes. First, Hughes *et al.* (2006) find evidence that demand has become more inelastic in recent decades. Second, very few estimates of the regional or state level elasticity of demand have been produced. Given that the proposed policy is being simulated for California, it is important to identify the aggregate response of California consumers to price changes. Third and finally, the simulation requires estimates of the elasticity of demand for both gasoline and diesel at a monthly frequency. Lin and Prince (2009) provide estimates of the annual elasticity of demand for gasoline in California. However, these estimates may overestimate the monthly response of consumers to price changes.

The Federal Highway Administration provides data on the monthly consumption of gasoline and diesel in California. Monthly average gasoline and diesel prices in California are collected from the Energy Information Administration. The Bureau of Economic Analysis provide quarterly income per capita for the state of California. Finally, the Employment Development Department of California provides information on the monthly state employment rate. The data spans January 2001 - March 2010.

Estimate of the elasticity of demand are made for both gasoline and diesel. The full specification estimated is shown below:

$$ln(C_t) = \alpha_m + \beta_1 \cdot ln(P_t) + \beta_2 \cdot ln(Y_t) + \beta_3 \cdot ln(E_t) + \varepsilon_t, \tag{3.1}$$

where C_t is the monthly consumption of gasoline or diesel (gallons), P_t is the monthly average price per gallon (2010 \$'s), Y_t is the quarterly income per capita (2010 \$'s), and E_t is the monthly employment rate in California. The fixed effect, α_m, is allowed to vary by month to capture the seasonal trends in consumption.

The parameter β_1 represents the elasticity of monthly gasoline or diesel consumption with respect to the monthly average retail price.

The estimation results are presented in Table 3.2. The central elasticity estimates, used in the counterfactual simulations, are 0.056 for gasoline and 0.033 for diesel. The estimate of the elasticity of demand for gasoline is in the middle of the range of values identified by Hughes *et al.*[36].

Table 3.2: Monthly Price Elasticity of Demand

	Dependent Variable	
	ln(Gas Consumption)	**ln(Diesel Consumption)**
ln(Retail Price)	-0.056	-0.034
	(0.020)**	(0.034)
ln(Income Per Capita)	-0.182	0.896
	(0.105)	(0.275)**
ln(Employment Rate)	1.388	1.893
	(0.092)**	(0.282)**
Constant	5.238	-5.294
	(0.849)**	(2.230)*
Monthly FE	Yes	Yes
N	111	111
R^2	0.85	0.75

Robust standard errors given in parentheses. * significant at 5%. ** significant at 1%. Consumption and Income are per capita. Retail Price and Income are in 2010 dollars.

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