Four Essays Analyzing the Impacts of Policy and System Changes on Power Sector Emissions

By

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A Thesis Submitted to the Graduate

Faculty of Rensselaer Polytechnic Institute

in Partial Fulfillment of the

Requirements for the degree of

DOCTOR OF PHILOSOPHY

Major Subject: ECOLOGICAL ECONOMICS

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April, 2015
(For Graduation May 2015)

CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGMENT

I first would like to thank Dan Shawhan, my advisor, for his endless support from my first day at RPI. He exposed me to energy economics and provided early opportunities to engage in important research. He has made so many things possible in my time at RPI and I cannot thank him enough. I also want to thank Joe Chow for his support which involved opening many doors into the electrical engineering side of the power system. Without both his and Dan’s support I would not have known I was capable of, and that I could, take classes in the electrical engineering department, attend conferences and events where most of the participants where electrical engineers, and be able to be a part of the research in the Global Climate Change and Energy Project (GCEP) and Center for Ultra-Wide-Area Resilient Electric Energy Transmission Networks (CURENT). I also thank the other two members of my committee, Arturo Estrella and Huaming Peng, for their feedback and support with many of the econometric questions my research has challenged me with.

I cannot thank all of my friends and colleagues as the list would get too long but I will mention a few special ones. Thanks to Stacy Foster for providing moral support during most of my time at RPI and always believing in me. A very special thanks to Hannes Lang who helped in innumerable ways from talking about research, to support, encouragement when things got hard, and for all the help he has provided me. I am very thankful for my undergraduate advisor Paul Djupe who first exposed me to the research process and got me excited about it and statistical work. I also want to thank Eklavya Singh, Michelle Bongard, Erin Lennox, and Nat Springer for their support and guidance.

Finally I would like to thank my family. My grandfather Lawrence Garfield has always inspired me to learn and push myself to be the best person I can be. His stories of his times in graduate school getting his PhD have always been a major source of inspiration for me in my journey. My parents Cindy Kindle and Kyle Kindle have always provided any support I needed and encouraged me to take on every challenge presented. Everything that I have accomplished and hope to accomplish is possible because of them and I could not be more thankful.

ABSTRACT

The Regional Greenhouse Gas Initiative (RGGI) is a regionally based carbon dioxide (CO_2) cap and trade policy. A potential weakness of regional emissions trading policies is that they can incur “leakage” if emission reductions in the targeted area are accomplished by relying more on imports, thereby causing offsetting emission increases in the regions supplying the imports. The member state of New York shares a long electrically interconnected border with non-member state Pennsylvania. Pennsylvania is a source of many coal plants and statewide emissions may increase if coal power is exported to New York. RGGI Leakage is empirically tested for using several models.

A method is demonstrated to empirically estimate emission and fuel use functions for fuel-burning electric generation units in Texas. Emission functions are necessary for estimating emissions and fuel use when measurements are not available such as in power system simulation scenarios, unit commitment and dispatch decisions, and when measurement equipment is absent, turned off, or malfunctioning. Commonly, the “functions” used assume that emissions of a generation unit are simply a constant multiple of its output. The functions include the impacts of ramping, startup, and shutdown on emissions. The method of their estimation is described and can be extended to any fuel-burning generator in the U.S. that reports hourly generation and emissions via the EPA’s Continuous Emissions Monitoring System (CEMS). The accuracy of the emission functions in predicting in-sample and forecasting out-of-sample is shown.

The regulations governing the reporting requirements for emissions under various EPA mandates offer a possible loophole by way of a calibration exemption. Generators that report emissions from CEMS equipment must calibrate the equipment once every 24 hours. During the hour of calibration generators can take advantage of different emission rates during that hour to under-report emissions. This has potential cost savings due to the need for generators to hold allowances for NO_x and SO_2 emissions. CEMS data containing the additional information of the hour in which generators calibrate is analyzed to determine if generators are utilizing this loophole. The emission functions, which can estimate the impact of calibration on reported emissions, are then used to determine the magnitude of unreported emissions.

The emission functions are then used to address a controversy about the emission effects of wind power. Because wind power increases the frequency of startups, shutdowns, and ramping by fuel-burning generators, some have claimed that wind power actually increases emissions. Some have also claimed that emissions reductions may not be as large as constant emissions rates would indicate. Emission functions are calculated for all of the combustion-based generators in Texas, and applied to the output of differing wind power penetration scenarios to carefully estimate the emission impacts of increased wind power penetration.

1. Introduction

Electricity generation in the United States is undergoing lots of change as the negative externalities of fuel fired generation and public awareness of these externalities grow. The main externality from fuel fired generation is the production of polluting emissions, especially Carbon Dioxide (CO_2), Nitrogen Oxides (NO_x), and Sulfur Dioxide (SO_2). Both CO_2 and NO_x are greenhouse gases contributing to global warming, while NO_x and SO_2 emissions can cause severe health impacts from their ability to form fine particulate matter in the atmosphere and the creation of acid rain. In 2011 CO_2 emissions from the electricity sector were 2.166 billion metric tons, accounting for 40% of all U.S. CO_2 emissions.

Non-emitting renewable generation such as wind and solar power has the potential to replace emitting thermal generation and allow for decreases in harmful emissions. Renewable generation must overcome significant barriers in order for them to have a more widespread impact. These barriers consist of their cost compared to conventional generation, technical constraints due to their intermittency, and problems from the lack of a relationship between the location of wind and solar irradiance and the location of population centers and electricity demand. Proper policies supporting clean renewable energy generation can help to overcome these obstacles and provide the incentives needed to support the adaption of clean renewable energy. More policies can be expected to be put in place in the future as CO_2 reductions become more important and relevant policies are backed by public opinion. This research supports the development of future policy through analysis of a regional CO_2 cap and trade program in the U.S. and the development of emission functions to better forecast electricity generator emissions.

My research consists of four essays that together can help to guide and inform future economic policy which would impact the electricity market and system. Such policies could be cap and trade programs, renewable portfolio standards, or emission taxes. When researching energy use it is particularly important to be aware of both the economic and physical underpinnings of the electricity system and market. Due to physical limits to electricity transfer such as transmission constraints, reliability requirements, and generator limits, economic concepts can be constrained. Additionally the physical aspects of electricity play a large role in all power markets due to the fact that electricity cannot be stored and power supply must always equal power demand. All of the research presented in this dissertation addresses these issues and offers some insight into the importance of considering them when designing economic policies to reduce emissions. This research also hopes to spur future research in energy to consider both the economic and physical aspects of the power system.

The first of the four essays, Chapter 2, focuses on the potential impact of emissions leakage from a regional cap and trade program. Emissions leakage can occur when a cost increase incurred in the production of an emitting good in one region causes the production of that good to be moved to a region that does not face the cost increase and is therefore cheaper. There are no national policies regulating CO_2 emissions in the electricity sector. Several states in the North East are currently under a program designed to reduce CO_2 emissions. This program, the Regional Greenhouse Gas Initiative (RGGI), is a cap and trade program requiring all emitting generators larger than 25 MW in size to hold allowances for each ton of CO_2 emissions they emit. The program has only regional influence with 9 states currently members. One of the concerns of this is the potential for the costs imposed on emissions to create incentives to export emissions to neighboring non-member states. One of the important considerations of this study are the factors of the electricity system which can mitigate emissions leakage. A brief discussion of these factors is included in the chapter and their relation to the question of leakage from regional cap and trade policies. This can provide information for future policies or analyses of policies on the impacts of leakage from regional or sub-national cap and trade programs.

Chapter 3 focuses on building an econometric model to accurately forecast generator emissions based upon their electricity generation. These emission functions are generator specific and can accurately forecast emissions under all important generator operations; startup, shutdown, and ramping. It is important to be able to forecast emissions under these operations because policies addressing emissions from the electricity sector inherently impact these operations. Economic policies reduce emissions in the electricity sector by changing and interrupting the dispatch of generators. Deregulated electricity markets rely on dispatch curves created by generators submitting marginal cost bids to the system operator. Generators are then dispatched from lowest cost to highest cost, constrained by transmission limits and congestion, as well as limits to generator operation such as minimum off and on times, and ramping limits. Generators produce electricity according to their dispatch by the system operator at a marginal price set by the last generator producing electricity in or providing electricity to their location. These generator dispatches and prices update quickly as the load that is being served changes. The result is that generators are often required to change output quickly (ramp), startup, or shutdown. More wind generation or other stochastic generation on a system result in more of these changes due to an additional time variant besides load, that is, the ability of these generators to produce electricity. Stochastic renewable energy relies on non-controllables such as wind or solar to produce their electricity, so when they are unable to produce power in times when the wind is low, fossil fuel generators must fill in.

Changing the operating profiles of generators under differing wind levels can result in changes to their emission rates that cannot be captured by simple models or constant emission rate assumptions. Models which do not take into account the impacts of ramping, startup, and shutdown will not accurately forecast emissions during these times. The impact on generation from imposing a cost on emissions can be modeled using dispatch simulation methods. The resulting emissions from these simulations are not as simple as multiplying total generation by a constant emissions rate. This chapter addresses that issue by providing a forecasting model which can accurately predict emissions in all types of operating hours.

Chapter 4 uses the emission functions from chapter 3 to analyze the potential for generators to under report emissions due to a potential loophole in continuous emission monitoring system reporting requirements. Any economic policy which inflicts a cost on emissions will result in profit oriented companies trying to reduce these costs. Usually these are by traditional ways such as emissions controls, purchasing emission offsets, and other abatement methods. The regulation may offer a loophole allowing generators to under report their emissions and therefore reduce the costs they face from the Clean Air Interstate Rule and Acid Rain Program's which require generators to hold NO_x and SO_2 allowances for every ton of those emissions they generate. The loophole allows for generators to include only a portion of an operating hour in their emissions measurement. By calibrating during high emission rate portions of hours which are characterized by large differences in emission rates, generators can report lower average emissions. This issue is analyzed using the emission functions in order to determine if generators are engaging in this behavior, and if they are, to what extent.

Chapter 5 illustrates the importance in accounting for generation operation when forecasting emissions. Some reports have found that wind power can increase emissions from electricity generators. They find that, due to increased ramping and startups, expected reductions from increased wind generation are either not entirely occurring or actually becoming increases in emissions. Using the emission functions developed in chapter 3 this question is addressed more thoroughly. Simulated data is used from 5 different wind penetration scenarios to determine the impact on generator emissions in Texas. From a low wind penetration scenario of 3500 MW of wind capacity to a high wind penetration scenario of 29,500 MW of wind capacity generators change their operations significantly. The main concern is coal generators which are forced to ramp, startup, and shutdown more often as wind penetration increases. These operations impact their emissions in a complicated manner that cannot be estimated using simple models or emission rate assumptions. This type of analysis could be done for any policy or other factors that would change how generators operate.

These four chapters provide research to support future economic policies to reduce emissions from the electricity system. The research presented in the dissertation also hopes to show the importance of accounting for economics and the physical electricity system when researching topics related to emissions from the power system.

2. An Empirical Test for Inter-State Carbon-Dioxide Emissions Leakage Resulting from the Regional Greenhouse Gas Initiative

2.1 Introduction

The Regional Greenhouse Gas Initiative (RGGI) is a regionally based carbon dioxide (CO_2) cap and trade policy. There can be weaknesses in regional emissions trading policies because they can incur "leakage" where emissions reductions in the targeted area are offset by outside emissions increases. Leakage occurs in regional or sub-national systems because when a policy only covers one region, that region will face increased costs while a nearby region which is not under the policy does not. Therefore the uncovered region can produce the regulated good at a lower cost than the region under the policy can. In the case of RGGI, producers inside the region face an increased cost to producing electricity which producers outside of the region do not face. As a result, the RGGI region may get more of its electricity than it otherwise would from the relatively cheaper unregulated region.

The states within the RGGI region during the time period analyzed consist of Maryland, Delaware, New Jersey, New York, Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and Maine. The 10 member states are organized into three interconnected systems consisting of the New York Independent System Operator (NYISO), ISO New England, and PJM. Of the RGGI states New England serves Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, and Connecticut. PJM serves Maryland, Delaware, and New Jersey. New York state is the only state served by the NYISO. Electricity is regularly transferred between states within and across each system as well as with neighboring provinces.

The member states in RGGI auction off, or in some cases give away, allowances that permit CO_2 emissions in the electricity sector. Once auctioned, allowances may be re-sold in secondary markets. At the end of each reconciliation period, an emitting generator larger than 25 MWs must turn in allowances equal in number to the amount of emissions that occurred during the period. The need for generators to own these allowances increases their marginal cost per MWh in proportion to their CO_2 emissions per MWh. This increase in marginal cost per MWh for generators required to hold allowances could make it economically viable for system operators to increase imports of cheaper power from generators in non-RGGI states. The RGGI state would incur a decrease in emissions because emitting generators would not be dispatched, and the non-RGGI state would incur an increase in emissions as their cheaper emitting generators are dispatched to meet this additional load.

The RGGI policy may be especially prone to emissions leakage due to the regular trade of electricity and the economic factors of the generation makeup of each state or system. Pennsylvania shares an expansive border with RGGI states and has a generation mix consisting of base load coal generation. This coal generation is historically cheap, abundant, and highly emitting. Electricity resulting from this generation is regularly traded between PJM and the NYISO region across four interfaces. The main interface is defined by PJM as the NYIS interface and consists of two buses, and by the NYISO as PJM Keystone. In addition there are three fixed contract lines connecting PJM to the NYISO: the Neptune Underwater Transmissions Line, the Linden Variable Frequency Transformer, and the Hudson DC line. These transmission lines, unlike the main interface, are on fixed rate contracts and not subject to daily prices. An illustration of the interface names and how prices and electricity flows are represented by them are found in the map in Figure 2.1 below.

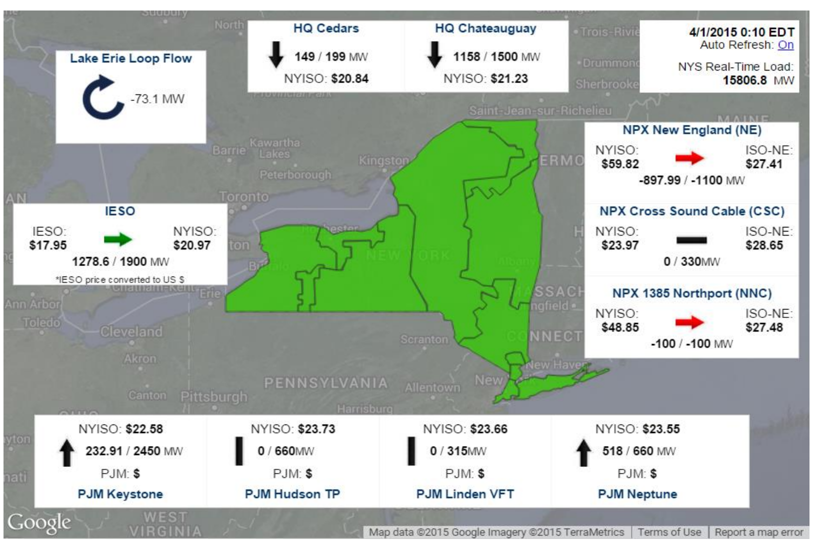

Figure 2.1 NYISO Interchange Map.

Source: http://www.nyiso.com/public/markets_operations/market_data/interregional_data/index.jsp (Date Last Accessed: April 3, 2015)

The bottom of the map shows the four interfaces with PJM that are described. This map shows the price of electricity in the NYISO, the price of electricity in PJM, how much electricity is flowing over the interface, and in what direction by the arrows.

Since the start of the initial compliance period on January 1, 2009, the price in the secondary market for RGGI allowances has never been higher than \$4.13. In July of 2010 the allowances began trading at or near the floor of \$1.86. Figure 2.2 below shows a history of RGGI allowance prices from the quarterly auctions and the secondary market.

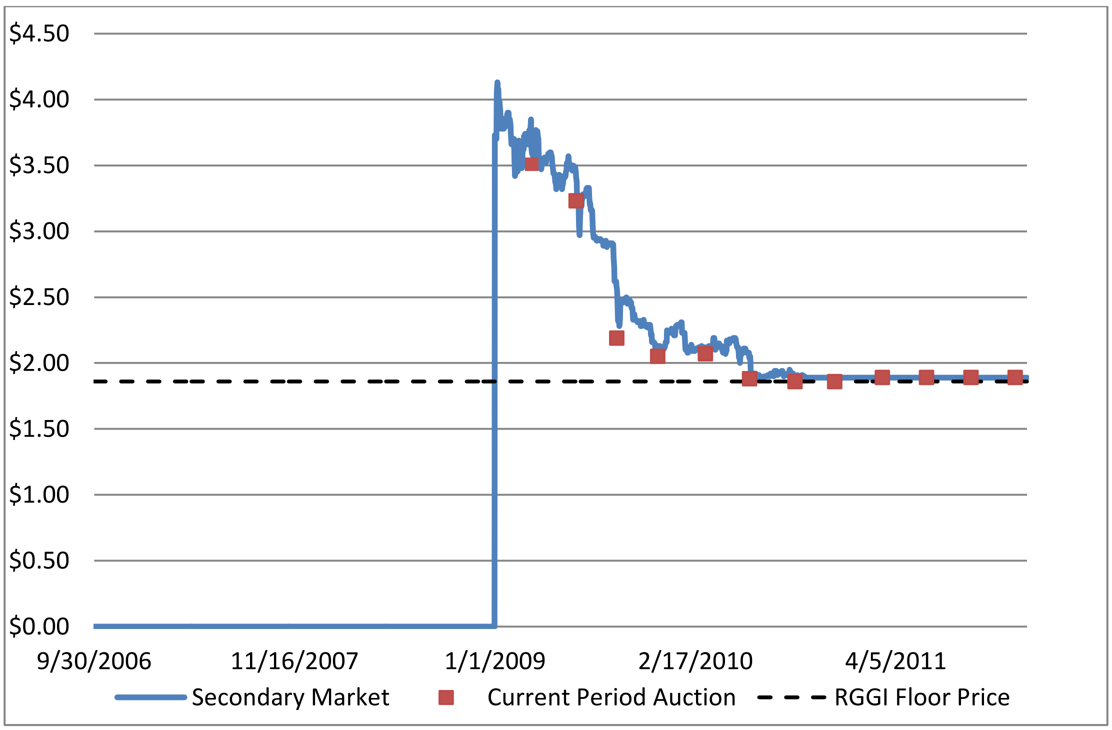

Figure 2.2: RGGI Auction and Secondary Market Prices

This paper hopes to help address the question of emissions leakage by using an econometric analysis of historical data covering the time period before and during the RGGI policy. Leakage can be detected by analyzing Pennsylvania CO_2 emissions and the imports or flows of electricity from Pennsylvania to New York. An increase in either Pennsylvania CO_2 emissions or imports of electricity associated with a positive and significant RGGI allowance price would indicate emissions leakage. The following section will discuss previous studies analyzing leakage from the RGGI policy. Then there will be discussion of the data, econometric methodology, and results.

2.2 Previous Literature

There has been some work written on emissions leakage from RGGI. Before RGGI was an official policy there was much speculation on the extent to which leakage would be an issue. In analyzing different methods of allocating emission permits Burtraw et al. (2005) compare how different auction types could impact leakage. While not offering any estimates on magnitude, they acknowledge that there is the potential for leakage under all auction types. Initial reports on leakage by the RGGI Emissions Leakage Multi-State Staff Working Group found that there was potential for significant levels of leakage (RGGI, 2007). They used simulations from ICF International and their Integrated Planning Model (IPM©) to predict 27% emissions leakage through 2015. This means that emissions in non-RGGI states are predicted to increase by 27% of the RGGI state reductions. The IPM uses a "pipe-and-bubble" (EIPC, 2010) model of the transmission system which accurately predicts the RGGI allowance price to remain in the range of \$2-\$3 through 2015 (ICF Consulting, 2006b). The study may overestimate RGGI leakage because one of the major leakage factors identified was new combined cycle gas-fired generators choosing to locate outside RGGI rather than inside. The Initial Report of the RGGI Emissions Leakage Multi-State Staff Working commented on this prediction, calling it "an outcome that staff deems to be unlikely in the real world" (RGGI Inc. E.-S., 2007a).

Using historical data, Chen (2009) looks at emissions leakage from New York to Pennsylvania by constructing demand and supply curves for imported electricity to New York and use them in simulations of the PJM electricity market. Results show positive emissions leakage that could exceed 90% when allowance prices are below \$7 per ton.

Wing and Kolodzieg (2009) use a computable general equilibrium model to find levels of emissions leakage of 49-57%. They make some assumptions which could make their estimates inaccurate such as identical thermodynamic efficiencies in electricity generation between regions, the ability to neutralize leakage through tariffs, and the inability to include transmission constraints.

In the third annual monitoring report from RGGI Inc. (2013), analysis is done on market dynamics and changes in CO_2 emissions within RGGI and outside of RGGI to conclude that there has been no increase in CO_2 emissions from non-RGGI generators. However, their analysis does not imply any causation or link between allowance prices or the RGGI program and changes in emissions within or outside of RGGI. They also do not use any statistical tests in the analysis of the data. Therefore a more thorough analysis of the historical data is still needed.

In trying to determine what has caused the large drop in emissions in the RGGI region Murray et al. (2014) delve slightly into the topic of RGGI emissions leakage. They find that in their tests for leakage from RGGI to PJM and subsections of PJM, that coal and gas utilization rates drop by more in RGGI states than the non-RGGI states. They assume the entire difference in utilization rate drops are from leakage. Their estimate of the magnitude of this leakage, using “back-of-the-envelope” calculations is that leakage could be as large as the entire emissions reduction from RGGI or leakage of 100%.

Shawhan et al. (2014) estimate a small amount of leakage using a detailed model of the electricity system taking into account realistic transmission constraints. They find that that a RGGI allowance price of $10 would lead to an initial level of leakage of 9.2%, decreasing over time to 2.6% in year 10, and -14.5% in year 20. Using a less detailed model of the electricity grid they get higher levels of leakage, illustrating the importance of transmission topology and constraints on limiting emissions leakage.

Another paper showing the importance of not just energy prices, but accounting for system conditions, is Sauma’s (2012) work which examines the impact of congestion and transmission limits on the magnitude of leakage that can occur. Using a two-node radial network they examine multiple scenarios of congestion, marginal generators, and allowance prices and come up with some important propositions based upon their assumptions. They find a condition under which there may be no leakage. Their first proposition notes that if the marginal cost of a marginal unit in the node that will be under cap and trade is higher than the marginal cost of the marginal unit in the uncapped region node, that there will be no CO_2 emissions leakage after cap and trade is introduced.

Most of these studies use simulation models to project leakage levels or do not make it their primary goal to estimate leakage. This paper aims to add to this literature by using historical data and sophisticated econometric techniques to try and detect the presence of emissions leakage from RGGI.

2.3 Background

In order for leakage to occur there must be the potential for emissions leakage. A key assumption is that additional generation in Pennsylvania would produce emissions, which is virtually certain. In PJM, the regional system that includes Pennsylvania, a coal-burning unit was the marginal unit 74% of the time and a gas-burning unit was the marginal unit 22% of the time (Monitoring Analytics, LLC, 2010). Therefore any increase in generation caused by RGGI would increase emissions. There is significant unused coal capacity in Pennsylvania, West Virginia, Virginia, and Ohio equal to a potential extra 64 million tons of CO_2 emissions annually (Rogers et al, 2008, p.15). Some portion of this could be released from Pennsylvania generators due to increased demand by New York.

The CO_2 emission reductions resulting from RGGI can be decomposed into five pairs of effects: short-run supply-side effects, long-run supply-side effects, short-run demand-side effects, long-run demand-side effects, and the effects of reinvestment of allowance auction proceeds. Each of these five pairs consists of an effect in the RGGI states and an effect in other states and provinces. In all five pairs, the effect in the RGGI states reduces emissions. In the first two pairs, the effect in other states and provinces is "positive leakage," meaning that it increases emissions, partially offsetting the emission reductions resulting from the policy. In the last three pairs, it is "negative leakage" or "emission reduction spillover," meaning that it further reduces emissions.

1. *Short-run supply-side effects*
    a. In RGGI states: The need to hold one allowance for every ton of CO_2 emitted reduces emissions by raising the marginal generation costs, and hence the offer prices, of higher-emitting generators more than those of lower-emitting generators and of generators not subject to the allowance

requirement, such as those in Pennsylvania. This causes higher-emitting generators subject to the allowance requirement to be used less.

b. In neighboring jurisdictions: Positive leakage. Since RGGI raises the offer prices of emitting generators subject to its allowance requirement, generators not subject to the requirement, such as those in neighboring states and provinces, are used more. This increases their emissions.

2. *Long-run supply-side effects*
    a. In RGGI states: Because RGGI reduces the use of higher-emitting generators that are subject to the allowance requirement, such units are more likely to be retired and fewer of them are likely to be built in the future.
    b. In neighboring jurisdictions: Positive leakage. Because RGGI may in the long run reduce emitting generation capacity in the RGGI states, the demand for electricity imports to these states may increase. This would be likely to result in more generation capacity, and more CO_2-emitting generation, in neighboring states and provinces.

3. *Short-run demand-side effects*
    a. In RGGI states: By raising the offer prices of generators, RGGI raises the market price of electricity, which induces an immediate reduction in consumption.
    b. In neighboring jurisdictions: Negative leakage. The higher offer prices within RGGI increase the demand for electricity from neighboring jurisdictions by RGGI states. This reduces the residual supply of generation in those jurisdictions, driving up the price and immediately reducing consumption in those jurisdictions. This effect partially offsets effect 1b, but can be expected to be substantially smaller than 1b.

4. *Long-run demand-side effects*
    a. In RGGI states: The consumption reduction becomes greater over a period of years. The reason is that as energy customers replace equipment and update their energy use practices, they take the higher electricity prices of recent years into account, and consequently choose more efficient equipment and practices.
    b. In neighboring jurisdictions: Negative leakage. As a result of the higher prices in neighboring jurisdictions (effect 3b), there is a long-run demand response in those jurisdictions, as in the RGGI states.

5. *Reinvestment of allowance proceeds*
    a. In RGGI states: Most of the RGGI allowance auction proceeds are slated to be spent on programs to help energy customers use energy more efficiently. This should further reduce CO_2 emissions.
    b. Outside of RGGI states: Negative leakage. Greater adoption of energy-efficient equipment in the RGGI states as a result of effect 5a (and effects 3 and 4) allows manufacturers of such equipment to move down their production cost learning curves and to achieve greater economies of scale, lowering the costs of more efficient equipment relative to less efficient equipment, nationally and internationally. This should further reduce CO_2 emissions.

The extent of each of these ten effects is unknown. Of the five leakage effects, the two short-run effects (1b and 3b) can be expected to affect emissions and power flows in proportion to the then-current RGGI allowance price. However, the short-run demand-side effect (3b) is reflected in load. Therefore, if one tests for an effect of the RGGI allowance price on load, and controls for load as one must, the type of leakage that remains to detect is short-run supply-side leakage (effect 1b). This short-run supply-side leakage is the most direct type of leakage, and it is what this paper attempts to detect in recent historical data. The long-run leakage effects (2b, 4b, and 5b) accumulate over the years rather than being a daily function of the current RGGI allowance price, and attempting to measure any of them would require a different approach than the one employed to measure short-term leakage.

2.4 Method

Leakage is estimated by building models to describe Pennsylvania CO_2 emissions and scheduled power flows from Pennsylvania to New York. Higher Pennsylvania CO_2 emissions and higher net flows from Pennsylvania to New York associated with higher RGGI allowance prices would indicate emissions leakage. The CO_2 emissions model and the flows models have different estimation techniques. The estimation methods are described for the CO_2 and flows models separately.

2.4.1 Pennsylvania CO_2 Emissions Method

The Pennsylvania CO_2 emissions model is an ARMAX model which consists of exogenous explanatory variables and has estimated auto-regressive moving average (ARMA) residuals using Box-Jenkins model identification (Box & Jenkins, 1970). This process involves ensuring stationarity of dependent variables and accounting for any seasonality, using autocorrelation and partial autocorrelation functions to determine lag lengths of the ARMA terms, and ensuring white noise residuals. This method is used because the OLS model has serial correlation of the errors. Serial correlation makes the standard errors smaller than their true value and can make coefficients look statistically significant when they are actually not. Therefore the errors are modeled and use the information in them in order to estimate accurate standard errors. The model takes the following general form:

$$Y_t = \alpha + \beta X_t + \gamma Month + \lambda Daily + \eta_t \quad (1)$$

$$\eta_t = \sum_{n=1}^{p} \phi_n \eta_{t-n} + \sum_{m}^{q} \theta_{m+1} \epsilon_{t-m} \quad (2)$$

where Y is the dependent variable, X a vector of independent variables with a vector of coefficients β, and monthly and daily dummy variables with vectors of coefficients γ and λ. The final term η is an error term which is modeled as an ARMA process with a vector of autoregressive components to p lags, η_{t-k}, and vector of moving average components ϵ to q lags. These terms both have a vector of coefficients ϕ and θ respectively.

It is important when estimating ARMA models to use stationary variables. To test dependent variables for stationarity three tests are used for robustness. These tests are an Augmented Dickey Fuller test (Dickey & Fuller, 1981), Phillips-Perron test (Phillips & Perron, 1988), and KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). All three are done on the deseasonalized dependent variable and find that it is stationary. Therefore no trend term is included in the Pennsylvania CO_2 emissions model.

Several dependent variables are identified which should impact Pennsylvania CO_2 emissions. The daily load of contiguous PJM and its squared value are included in the model. Load is the main determinant of emissions due to the fact that emitting generation must generate enough electricity to serve it, with the highest levels of load often being served by the most inefficient and polluting generators. Fuel prices also impact emissions. Depending on the relationship between coal and natural gas prices, the order of generators dispatched to serve load can change. When natural gas prices are higher than coal prices coal will be dispatched more often and when natural gas prices are less than coal prices natural gas will be dispatched more. Coal has a much higher CO_2 emissions rate than natural gas which can mean higher CO_2 emissions under higher natural gas prices and lower emissions under lower natural gas prices Also included is Pennsylvania nuclear generation since there is a significant amount of it serving as baseload generation and it is non-emitting. It is important to include nuclear generators because when they shut down they can spend long time periods offline, requiring emitting generation to replace them. Also important are the NO_x and SO_2 allowance prices because when they are high the most emitting generation becomes more expensive and may run less. Finally daily and monthly seasonalities are controlled for with day of the week and monthly dummy variables.

As will be discussed the flows models have a simultaneity bias with the RGGI allowance price variable. The CO_2 model does not have one. Pennsylvania CO_2 emissions are not generated under the RGGI program and therefore should not have an impact on the RGGI allowance price. Therefore the RGGI allowance price variable is treated as exogenous.

2.4.2 Pennsylvania to New York Electricity Flows Method

The regression model to describe flows from Pennsylvania to New York is a first order simplification of the model that describes the supply and demand functions for flows. Considering the flow of electricity from Pennsylvania to New York as a simple supply and demand model provides structure for analysis of potential endogeneity. Two measures of flows are considered, real time and day ahead flows.

The demand for imports depends on the difference between the price of electricity in New York and the price in Pennsylvania, as well as load in New York. If New York is facing a larger electrical load they may be faced with transmission constraints, generation shortages, or other problems requiring them to import more power from Pennsylvania regardless of price.

$$Q_{D\_Imports} = \theta_1 + B_1*(P_{NY} - P_{PA}) + B_2*NYLOAD + \epsilon \tag{3}$$

While most supply and demand functions only consider price it is the case that flows from Pennsylvania to New York do not always follow traditional economic signals. One of the drivers of non-economic flows may be the need to meet load regardless of price. Therefore load is included in both models, in the demand model to represent needs for imports and in the supply model as a limit to available generation to export.

The supply of imports depends on the price difference between the price of electricity in New York and the price in Pennsylvania, as well as the load in Pennsylvania. If Pennsylvania is facing a large load they may have less generation available to export.

$$Q_{S\_Imports} = \theta_2 + C_1*(P_{NY} - P_{PA}) + C_2*PALOAD + \epsilon \tag{4}$$

The price of electricity in New York and Pennsylvania can be decomposed into some more general prices which would cause marginal cost increases to generators on the margin of the bid stack. Each term can be thought of as a marginal cost increase to the marginal generator, summing into one marginal cost that a generator would bid. P_{Gen} represents the marginal unit, P_{RGGI} the marginal cost of RGGI permits required for CO_2 emissions associated with generation, P_{Fuel} the marginal cost of fuel for generation, P_{NOX} and P_{SO2} the marginal cost of NO_x and SO_2 permits required as part of the EPA Acid Rain Program (ARP) and Clean Air Interstate Rule (CAIR), and ϵ, a random price shock.

The generation of baseload power, nuclear and hydroelectric, is also added to both equations due to the large impacts having baseload generators offline can have. The RGGI price is added in both models because in New York it has a direct impact on marginal prices by increasing marginal costs of its generators. In Pennsylvania it has a different impact. It may impact Pennsylvania prices due to its impact on imports and subsequent changes to bid stacks, congestion, and losses.

$$P_{NY} = \alpha_1 + D_1*P_{GenNY} + D_2*P_{RGGI} + D_3*P_{FuelNY} + D_4*Gen_{baseload} + D_5*P_{NOX\_Permits} + D_6*P_{SO2\_Permits} + \epsilon \tag{5}$$

$$P_{PA} = \alpha_2 + E_1*P_{GenPA} + E_2*P_{RGGI} + E_3*P_{FuelPA} + E_4*Gen_{baseload} + E_5*P_{NOX\_Permits} + E_6*P_{SO2\_Permits} + \epsilon \tag{5a}$$

P_{GenNY} and P_{GenPA} are the prices for marginal generation in New York and Pennsylvania. P_{RGGI} is the RGGI allowance price, and P_{FuelNY} and P_{FuelPA} are the prices of fuel for the marginal generator in New York and Pennsylvania respectively. $Gen_{baseload}$ is the quantity of baseload generation which is on the system. This quantity has a large impact on the need for peaking (more expensive) generators. If baseload generators have tripped or are down for maintenance there is a large impact on prices. Finally $P_{NOX\_Permits}$ and $P_{SO2\_Permits}$ are the prices of NO_x and SO_2 allowances. All of these prices have some endogeneity. However, the coefficient which needs an unbiased estimate is the coefficient on the RGGI price variable. The regression equation used is described next and then a discussion of the endogeneity of the RGGI price will follow.

A reduced form regression equation is estimated for both the measures of flows in the real time market and day ahead market. The reduced form is determined from the consideration of the relationships described in the structural supply and demand equations in (3), (4), and (5). From the demand and supply equations it can be determined that the major variables that must be controlled for are variables describing the price difference between New York and Pennsylvania and then the system loads for the NYISO and PJM. Therefore the regression equation contains all the major determinants of price found in equations (5) and (5a) which make up the price difference between New York and Pennsylvania as well as the system loads found in (3) and (4).

Some constraints to this are that it is impossible to tease out the price differences from the NO_x and SO_2 allowance programs, as well as what the marginal unit is at any given point in time. Therefore only the SO_2 and NO_x allowance price series are included in order to control for their impacts. Also included are the loads for New York and PJM as a best representation for the marginal unit. In addition the New York load is important to include based upon the demand equation (1). The output of hydro and nuclear generation is included in the regression equation as well. These make up the baseload generation in New York. Therefore they are a major driver in determining how much of the remaining portion of load not served by them must be served by emitting generation. They are also non-emitting sources of generation and are not impacted by the RGGI price unlike coal, gas, or oil generation. Equation 6, below, is the reduced form regression equation that is estimated.

$$\begin{gathered}\text{Flows} = \beta_0 + \beta_1 {*} P_{RGGI} + \beta_2 {*}\text{NY Average Hourly Load} + \beta_3 {*}\text{ PJM Average Hourly} \\ \text{Load} + \beta_4 {*}\text{NY Hydro} + \beta_5 {*}\text{NY Nuclear} + \beta_6 {*}\text{NY Natural Gas Price} + \beta_7 {*}\text{PA} \\ \text{Natural Gas Price} + \beta_8 {*} SO_2 \text{ Allowance Price} + \beta_9 {*} NO_x \text{ Allowance Price} + \\ \beta_{10} {*}\text{Time} + \beta_{11\text{-}16} {*}\text{Day of Week Dummies} + \beta_{17\text{-}27} {*}\text{Month of Year Dummies} + \epsilon_1\end{gathered} \tag{6}$$

Since the RGGI allowance price is a price in a demand model it has an endogeneity problem. This comes from a simultaneity bias in both flows models with the RGGI allowance price. The RGGI price may impact flows for the aforementioned reasons and in the opposite direction flows also impact the RGGI price. An increase in flows due to the RGGI price decreases emitting generation within New York. With less emitting generation in New York there is less demand for RGGI allowances and therefore a fall in the RGGI price. Therefore the direction of causality does not just go from the RGGI allowance price to flows but also from flows to the RGGI allowance price. Without controlling for this, the coefficient on the RGGI variable will have a downward bias.

This endogeneity is dealt with by instrumenting the RGGI variable with two instruments. The estimator used is the General Methods of Moments (GMM) continuously updated estimator as defined in Hansen et al. (1996). The first instrument used is coal generation in ISO New England. Since all of ISO New England is covered by RGGI, emitting generation should have an impact on the RGGI price. The second instrument is a gross domestic product (GDP) expectations variable which is constructed to capture future economic outlook and known, historic, economic activity. A higher GDP is generally means there is a need for more electricity. If operators think that the economy is going to grow in the future then they will expect to need more RGGI allowances in order to keep up with higher generation demands. The construction of this variable is described in the data section.

GMM allows for us to choose a weighting matrix which can be used to control for serial correlation and heteroskedasticity. Tests for both flows models indicate the need for errors robust to both heteroskedasticity and autocorrelation. The test for heteroskedasticity uses the Pagan-Hall statistic (Pagan & Hall, 1983) which tests a null hypothesis of homoskedasticity. The test for autocorrelation applies the Cumby-Huizinga statistic (Cumby & Huizinga, 1992) which unlike many other autocorrelation test statistics is valid given the presence of both endogenous regressors and heteroskedasticity. It has a null hypothesis of uncorrelated errors of the first order. Both test results are found in Table 2.1, below.

Table 2.1: i.i.d. Tests

	DAM Imports	RT Imports
Pagan-Hall statistic	130.98	125.02
χ^2 p-value	0.000	0.000
Cumby-Huizinga statistic	69.86	57.05
χ^2 p-value	0.000	0.000

The presence of autocorrelation and heteroskedasticity in both models is confirmed due to the tests rejecting their respective null hypotheses at a high level of significance. Therefore HAC standard errors are reported in the results.

2.5 Data

This study attempts to directly measure emissions leakage by examining historical data covering the time period of September 30th, 2006 to December 31st, 2011. This time period is chosen because there are no significant changes in NYISO or PJM rules, besides the RGGI program itself. There are also no significant changes in the RGGI policy. After this time period there is a significant change to RGGI due to the exit of New Jersey from the program. Different time periods were experimented with, specifically shortening the time period before and after the RGGI program start date, as well as only using data from time spans when the RGGI program was in force. Changing the time spans like this did not alter results or conclusions obtained from the long time period of 2006 to 2011. The data has a daily time step.

All the models use daily data taken from a combination of sources consisting of proprietary data from the NYISO, EPA Continuous Emissions Monitoring System (CEMS) data, and generator information from the Energy Information Agency (EIA) form 860. Data on electricity prices are taken from data search queries from the NYISO and PJM's respective websites[1,2]. Data on ISO New England coal generation was pulled from search queries from their website[3].

The GDP variable used for instrumenting the RGGI variable is constructed from actual GDP values from the U.S. Bureau of Economic Analysis and forecasted GDP is taken from the Survey of Professional Forecasters which is obtained from the Federal Reserve Bank of Philadelphia[4]. The Survey of Professional Forecasters is released quarterly and beginning in the second quarter of 2009 gives 4 quarters ahead and 1, 2, and 3 year ahead forecasts of real GDP. The GDP forecast variable consists of the forecast of real GDP until the end of 2011 added to actual GDP starting in 2009. For example, the first quarter of 2010 has observations consisting of the first quarter of 2010's forecasts of the rest of 2010 plus the forecast for 2011 plus the actual real GDP

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[1] http://www.pjm.com/markets-and-operations/energy.aspx (Date Last Accessed: April 3, 2015)
[2] http://www.nyiso.com/public/markets_operations/market_data/pricing_data/index.jsp (Date Last Accessed: April 3, 2015)
[3] http://www.iso-ne.com/isoexpress/web/reports/operations/-/tree/daily-gen-fuel-type (Date Last Accessed: April 3, 2015)
[4] http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/ (Date Last Accessed: April 3, 2015)

for 2009. Since the data is quarterly, the data changes for the next quarter of observations on the day the survey is released. The survey only began giving 3 year ahead forecasts in the second quarter of 2009. Therefore interpolated values are used for the first quarter of 2009. Previously, the survey had only reported forecasts for 2 years. The interpolated value is created by calculating the increase in forecasted GDP across two years for the 4th quarter of 2008 and the first quarter of 2009 and assuming those forecasted rates of growth would continue into the 3rd year. Those, along with the actual forecasted growth rate for three years out GDP, from the second quarter of 2009 survey are averaged. This growth rate is then applied to the 2009 1st quarter 2 year forecast, to create a prediction of what the 3 year forecast would have been.

Some variables included in the models require further explanation. Since it is unknown exactly what load the electricity from Pennsylvania generators serves, all potentially serviced loads of contiguous PJM are used, defined as the following load zones: Public Service, Exelon: PECO, PP&L, UGI, Baltimore Gas & Electric, First Energy: Jersey Central, First Energy: MetEd, First Energy: PennElec, PEPCO, Connectiv: Atlantic Electric, Connectiv: Delmarva Power & Light, Rockland Electric, Dominion Virginia, Allegheny Energy, AEP, Dayton Power & Light, and Duequesne Light Co. Both variables measuring load in PJM and the NYISO are measures of total load for each day.

While the series for both day ahead and real time flows is similar there are some differences between the two. Day ahead flows may have more economically explainable variation than real time scheduled flows because they are not as affected by unpredictable events that arise less than a day in advance. Some unpredictable events that can occur in real time are generator trips, differences from forecasted load, and transmission line constraints or outages. In general the day ahead scheduled flows are higher than the real time scheduled flows. Figure 2.3 shows scatterplots of day ahead and real time flows overlaid. It can be seen that they trend in the same manner but do not overlap and are often fairly different in size.

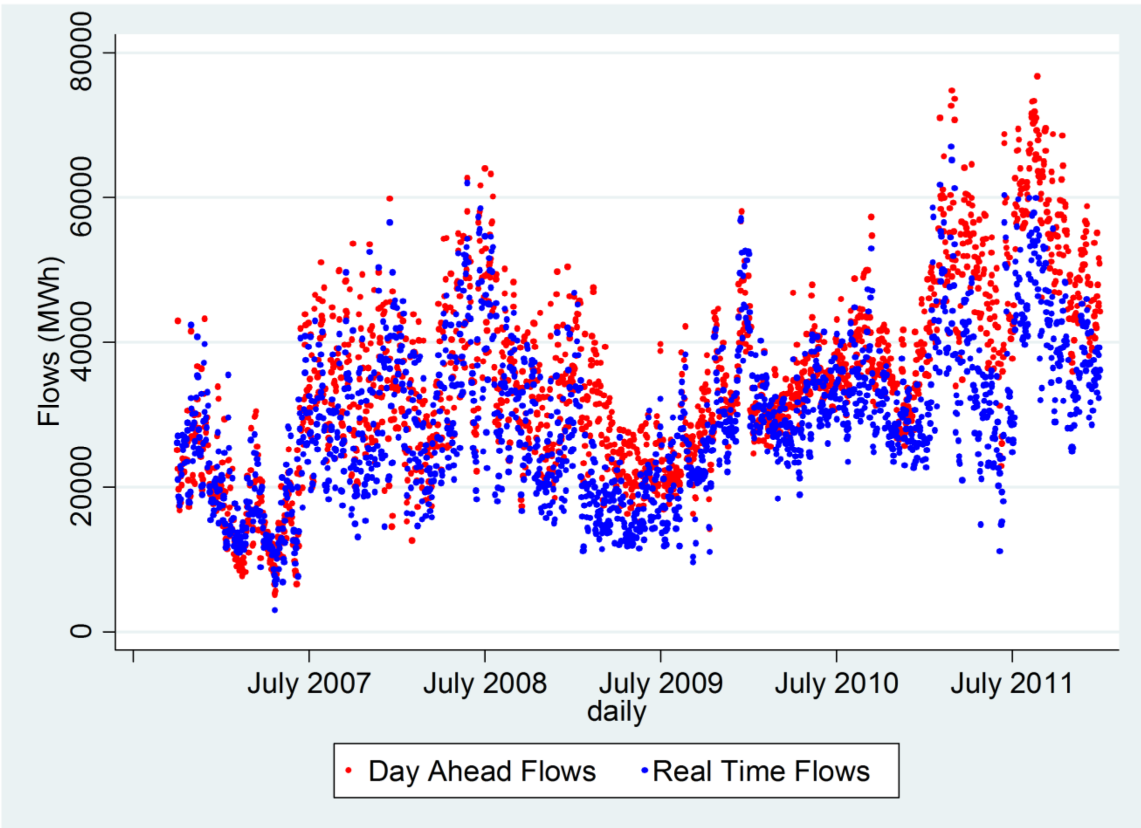

Figure 2.3: Day Ahead and Real Time Flows. September, 2006 – December, 2011

Scheduled flows attributable to wheel-through transactions, which are intended to pass through rather than sink in a control area, are not included in either of the dependent variables. In the time period studied, wheel-through transactions constituted only 2% of day ahead and real time flows from Pennsylvania by volume. Summary statistics and short descriptions of all variables used can be found in Table 2.2 below. On average day ahead flows are higher than real time flows and they also have a larger standard deviation. Also worth noting are the large standard deviations of the NO_x and SO_2 allowance prices. Due to a ruling in the U.S. Court of Appeals the regulations governing the NO_x and SO_2 markets were significantly weakened. This led to a large drop in their prices which occurred in 2008.

Table 2.2: Summary Statistics

Variable	Definition	Units	Average	Standard Deviation
Day Ahead Scheduled Flows[1]	Daily imports from Pennsylvania across the PJM Keystone Proxy Bus to New York scheduled in the day ahead market	MWh	34,773	12,899
Real Time Scheduled Flows[1]	Daily imports from Pennsylvania across the PJM Keystone Proxy Bus to New York scheduled 75 minutes ahead	MWh	29,191	10,513
PA CO2 Emissions[1]	Daily CO2 emissions from all electricity generating power plants in Pennsylvania	1000 Tons	328.59	51.28
NY Load	Daily load in New York	MWh	446,891	5,4044
PJM Contiguous Load	Daily load in what is called “contiguous-zone PJM,” which excludes the portion of PJM in Illinois served by Commonwealth Edison	MWh	1,647,166	214,266
NY Nuclear Output	Daily nuclear generation output from all nuclear power plants in New York	MWh	117,273	14,297
NY Hydro Output	Daily hydroelectric generation output from all hydroelectric power plants in New York	MWh	68,081	9,079
PA Nuclear Output	Daily nuclear generation output from all nuclear power plants in Pennsylvania	MWh	192,375	19,782

Variable	Definition	Units	Average	Standard Deviation
RGGI CO_2 Allowance Price	Daily price of RGGI CO_2 allowance prices (0 until compliance is required, January 1st, 2009). Average and Standard Deviation to the right pertain to the time period of 1/1/2009 – 9/30/2010	$	2.32	0.63
PA Natural Gas Price	Daily spot price of natural gas from Tetco M-3 hub	$/MMBtu	6.47	2.66
NY Natural Gas Price	Price per MMBtu of NY natural gas from Transco-Zone 6	$/MMBtu	6.75	3.06
PA Coal Price	Daily 12,000 BTU OTC Market NYMEX Big Sandy Barge price	$/tonne	63.46	20.73
NO_x Allowance Price	Price of NO_x emission allowances	$	415.21	376.56
SO_2 Emissions Allowances Price	Daily price of SO_2 emissions allowance prices	$	197.12	216.32
GDP Forecast Variable	Sum of 12 Quarters of Actual and Forecasted Real GDP	Trillions of 2009 Chain Weighted $	152.559	42.766
ISO NE Coal Generation	Daily coal generation	MWh	40,835	16,237

[1]Dependent Variable

Data supplied from SNL, the NYISO, the EPA, and the EIA

2.6 Results

CO_2 emissions leakage from New York, a RGGI state, to Pennsylvania, which is not a member of RGGI, is empirically tested for. Unlike previous studies on leakage that have used simulations of the physical energy network and energy market to predict leakage under various scenarios, this study attempts to directly measure emissions leakage by examining historical data. Equations (1) and (2) are estimated for Pennsylvania CO_2 emissions and then equation (6) for real time scheduled flows and day ahead scheduled flows.

2.6.1 Pennsylvania CO_2 Emissions

The first means for attempting to detect leakage is to test for a statistically significant effect of the RGGI allowance price on daily CO_2 emissions from Pennsylvania's electric power sector. The Pennsylvania CO_2 emissions model is a less direct measurement of the leakage potential than the actual flow measurements.

Pennsylvania CO_2 emissions are stationary when the deseasonalized data is analyzed. The emissions series is highly seasonal as emissions are higher in summer and winter when loads are highest. OLS regressions show highly autocorrelated residuals so the residuals are modeled using ARMA terms. Results from both models, which only differ by how fuel prices are included, are found in Table 2.3. All variables are standardized so that coefficients represent changes in the standard deviation of the dependent variable. This makes interpretations of variables with different units easier.

Table 2.3: PA CO_2 Emissions Regression Results

	ARMA(2,2) Model 1	ARMA(2,2) Model 2
RGGI Permit Price	-0.00482 (0.0895)	-0.00216 (0.0828)
PJM Load	0.816*** (0.0121)	0.815*** (0.012)
Squared PJM Load	-0.0402*** (0.00507)	-0.0407*** (0.00504)
PA Natural Gas Price	0.0316* (0.0137)	
PA Coal Price	-0.0294 (0.0578)	
PA Nat Gas to Coal Price Ratio		0.0425** (0.0144)
PA Nuclear Output	-0.0605*** (0.0167)	-0.0605*** (0.0167)
NO_x Allowance Price	-0.0158 (0.0805)	-0.0195 (0.0796)
SO_2 Allowance Price	-0.0423 (0.101)	-0.0437 (0.0917)
Constant	0.213*** (0.003)	0.213*** (0.003)
Month Dummies	Yes***	Yes**
Daily Dummies	Yes***	Yes***
AR(1)	1.533*** (0.071)	1.530*** (0.0717)
AR(2)	-0.549*** (0.0651)	-0.547*** (0.0657)

	ARMA(2,2) Model 1	ARMA(2,2) Model 2
MA(1)	-0.620*** (0.0718)	-0.618*** (0.0725)
MA(2)	-0.180*** (0.0275)	-0.180*** (0.0274)
AIC	-426.2	-429.9
BIC	-253.8	-263.1
Adjusted R^2	0.955	0.955

Variables are standardized and represent standard deviations
Standard errors in parentheses
+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Using the two measures of fuel prices in the model provides very similar results. Both models fit the data well with Adjusted R^2 values of 0.955. All the explanatory variables, except the RGGI allowance price have the correct signs and are significant. The RGGI permit price has a negative coefficient but it is highly insignificant in both models indicating that there is not a significant impact of the RGGI permit price on Pennsylvania CO_2 emissions. The relationship between emissions and load is significant and positive. A one standard deviation in PJM load increases emissions by 0.776 standard deviations in model 1 and 0.774 standard deviations in model 2. The natural gas price in Pennsylvania turns out to also be a significant driver of emissions. Increasing natural gas prices can increase CO_2 emissions by causing fuel switching or from gas to coal generation. The insignificance of the RGGI allowance price may be due to its lack of variation, the low allowance prices that occurred over the time period, or the fact that emissions are almost entirely determined by the other variables. A more direct measure of the impact of the RGGI allowance price on leakage is the flows models.

2.6.2 Pennsylvania to New York Electricity Flows

The second method of detecting emissions leakage to Pennsylvania is to estimate the impact of the RGGI allowance price on imports of electricity from Pennsylvania to New York. A positive and significant coefficient on the RGGI allowance price would be evidence of emissions leakage. These models are estimated using GMM and instrumenting the RGGI variable with ISO New England coal generation and the GDP forecast variable. Results of the real time and day ahead flows models are found below in Table 2.4.

Table 2.4: Pennsylvania to New York Electricity Flows Regression Results

	Real Time		Day Ahead	
	OLS	GMM Model[1]	OLS	GMM Model[1]
RGGI Allowance Price	-1812.2*** (272.5)	1166.8 (1541)	-709.4* (302.4)	1365.2 (1678)
NY Average Load	0.159*** (0.01)	0.166*** (0.01)	0.134*** (0.01)	0.139*** (0.02)
PJM Average Load	-0.048*** (0.003)	-0.050*** (0.004)	-0.042*** (0.003)	-0.044*** (0.004)
NY Natural Gas Price	-315.6 (199.1)	-590.6+ (305.6)	-354.3+ (214.9)	-528.9+ (318.5)
PA Natural Gas Price	2198*** (248.0)	3047*** (601.3)	2002*** (275.2)	2572*** (620.6)
SO_2 Allowance Price	9.39*** (2.22)	22.54** (7.24)	26.99*** (2.46)	36.05*** (8.27)
NO_x Allowance Price	-7.53*** (1.28)	-4.58+ (2.41)	4.15** (1.42)	6.15** (2.59)
NY Nuclear Generation	-0.09*** (0.01)	-0.098*** (0.02)	-0.053** (0.02)	-0.061** (0.03)
NY Hydro Generation	-0.23*** (0.02)	-0.24*** (0.03)	-0.18*** (0.03)	-0.191*** (0.04)
Time	14.72*** (1.02)	18.21*** (2.32)	31.59*** (1.14)	33.99*** (2.67)
Month of Year Dummies	Yes***	Yes***	Yes***	Yes***
Constant	-204857*** (19121)	-275847*** (45211)	-519306*** (21219)	-567955*** (51918)
N	1919	1919	1919	1919

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001
Standard Errors in Parentheses
[1]Heteroskedasticity – Autocorrelation Robust Standard Errors Reported

The first set of results for each of the models is the OLS results. These results show a highly significant and negative RGGI price. It is important to note that due to the endogeneity discussed, this coefficient is biased downwards. Therefore the GMM results are the ones to consider. The GMM model for each of the dependent flows variables shows a large change from the OLS models in the magnitude of the RGGI variable coefficient. The OLS coefficient is large and negative but by instrumenting with GDP expectations and ISO New England coal generation the coefficient becomes positive as is theoretically expected. The coefficient is insignificant in both GMM models indicating that a significantly different from zero impact of the RGGI allowance price on flows is not found.

To ascertain the validity of the instruments three things are tested for: underidentification, weakness of instruments, and exogeneity of instruments to the error term. The first test determines the power of the instruments in explaining the endogenous regressor. Instruments with no explanatory power result in a model that has no identification. Under no identification the coefficients will have bias equal to the bias under OLS (Hahn & Hausman, 2002). Weak instruments, those that have little explanatory power, also result in biased coefficients and asymptotic problems (Stock, Wright, & Yogo, 2002). There are appropriate tests to determine if either underidentification or weak identification is a problem.

The test for underidentification uses a Kleibergen and Paap rk LM statistic, which has a chi-squared distribution (Kleibergen & Paap, 2006). Results are found below in Table 2.5 and reject the null hypothesis of underidentification for both models.

Table 2.5: Underidentification test

	Real Time GMM 1	Day Ahead GMM 1
rk-Statistic	27.23	27.23
χ^2 p-value	0.000	0.000

There are several tests for the weakness of instruments. The appropriate test for a GMM model is the Cragg-Donald Wald F statistic (Cragg & Donald, 1993) compared to critical values provided by Stock and Yogo (2005). This comparison is only valid under an assumption of i.i.d errors. The extension to robustness under non-i.i.d assumptions results in the need to use a statistic robust to heteroskedastic and autocorrelated errors (Baum & Schaffer, 2007). The statistic which is robust to this for testing weak identification is the Kleibergen Paap rk Wald F-statistic (Kleibergen & Paap, 2006). This statistic is used and compared to the Stock and Yogo critical values. These critical values are test values at a 5% significance level. If the test is significant it indicates that the instruments are strong and induce a bias of no more than 10% of the bias from OLS (Stock and Yogo, 2005). Model results for this test are found in Table 2.6. It can be seen from the results that the test statistics for both models surpass the critical value.

Table 2.6: Test for Weak Instruments

	Real Time GMM	Day Ahead GMM
rk Wald F-statistic	13.28	13.28
Stock and Yogo Critical Value (10% Maximal LIML Size)	8.68	8.68

The final test is to determine if the instruments are exogenous to the error term. In the methods section it was described that there may be non-economic factors left in the error term. If any of these are correlated with the instruments it would invalidate them. All models are overidentified with one endogenous variables and two excluded instruments, allowing for testing of the validity of the assumption that the instruments are uncorrelated with the error term. The Hansen J statistic (Hansen, 1982) is used for the test of overidentifying restrictions. This tests the null hypothesis that the overidentifying restrictions, or the instruments, are valid. This test is robust under non-i.i.d. error assumptions (Baum, Schaffer, & Stillman, 2003). Results are found below in Table 2.7. The test of overidentifying restrictions fails to reject the null hypothesis indicating that the instruments in both GMM models are uncorrelated with the error term.

Table 2.7: Hansen Test

	Real Time GMM 1	Day Ahead GMM 1
J-Statistic	0.828	0.066
χ_2^2 p-value	0.36	0.80

In the GMM real time flows model most of the coefficients take their expected sign. New York and PJM load are important predictors of flows with a one MWh increase in load in New York causing an increase in flows by 0.166 MWh. A one MWh increase in average hourly load in PJM causes a decrease in flows by 0.05 MWh. The New York natural gas price has a negative relationship with flows which is unexpected. Similarly increases in the natural gas price in Pennsylvania are associated with higher flows which is also unexpected.

Increases in the cost of SO_2 allowance price have a positive impact on flows which goes against the theoretical predictions. The hypothesis for this variable is that generation on the margin in Pennsylvania is probably higher emitting than the generation in New York because of the preponderance of coal in Pennsylvania, especially compared to New York. Therefore a higher SO_2 allowance price would increase electricity prices in Pennsylvania compared to New York and subsequently reduce the incentive for imports. There may be a few explanations for the unexpected sign in the results. Marginal generators in New York may emit SO_2 at a higher rate. Average oil emission rates are 12 lbs/MWh of SO_2 and average coal rates are 13 lbs/MWh (Environmental Protection Agency, 2004). With many large coal plants having emission controls this rate could be much lower. The NYISO has a minimum oil burn or loss of gas reliability rule requiring dual fuel units to burn oil at certain load levels or in the case of natural gas supply disruption (New York Independent System Operator, 2014). High SO_2 allowance prices could disproportionately impact these highly emitting units and thus electricity prices in New York, incentivizing increased imports.

The RGGI allowance price variable, the main focus of the study, is positive and insignificant. This coefficient is in the theoretically predicted direction but the insignificance of the coefficient makes for a lack of confidence on the size of the allowance price impact. It is notable that the use of instruments changes the sign on the RGGI variable to being positive. There is a downward bias from the endogeneity in the OLS estimate explaining the negative sign. There is no economic reason for the coefficient to be negative. This study therefore reports that there is no significant leakage due to the RGGI policy.

Despite the potential for emissions leakage due to the RGGI policy this finding may be because leakage actually does not occur or is too small in magnitude to detect. In initial analysis of the policy, reducing electricity demand within the RGGI region was identified as a powerful means to mitigate emissions leakage (RGGI Inc. E.-S. , 2007a). Electricity demand has decreased in the time period that the RGGI policy has been in effect. Explanations for decreases in New York load are weather, energy efficiency programs, increases in on-site customer generation, and the economic downturn (RGGI Inc., 2010). This decrease in electric demand could effectively remove the load that would be served by otherwise priced out generators and therefore reduce the need for increased imports because of allowance holding requirements. Transmission constraints and local capacity requirements could also mitigate emissions leakage. Transmission thermal ratings and system stability requirements limit the amount of electric power that can be imported into New York, regardless of short-term economics. For example, total transmission capability for imports from the PJM Interconnection is typically limited to a range of 2,800 to 3,660 MW[5]. Additionally, flows from Pennsylvania to New York often do not follow economic signals.

In 2010, 2011, and 2012 the average price between the NYISO and PJM was found to be inconsistent with the direction of average flows in yearly analyses of the PJM market (Monitoring Analytics, LLC, 2011, 2012, and 2013). Over the total time period analyzed, the average real time price difference between New York and Pennsylvania at their border zones was -$2.34 and in the day ahead market $0.05. In addition there were 1198 days where the average price difference was negative in the real time market and

[5] http://mis.nyiso.com/public/P-8list.htm (Date Last Accessed: April 3, 2015)

913 days during which the average price difference was negative in the day ahead market. Despite the negative average price differences, New York was a net importer from Pennsylvania on every day during the time period. Finally, the correlation coefficients between real time and day ahead imports and the price difference between New York and Pennsylvania at their border are only -0.018 and -0.023. This low correlation casts further doubt on flows following traditional economic signals.

There are a variety of situations where system operators may schedule flows for non-economic reasons such as line congestion, generator trips, and other events that occur on the system. Many of the larger load areas in New York also have reliability requirements for the amount of generation that must be locally produced. In addition, State of the Market reports for PJM by Monitoring Analytics (2011), identify several reasons for unexpected prices and transaction levels: different rules governing external transactions for the NYISO and PJM, a lack of built in time lag for those rules, and the risk of external transactions. All of these reasons could contribute to the inability of the RGGI allowance price to have an impact on imports.

2.7 Conclusion

This chapter develops models of Pennsylvania CO_2 emissions and the flows from Pennsylvania to New York in an attempt to determine if there has been leakage from the Regional Greenhouse Gas Initiative. The Pennsylvania CO_2 emissions model tests for an impact of the RGGI allowance price on emissions holding load, fuel prices, NO_x and SO_2 allowance prices, and nuclear generation constant. The flows models use the major determinants of the price difference between New York and Pennsylvania. Due to simultaneity bias between flows and the RGGI allowance price it is instrumented with GDP expectations and ISO New England coal generation. The coefficient estimates are negative in the emissions model and positive, as predicted, in the flows models. The coefficients on the RGGI allowance price are insignificant in both the emission and flows models. As a result this research is unable to conclude that the RGGI program and associated allowance price has resulted in emissions leakage.

There are several reasons the impact of the RGGI allowance price on flows could be small or negligible. Predominantly, flows from Pennsylvania to New York do not follow economic price signals as the prices in PJM are, on average higher. Despite this, total daily flows during the time span never go from New York to Pennsylvania. There are also many differences in rules between the NYISO and PJM systems, reliability rules, and transmission limits which may limit the incentives of economic signals, and prevent the RGGI policy from impacting imports.

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3. Estimating Generator Specific Emission Functions

3.1 Introduction

The power generation sector is one of the largest producers of greenhouse gas emissions in the United States. The Environmental Protection Agency (EPA) estimates that 32% of U.S. greenhouse gases are produced by the power generation sector[6]. The main three pollutants in this sector are carbon dioxide (CO_2), sulphur dioxide (SO_2), and nitrous oxides (NO_x). The latter two are large contributors to health related pollution problems such as acid rain. The EPA requires most generators to report hourly SO_2 and NO_x emissions as part of their Acid Rain Program (ARP) and the Clean Air Interstate Rule (CAIR) in Part 75 of Title 40 of the code of federal regulations. These programs reduce emissions by establishing cap and trade markets for NO_x and SO_2 emissions allowances. Additionally a CO_2 cap and trade market exists amongst some Northeast states in the form of the Regional Greenhouse Gas Initiative (RGGI). There are also renewable portfolio energy standards and wind generation tax credits supporting wind generation. In order to address climate change much further work has to be done in regulating emissions and incentivizing changes to the power sector as it moves to clean renewable energy. In order to analyze the impact of future policies or changes in the electricity system on emissions it is important to have good models that can accurately predict emissions. This provides the ability to analyze the impacts on emissions from different policies.

Emissions from electric generators are complicated due to the fact that they are produced at different rates depending on internal generator factors such as the temperature of combustion, how much oxygen is available to burn with the fuel, the type of fuel, and emission controls to name a few aspects. Using simple assumptions such as constant heat rates, emissions that increase linearly with generation, or omitting large generator operation changes such as startup, shutdown, and ramping can lead to inaccurate emission estimates.

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[6] http://www.epa.gov/climatechange/ghgemissions/sources/electricity.html (Date Last Accessed: April 3, 2015)

As policies targeting emissions from the power sector become more common, especially for CO2 emissions, it will be important to be able to have accurate forecasts of emissions in order to create effective emission caps. Functions can also be used to estimate emissions if continuous monitoring system (CEMS) data is unavailable or monitoring equipment is down. Simulations of power generation can also use the functions to accurately estimate emissions under different dispatch scenarios or network changes that would change generator operation, such as scenarios where wind penetration is promoted.

These emission functions improve the accuracy of emission predictions over simpler models or assumptions and have a variety of uses. They can be used to estimate the impacts of any policy which may change the operation of generators. For example, when there is more wind power on the system generators often have to back it up by ramping up and down because of the stochastic nature of wind generation without battery back-up. In order to forecast emissions under this scenario the model must be able to accurately forecast emissions during ramping, startup, and shutdown. Accurate hourly emission functions are estimated which take into account all of these factors.

3.2 Background

Emission functions are estimated which accurately estimate emissions given hourly generation of a generator. The functions are designed for NO_x, SO_2, and heat input (which is proportional to CO_2 emissions). By taking into account the impacts of startup, shutdown, upramp, and downramp, these functions can predict emissions for the full spectrum of generator operation. They are estimated specifically for each individual generator in an automated way making their implementation relatively easy. The results are functions that can estimate accurately over all types of hours.

The emission functions are designed for three different types of generators. The first type is a steam turbine which in the data set used here is fired by coal or natural gas. These generators burn fuel to heat water and convert it into steam. The heated steam is used to turn a turbine and produce electricity. It is then condensed and heated again in a closed cycle where the fuel never interacts with the turbine or water. The second type is a simple cycle generator which is fueled by natural gas for all generators researched in this chapter, but can also be fueled by oil. These generators use a combustion turbine which ignites the fuel in a chamber with compressed air. This hot gaseous mixture is then sent to the turbine where it expands and drives the turbine to generate electricity. The third type is a combined cycle generator. It consists of a combustion turbine and a steam turbine. Waste heat from the combustion turbine portion is used to generate steam which drives the steam turbine.

In order to produce electricity generators must burn fuel. During combustion there are a variety of thermodynamic and chemical reactions which occur to produce emissions. Depending on how efficiently the generator is transferring heat from combustion into steam creation and how efficiently the fuel is burning emission rates can vary greatly. The creation of CO_2 and SO_2 emissions are a result of this fuel combustion. Both carbon (C) and sulfur (S) are found in fossil fuels. When the fuel burns they react with oxygen to create heat, carbon dioxide, and sulfur dioxide:

$$C + O_2 \rightarrow CO_2 + 14{,}093 \text{ Btu/lb}$$

$$S + O_2 \rightarrow SO_2 + 3{,}984 \text{ Btu/lb}$$

Nitrous oxides come from both thermal and fuel reactions due to nitrogen being found in the air and in some fossil fuels, especially coal. Natural gas fired units mostly have thermal NO_x emissions while 75% of NO_x emissions produced by coal generators can come from fuel burning (The Babcock & Wilcox Company, 2005). Thermal NO_x emissions exponentially increase with temperature and are also dependent on oxygen. Excess oxygen can promote higher flame temperatures which promotes NO_x formation.

Generators convert heat energy into electricity and do this at different efficiencies depending on generator design and operation. The major impact on this conversion efficiency is heat loss. Heat can be lost in a variety of ways in the generator. Excess air in the combustion chamber can absorb heat, the emission of flue gas out of the stack removes heat from the system, there is transfer of heat through walls, and losses of unburned fuel from incomplete combustion. Major generation changes can change many of these factors.

Startup can impact emissions and heat input depending on the state the generator is in. Startup is generally initiated with natural gas or residual oil due to low heat rates, inefficient combustion, and safety factors (The Babcock & Wilcox Company, 2005).

Cold starts, or startups after long periods of not running, can result in the lowest combustion efficiency and can require long periods of time before the generator is operating. Generators must fire at low heat in order to avoid materials expanding too quickly. Additionally low load operation of generators can lead to poor distribution of air to burners which can lead to low levels of fuel-air mixing and inefficient combustion. Incomplete combustion is a large heat loss and waste of fuel that could be converted into generation.

Shutdown of units is done whenever possible in a controlled manner over time. The firing rate of the generator is reduced until operating at a minimum capacity before the fuel is shut off and boiler is purged with air, effectively ending generation and emissions. Fuel shut off and boiler purging is performed immediately in the case of emergency shutdowns.

The ramping of units up and down requires controlling excess air in order to burn fuel at different rates. When downramping generators may maintain excess air if they expect to upramp again, or will adjust the air-fuel mixture after downramping. Excess air can promote NOx emissions and cause fuel to burn quicker. Adjustments to the burner to ramp a unit can also vary the turbulence of air and fuel flow rates in the burners. The result of this is an increase in air-fuel mixing which causes an increase in combustion intensity, allowing for operation with less air, and increased boiler efficiency (The Babcock & Wilcox Company, 2005). This could cause upramps to momentarily increase generator efficiency.

Due to these complicated operations it is important to estimate emission functions for individual generators instead of choosing one function for all generators or even all generators of a given type. All of the operations above change depending on the type of generator, the fuel used, the operation of the generator, and the design of the generator. For example, cold starts of coal steam turbine generators require a long lead time because their superheaters cannot quickly go from being cold to very hot. Gas steam turbine generators operating under lower pressure can startup much quicker and combined cycle and simple cycle units can startup almost instantly (The Babcock & Wilcox Company, 2005). Many of these operations may have lasting effects over time. Some generator types such as combined cycle and simple cycle units are designed to be able to change generation output quickly and efficiently. This may result in lower impacts of operation changes than steam turbine units fired by coal or natural gas. All of this points for the need to allow for emission functions to be estimated specifically for each individual generator and to allow for different time spans of operation impact, and different coefficient estimates on those impacts.

3.3 Emission Functions Data

Data for estimating emission functions is taken from 2010 U.S. Environmental Protection Agency (EPA) Continuous Emissions Monitoring Systems (CEMs) data. The dataset contains information on the variables found below in Table 3.1.

Table 3.1: CEMS Variables

Variable Name	Description	Measure
GLOAD	Gross Generator Output	MWh
NOXMASS	Nitrogen Oxide Emissions	lb/hour
SO2MASS	Sulfur Dioxide Emissions	lb/hour
HTINPUT	Heat Input	mmBtu/hour

These variables have hourly observations for the entire year. The dataset covers every electric generator in the U.S. larger than 25 megawatts (MW) in size that produces NO_x or SO_2 emissions. Each generator in the dataset is identified by an ORIS ID and boiler id. In order to determine the location of each generator this identification must be matched with the identification numbers found in the Energy Information Agency (EIA) form 860. These numbers in many cases do not match exactly. In these cases there are multiple EIA identification numbers that are similar and so additional information is used to ensure a correct match. The EIA dataset reports the max output of each generator and so by calculating the maximum reported output in the EPA dataset this can be used to further match generators. Upon matching generators information is added on location, emission control equipment, boiler type, and fuel type to the EPA data. Finally, the aggregated EPA dataset is broken down into individual data sets for each generator which are put into four categories. Those four categories are coal fired steam turbines, natural gas fired steam turbines, combined cycle, and simple cycle units.

In addition to the variables given in the datset, additional variables are created. These created variables are found below in Table 3.2 with descriptions of the calculations used to create them. In order to estimate the emissions impacts on CO_2, which is not reported in the EPA dataset, heat input can be converted into CO_2 emissions. The conversion is a proportional multiplier to heat input which can be found in an EPA report on emissions factors (Environmental Protection Agency, 2004). Heat input and CO_2 emissions are referred to interchangeably.

Table 3.2: Created Variables

Variable Name	Calculation	Unit
Upramp	$\begin{cases} GLOAD_t - GLOAD_{t-1} \; if \geq 0 \\ Else\ 0 \end{cases}$	MWh
Downramp	$\begin{cases} GLOAD_t - GLOAD_{t-1} \; if \leq \; 0 \\ Else\ 0 \end{cases}$	MWh
Startup	1 if generator has started up in the previous hour. 0 otherwise.	Dummy Variable
Shutdown	1 if generator Shutdown in the following hour. 0 otherwise	Dummy Variable
GenOn	1 if the generator is on (has htinput > 0) 0 if the generator is off (has htinput = 0)	Dummy Variable

The CEMS data is primarily measured data from CEMS for each generator. There are hours for each generator when they do not report emissions over the entire hour, or use calculated instead of measured values. Once per day generators are required to calibrate their CEMS equipment. During this calibration hour generators only need to use two 15 minute apart data points to calculate hourly emissions instead of the usual minimum of 4 data points. Whenever the CEMS equipment is down for reasons other than the calibration, the calibration test results in the a determination that the CEMS equipment is out of control, or if at any other point the CEMS equipment is determined to be out of control, then calculated emissions are used. In order to ensure this change in measurement of emissions does not bias the results it is controled for. Data was obtained by special request from the EPA containing information on calibration hours and the method of determination codes (MODC) for each hour. Using the calibration data a dummy variable is created capturing whether or not a unit calibrated during a given hour. Included with the calibration dummy variable are interactions between it and startup, shutdown, upramp, and downramp. This is because generators may try to calibrate during hours which have the characteristic of different average emission rates in different parts of the hour. In this way they can calibrate during a high emission rate portion of the hour, and not use that portion of the hour in the calculation of hourly emissions. Hours of startup, shutdown, upramp, and downramp all can have the characteristic of different emission rates during different parts of the hour.

The MODC data provides information on wether the data provided is measured or not. The MODC information is represented in five different dummy variables. The dummy variables take a value of 1 if the associated reported data is anything but measured by the CEMS equipment.These five different variables cover measurements of the flow of fuel, level of oxygen in the burner, CO_2 measurement, NO_x measurement, and SO_2 measurement. For functions of heat input the flow, oxygen, and CO_2 MODC dummy variables are included. The flows variable is included because heat input is calculated by the flow of fuel into the generator. The CO_2 and O_2 are included because their measurement may be needed for additional calculations of heat input since the level of oxygen should impact the heat of the unit. CO_2 is another way to calculate the amount of fuel burned if flow is not being measured. In the NO_x emission model the NO_x MODC dummy variable as well as the flow and oxygen dummy variables are included since both fuel input and oxygen can be used to calculate NO_x emissions. Similarly, for SO_2 emission models the SO_2 MODC dummy variable as well as the flow and oxygen dummy variables are included. By including these measurement dummy variables as well as the calibration variables, any bias that would have been introduced from calculating heat input or emissions is controlled for.

3.4 Emission Function Methodology

Ordinary least squares (OLS) estimates of time series data often exhibit strong serial correlation in their errors, meaning that current errors are correlated with past errors. This violates the standard assumptions of OLS regression, resulting in standard errors that are biased and estimates which are no longer efficient. This problem is readily apparent in the data and can be seen in the Autocorrelation Function (ACF) and Partial-autocorrelation Function (PACF) graphs which are provided in Figure 3.11 for both the raw and deseasonalized data.

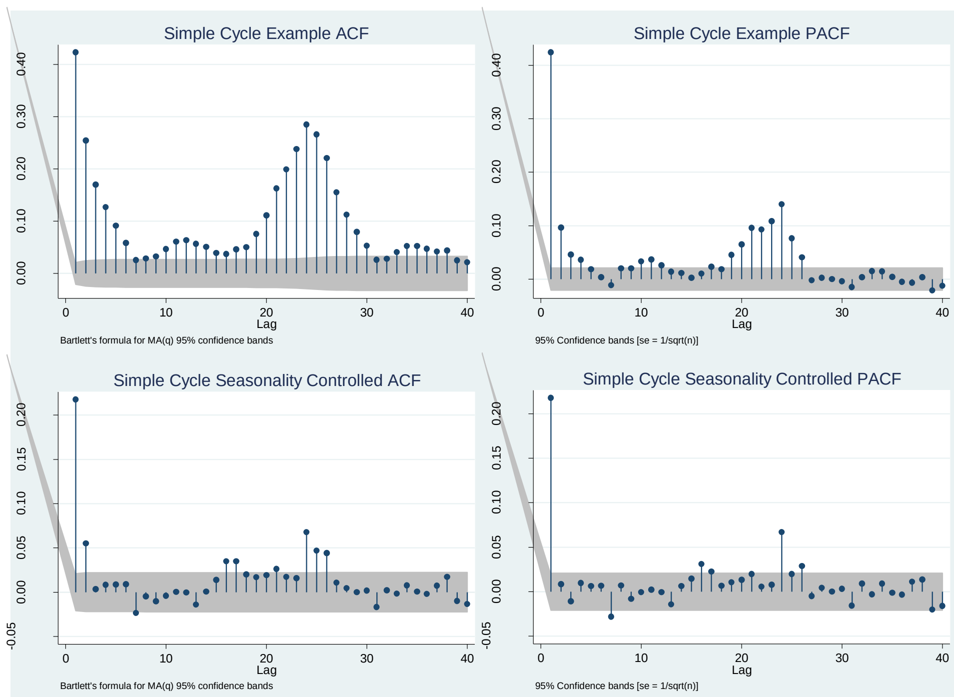

Figure 3.1: ACF and PACF

In the raw graphs there is both hourly and monthly seasonality in the data. Hourly seasonality comes from the hourly electricity demand patterns that occur everyday, with peak demand occuring in the middle of the day, and a valley late in the night or early in the morning. Monthly seasonality comes from patterns through the year of electricity demand, primarily based on temperature with a maximum at the hieight of summer, another peak in the middle of winter, and then valleys in the shoulder months (Spring and Fall).

Removing the impact of seasonality allows a closer inspection of the ACF and PACF plots, as well as allowing for tests on stationarity of the data. Dependent variables are tested for stationarity with three tests for robustness for 2 generators of each of the four generator classes. An Augmented Dickey Fuller test (Dickey & Fuller, 1981), Phillips-Perron test (Phillips & Perron, 1988), and KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) on the deseasonalized dependent variables. All the dependent variable specifications are found to be stationary for the 8 generators tested

There are two solutions to the serial correlation problem. The standard errors can be corrected or additional information can be utilized from the dynamics of the serial correlation. By incorporating the dynamics in the errors it is possible to improve the accuracy of out-of-sample forecasts. This is important since the emission functions are designed with forecasting in mind.

The emission functions for each generator in the Texas are estimated using ARMAX models. ARMAX allows for forecasts to include underlying data generating processes from autoregressive (AR) and moving average (MA) components in addition to the use of exogenous explanatory variables (denoted by the "X" in ARMAX). ARMAX models are often used to forecast engineered and electric systems including the behavior of electric load, electricity prices, and wind generation (Alfares & Nazeeruddin, 2002), (Aggarwal, Saini, & Kumar, 2009), and (Soman, Zareipour, Malik, & Mandal, 2010). The final estimated emission equations have the following form for generator *i* and emission type *e* (NO_x, SO_2, or CO_2):

$$E_{iet} = \omega_1 \mathrm{GenOn}_{it} + \sum_{a=1}^{23} g_a \mathit{HourlyInteraction}_{it} + \sum_{aa=1}^{11} h_{aa} \mathrm{MonthlyInteraction}_{it} + \alpha_1 \mathit{GLOAD}_{it} + \alpha_2 (\mathit{GLOAD}_{it})^2 + \sum_b^z \beta_b \mathit{Upramp}_{i(t-b)} + \sum_c^y \gamma_c (\mathit{Upramp}_{i(t-c)})^2 + \sum_d^x \delta_d (\mathit{Upramp}_{i(t-d)} * \mathit{GLOAD}_{i(t-d)}) + \sum_e^w \epsilon_e \mathit{Downramp}_{i(t-e)} + \sum_f^v \zeta_f (\mathit{Downramp}_{i(t-f)})^2 + \sum_g^u \eta_g (\mathit{Downramp}_{i(t-g)} * \mathit{GLOAD}_{i(t-g)}) + \sum_{h=}^T \kappa_h \mathit{Startup}_{i(t-h)} + \sum_j^S \lambda_j \mathit{Warmstart}_{i(t+j)} + \sum_k^r \mu_k \mathit{Coldstart}_{i(t+k)} + \sum_l^q \xi_l \mathit{Shutdown}_{i(t+l)} + \sum_m^p \pi_{m\rightarrow\rho} \mathrm{CalibrationVars} + \sum_n^o \rho_{n\rightarrow o} \mathrm{MODCVars} + v_t$$

$$v_t = \sum_{n=1}^p \phi_n E_{ie(t-n)} + \sum_m^q \theta_m \epsilon_{t-m}$$

where v_t is the error term and ϕ is the n^{th} order autocorrelation parameter and θ the m^{th} order moving-average parameter. The parameters lag and lead length are iteratively chosen with max and minimums: $-1 \leq b, c, d, e, f, g, l \leq 20$, and $10 \geq j, k \leq 0$, and $-10 \leq h \leq 20$, and $1 \geq n \leq 3$ and $0 \geq m \leq 3$. HourlyInteraction and MonthlyInteraction are seasonal dummy variables interacted with unit hourly generation to allow for different seasonal impacts. GLOAD, Upramp, Downramp, Startup, and Shutdown variables are described in Table 3.2. Warmstart and Coldstart are dummy variables capturing how long a generator has been offline for and are described in more detail in following paragraphs. CalibrationVars and MODCVars are controls for times when the generator is not reporting measured data for an entire hour and are described in more detail in the following paragraphs.

The equation has no constant when the unit is off but does when the unit is on. This is done by estimating the equation without a constant and includes the GenOn dummy variable. This forces the y-interecept to be zero when the unit is off and has no heat input. At these times it is impossible for there to be emissions produced because there is no combustion taking place. When the generator is on it will then have a constant which will be the ω coefficient on the GenOn variable.

Included in the equation are hourly and monthly seasonal impacts. 23 hourly dummy variables and 11 monthly dummy variables are created and multiplied by unit output in order to allow the seasonal impact to vary with the level of generator output.

Following the seasonal variables are the impacts of unit electricity output. This is modeled as a quadratic function as emissions are a non-linear function of generator output. The upramp and downramp variables are modeled in the same way. Each of them have a quadratic function and then both are interacted with unit output. Larger upramps may be fundamentally different from smaller upramps. Larger upramps mean moving to a much different set point while smaller ones may just be load following adjustments. These probably have different magnitudes and allowing for a non-linear impact of upramp can capture this. The interaction with unit output allows for the model to control for the impact of ramping up, down, to, and from different generator set points.

The ramping and startup variables can have up to 20 hourly lags and the shutdown variable can have 20 hourly leads. Depending on the generator type the impacts of these three operations will last for differing amounts of time. Coal steam turbine generators take a long time to move from one set point to another, to startup, and shutdown. Therefore they will likely have more persistent impacts from these operations. A combined cycle or simple cycle generator is designed to be very efficient at all of these operations and therefore may have less lags or smaller impacts on emissions and heat input for these lags.

The impacts of startup occur for some units before they have started generating electricity. In this time span before they produce electricity they are burning fuel and producing emissions and working on getting equipment online and slowly heating up the inside of the generator. Depending on how long the generator has been off, what kind of generator it is, and what kind of fuel is used for startup, the impacts on emissions and heat input during these hours can change. In order to capture the impact of how long a generator has been off before starting up, dummy variables are created for cold startup, warm startup, and hot startup.

A cold start is considered to be when a unit has been off by 120 hours or more. A warm start is when a generator has been off for 25-119 hours and a hot start if the unit has been off for 24 hours or less. These categories of start are used by the EPA (Kokopeli, Schreifels, & Forte, 2013) and are defined by Steven Lefton and Douglas Hilleman (2011). Up to 10 leads are allowed of the dummy variables capturing both the length of startup, depending on its type, and the different emission impacts of the startup period. Once a generator has started producing electricity it is not considered to have impacts differing based upon the type of startup it underwent. Therefore only the dummy variables capturing type of startup as leads and not lags are included. Startup itself is included with both leads and lags, making the type of startup dummy variables modifiers during the time when the generator is preparing itself to generate electricity. Then when the generator starts producing electricity, all startups are treated the same.

3.4.1 Automated Function Estimation

Emission functions are estimated for 244 generators in Texas. To estimate functions by hand for every generator would be time consuming. Therefore an automated procedure has been coded to estimate the functions of each emission type for each generator. The estimation procedure consists of two steps. The first is an iterative procedure to determine the number of lags and leads for each each variable for a particular generator and emission type. All generator types and emission types are assumed to have at least an autoregressive structure. Therefore the first step is estimated with Newey-West standard errors since errors under standard OLS are known to be incorrect due to the autocorrelation. An iterative procedure is used to determine the lag or lead length of each variable. The function always includes at least the unlagged variable.

The iteration procedure begins by estimating the base equation which consists of the GenOn variable, the seasonal controls, the associated MODC dummy variables, the calibration controls, and the quadratic unit output function. The first variable is added with 20 lags. If the last lag is insignificant it is removed. This removal process is repeated until the last lag is significant at the 5% level or better. When this is done for the first variable the next variable is added and the same process occurs. Once the number of lags for the added variable are determined the previous variable is rechecked. The rechecking process occurs by adding lags until an insignificant lag is added. Then it is reduced again until the final lag is significant. By repeating the process the number of lags can change dynamically as variables are added to the equation. Lags of all previously added variables can be added or removed whenever a new variable is introduced. The following results give a snapshot from the middle of this process. 20 startup lags are added to the model and reduced one by one down to lag 13.

Variable	Coefficient	P-Value
L12.startup	197.4	0.017
L13.startup	138.7	0.079

Lag 13 is removed because its p-value is greater than 0.05.

L11.startup	149.6	0.060
L12.startup	196.7	0.017

The iteration on startup lags stops because lag 12 of startup has a p-value of 0.017 which is less than 0.05, the significance cut-off. 20 leads of shutdown are then added to the model. These are reduced one by one until a significant one is found. In this case lead 6 has a p-value less than 0.05.

Variable	Coefficient	P-Value
l11startup	148.6606	0.062
l12startup	196.1282	0.017
shutdown	-656.0645	0.001
fshutdown	-42.48822	0.223
f2shutdown	59.05545	0.094
f3shutdown	82.18836	0.204
f4shutdown	11.61049	0.885
f5shutdown	-103.1538	0.141
f6shutdown	-194.2337	0.029

Now that the number of leads of shutdown has been determined, the program rechecks the startup variable by adding back in lag 13, to see if it has become significant due to the change in model specification.

Variable	Coefficient	P-Value
l11startup	149.3362	0.061
l12startup	196.8841	0.017
l13startup	138.1024	0.081

Lag 13 has not become significant so the program reduces lags for startup again until finding a significant lag. Once again the 12th lag is significant so the program stops removing startup lags there.

l11startup	148.6606	0.062
l12startup	196.1282	0.017

The program adds in the next variable and continues this process of determining the lag length of the new variable and then rechecking previously added variables until the full model is chosen.

Once the first step of choosing lag and lead lengths is completeted the ARMA structure of the error term is estimated. The chosen model from the first step is estimated with each combination of AR and MA terms up to 3 AR and 3 MA terms. Increasing the number of terms past 3 makes the estimation take an infeasible amount of time. In order to choose the best ARMA structure the model with the lowest Akaike Information Criterion (AIC) value is used. Upon completion of the two step estimation the fully estimated equation is saved and can be used to forecast or determine the estimated impacts on emissions of different generator operations

3.4.2 Example Results

The following section shows some graphs to illustrate what some of the data looks like and what the functions results end up looking like. Used in the example is a coal generator. Figure 3.2 shows a graph of a coal unit's generation and emissions in 2010. Each of the scatter plots show daily observations of a single coal generator's generation (MW), heat input (mmBtu), NO_x emissions (lbs), and SO_2 emissions (lbs).

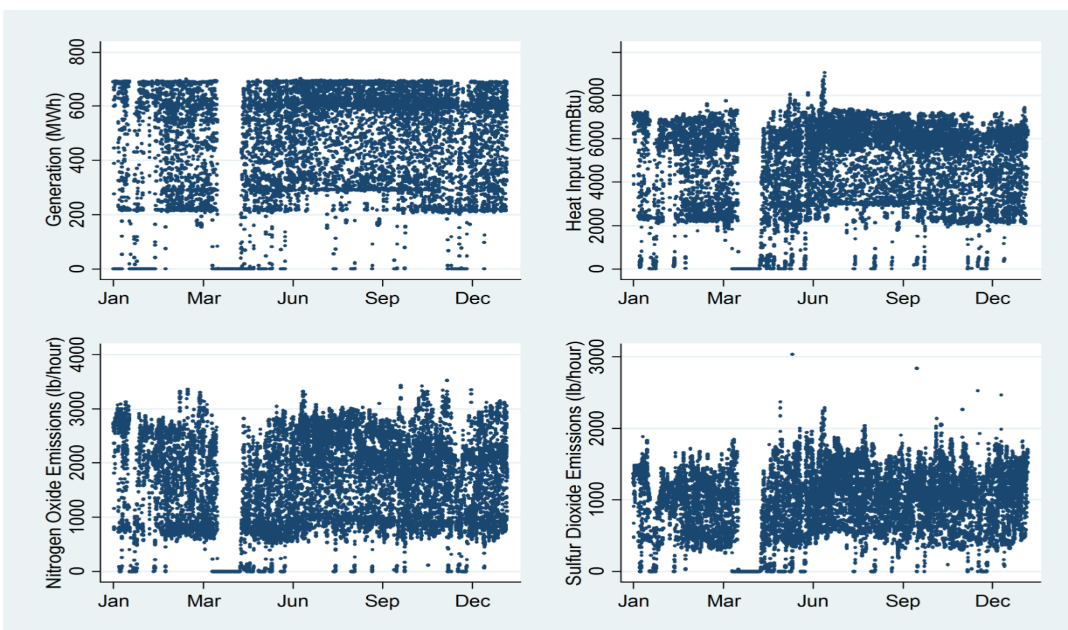

Figure 3.2: Coal Unit. Generation and Emissions through Time

Looking at the top left graph of generation it can be seen that despite the large number of data points they cluster around a few different levels. At 0 generation are extended periods of time when the coal unit is not running. At the top of the generation graph is maximum capacity. There is another line of generation just below this, and then a minimum generation line. It can be seen in that in the summer months this minimum is higher than the other months. The emissions graphs reflect the generation to a large extend but show much larger variation. The heat input graph in the top right and the NO_x emissions graph in the bottom left show some of the same characteristics as the generation graph. They both show clusters of data at max and minimum generation, with the NO_x emissions graph having more variation. The SO_2 emissions graph in the bottom right of Figure 3.2 shows a lot of variance and less clustering within any specific range.

Figure 3.3, below, shows a graph of some of the relationships between emissions and generator output for the same coal unit as Figure 3.2. The top left graph displays heat input (mmBtu) on the vertical axis, the top right graph NO_x emissions (lbs), and the bottom left graph has SO_2 emissions (lbs). All three of these are graphed against generation (MWh) on the horizontal axis in order to examine their relationship. The main predictor in the emission functions is the generation each unit. The graph for heat input is relatively linear with heteroskedasticity as generation increases. The NO_x emissions graph is very non-linear and the graph for SO_2 emissions shows the strongest heteroskedasticity as generation increases.

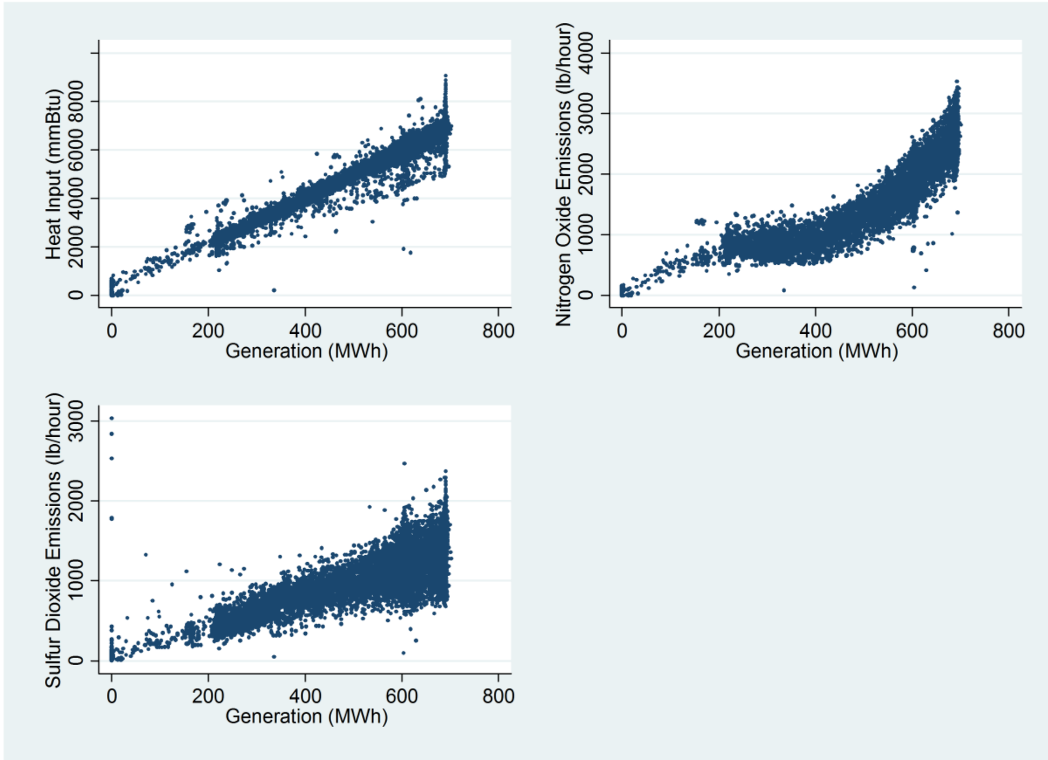

Figure 3.3: Coal Unit. Emissions vs Generator Output

Table 3.3, below, shows an example output of regression results for a coal generator. In order to limit the amount of space the table takes up variables are in shorthand and are organized into multiple columns. GLOAD is the variable for generator output. A f and *l* followed by a number indicate leads and lags of that number respectively. This generator did not have any hours in which it did not report measured data, therefore no MODC code variables are in the output. From this output one can see the various lag lengths chosen for the different variables. For example, 19 startup lags were chosen and only 2 shutdown leads were selected.

Table 3.3: Example Regression Results. Coal Generator. Heat Input (mmBtu)

Base function, Startup, Shutdown	Coefficients[1]	Downramp and Interactions	Coefficients[1]	Upramp and Interactions	Coefficients[1]
gload2	11.20***	fdownramp	-0.625***	fupramp	0.176***
sqgload2	-0.0144***	downramp	2.195***	upramp	-1.332***
genon	27.37***	Ldownramp	2.099***	lupramp	-2.006***
cal dummy	5.371***	l2downramp	2.039***	l2upramp	-1.980***
cal*fupramp	-0.130***	l3downramp	2.050***	l3upramp	-1.774***

Base function, Startup, Shutdown	Coefficients[1]	Downramp and Interactions	Coefficients[1]	Upramp and Interactions	Coefficients[1]
cal*fdownramp	-0.0258***	l4downramp	1.984***	l4upramp	-2.066***
cal*upramp	-0.104***	l5downramp	1.966***	l5upramp	-2.006***
cal*downramp	-0.00473	l6downramp	1.662***	l6upramp	-1.980***
cal*gload	-26.89***	l7downramp	1.598***	l7upramp	-1.774***
cal*startup	13.85***	l8downramp	1.416***	l8upramp	-1.644***
cal*shutdown	-0.102***	l9downramp	1.251***	l9upramp	-1.359***
startup	13.42***	l10downramp	1.148***	l10upramp	-1.367***
lstartup	83.47***	l11downramp	1.014***	l11upramp	-1.173***
l2startup	70.30***	l12downramp	0.676***	l12upramp	-1.061***
l3startup	61.35***	l13downramp	0.606***	l13upramp	-0.823***
l4startup	52.45***	l14downramp	0.400***	l14upramp	-0.699***
l5startup	49.47***	l15downramp	0.354***	l15upramp	-0.538***
l6startup	44.81***	l16downramp	0.214***	l16upramp	-0.377***
l7startup	44.40***	l17downramp	0.109**	l17upramp	-0.243***
l8startup	40.96***	l18downramp	0.0925**	l18upramp	-0.151***
l9startup	38.27***	fsqdownramp	0.00212***	fsqupramp	-0.000554**
l10startup	27.94***	sqdownramp	0.00148***	squpramp	-0.00272***
l11startup	30.92***	lsqdownramp	-0.000408	lsqupramp	0.00120***
l12startup	29.18***	l2sqdownramp	0.00164***	l2squpramp	0.000106
l13startup	22.03***	l3sqdownramp	0.000269	l3squpramp	0.0000929
l14startup	21.57***	l4sqdownramp	0.000726**	l4squpramp	0.000262
l15startup	16.26***	l5sqdownramp	0.000391	l5squpramp	0.000182
l16startup	10.72***	l6sqdownramp	0.00141***	l6squpramp	0.00172***
l17startup	10.03***	l7sqdownramp	0.000993**	l7squpramp	0.00125***
l18startup	5.679***	l8sqdownramp	0.000395	l8squpramp	0.00117***
l19startup	4.701***	l9sqdownramp	0.00127**	l9squpramp	0.00126**
f3warmstart	1.034	fdowngload	0.00409***	l10squpramp	0.000732
f2warmstart	2.971	downgload	-0.0304***	l11squpramp	0.000265
fwarmstart	3.027	ldowngload	-0.0244***	l12squpramp	0.000939*
warmstart	14.79***	l2downgload	-0.0257***	l13squpramp	0.000419
f3hotstart	-2.636***	l3downgload	-0.0246***	l14squpramp	0.00117*
f2hotstart	1.437	l4downgload	-0.0243***	l15squpramp	0.00148**
fhotstart	1.384	l5downgload	-0.0238***	fupgload	-0.00137***
hotstart	17.25***	l6downgload	-0.0214***	upgload	0.0202***
shutdown	-56.55***	l7downgload	-0.0201***	lupgload	0.0285***
fshutdown	-3.661***	l8downgload	-0.0177***	l2upgload	0.0259***
f2shutdown	2.759***	l9downgload	-0.0162***	l3upgload	0.0250***
		l10downgload	-0.0148***	l4upgload	0.0240***
L.AR	-0.702***	l11downgload	-0.0135***	l5upgload	0.0232***
L2.AR	0.595***	l12downgload	-0.0104***	l6upgload	0.0215***
L3.AR	0.896***	l13downgload	-0.00807***	l7upgload	0.0198***
L.MA	0.802***	l14downgload	-0.00556***	l8upgload	0.0178***
L2.MA	-0.414***	l15downgload	-0.00581***	l9upgload	0.0144***
L3.MA	-0.798***	l16downgload	-0.00297***	l10upgload	0.0153***
		l17downgload	-0.00142**	l11upgload	0.0132***

Base function, Startup, Shutdown	Coefficients[1]	Downramp and Interactions	Coefficients[1]	Upramp and Interactions	Coefficients[1]
Monthly Controls	Yes***	l18downgload	-0.00166***	l12upgload	0.0111***
Hourly Controls	Yes***	l19downgload	-0.000486***	l13upgload	0.00924***
				l14upgload	0.00690***
N	8736			l15upgload	0.00483***
[1] + p<0.10, * p<0.05, ** p<0.01, *** p<0.001				l16upgload	0.00380***
				l17upgload	0.00271***
				l18upgload	0.00139**

The results are meant to be illustrative. For each type of unit the average results from the model are reported for each of the various hourly operation types. These results come from sums of coefficients like those listed above. Most generators do not have so many lagged impacts but summing across all the lags and leads allow for an estimate of the total impact of that operation. In this way the total impact through time of startup, shutdown, upramp, and downramp on emissions can be estimated.

3.5 Coal Results

The first result to report is how well the emission functions work. In order to do this out-of-sample emissions are estimated for each generator's function. Applying each estimated function to 2012 CEMS data provides us with forecasts of each emission type. These results are then compared to simpler models in order to make the case that the complexity of the emission functions is useful and not over fitting. The best model that can be generalized and applied to many generators to estimate emissions under different scenarios, simulations, or other purposes is one which can accurately estimate total emissions, as well as emissions under different operating hour types. If a model cannot accurately predict emissions during hours in which a generator upramps, downramps, starts up, or shuts down, then any application of that model to a scenario with many instances of them will be inaccurate.

There are two performance metrics used to determine how well a model predicts. The first metric for in-sample predictions and out-of-sample forecasts is percentage error. This performance metric is used because emissions totals have interpretable meaning for most potential emissions function applications. Analyzing total emissions is often used to determine societal damages, cap and trade program emission limits and costs, and environmental impacts. Therefore the ability for the functions to estimate total emissions over the time span is important. Percentage error is calculated as:

$$100 * (\sum_{i=1}^{n} f_i - \sum_{i=1}^{n} y_i)$$

where f_i is each i hour's forecasted emissions and y_i is each i hour's actual emissions. The percentage error can be interpreted as a measure of bias in the calculation of total emissions.

The second metric is the mean absolute error. This second metric allows for a comparison to be made of how accurate the models are. Mean absolute error is calculated as:

$$\frac{1}{n} * \sum_{i=1}^{n} |f_i - y_i|.$$

where f_i is each i hour's forecasted emissions and y_i is each i hour's actual emissions. This is a measure of, on average, how accurate each individual observation and by extension, how accurate the model predicts.

Both metrics are calculated over the entire year, and for subsets of hours: only upramp hours, downramp hours, startup hours, and shutdown hours. For the subsets of hours the percentage error is calculated at different points in time. These different points of time for upramp, downramp, and startup are at time t when a generator has just performed the relevant operation, hour t+1 or the hour just after the relevant operation, and hour t+4 or four hours after the relevant operation. For shutdown the hours are t, t-1, and t-4 since the hours before shutdown occurs are important. The best model is one that can consistently forecast accurate emissions totals in all hour types. The percentage error is reported in each table with the mean absolute error in parentheses below it.

Table 3.4: Model Predictions and Forecasts: Heat Input

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	“Base” Model	Estimated Model	ARMA Only Model	“Base” Model
All hours	-0.36 (21.3)	-0.17 (95.2)	-0.05 (22.1)	0.26 (34.9)	-3.62 (205)	-0.35 (46.1)
Upramp hours	-0.41 (48.8)	-3.72 (190)	-0.06 (38.5)	-0.31 (45.2)	-4.78 (251)	-4.02 (48.1)
Upramp hours t+1	-0.43 (48.2)	-0.62 (172)	-0.04 (37.1)	-0.51 (44.7)	-4.2 (246)	-1.97 (46.4)
Upramp hours t+4	-0.46 (47.0)	-0.14 (162)	-0.04 (35.0)	-0.38 (41.6)	-4.6 (196)	0.30 (41.4)
Downramp hours	-0.38 (47.6)	3.73 (188)	-0.02 (35.5)	0.40 (40.4)	5.26 (246)	-3.14 (41.9)
Downramp hours t+1	-0.38 (47.4)	0.31 (195)	-0.09 (35.8)	-0.24 (39.8)	-3.14 (235)	2.6 (41.4)
Downramp hours t+4	-0.45 (46.9)	-0.28 (177)	-0.07 (35.1)	-0.42 (39.7)	-3.69 (213)	0.67 (40.4)
Startup hours	-2.3 (108)	-3.71 (214)	-0.74 (247)	-1.29 (141)	13.6 (209)	-92.8 (252)
Startup hours t+1	-5.6 (91.0)	-21.9 (476)	-48.4 (200)	5.76 (56.2)	-84.2 (398)	-85.9 (73.7)
Startup hours t+4	-5.5 (46.0)	-7.89 (386)	-14.2 (71.9)	4.39 (13.5)	-89.0 (290)	-24.1 (48.9)
Shutdown hours	0.66 (43.6)	142.5 (1494)	13.1 (648)	-5.14 (59.2)	150.9 (1587)	34.3 (959)
Shutdown hours t-1	0.76 (90.3)	-24.4 (792)	20.3 (83.5)	-1.50 (53.0)	70.6 (496)	13.5 (73.3)
Shutdowns hours t-4	-0.32 (39.7)	-36.0 (152)	0.30 (39.8)	-1.02 (12.6)	75.2 (269)	4.02 (37.7)

Table 3.4, found above, reports these results for three models. Estimated model refers to the emission function determined by the methodology of this chapter. The ARMA only model is a pure ARMA forecast model of emissions. This model has no explanatory variables and only uses the ARMA terms determined as having the lowest AIC for the specific emission type and generator. The base model consists of a bare bones version of the fully estimated model. It contains generation, generation squared,

hourly and monthly controls, and the unlagged and unlead variables of startup, shutdown, upramp, and downramp as well as ARMA terms.

The results of predicting and forecasting heat input for coal generators show that both the full estimated model and base model predict emissions well both within and out-of-sample. Within-sample the base model predicts with less bias in all hours except shutdown hours where it over predicts heat input by 13.1% at the time of shutdown and 20.3% and hour before shutdown. The full estimated model is not as accurate in some of the hours. Considering the mean absolute error as a measure of accuracy, the base model is the most accurate in the ramping hours. However, in startup and shutdown hours the full estimated model is the most accurate in sample.

For out-of-sample forecasts, the full estimated model outperforms the base model. Considering the bias in estimated emissions, as measured by percentage error, the total forecasted emissions over the entire year are only 0.26% higher than actual emissions. The full estimated model predicts accurately in the hours of ramping and following ramping. It predicts with less bias than the base model in the hour of upramps and downramps as well as the hour after. Four hours after, the models perform almost equally. The fully estimated model performs better in the hour of and hours after startup and shutdown compared to the base model and ARMA only model. In terms of accuracy the full estimated model is more accurate in every single hour type. All the hours of operation, and time periods before or after them, show lower mean absolute error values than the base model or ARMA only model. This means that the fully estimated model outperforms the base model in all the subset hours. This is important because the goal is to provide a forecasting model which can be used to forecast emissions under scenarios where upramps, downramps, startups, and shutdowns change in frequency and magnitude. If the model does not predict accurately in these types of hours to being with, then it would predict even worse when these types of hours occurred more often. In Table 3.5, below, the same results are reported for the models of NO_x emissions. Again the values represent averages across all coal generators.

Table 3.5: Model Predictions and Forecasts: NO_x Emissions

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
All hours	-0.38 (11.8)	-0.27 (19.9)	-0.11 (12.6)	0.43 (38.3)	-3.51 (40.7)	-0.35 (26.4)
Upramp hours	-0.50 (27.8)	-3.85 (42.2)	-0.39 (27.7)	-0.31 (30.3)	-4.18 (49.9)	-3.82 (35.2)
Upramp hours t+1	-0.46 (27.2)	-1.16 (39.6)	-0.18 (26.4)	-0.32 (30.9)	-3.95 (50.0)	-2.21 (34.8)
Upramp hours t+4	-0.50 (25.8)	-0.35 (37.8)	-0.08 (25.6)	-0.48 (31.0)	-4.50 (43.3)	-0.27 (30.9)
Downramp hours	-0.26 (27.3)	3.72 (41.7)	0.22 (27.4)	-0.40 (30.8)	5.08 (50.1)	-2.93 (33.3)
Downramp hours t+1	-0.37 (27.4)	0.74 (42.8)	-0.08 (27.9)	-0.15 (29.6)	-3.21 (48.8)	3.16 (32.4)
Downramp hours t+4	-0.45 (27.1)	-0.12 (40.0)	-0.88 (26.2)	-0.80 (30.1)	-3.62 (45.5)	1.29 (30.3)
Startup hours	2.4 (47.9)	-6.3 (69.8)	-80.4 (77.8)	11.5 (72.5)	99.5 (94.4)	-92.8 (96.2)
Startup hours t+1	-13.8 (71.3)	-42.2 (166)	-60.2 (103)	-4.52 (44.3)	-70.4 (357)	-80.4 (102)
Startup hours t+4	-6.4 (51.8)	-33.3 (98.5)	-48.0 (94.3)	4.67 (38.7)	-84.6 (452)	-24.5 (68.2)
Shutdown hours	-0.21 (108)	175.2 (277)	37.1 (130)	-3.47 (153)	135.5 (285)	34.3 (199)
Shutdown hours t-1	-5.37 (68.6)	7.22 (128)	-21.1 (85.9)	-4.23 (63.7)	-64.5 (389)	8.46 (90.6)
Shutdowns hours t-4	-0.91 (21.7)	0.15 (41.0)	-34.4 (27.5)	-0.79 (35.7)	-70.4 (437)	3.68 (50.5)

The models for NO_x emissions have within-sample predictions and out-of-sample forecasts with low bias. The base model predicts, within-sample, the total level of emissions in all ramping hours with less bias than the fully estimated model. It has a percentage error that is higher in magnitude in all shutdown and startup hours even compared to the ARMA only model. In terms of accuracy, the fully estimated model is the most accurate in all hours except for a few of the ramping hours. In the few ramping hours where the base model is more accurate, the mean absolute error is very close in value indicating there is not much of a difference in the predictive accuracy of the models in those hours type.

Out-of-sample, the fully estimated model and base model have a much lower in magnitude percentage error than the ARMA model. Total emissions are forecasted with low bias by both the base and fully estimated model with a percentage error that is -0.35 and 0.43 respectively. The fully estimated model forecasts with less bias in all the subsets of operating hours. It forecasts in all ramping hours with a percentage error less than 1. For startup and shutdown the bias is larger with all but contemporaneous startup hours having prediction errors smaller in magnitude than 4.7. During the actual startup hour the percentage error is 11.5 which is large in magnitude but is still much smaller in magnitude than the base model and ARMA only model which have percentage errors of -92.8 and 99.5 respectively. The accuracy of the fully estimated model, as measured by the mean absolute error, is better than the ARMA only model and base model in all of the subset operation hours except for the group of four hours after upramp. The base model is the most accurate in all hours with the lowest mean absolute error over all hours. Given the accuracy of the fully estimated model in the different operating hour types, and the low amount of bias in those hour types, it can be considered to be the better model.

Table 3.6: Model Predictions and Forecasts: SO_2 Emissions

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	“Base” Model	Estimated Model	ARMA Only Model	“Base” Model
All hours	-0.25 (69.4)	0.01 (81.8)	-0.02 (69.8)	-2.04 (159)	14.1 (483)	-0.07 (129)
Upramp hours	-0.30 (173)	-2.69 (192)	-0.24 (170)	-2.40 (174)	-2.60 (204)	-1.05 (151)
Upramp hours t+1	-0.32 (173)	-1.02 (193)	0.02 (174)	-0.52 (152)	-2.31 (210)	-1.29 (173)
Upramp hours t+4	-0.24 (161)	-0.37 (182)	0.03 (163)	-0.30 (159)	-2.54 (208)	-0.05 (143)

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
Downramp hours	-0.25 (156)	2.10 (191)	0.11 (159)	-1.85 (137)	2.42 (181)	0.11 (169)
Downramp hours t+1	-0.24 (156)	-0.40 (188)	-0.15 (156)	-2.37 (138)	0.64 (187)	-0.81 (171)
Downramp hours t+4	-0.33 (163)	-0.47 (189)	-0.13 (164)	-2.47 (141)	-0.63 (195)	-0.87 (172)
Startup hours	28.6 (76.3)	71.6 (388)	-196 (155)	6.85 (295)	56.4 (76.9)	-110 (305)
Startup hours t+1	-29.1 (316)	-29.8 (434)	-50.8 (360)	2.11 (171)	-79.3 (174)	-84.4 (594)
Startup hours t+4	-21.3 (304)	-4.80 (314)	-1.22 (366)	2.40 (118)	-56.8 (257)	-24.6 (144)
Shutdown hours	5.13 (361)	191 (610)	34.3 (375)	-10.7 (183)	171 (796)	-22.2 (238)
Shutdown hours t-1	-21.1 (251)	37.1 (621)	6.56 (275)	-1.89 (177)	-64.5 (296)	10.3 (107)
Shutdowns hours t-4	-34.4 (109)	-0.54 (302)	-2.49 (196)	-2.40 (255)	-70.4 (155)	0.34 (140)

In Table 3.6 the models for SO_2 emissions show low magnitude percentage error predictions of total emissions within-sample. The ARMA only model has the lowest forecast error and the base model has the second lowers in magnitude. All three models do a poor job of predicting emissions during startup. The fully specified estimated model is the only one which does a reasonable job of predicting emissions during shutdowns with a forecast error of 5.13% compared to an error of 191% for the ARMA only model and 34.3% for the base model. The three models are very close in the value of their mean absolute error. For all the startup and shutdown hours the mean absolute error shows that the fully estimated model is the most accurate.

Out-of-sample forecasts differentiate the three models in terms of bias as measured by percentage error. The base model outperforms both the fully estimated model and ARMA only model when predicting emissions over the whole year. It forecasts total 2012 yearly emissions to within 0.07% of actual emissions. The base model also outperforms the fully estimated model in almost all upramp and downramp hours. The fully estimated model has a forecast with lower bias in the hour after an upramp occurs with a percentage error of -0.52 compared to the base model's -1.29. The base model performs very poorly in both startup and shutdown hours. It under predicts emissions during the hour of startup by 110% of actual emissions and under predicts emissions during the hour of shutdown by 22.2% of actual emissions. The fully estimated model has less bias in these hours and the hours after startup and before shutdown. The accuracy of the fully estimated model, as measured by the mean absolute error, is not better than the other models for all hours. There are mixed results for the ramping hours with the full estimated model being more accurate in some cases and the base model more accurate in others. The full model is the most accurate in all startup hours and in the hour of shutdown, but not the hours before shutdown.

These mixed results make the decision on which model is better for forecasting more difficult since both the full estimated model and base model do better in different categories. If forecasting emissions in scenarios with different startup and shutdown frequencies and characteristics than the data is estimated on, it is likely that the fully estimated model will provide more accurate results given the lower bias in these hours and better accuracy. If forecasting emissions in scenarios where startups and shutdowns have the same frequency and characteristics as the data used to estimate the function, then it is likely the base model will provide the most accurate results.

The overall results comparing the fully specified emission function with the simpler models, is that it is has very low bias and better accuracy for heat input and NO_x emissions. It predicts well for these emission types in all types of hours when compared to the simpler ARMA only and base models. For SO_2 emissions the fully specified emission function does not predict emission totals as well as the simpler base function model, but still predicts with less bias and more accuracy than the ARMA only model. The fully specified emission function model performs better than the base model during startup and shutdown hours compared to the base model. This means that the fully specified emission function, for SO_2 emissions, is best suited to forecasting when startup and shutdown hour accuracy is particularly important. If not, then the base model will likely produce more accurate forecasts.

Having shown the predictive ability of the models the function results are reported. The average, across all generators of a type, of the estimated impact on emissions startup, shutdown, and ramping are reported. Startup and shutdown impacts for an individual generator are simply the sum of the coefficient estimates of the associated dummy variables. Ramping impacts are non-linear and depend upon generator set point. To make them comparable the impacts of ramps that are sized and centered relative to each generator's max capacity are calculated. Ramps sized at 1%, 25%, and 50% of generation capacity are centered on 50% of generation capacity. For example, a 25% upramp for a 200 MW generator would involve a generator starting at 175 MW and ramping up 50 MW to 225 MW. These ramp sizes are then converted into per MW ramps by dividing by the ramp size.

The results for ramping estimates in Table 3.7 below find that on average units are more efficient in the hour of and following an upramp compared to the same time span of steady state operation. On average, a one percent upramp has a reduction in heat input by 0.70 mmBtu, a reduction in NO_x emissions by 0.04 lbs, and SO_2 emissions by 1.41 lbs. The non-linearity in ramp can be seen by looking at the 25% and 50% upramp values. They all have a different per MW ramp impact. On average a 50% upramp decreases heat input by 1.86 mmBtu, decreases NO_x emissions by 1.87 lbs, and has no impact on SO_2 emissions. The post startup impact on emissions is the impact of a startup on emissions in the hours after the hour of startup. The average coal generator has an increase in heat input of 1550 mmBtu in the hours after startup. If that startup is a warm start, when the generator has been off for more than 24 hours but less than 120, there is an additional increase in heat input in the hours before startup of 408 mmBtu. From this it can be seen that warm and cold starts both increase the heat input by more than a hot start. This fits the profile of a coal generator's startup since they must startup slower during a cold start due to limits to the rate of heating their equipment can undergo when initially cold.

Table 3.7: Coal Model Estimates

	Heat Input (mmBtu)	NO_x Emissions (lbs)	SO_2 Emissions (lbs)
1% Upramp (per MW ramp)	-0.70	-0.04	1.41
25% Upramp (per MW ramp)	-1.27	-0.94	0.72
50% Upramp (per MW ramp)	-1.86	-1.87	0.00
1% Downramp (per MW ramp)	2.98	2.77	1.32
25% Downramp (per MW ramp)	4.24	3.17	1.20
50% Downramp(per MW ramp)	5.55	3.59	1.07
Warm Start, Pre-startup (per startup instance)	404	-77.5	-563
Hot Start, Pre-startup (per startup instance)	302	-185	-433
Cold Start, Pre-startup (per startup instance)	408	-148	-172
Post-Startup (per startup instance)	1550	1857	1307
Shutdown (per shutdown)	-1712	-161	-47

3.6 Gas Steam Turbine Results

The results for gas steam turbines are analyzed. These results do not differ in their estimation method from the coal generator results. The only difference is that there are no estimates for SO_2 emissions. This is due to the fact that natural gas has very little sulfur in it, so SO_2 emissions from the burning of natural gas are fairly negligible. The EPA reports that they are, on average, 0.1 lbs per MWh (Environmental Protection Agency, 2004). Table 3.8, below, provides the results of the fully specified estimated model , the ARMA only model, and the base model for in-sample predictions and out-of-sample forecasts. Percentage error values are reported along with mean absolute errors in parentheses below them.

Table 3.8: Model Predictions and Forecasts: Heat Input

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
All hours	-0.15 (4.12)	-6.11 (42.7)	-1.07 (5.67)	-3.01 (8.22)	-4.46 (63.0)	-2.69 (11.8)
Upramp hours	-0.06 (27.1)	-24.7 (355)	-0.44 (38.1)	-2.58 (35.9)	-23.5 (329)	-2.54 (55.3)
Upramp hours t+1	-0.13 (27.7)	-7.41 (346)	-0.17 (38.4)	0.96 (35.8)	-11.4 (330)	-2.68 (56.3)
Upramp hours t+4	-0.13 (25.8)	-2.83 (303)	-0.27 (34.3)	1.07 (35.2)	1.98 (304)	-2.49 (53.9)
Downramp hours	-0.20 (28.7)	20.2 (301)	-0.46 (40.3)	1.12 (38.4)	22.1 (303)	-2.65 (56.8)
Downramp hours t+1	-0.05 (26.6)	0.50 (305)	-0.71 (35.7)	0.21 (37.5)	11.5 (316)	-2.38 (54.3)
Downramp hours t+4	0.02 (26.2)	1.48 (280)	-0.23 (33.8)	-1.90 (38.9)	13.2 (280)	-2.45 (53.3)
Startup hours	-0.34 (52.8)	-60.5 (234)	-14.2 (88.1)	0.46 (53.8)	-40.1 (190)	-3.76 (68.3)
Startup hours t+1	-1.26 (43.4)	-41.7 (373)	-12.4 (90.6)	-1.91 (44.4)	-44.6 (382)	-14.0 (80.2)
Startup hours t+4	-1.98 (29.7)	-11.9 (312)	15.9 (217)	-1.42 (33.5)	-12.8 (279)	-13.2 (55.5)
Shutdown hours	-0.09 (95.5)	160 (496)	13.3 (123)	1.22 (141)	168 (576)	18.0 (186)
Shutdown hours t-1	-0.01 (29.7)	7.98 (298)	-1.00 (38.1)	-4.03 (32.5)	9.51 (290)	-5.92 (44.7)
Shutdowns hours t-4	-0.37 (23.5)	-5.11 (297)	-0.41 (31.0)	-2.96 (26.9)	-5.23 (293)	-12.0 (49.6)

The fully specified estimated model provides in-sample results with the least bias, under predicting emissions by only 0.15% of actual emissions compared to 6.11% for the ARMA only model and 1.07% for the base model. It also has less bias in each of the different operating hours and the hours after or before them. It is more accurate in all of the hour types as well with the lowest mean absolute error in each hour type compared to the other two models.

Out-of-sample the fully specified model has the least bias, under forecasting emissions on average by only 3% over all hours. The base model does a slightly better job for total emissions, under forecasting by 2.69% of actual emissions on average. The base model has the same bias as the fully estimated model in the hours of upramp. In the hours after upramp the fully estimated model has a less biased forecast. The fully estimated model also has a lower bias during and after downramp, startup, and during and before shutdown. There is consistency in the mean absolute error values as well. The fully estimated model has the lowest mean absolute error in all hour types compared to the other two models. The base model has the second lowest values in all hour types.

In choosing between the fully specified model and the base model, there are only marginal improvements in overall bias with the base model, and fairly large improvements for startup and shutdown hours for the fully specified model. It is also the most accurate in all hour types. This means that the fully specified model meets the goal set forth of being able to estimate under a variety of scenarios where the characteristics and frequencies of ramping, startups, and shutdowns change. Table 3.9, below, provides the results for NO_x emissions.

Table 3.9: Model Predictions and Forecasts: NO_x Emissions

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	“Base” Model	Estimated Model	ARMA Only Model	“Base” Model
All hours	-0.17 (2.15)	-9.63 (16.3)	-1.44 (2.50)	-1.82 (4.47)	-8.27 (9.83)	1.15 (5.46)
Upramp hours	-0.14 (15.0)	-31.9 (50.4)	-1.39 (18.8)	-2.30 (23.3)	-32.0 (55.2)	-0.52 (29.7)
Upramp hours t+1	-0.18 (16.0)	-13.6 (52.5)	-0.55 (20.0)	-0.86 (25.6)	-18.3 (58.2)	-2.90 (32.5)
Upramp hours t+4	-0.11 (15.0)	-6.31 (47.5)	-0.20 (18.1)	0.50 (24.3)	-2.6 (54.6)	-2.40 (30.8)
Downramp hours	-0.34 (12.9)	22.0 (40.6)	1.10 (16.0)	-1.69 (19.7)	24.8 (46.8)	5.17 (25.1)
Downramp hours t+1	-0.07 (12.1)	-0.31 (38.0)	-1.50 (14.7)	-2.02 (17.9)	13.4 (45.7)	-2.27 (23.3)

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
Downramp hours t+4	-0.23 (11.4)	-0.87 (36.0)	4.89 (13.9)	-3.19 (15.8)	10.7 (36.3)	4.82 (19.1)
Startup hours	-0.90 (11.2)	-56.0 (22.8)	-44.5 (18.6)	-3.22 (10.3)	-38.2 (21.9)	-18.3 (17.2)
Startup hours t+1	-1.30 (14.8)	-48.6 (40.2)	-22.4 (21.6)	-3.76 (20.3)	-51.0 (46.2)	-16.4 (23.0)
Startup hours t+4	-7.73 (15.3)	-17.8 (47.3)	-3.37 (18.9)	-9.5 (32.6)	-11.5 (53.1)	-12.7 (31.7)
Shutdown hours	1.57 (15.4)	159 (46.8)	33.3 (19.1)	7.70 (20.1)	188 (60.1)	41.9 (30.8)
Shutdown hours t-1	0.32 (11.0)	14.4 (36.0)	-3.97 (14.3)	-4.05 (19.2)	16.4 (42.2)	5.12 (22.2)
Shutdowns hours t-4	-0.10 (13.7)	-8.86 (43.3)	0.43 (16.9)	-3.47 (33.4)	-7.19 (51.1)	11.3 (29.8)

The NO_x emissions results for the within-sample predictions in Table 3.9 show the fully specified model predicts the best in all hours and in each subset of hour type. The ARMA only model has a large bias in all hours, under predicting by 9.63% over all hours. The base model predicts well in total with a forecast error of -1.44%. It also predicts well in upramp and downramp hours but has a large magnitude percentage error during startups and shutdowns. The fully estimated model is the most accurate as measured by the absolute mean error with the lowest values in all hour types compared to the other two model types. The base model is the next most accurate with values only a little bit larger.

The out-of-sample results mirror the in-sample results. Both the fully specified model and the base model forecast with a low bias. The fully specified model under forecasts emissions by 1.82% of actual emissions and the base model over forecasts emissions by 1.15% of actual emissions. The base model also has a low bias during the hour of an upramp with a forecast error of -0.52% compared to the fully estimated model's percentage error of -2.30%. In the hours following upramp the fully estimated model is less biased with percentage errors of -0.86 and 0.50 in the hour after and four hours after compared to -2.90 and -2.40 for the base model. The fully specified model is less biased in the hour of downramp and about equal in the hours after. There is a low bias in the hour of and hours after startup and also the hour of and hours before shutdown. The fully estimated model is the most accurate model in almost all hour types. Only in the fourth hour after startup and four hours before shutdown is the base model more accurate. In these two hour types the base model is only slightly more accurate with a mean absolute error of 31.7 and 29.8 for the shutdown and startup hours respectively compared to the fully estimated model's values of 32.6 and 33.4.

These results indicate that the fully specified model, despite being a little worse at forecasting during the hour of upramp, is better overall given its accuracy in downramp, startup, and shutdown hours. The bias during the hour of upramp is offset somewhat by the forecast accuracy in that hour. The fully estimated model has a lower mean absolute error during the hour of upramp compared to the base model with values of 23.3 and 29.7 respectively. The measurement metrics all indicate that the fully specified model performs well in the different hour types and their respective lags and leads. This shows the importance of including lags and leads in improving the accuracy of forecasts in the hours after ramping and startup, and before shutdown.

Table 3.10, below, provides the functions results themselves. All values are calculated in the same manner as the calculations for coal in Table 3.8. Therefore their interpretations are the same except that they are only applicable to gas steam turbine units. For gas steam turbines, upramps decrease efficiency and increase emissions on average. A 1% upramp results in an increase in heat input by 2.87 mmBtu per MW ramp and an increase of 1.22 lbs per MW ramp of NO_x emissions. Larger upramps have only slightly larger per MW ramp impacts on heat input and NO_x emissions. The type of startup; warm, hot, or cold, has less of an impact for gas steam turbines than the coal units. A warm start increases heat input by only 22.48 mmBtu while hot starts and cold starts reduce heat input by 28.75 mmBtu and 14.4 mmBtu respectively. The post startup period increases heat input by 500 mmBtu and NO_x emissions by 251 lbs while a shutdown decreases heat input by 51.9 mmBtu and NO_x emissions by 71.2 lbs.

Table 3.10: Gas Steam Turbine Model Estimates

	Heat Input (mmBtu)	NO_x Emissions (lbs)
1% Upramp (per MW ramp)	2.87	1.22
25% Upramp (per MW ramp)	3.42	1.57
50% Upramp (per MW ramp)	3.98	1.92
1% Downramp (per MW ramp)	-3.22	1.18
25% Downramp (per MW ramp)	-3.67	0.67
50% Downramp(per MW ramp)	-4.13	0.14
Warm Start, Pre-startup (per startup instance)	22.48	-24.3
Hot Start, Pre-startup (per startup instance)	-28.75	-37.6
Cold Start, Pre-startup (per startup instance)	-14.4	-28.5
Post-Startup (per startup instance)	500	251
Shutdown (per shutdown)	-51.8	-71.2

3.7 Combined Cycle Results

The combined cycle results are reported below. Combined cycle units are fast ramping units that are very efficient in their operation due to the capturing of waste heat from the gas turbine portion of their generator and using it to power a steam turbine. As with the gas steam turbine results, since the combined cycle generators are fired by natural gas, results are only reported for heat input and NO_x emissions. Table 3.11, below, reports the prediction and forecast errors for heat input.

Table 3.11: Model Predictions and Forecasts: Heat Input

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
All hours	-0.15 (5.28)	-2.66 (34.4)	-0.21 (7.48)	-1.22 (17.7)	-1.71 (62.7)	1.16 (18.4)
Upramp hours	-0.11 (20.7)	-11.33 (162)	-0.46 (34.8)	-1.66 (35.2)	-8.42 (136)	-0.47 (38.9)
Upramp hours t+1	-0.17 (18.6)	-3.15 (144)	-0.39 (31.7)	-0.34 (32.6)	-3.68 (123)	-3.84 (35.9)
Upramp hours t+4	-0.19 (16.2)	-0.62 (108)	-0.02 (21.4)	0.03 (28.4)	-0.90 (94.0)	-4.04 (27.4)
Downramp hours	-0.21 (18.6)	7.50 (127)	0.10 (23.7)	-2.15 (35.9)	7.42 (122)	2.58 (37.7)
Downramp hours t+1	-0.21 (16.9)	-0.11 (131)	0.13 (21.8)	1.05 (32.9)	1.55 (120)	-2.32 (32.8)
Downramp hours t+4	-0.18 (15.9)	-0.89 (111)	0.05 (20.0)	0.57 (31.7)	0.73 (105)	-2.91 (29.8)
Startup hours	-0.52 (76.4)	-79.5 (261)	-20.3 (102)	-8.05 (118)	38.9 (358)	-12.2 (151)
Startup hours t+1	-1.95 (53.2)	-41.8 (463)	-21.3 (177)	-8.24 (72.4)	-47.3 (435)	-35.1 (173)
Startup hours t+4	-4.39 (22.1)	-3.14 (127)	-0.67 (33.2)	-1.22 (27.8)	-33.7 (95.7)	-23.4 (30.7)
Shutdown hours	0.39 (78.9)	255 (653)	6.3 (98.8)	28.2 (176)	318 (864)	53.3 (233)
Shutdown hours t-1	-0.60 (22.7)	-1.48 (109)	0.19 (24.2)	0.87 (38.2)	-16.1 (123)	0.49 (43.6)
Shutdowns hours t-4	-1.35 (15.4)	-3.77 (108)	0.00 (23.0)	-0.43 (23.0)	-31.9 (95.2)	-2.47 (29.3)

The fully specified model and base model have similarly low biases, as measured by percentage error, for within-sample predictions. The fully specified model has a prediction error of only -0.15% and the base model -0.21%. Their bias is similar in both upramp and downramp hours. The fully specified model performs better in bother startup and shutdown hours with a prediction error of -0.52% in startup hours and 0.39% in shutdown hours. The base model's bias is not as low with an in-sample percentage error of -20.3% in startup hours and 6.3% in shutdown hours. The ARMA only model has a percentage error of -2.66% for in-sample total emissions but has a large bias in upramp, downramp, startup, and shutdown errors. In terms of accuracy the fully estimated model is the most accurate with the lowest mean absolute error across all hour types.

Out-of-sample the three models all forecast with a low bias having percentage errors no larger than 1.80 in magnitude. The ARMA only model forecast is highly biased in the majority of the different operating hours. The fully estimated model has a higher bias than the base model during the hour of upramp. The hour after and four hours after, the fully estimated model has a lower bias than the base model. For the hour of downramp the fully estimated model is more biased than the base model and the hours after downramp are much less biased. The fully estimated model forecasts startup hours with less bias than the base model as well. However, the hour of and just after startup have a percentage error of about -8 each which is high. The hour of shutdown is forecasted with high bias in all three models but the fully estimated model is the least biased of them with a percentage error of 28.2 compared to the base model's 53.3. The hour before shutdown the fully estimated model and base model perform about equally while four hours before, the fully estimated model has less bias. In terms of accuracy as measured by mean absolute error, the fully estimated model and base model are almost equal for all hours and ramping hours. The fully estimated model is more accurate in the hours of startup and shutdown, including the hours after startup and before shutdown.

These results show that the fully estimated model performs better than the base model or the ARMA only model. This is especially the case in the hours after ramping and startup, and the hours before shutdown. These hours have a much lower bias and, for startup and shutdown, are much more accurate.

Table 3.12: Model Predictions and Forecasts: NO_x Emissions

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
All hours	0.08 (1.17)	-14.5 (1.95)	-2.42 (1.48)	-6.71 (3.51)	-6.10 (3.23)	6.76 (3.37)
Upramp hours	0.23 (5.89)	-23.6 (11.8)	-4.14 (8.00)	-7.71 (8.79)	-13.1 (8.91)	-2.23 (8.80)
Upramp hours t+1	-0.32 (4.66)	-4.3 (7.82)	-1.29 (6.38)	-5.06 (7.62)	-11.7 (7.03)	12.0 (7.06)
Upramp hours t+4	-0.03 (2.91)	-8.62 (4.69)	0.18 (3.32)	3.24 (6.10)	-2.33 (7.15)	12.5 (6.59)
Downramp hours	1.59 (3.04)	-3.09 (5.09)	0.79 (3.34)	5.79 (5.92)	3.80 (7.84)	6.07 (6.12)
Downramp hours t+1	0.28 (2.82)	-4.8 (5.03)	2.98 (3.26)	-6.13 (5.85)	1.56 (7.81)	9.41 (6.79)
Downramp hours t+4	-0.05 (2.71)	-1.07 (4.30)	1.98 (3.06)	-5.04 (5.71)	-6.71 (7.25)	10.5 (6.51)
Startup hours	0.46 (35.8)	-90.4 (82.1)	-12.9 (46.2)	9.39 (50.9)	59.6 (81.3)	28.7 (70.2)
Startup hours t+1	-2.30 (31.1)	-11.0 (58.7)	-52.8 (59.5)	-12.2 (34.3)	-27.8 (47.0)	-51.2 (47.6)
Startup hours t+4	-1.91 (6.08)	0.91 (8.33)	11.8 (8.17)	-6.4 (7.06)	19.8 (12.5)	-38.0 (14.79)
Shutdown hours	1.59 (16.8)	39.2 (24.2)	6.17 (14.3)	5.79 (18.4)	90.4 (24.2)	76.8 (23.1)
Shutdown hours t-1	0.35 (6.68)	-10.1 (9.21)	-3.1 (8.39)	-2.17 (10.8)	-5.86 (7.23)	-18.8 (8.14)
Shutdowns hours t-4	-0.24 (3.10)	-5.06 (5.32)	0.92 (3.75)	-1.01 (12.8)	-8.45 (4.80)	-41.0 (5.15)

Table 3.12, above, provides the results for the combined cycle unit's models of NO_x emissions. The within-sample results show that the fully specified model has the least bias, as measured by percentage error, when predicting emissions within sample. The base model only predicts with the least amount of bias during downramp hours and the ARMA only model has a high magnitude percentage error during all hours and in total.

In terms of accuracy as measured by mean absolute error, the fully estimated model has the lowest values in all hours making it the most accurate of the three models for within sample predictions.

The out-of-sample results have a percentage error with larger magnitude than any of the previous generator's or emission type's out-of-sample results. All three types of models forecast total emissions with about a 6 percent forecasting error with the base model over forecasting by this much and the fully specified and ARMA only model under forecasting. The base model has the least bias during upramp hours with a forecast error of -2.23% compared to the fully estimated model's -7.71%. The hour after and four hours after upramp are more accurately forecasted by the fully estimated model. The base model is the least accurate during downramps and after them. The fully estimated model's lowest magnitude of percentage error hour type is the hour of startup when the model over forecasts emissions by 9.39% of actual emissions and the hour after startup where it under forecasts by 12.2%. The ARMA only model and base model have a high bias during startup hours with a forecast error of 59.6% and 28.7% respectively. Their forecasts in the hours after startup also have more bias than the fully estimated model's forecasts. Finally, the fully estimated model has the lowest bias in the hour of and hours before shutdown. The mean absolute errors indicate that the fully specified model is the most accurate at out-of-sample forecasting. For all hour types except the hours before shutdown, it is the most accurate model type. On average the fully estimated model is forecasting each individual hour of the year with the lowest error compared to the ARMA only model and base model.

The fully estimated model is consistently the least biased across the different operating hour types and is therefore considered the best, although the bias is higher than previous models for coal and gas steam turbines. The fully estimated model consistently is the most accurate as well adding more evidence that it is better at out-of-sample forecasting than the two simpler models.

The functions results for combined cycle units are reported below in Table 3.13. Combined cycle units are able to startup very quickly and do not require the pre-startup time which gas and coal steam turbines require. Therefore, the estimates of warm, hot, and cold starts are not included as they were not significant explanatory variables in the models.

Table 3.13: Combined Cycle Model Estimates

	Heat Input (mmBtu)	NO_x Emissions (lbs)
1% Upramp (per MW ramp)	0.55	0.08
25% Upramp (per MW ramp)	10.89	-14
50% Upramp (per MW ramp)	15.56	-61.2
1% Downramp (per MW ramp)	3.70	0.91
25% Downramp (per MW ramp)	95.0	26.9
50% Downramp (per MW ramp)	195	65
Post-Startup (per startup instance)	857	330
Shutdown (per shutdown)	-226	5.11

The upramp results for combined cycle units indicate that upramps increase inefficiency compared to other hours. A 1% upramp increases heat input by 0.55 mmBtu per MW ramp and this increases quickly to 15.56 mmBtu per MW ramp for a 50% upramp. NO_x emissions on the other hand go from increasing by 0.08 per MW ramp for a 1% upramp to decreasing by 61.2 lbs per MW ramp for a 50% upramp. Both heat input and NO_x emissions increase under all sizes of downramp and increase quickly with downramp size. The post startup period increases heat input by 857 mmBtu and 330 lbs of NO_x emissions. Shutdowns decrease heat input by 226 mmBtu and increase NO_x emissions by 5.11 lbs.

3.8 Simple Cycle Results

The results for simple cycle generators follow. Simple cycle units are fast ramping units primarily used to serve peak load using a combustion turbine. The prediction and forecast errors for heat input models are reported below in Table 3.14.

Table 3.14: Model Predictions and Forecasts: Heat Input

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
All hours	-0.89 (2.10)	-21.2 (9.28)	-2.12 (2.23)	-0.25 (2.89)	-20.8 (17.6)	-3.08 (4.65)
Upramp hours	-1.16 (25.0)	-48.2 (151)	-0.46 (30.8)	-0.60 (27.2)	-49.1 (168)	-0.47 (45.3)
Upramp hours t+1	-0.35 (21.4)	-18.5 (123)	-1.43 (24.2)	-0.47 (18.4)	-20.2 (128)	-3.91 (33.4)
Upramp hours t+4	-0.68 (19.9)	-4.34 (94.9)	-0.67 (22.1)	0.84 (17.2)	-10.4 (106)	-1.04 (30.1)
Downramp hours	-1.49 (23.8)	20.2 (100)	0.10 (28.6)	-0.18 (26.5)	29.9 (122)	1.58 (42.1)
Downramp hours t+1	-0.75 (21.9)	-1.81 (105)	-1.67 (26.2)	-0.20 (18.7)	-8.21 (112)	-2.92 (31.3)
Downramp hours t+4	-0.30 (20.0)	-6.88 (89.8)	1.25 (30.0)	0.91 (17.8)	4.10 (116)	0.59 (30.4)
Startup hours	-4.76 (33.2)	-91.6 (175)	-20.3 (44.6)	-0.92 (42.6)	-92.6 (204)	-12.2 (66.4)
Startup hours t+1	-0.20 (23.9)	-44.3 (200)	-3.17 (29.5)	-1.06 (20.9)	-44.2 (204)	-7.00 (41.5)
Startup hours t+4	-0.62 (19.0)	-10.9 (92.9)	-0.56 (20.2)	0.35 (16.6)	-6.73 (103)	-0.85 (28.9)
Shutdown hours	-3.47 (31.2)	255 (177)	6.35 (42.3)	2.42 (38.9)	318 (198)	52.3 (59.5)
Shutdown hours t-1	-0.28 (19.5)	-26.9 (107)	-3.25 (24.8)	-0.05 (16.8)	-23.7 (101)	-3.78 (30.3)
Shutdowns hours t-4	-0.74 (21.0)	-31.9 (123)	-1.36 (23.0)	-0.27 (19.4)	-30.1 (121)	-4.31 (33.0)

For simple cycle units the fully specified model has within-sample predictions for total yearly emissions with the least bias. The base model has the least bias during upramps and downramps but the fully specified model is still accurate with a prediction error of -1.16% during upramps and -1.49% during downramps. The fully specified model has the least bias during startups and shutdowns. The ARMA only model has a large bias in all hours and in total. Considering accuracy, as measured by the mean absolute error, the fully estimated model has the lowest values across all hour types. The base model is the next most accurate with values only slightly higher than the fully estimated model.

For out-of-sample forecasting, the fully specified model has a very low bias, under forecasting emissions by only 0.25% of actual heat input in total. It is equally biased as the base model in the hour of upramp with a forecast error of -0.60% for the fully specified model compared to -0.47% for the base model. The fully specified model has a lower bias in the hours after upramp than the base model indicating the benefit of upramp lags. The fully specified model also has a lower bias than the base model in the hour of downramp and hour after downramp. The base model is equally biased four hours after a downramp. The fully specified model is much less biased in the hour of and hours after startup as well as the hour of and hours before shutdown. The ARMA only model is biased in all hours and in total with percentage errors that are large in magnitude. The mean absolute error values indicate that the fully estimated model is the most accurate in all hour types compared to the other two model types. When considering bias the base model had some hour types with similar percentage error values, but in the case of accuracy, there are no hours like that. The fully estimated model always has a lower mean absolute error indicating that it is the most accurate at forecasting hourly emissions.

These results show that the fully specified model is the best forecasting model for simple cycle heat input in all hour types and in total. It has the least bias when forecasting total emissions in all hour types, and is the most accurate at forecasting hourly emissions for all hour types. The importance of the inclusion of lags and leads in the forecasting model is also displayed by its greater accuracy and lower bias in the hours after ramping and startup as well as the hours before shutdown.

Table 3.15: Model Predictions and Forecasts: NO_x Emissions

Percent Error (Mean Absolute Error in Parentheses)						
	In-sample (2010)			Out-of-sample (2012)		
	Estimated Model	ARMA Only Model	"Base" Model	Estimated Model	ARMA Only Model	"Base" Model
All hours	-1.31 (0.21)	-44.7 (0.25)	-3.16 (0.20)	-5.86 (0.29)	-45.0 (0.50)	-8.69 (0.35)
Upramp hours	-1.81 (2.55)	-61.5 (4.13)	-4.14 (2.40)	-10.6 (4.20)	-63.6 (6.88)	-9.24 (4.72)
Upramp hours t+1	-1.66 (2.25)	-34.7 (2.52)	-0.81 (1.96)	2.49 (2.98)	-20.0 (3.72)	4.16 (3.14)
Upramp hours t+4	-1.13 (2.15)	-33.3 (2.30)	-4.73 (1.92)	1.38 (1.34)	-22.3 (1.79)	35.3 (1.70)
Downramp hours	-1.87 (1.99)	-14.3 (2.78)	0.79 (1.78)	16.7 (1.89)	18.4 (2.29)	-11.1 (1.87)
Downramp hours t+1	9.42 (1.63)	-20.6 (1.90)	10.1 (1.38)	9.47 (1.58)	-9.25 (2.06)	21.7 (1.72)
Downramp hours t+4	10.3 (1.52)	-30.1 (1.84)	23.8 (1.49)	3.53 (1.49)	-8.22 (2.07)	15.1 (1.49)
Startup hours	-4.61 (3.34)	-92.5 (8.36)	-12.9 (3.52)	-15.4 (5.33)	-94.8 (11.9)	28.7 (6.31)
Startup hours t+1	0.06 (3.32)	-34.8 (5.00)	0.75 (3.99)	-2.80 (4.47)	-20.0 (6.66)	5.06 (5.39)
Startup hours t+4	4.48 (2.11)	-33.7 (2.25)	1.52 (1.96)	1.96 (1.37)	-21.2 (1.78)	33.5 (1.61)
Shutdown hours	0.17 (2.59)	39.2 (3.70)	6.17 (2.68)	2.36 (2.41)	90.4 (3.58)	76.8 (2.54)
Shutdown hours t-1	-2.79 (3.60)	-50.5 (3.94)	-4.35 (3.08)	1.79 (3.12)	-41.1 (3.51)	-10.5 (3.27)
Shutdowns hours t-4	-3.39 (2.38)	-51.5 (3.48)	-0.68 (2.39)	5.65 (2.37)	-37.9 (3.76)	6.20 (2.48)

Simple cycle NO_x emission model results are found in Table 3.15. These results, similar to the combined cycle NO_x emission results have a high bias compared to the NO_x emission models of coal and gas team turbine generators. The within-sample predictions have a low bias for both the fully specified model and the base model with the fully specified model being the least biased in total and in all hour types except downramp. The base model is the most accurate in most hour types for within sample predictions but all three model types are very close in their values of mean absolute error.

The out-of-sample results show that the fully specified model is the least biased for total emissions in all hours with a forecast error of -5.86% compared to the base model's -8.69% forecast error. The base model is the least biased in the hour of upramp and downramp. However, the base model is much more biased than the fully specified model in the hours after upramp and downramp. The base model is more biased during and after startup as well as during and before shutdown. The base model over forecasts emissions by 76.8% during shutdown hours compared to 2.36% for the fully specified model. Since simple cycle units startup and shutdown often due to their usage as peak load units, so the low bias of the fully specified model is relatively important during these operational hours. Despite the base model being the most accurate, as measured by the mean absolute error, in within sample predictions, it is not the most accurate at forecasting. The fully specified model is the most accurate in all hour types except the hour of downramp where it has a mean absolute error of 1.89 compared to the base model's 1.87.

The relative bias and accuracy of the fully specified model in the hours after upramp, downramp, startup and before shutdown indicate the importance of lags and leads. The best forecasting model based on the criteria of having a low bias and accurate hourly forecasts in all hour types, is the fully specified model.

Table 3.16: Simple Cycle Model Estimates

	Heat Input (mmBtu)	NO_x Emissions (lbs)
1% Upramp (per MW ramp)	-2.30	0.21
25% Upramp (per MW ramp)	-22.4	6.71
50% Upramp (per MW ramp)	28.5	16.3
1% Downramp (per MW ramp)	22.6	0.17
25% Downramp (per MW ramp)	262	-1.40
50% Downramp (per MW ramp)	-107	-14.4
Post-Startup (per startup instance)	204	-22.3
Shutdown (per shutdown)	358	-6.32

Table 3.16, above, provides the estimated function results for the different operations of the simple cycle units. Simple cycle units get more efficient with ramps sized at 1% and 25% of maximum capacity. Larger, 50% ramps increase inefficiency by increasing heat input by 28.5 mmBtu per MW ramp. NO_x emissions increase under all sized upramps. They also increase by 0.17 lbs per MW ramp for small 1% downramps but increase by 6.71 lbs per MW ramp and 16.3 lbs per MW ramp for 25% and 50% sized downramps respectively. The post-startup period increases heat input by 204 mmBtu on average and reduces NO_x emissions by 22.3 lbs. Shutdown increases heat input by 358 mmBtu on average and decreases NO_x emissions by 6.32 lbs.

3.9 Conclusion

This chapter sets out to estimate emission functions for use in scenarios, simulations, and other applications which could accurately forecast emissions given a variety of criteria. They need to accurately forecast levels of emissions generally and accurately forecast emissions during times when generators undergo certain operational changes. These operational changes are times of upramp, downramp, startup, and shutdown. These operations are often non-linear in impact, changing the emission and heat rates of generators, and can have lasting impacts through time. There are many cases where emissions need to be forecasted accurately during these time periods because of their increase in importance under some scenarios. Any change in the dispatch of generation which requires generators to make larger upramps, downramps, or more upramps, downramps, startups, and shutdowns, will need accurate forecasts of emissions during these types of hours.

The inclusion of non-linearities and lagged and leading impacts allows for accurate forecasts of emissions during all types of operation. By comparing out-of-sample forecasts with simpler models, it is shown that only the fully specified emission functions that we estimate can accurately forecast emissions in all types of hours. While there were some cases of the simpler functions forecasting overall emissions with equal or greater accuracy, only the fully specified emission functions could consistently and accurately forecast emissions in upramp, downramp, startup, and shutdown hours.

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4. The Calibration Exemption and Its Impact on Reported Emissions

4.1 Introduction

Most fuel burning generators in the United States are required to monitor, record, and report NO_x and SO_2 emissions under Title 40 of the code of federal regulations, Part 75. These regulations come from the US EPA Acid Rain Program but are expanded to cover units which are subject to other state or federal NO_x emission reduction programs by Part 75.2. The rest of the regulation provides information on the requirements for installing, maintaining, certifying, and operating the continuous emission monitoring systems needed to measure SO_2 and NO_x emissions. The US EPA establishes cap and trade programs for NO_x and SO_2 emissions under the Acid Rain Program (ARP) and the Clean Air Interstate Rule (CAIR). These programs create the need for generators to hold allowances for each ton of both SO_2 and NO_x emissions they emit. In order to ensure accountability it is important for emissions to be accurately measured and reported (Schakenbach, Vollaro, & Forte, 2006). Generators face an increase in their marginal cost in proportion to their emissions rate due to the need to hold allowance prices. This cost increase is the incentive to reduce emissions.

The emissions of generators for most hours of the year are measured by Continuous Emission Monitoring Systems (CEMS). There is an exemption to this which applies once a day which may allow generators to under report emissions during that hour. That exemption is the fact that generators are required to calibrate their emissions equipment once every 26 hours. When calibrating, generators do not need to use that portion of the hour in calculating that hours emissions. Therefore during any hour during which there is a large discrepancy in emission rate in one half of the hour compared to the other half, it is possible to report a lower average hourly emission rate in part of the hour than would be reported if the whole hour was used. Any hour that has this characteristic could be used as an opportunity to under report emissions by calibrating during the portion of the hour with a higher emissions rate. This paper attempts to determine if generators engage in this behavior and to estimate how large an impact it may have.

4.2 Background

There is the potential for a small loophole to allow for a reduction in a generator's reported emissions. This comes from the regulations governing operating requirements for the CEMs equipment, part 75.10. This part declares:

> "(1) The owner or operator shall ensure that each continuous emission monitoring system is capable of completing a minimum of one cycle of operation (sampling, analyzing, and data recording) for each successive 15-min interval. The owner or operator shall reduce all SO_2 concentrations, volumetric flow, SO_2 mass emissions, CO_2 concentration, O_2concentration, CO_2 mass emissions (if applicable), NO_X concentration, and NO_X emission rate data collected by the monitors to hourly averages. Hourly averages shall be computed using at least one data point in each fifteen minute quadrant of an hour, where the unit combusted fuel during that quadrant of an hour. Notwithstanding this requirement, an hourly average may be computed from at least two data points separated by a minimum of 15 minutes (where the unit operates for more than one quadrant of an hour) if data are unavailable as a result of the performance of calibration, quality assurance, or preventive maintenance activities pursuant to §75.21 and appendix B of this part, or backups of data from the data acquisition and handling system, or recertification, pursuant to §75.20. The owner or operator shall use all valid measurements or data points collected during an hour to calculate the hourly averages. All data points collected during an hour shall be, to the extent practicable, evenly spaced over the hour."

This section means that reported hourly emissions are generated by taking an average of CEMS measured emissions from at least 4 observations that are equally spaced out by 15 minute time periods within each hour. However, generators can use only two data points spaced fifteen minutes apart if they are undergoing calibration of their CEMs equipment. This means that generators, when operating in a time period covered under this exemption, could use two data points during an efficient operating period of an hour, and not use the remaining time in the calculation of average emissions. If they perform calibration during periods of greatest generation inefficiency, they can lower their reported average hourly emissions. This can occur if, within an hour, the average emission rate when the CEMs equipment is running is lower than the average emission rate when the CEMs equipment is not running and is undergoing calibration.

The calibration process involves a zero injection where a neutral gas is injected into the monitor. When clear of everything but this neutral gas, upscale injections of test gases of various known concentrations and amounts are injected into the monitor. As long as these are all properly measured the calibration is determined to be successful and the CEMS equipment can run again. If measured wrong the equipment is determined to be out of control and the generator must report calculated values until the equipment is determined to be measuring properly again. The calculated values are designed to over-estimate emissions to ensure that generators are incentivized to always have their CEMS equipment measuring emissions.

Generators are required to calibrate their CEMs equipment every 24 hours with a 2 hour grace period extending this to 26 hours. Therefore generators could effectively choose, about once per day, to calibrate their CEMs equipment during an operating hour characterized by a large difference in emissions rate during one part of the hour compared to the other part. This would reduce their reported emissions and lower their operating cost by reducing the amount of allowances they need to hold. There are four types of operation which can occur over an hour and allow for a reduction in reported emissions due to calibration.

Any hour during which the emissions rate is higher in one part of it than another allows for an opportunity to report lower emissions due to the calibration exemption. Hours that have this characteristic are ones in which the generator ramps up or down and hours of startup or shutdown. Averages which are calculated using emissions measured during the portion of the hour with a lower emission rate than the other portion would be lower than if the averages were calculated from the whole hour. This would result in lower reported emissions to the EPA than the generator actually emitted.

It is possible that not all generators engage in or know of this possibility, or that, depending on their emissions rates, that it is not worth it for them to schedule calibration so deliberately. It can take a significant amount of time and training of personnel in order to run the CEMs equipment, and oftentimes those in charge of the equipment are required to be present at the generator at the time of calibration (EPRI, 2003). Deliberate calibration during times when the generator recognizes it is undergoing an inefficient operation, may incur extra costs due to these factors.

From many literature searches, it is apparent that no one has tried to determine the impacts of this calibration exemption. Only one other study has attempted to estimate the cost of a specific regulation's loophole (Anderson & Sallee, 2011). They estimated auto-makers' marginal costs of improved car emissions by examining if they used a loophole in the Corporate Average Fuel Economy (CAFE). The case presented here is different because it has implications not just for cost savings by generators, but also has impacts on overall emissions since a reduction in reported emissions means that those emissions are not facing costs from the emission allowance markets. If the emissions had been subject to that cost by being reported, they may have been abated.

4.3 Method

In order to determine if and how much generators are taking advantage of the calibration exemption two sets of statistics are reported. The first shows how generators are operating in calibration hours compared to other hours. Generators that choose calibration more often in hours with startup, shutdown, or large ramps, are more likely to be using the calibration exemption. So, summary statistics are shown to try and capture and explain when generators are deciding to calibrate their CEMs equipment.

The second set of results are the statistically estimated impacts of calibration on reported emissions by generators in Texas. These results are more robust than the first set and should show if generators are reporting lower emissions in hours during which they calibrate. To determine this emission function models are estimated for 22 coal, 23 combined cycle, 16 simple cycle, and 31 natural gas steam turbine generators in Texas. A brief discussion of the differences between these generator types can be found in chapter 3, page 37. Variables indicating the hour of the day which the generators calibrate their CEMs equipment are included in these models. Using this and interactions with the calibration variable, the impact of calibration on various generator operating states is estimated, controlling for the normal emission impacts of these operating states.

Emission functions are estimated using an ARMAX regression which takes into account the various impact on emissions of a generator. The functions estimate an equation for each emission type and each generator taking into account the impacts of generator electric output, the contemporaneous and lagged impacts of upramp, downramp, and startup, and the leading and contemporaneous impact of shutdown. The result is a specific equation for each generator with specific lag and lead impacts of each variable that best explains the emissions of that generator. In this way emissions can be accurately predicted for any generator. By including variables that capture the hour when calibration occurs, and controlling for all other generator operation, the impact of calibration on reported emissions is estimated. The emission function equation estimated is displayed below for generator *i* and emission type *e*. Description of all the variables are found in Section 3.4 of Chapter 3 and Table 3.2

$$
\begin{gathered}
E_{iet} = \omega_1 \mathrm{GenOn}_{it} + \textstyle\sum_{a=1}^{23} \mathrm{g}_a \mathit{HourlyInteraction}_{it} + \sum_{aa=1}^{11} \mathrm{h}_{aa} \mathrm{MonthlyInteraction}_{it} + \\
\alpha_1 \mathit{GLOAD}_{it} + \alpha_2 (\mathit{GLOAD}_{it})^2 + \textstyle\sum_{b}^{z} \beta_b \mathit{Upramp}_{i(t-b)} + \sum_{c}^{y} \gamma_c (\mathit{Upramp}_{i(t-c)})^2 + \sum_{d}^{x} \delta_d (\mathit{Upramp}_{i(t-d)} \\
{}^{*}\mathit{GLOAD}_{i(t-d)}) + \textstyle\sum_{e}^{w} \epsilon_e \mathit{Downramp}_{i(t-e)} + \sum_{f}^{v} \zeta_f (\mathit{Downramp}_{i(t-f)})^2 + \sum_{g}^{u} \eta_g (\mathit{Downramp}_{i(t-g)} \\
{}^{*}\mathit{GLOAD}_{i(t-g)}) + \textstyle\sum_{h=}^{T} \kappa_h \mathit{Startup}_{i(t-h)} + \sum_{j}^{S} \lambda_j \mathit{Warmstart}_{i(t+j)} + \sum_{k}^{r} \mu_k \mathit{Coldstart}_{i(t+k)} + \\
\textstyle\sum_{l}^{q} \xi_l \mathit{Shutdown}_{i(t+l)} + \sum_{m}^{p} \pi_{m \to \rho} \mathrm{CalibrationVars} + \sum_{n}^{o} \rho_{n \to o} \mathrm{MODCVars} + v_t \\
v_t = \textstyle\sum_{n=1}^{p} \phi_n E_{ie(t-n)} + \sum_{m}^{q} \theta_m \epsilon_{t-m}
\end{gathered}
$$

Seven variables capture the impact of calibration summarized in the CalibrationVars term. The calibration dummy variable takes a value of 1 if the hour was an hour during which the generator performed a calibration of their CEMs equipment. The other six calibration variables are interactions between startup, shutdown, upramp, downramp, and a lead of upramp and downramp with the calibration dummy variable. Startup and shutdown are both dummy variables taking a value of 1 if the generator is in the first hour of operation for startup or last hour of operation for shutdown. Upramp is a measure of how much the generator increased its generation from hour t-1 to hour t. If the generator did not increase generation from hour t-1 to hour t then it takes a value of zero. Downramp is a measure of how much the generation decreased its generation from hour t-1 to hour t. If the generator did not decrease generation from hour t-1 to hour t then it takes a value of zero. Both the upramp and downramp interactions include one lead of upramp and downramp interacted with contemporaneous calibration as well as the contemporaneous upramp and downramp interacted with contemporaneous calibration. The reason for this is that the actual hour of the upramp cannot be known. A generator that increases output from hour t-1 to hour t could begin its ramp up halfway through the t-1 hour and finish it in the t hour. This would result in an increase in output from hour t-1 to hour t. It could also upramp entirely in the t-1 or t hour and still result in an increase in output from hour t-1 to hour t. Depending on which hour the ramp took place in, the impact of calibration in hour t could be different.

The estimation of these seven calibration variables provides point estimates for each generator of the impact of calibration on reported emissions during upramp, downramp, startup, and shutdown while controlling for these operations during non-calibration hours. After analyzing the emission functions and the estimates of calibration impact on these types of hours the average impacts of calibration are estimated across different scenarios. This will provide an estimate of the impact calibration has on reported emissions during the analyzed year compared to hours of normal operation.

4.4 Data

Data for the estimation of the emissions functions primarily comes from the EPA Continuous Emission Monitoring System data which is pulled from search queries of the EPA's Air Market Program Data tool[7]. This provides hourly data on individual generator's generation output, heat input, SO_2, and NO_x emissions. Using the hourly generation output additional variables are generated capturing startup, shutdown, and ramping of the generators.

Data on calibration was provided by special request from the EPA. It contains, to the minute, when calibration started, that is when the zero gas is injected into the CEMs equipment, and another minute value for when the upscale injection takes place. A dummy variable value of 1 is created for any hour during which calibration is started or upscale injection occurs. In this way, if calibration is done at the end of an hour, and continues into the next hour, there is the best chance of capturing the fact that calibration occurred in both hours. While the CEMs equipment does not come back on line immediately after the upscale injection, the knowledge of when the upscale injection occurs is the last data point available to capture the length of calibration time.

[7] http://ampd.epa.gov/ampd/ (Date Last Accessed: April 3, 2015)

4.5 Ramping Analysis

The fact that generators are calibrating much more often in hours of upramp than any other type of hour is illustrated first. Table 4.1 shows the percentage of hours a generator calibrates which are during upramp and downramp.

Table 4.1: When do generators calibrate? - Ramping

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Calibration during upramp hours (% of calibration hours)	55.1	40.1	54.6	59.7
Calibration during downramp hours (% of calibration hours)	26.4	10.6	21.4	11.9
Hours of year generator upramps (% of all hours)	39.6	39.4	42.5	44.4
Hours of year generator downramps (% of all hours)	38.0	31.2	37.0	32.1

Table 4.1 shows that coal, combined cycle, and simple cycle choose to calibrate during upramp over 50% of the time. This is the case despite the fact these generators upramp in only around 40% of its hours. It would be expected that if a generator chose to calibrate randomly, that it would choose to calibrate in each type of hour in proportion to how often that hour occurs in all hours. If a generator upramps in 40% of its hours, it would randomly choose to calibrate during upramp about 40% of the time. The differences in table 1 can be statistically tested for using a simple two-sample t-Test. With a null hypothesis that the difference in means is zero, a one tailed t-Test that assumes unequal variances finds that the difference in means for coal, combined cycle, and simple cycle are all significant at the 1% level.

This is not full evidence of generators choosing to calibrate specifically during upramp hours because upramp hours are times in which there is the potential to reduce reported emissions. It could be that generators are primarily calibrating in the morning when they are more likely to upramp, or generally calibrate during the day when it may be more likely that there is a technician on site. Many generators choose to calibrate only when a technician is available in order to oversee it (EPRI, 2003). Table 4.2 examines this question by looking at how generators behave during "daytime work hours".

Table 4.2: Calibration and Ramping from 8 am to 6 pm

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Calibration during upramp hours (% of all calibration hours)	7.6	30.1	41.7	46.3
Calibration during downramp hours (% of all calibration hours)	4.9	7.1	18.1	7.3
Daytime generator upramps (% of all upramp hours)	41.7	55.6	46.2	51.4
Daytime generator downramps (% of all downramp hours)	34.0	29.8	32.3	28.9

From the table it can be seen that generators can be grouped by type. Coal units are rarely calibrating during the daytime work hours while ST, CC, and SC generators are more often calibrating during work hours. Delving further into the choice of hour to calibrate for the generators can further describe the issue. Coal units are predominantly calibrating during upramps around 6 am or 7 am. This is in most cases, the hour of, or the hour after their largest average upramp. The other three generator types have less pattern to their calibration choice. Looking at the distribution of average upramps compared to hour of the day, their choice of hour to calibrate has much less correlation with upramp size. These distributions are found in Figures 4.2-4.4.

The reason coal units may uniformly choose the hour of the day which offers them the best opportunity to under report emissions is that they have the highest emission rates of the four types of generators so they would have the most to gain monetarily. Also, since they are base load, they may be able to better predict and know when their largest upramp will be. Figure 4.1, 4.2, 4.3, and 4.4 displays graphs for each individual generator overlaying two distributions. In blue are the average upramp sizes during each hour and in red are the number of times calibration was performed in a given hour of the day. The number of calibrations are divided by twenty so that they are more comparable in size to the average upramps.

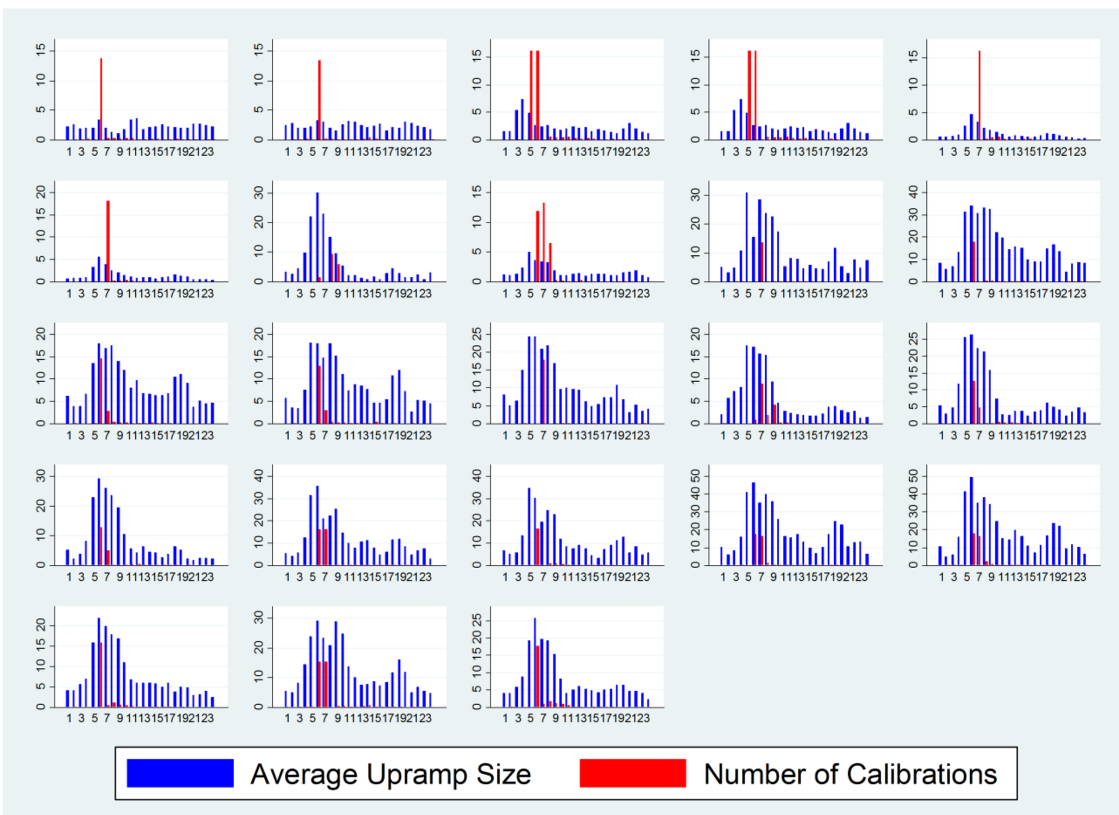

Figure 4.1 Coal Units. Average upramp and number of calibrations in each hour of the day

Figure 4.1, above, indicates the pattern of calibration by coal units. Almost of all of them are calibrating in the hour of or hour after their largest average upramp. Across all the coal generators the average upramp, when a unit is upramping, is 22.4 MW. The average upramp when a unit calibrates during an upramp is 34.6 MW. This is numerical evidence of the conclusions from Figure 4.1.

Figures 4.2-4.4 show the different behavior of the steam turbine, combined cycle, and simple cycle units. Most of them do not upramp during the largest mean upramp hour and they often are spreading out calibration hours over different hours of the day. In considering averages of upramp size across all generators of each type, compared to averages of upramp size when a unit calibrates during an upramp, there is very little difference. Gas steam turbines have an average upramp size of 32.1 MW, while their average upramp during an upramp calibration hour is 29.3 MW. Simple cycle units average upramp is 19.9 MW and their average upramp during an upramp calibration hour is 16.1 MW. Finally, combined cycle units have an average upramp 21.0 MW and an average upramp during a calibration hour of 22.1 MW. The graphs and average upramp statistics do not support there being a concerted effort by these generator types to calibrate in hours of larger than normal upramps.

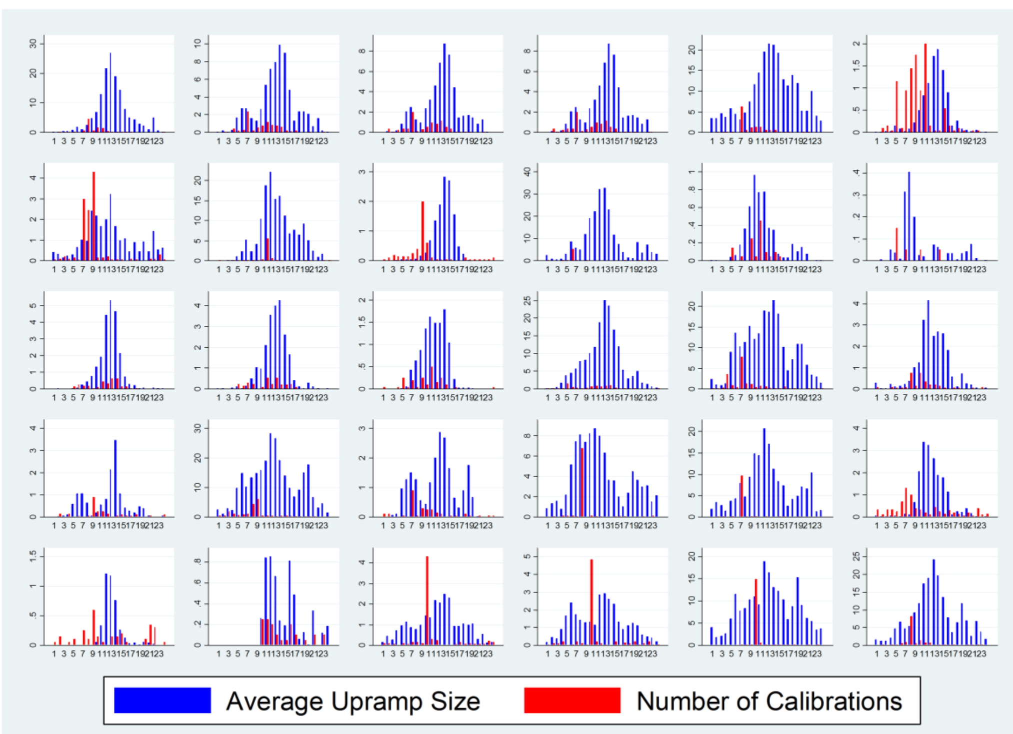

Figure 4.2: Gas Steam Turbines: Average upramp and number of calibrations in each hour of the day

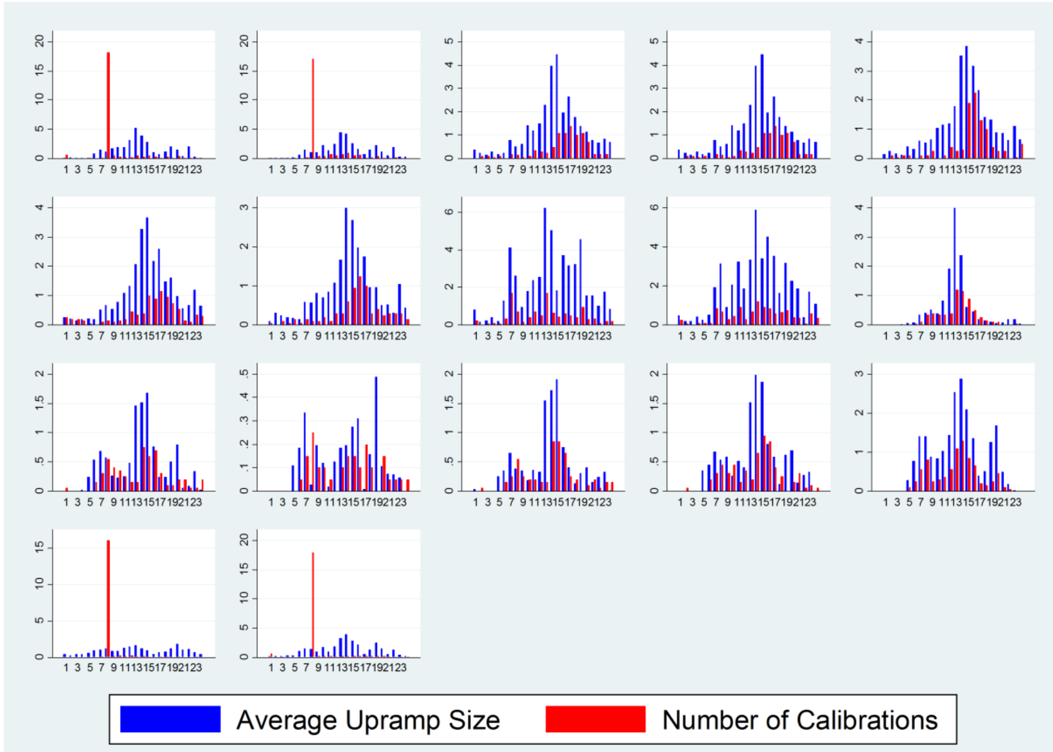

Figure 4.3 Simple Cycle: Average upramp and number of calibrations in each hour of the day

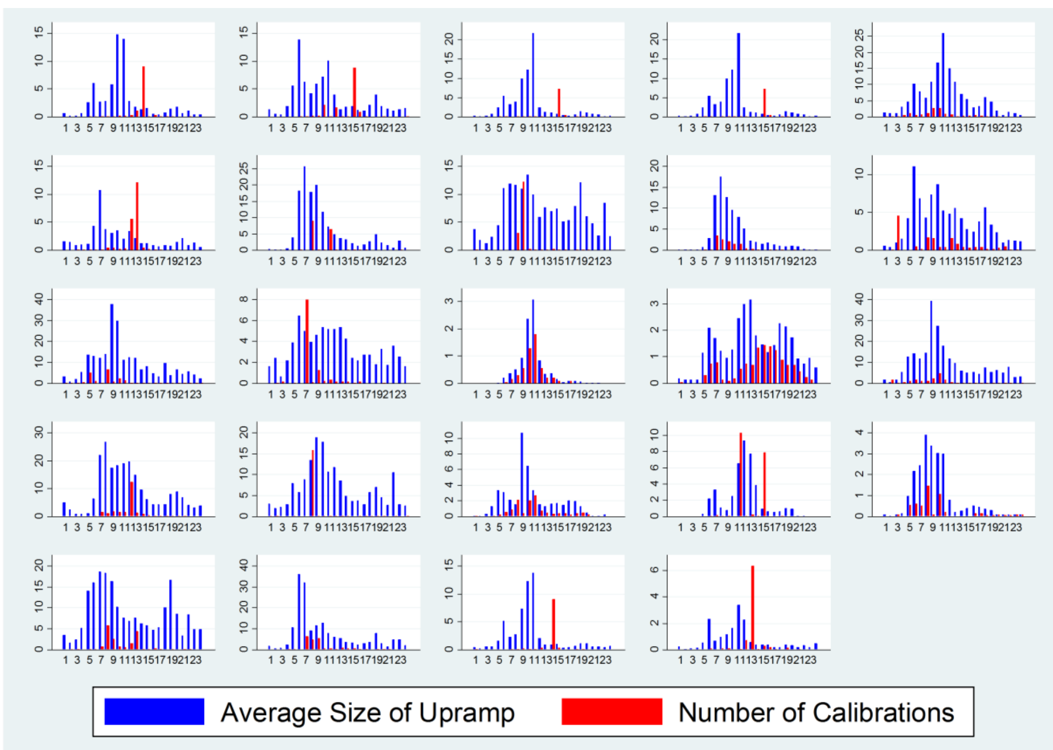

Figure 4.4 Combined Cycle: Average upramp and number of calibrations in each hour of the day

4.6 Emission Function Results

Estimating emission functions that include variables to capture the impact of calibration allows for estimation of the impact of calibration on reported emissions while controlling for standard generation operations. Table 3 reports the average estimated impact of calibration on reported heat input for each type of generator for an upramp and downramp that is 25% of a generator's capacity, and centered on 50% of a generators capacity. To better illustrate this calculation an example is provided. A coal generator has the following estimates for the calibration variables used in calculating the impact of calibrating during an upramp on emissions:

Calibration Dummy (π_1): -4.5
Calibration*Upramp (π_2): -1.63
Calibration*F.Upramp (π_3): -0.70
Calibration*GLOAD (π_4): -0.179

This generator has a maximum capacity of 445 MW. So, a 25% ramp is 111.25 MW and moves generation output from 166.9 MWh to 278.1 MWh for an average hourly generation of 222.5 MWh. The ramp is assumed to be reported half in the hour of upramp and half in the hour after upramp in order to capture both the contemporaneous upramp and leading upramp coefficients. The heat input impact of this ramp is therefore calculated as:

$$\text{Heat Input (mmBtu)} = \alpha_1 + \alpha_2*55.6 + \alpha_3*55.6 + \alpha_4*222.5$$

$$-4.5 + -1.63*55.6 + -0.70*55.6 + -0.179*222.5 = -173.9 \text{ mmBtu}$$

Dividing this by the size of the ramp (111.25 MW) gives a value of -1.56 mmBtu/MW ramp. This calculation is done for each generator and emission type to provide the average values found in Table 4.3. A similar process is also done for downramp. Startup and shutdown impacts are simply averages of the coefficients on the startup and shutdown calibration interaction variables.

Table 4.3: Impact of Calibration on Reported Heat Input (mmBtu/MW ramp)

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Average Impact of Calibration During Upramp	-0.29	0.64	0.15	1.93
Average Impact of Calibration During Downramp	-0.51	-0.68	0.19	0.15
Number of Generators	22	29	23	16

Results on heat input show that coal generators, for upramp and downramp, have lower reported heat input when calibrating than during non-calibration upramp and downramp hours. The average estimated impact of calibration on reported heat input during a 25% of generation ramp, centered on 50% of generation, was -0.35 mmBtu per MW ramp. Sub-bituminous coal, for reference, has an emission factor of 211.91 lbs CO_2 / mmBtu (Environmental Protection Agency, 2004). If CO_2 were calculated from the estimate mmBtu/MW ramp impact, it would be a reduction in reported CO_2 by 75 lbs / MW ramp. Since there are not any CO_2 limits from cap and trade or other regulations in Texas, there is not much of an incentive for generators to under-report heat input or CO_2 emissions. Thus, the reduction in heat input during calibration hours may be a byproduct of NO_x and SO_2 reporting.

All three types of natural gas units have positive estimates on the impact of calibration on reported heat input during ramping. This is unexpected but could be related to the different behavior they display in their profiles of when they calibrate. Coal generators are choosing hours with upramps that are larger on average, than other hours. The gas steam turbine, simple cycle, and combined cycle generators are not choosing to calibrating in hours where this is the case.

Table 4.4: Impact of Calibration on Reported NO_x Emissions (lbs/MW ramp)

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Average Impact of Calibration During Upramp	-0.16	0.17	0.04	0.30
Average Impact of Calibration During Downramp	-0.03	-1.14	0.56	-0.06
Number of Generators	22	29	23	16

Table 4.4 shows the estimated impact of calibration on reported NO_x emissions during ramping hours. Coal units, on average, have a negative impact in both upramp and downramp hours. The average impact of calibration on reported NO_x emissions is larger in upramp hours compared to downramp hours. Gas steam turbines also have a negative impact of calibration on reported NO_x emissions during upramps but have a positive impact during downramps. Combined cycle and simple cycle units both have a positive estimate during upramp hours and negative estimate during downramp hours. The expectation for the impacts of calibration on reported NO_x emissions were negative for generators that use the calibration exemption as an opportunity to operate differently during the hour of calibration. Positive coefficients could be the result of generators not engaging in this behavior and be byproducts of some other factor. Other factors could be that calibration can find "out of control" readings which mean that generators would need to report calculated emissions instead of measured emissions. Calibration could also occur, for gas generators, during hours that regularly have higher emission rates than other hours. If that is the case, and they do not use the exemption to reduce their reported emissions, then it could result in a positive estimate.

Table 4.5: Impact of Calibration on Reported SO_2 Emissions (lbs/MW ramp)

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Average Impact of Calibration During Upramp	-0.35	NA	NA	NA
Average Impact of Calibration During Downramp	0.48	NA	NA	NA
Number of Generators	22	NA	NA	NA

The results in Table 4.5 show the impact of calibration on reported SO_2 emissions during upramp and downramp. Only the results for coal units are reported as the functions used do not estimate SO_2 emissions for gas units. This is because of the very low SO_2 emission rates associated with generation from natural gas. Coal units have a negative impact of calibration on reported SO_2emissions during hours of upramp. They have a positive impact on reported emissions during downramp. This positive impact could be due to other factors as stated previously.

The overall result is that it is primarily coal units who may be using the calibration hour to reduce their reported emissions. Looking at the types of hours they calibrate in, and the estimated impacts of calibration, provides several pieces of information indicating they may be engaging in this behavior. The results for the three types of natural gas generators are more mixed. They often have positive estimates during upramp and downramp hours, and do not show any consistent pattern of choosing to operate during hours which have larger upramps.

4.7 Startup and Shutdown Results

Another hour type that has the opportunity to manipulate reported emissions are startup and shutdown hours. As with ramping hours, these hours can undergo significant differences in operation from the beginning of the hour to the end of the hour. As such, it is possible to report a lower average emissions in one half of the hour, compared to what it would be if the whole hour was considered. The fact that units calibrate at all during startups may be indicative of the incentive to use the calibration exemption to under report emissions. This is because section 2.1.5.2 in Appendix B of Part 75 denotes a grace period after startup during which generators do not need to calibrate. If the unit has passed its quarterly and annual CEMs assessments, a calibration was performed and passed within 26 hours of the last time the unit was operating, and the unit has been off for at least 1 hour, then a generator can consider their first 8 hours of data as quality assured, and do not need to do their daily calibration until after this time period is up. Table 4.6 reports average startup and shutdown operation statistics for the four types of generators. The statistics in Table 4.6 are slightly different than those in Table 4.2. The occurrence of startup and shutdown may not be as predictable as upramp and downramp for some units. As such, instead of reporting the percentage of calibration hours that are during startup, the percentage of startup hours that have calibration are reported.

Table 4.6: When do generators calibrate? – Startup and Shutdown

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Calibration during startup hours (% of startup hours)	6.92	18.32	10.84	20.81
Average Number of Startups in Year	10.77	70.14	121.4	179.2
Calibration during shutdown hours (% of shutdown hours)	4.68	1.65	0.77	7.61
Average Number of Shutdowns in Year	10.82	70.28	121.5	179.3

The main interpretation of this table is that generators, despite not being required to calibrate in the first hour of startup, are doing so anyways. In order to determine if these calibrations during startup are reporting a lower amount of emissions than other startup hours the estimation results are reported. These results come from the interaction of the startup and shutdown dummy variables with the calibration dummy variable. The estimations for the impact of shutdown and startup are reported in Table 4.7. These results are the average of all units which had instances of calibration during startup or shutdown of each generator type.

Table 4.7: Impact of Calibration on Reported Emissions - Startup and Shutdown

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Heat Input (mmBtu)				
Average Impact of Calibration During Startup	-177	9.14	-30.1	-1.79
Average Impact of Calibration During Shutdown	-753.1	74.8	-8.37	52.6
NO_x Emissions (lbs)				
Average Impact of Calibration During Startup	-15.83	2.41	-6.98	-1.17
Average Impact of Calibration During Shutdown	68.98	-0.95	0.17	3.16
SO_2 Emissions (lbs)				
Average Impact of Calibration During Startup	-142.7	N/A		
Average Impact of Calibration During Shutdown	-168.2			

The results in Table 4.7 tell a similar story to the ramping results. Coal units predominantly report lower heat input and emissions in startup and shutdown hours of calibration compared to startup and shutdown hours that do not have calibration. As an example of how to interpret the results, the average coal unit reports a lower heat input during a startup hour in which they calibrate by 177 mmBtu compared to a startup hour in which they do not calibrate. They report lower NO_x emissions by 15.83 lbs during a startup hour in which they calibrate compared to a non-calibration startup hour and lower SO_2 emissions by 142.7 lbs. The results for gas steam turbines are positive for heat input in hours of startup and shutdown as well as for NO_x during startup. It is negative for NO_x emissions during shutdown but very close to zero. Combined cycle generators have negative estimates for heat input during startup and shutdown. For NO_x reported emissions are lower during startup hours and slightly higher during upramp compared to startup and shutdown hours when there is no calibration. Simple cycle results show lower reported heat input and NO_x emissions during startup hours compared to non-calibration startup hours and higher reported heat input and NO_x emissions during shutdown hours.

The results presented on startups and shutdowns indicate that coal units are consistently reporting lower emissions during calibration. Except for NO_x emissions during shutdown, all the estimates for heat input, NO_x and SO_2 are negative. This consistency in results between ramping, startup, and shutdown indicate they may be using the calibration hour to under-report emissions. The same consistency in results is not found in the three other generator categories. They find mixed results with some categories of operating hours having lower reported emissions during calibration and others having higher reported emissions. These units also do not appear to have engaged in the behavior of choosing hours with the potential for large differences in emission rates within the hour. Therefore conclusions cannot be drawn as readily for gas steam turbine, combined cycle, and simple cycle generators. This may be expected given that they have lower emission rates than coal fired generators and therefore have less to gain by under-reporting emission.

4.8 Cost Reductions

In order to determine the magnitude of the calibration impacts estimated coefficients are applied, for each generator, to their 2010 data to determine the impact on emissions reported for the entire year. This is calculated by predicting emissions over the entire year assuming there was no calibration and subtracting predicted emissions over the year with the calibration hours accounted for. This difference is the estimated impact from calibration on total emissions over the year. Averages across each generator type are reported in Table 4.8.

Table 4.8: Estimated Impact of Calibration on 2010 Reported Emissions

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Heat Input (mmBtu)	-1562	507	1315	1791
NO_x Emissions (lbs)	-6516	801	132	77
SO_2 Emissions (lbs)	-11625	N/A	N/A	N/A

These results indicate that gas steam, combined cycle, and simple cycle units are not using the calibration hour to under report emissions. Their positive estimates have no interpretation and are taken as evidence of them not using calibration strategically. Coal units report reduced heat input, NO_x emissions, and SO_2 emissions. This indicates that they may be using calibration to report fewer emissions. In order to get perspective on the magnitude of unreported emissions several calculations are done. The cost savings in allowances not needed is calculated for two different allowance price levels. Also, the cost of the un-reported emissions to society are calculated.

Coal units may be under reporting emissions and saving a significant amount of money by purchasing fewer NO_x and SO_2 allowances. The average NO_x allowance price in 2010 was 48.78 $/ton and the average SO_2 allowance price was 16.98 $/ton. This means that the average coal plant saved, over the entire year, about $158.00 in NO_x allowances and $98.69 in SO_2 allowances. This is not very much of an incentive to calibrate strategically. Units may have established their calibration policies when the allowance prices were higher. In July of 2008 the D.C. Court of Appeals struck down parts of CAIR causing allowance prices for both NO_x and SO_2 allowance prices to plummet. Since the coal units from Figure 4.1 seem to all calibrate in morning hours they may have made it a policy to do calibrate in these hours knowing that was when they were likely to undergo large ramps. Yearly cost savings are calculated using allowance prices from before the court decision. The largest price the allowances got to were 1450 \$/ton for NO_x and 720 \$/ton for SO_2. Calculating savings with these prices results in yearly savings for the average coal generator of \$4,724 from NO_x and \$4,185 for SO_2. Across all 22 coal generators estimated this adds up to \$104,000 dollars in savings a year for NO_x allowances and \$92,000 in savings a year for SO_2 allowances. It may be the case that the higher allowance prices incentivized using the calibration period and the behavior continued even after allowance prices plummeted.

Another way to estimate the impact of the estimated reduction in reported emissions is to use the estimated marginal damages of NO_x and SO_2 to determine the societal cost the emissions incur. This assumes that the unreported emissions would have been abated. Two values for NO_x and SO_2 marginal damages are used to estimate these costs. They come from estimates by the National Research Council of the National Academies (2010) and Muller and Mendelsohn (2009). The National Research Council estimates marginal damages for NO_x and SO_2 emissions as 1600 \$/ton and 5800 \$/ton respectively. Muller and Mendelsohn calculate the marginal damages for NO_x and SO_2 emissions as 260 \$/ton and 1310 \$/ton respectively. Both sets of costs include the estimated emissions damages on human health, agricultural yields, building materials, recreation, and visibility. Using these damages the estimated yearly cost of the unreported emissions for coal generators in Texas is between \$115,000 and \$18,600 for NO_x emissions and between \$742,000 and \$167,500 for SO_2 emissions.

4.9 Conclusion

Generators may be able to use an exemption in emission reporting requirements to under report emissions. This comes from Part 75 language allowing generators to not use data points to calculate hourly emissions when calibrating CEMS equipment. Generators could take advantage of this by calibrating during the part of an hour with a higher emission rate than the other part of the hour. There are certain types of hours which have the characteristics that allow for emission rates to be different in different parts of the hour. Hours in which a unit upramps, downramps, starts up, or shuts down can all have very different emission rates within the hour. Calibrating during these types of hours could allow generators to reduce hourly reported emissions from what reported emissions would have been when calculated over the entire hour. In order to determine if this is occurring an analysis is done on the pattern of coal steam turbine, gas steam turbine, simple cycle, and combined cycle's choice in what hour to calibrate.

Analyses of the type of hour these units are calibrating in indicate that they are often calibrating during the types of hours which would allow for an advantageous use of the calibration exemption. Coal units are often calibrating during ramping hours, especially upramp hours. These upramp hours, additionally, have larger upramps than the average upramp hour when calibration is not occurring. The three other types of units may calibrate more often during ramping hours, but these ramp hours are not different from other ramp hours. Statistical analysis using emission functions provides some indication of the impact of calibrating during hours that have the potential for large differences in emissions rates within the hour. Only coal units show reduced reported emissions during upramp. Other types of hours have different results depending on the type of generator. Applying the coefficient estimates from the calibration to data from 2010 allows for an estimate of the under-reported emissions. Results for coal generators found lower reported emissions due to calibration while the other generator categories found positive reported emissions from calibration. As a result, only coal units seem to be using the calibration hour to report fewer emissions. This reduction in reported emissions is relatively small and the results shows only small savings using the low allowance prices of 2010. Using prices from when the NO_x and SO_2 allowance prices were higher results in more significant cost savings across Texas coal generators of $104,000 per year for NO_x allowances and $92,000 for SO_2 allowances. The societal damages from these emissions may be even larger assuming the under-reported emissions would be abated. The estimated damages on human health are estimated to be between $115,000 and $18,600 for NO_x emissions and $742,000 and $167,500 for SO_2 emissions. These two sets of cost metrics can allow for readers to determine for themselves the importance of the calibration exemption.

4.10 Works Cited

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5. Improved Emission Functions for Generators, and How They Help Resolve a Controversy about the Emission Effects of Wind Power

5.1 Introduction

Wind power continues to be integrated into the power system at a rapid pace. Wind power is a low marginal cost and non-dispatchable source of energy that can only be produced when the wind blows. Most systems take all wind generation due to its low marginal cost and lack of emissions. This means that fossil-fuel fired generation must be dispatched differently and have output changed depending on the amount of wind generation available at any given time. Variability in fossil-fueled generation output and dispatch means an increase in the instances and magnitude of ramping generators from one set point to another. Very high levels of wind can mean increasing the times a generator must startup or shutdown. During times of ramping or startup, the change in heat input required to move a generator from one level of generation output to another, can change the emissions rate of the generator. If the average effect of ramping, startup, and shutdown on emissions, averaged across the generation units in a region, is positive, this will partially offset the emissions reductions that wind power offers. The offset of emissions reductions may have implications for policies which support wind generation such as tax credits for wind generation.

Unexpected changes in emissions when fossil fuel generators operate differently may impact economic policies that target those generators. Estimating the impact wind penetration has on generator operation and subsequent emissions is important in order to determine the impacts on emissions these policies may have. For example, if wind penetration increases in a region with an emissions cap and trade policy, there may be unexpected changes in emissions which would impact allowance markets, generators costs, and emission limits. It is therefore important to be able to accurately forecast emissions when generator operation may change.

The impact on emissions from changing generation operation under differing levels of wind penetration is analyzed in this chapter. This is done by estimating emission functions which can accurately predict emissions under all types of generator operating hours, including ramping, startup, and shutdown. Wind power may increase emissions because it increases instances of ramping, and startups of fuel-fired generation. The functions, which incorporate these impacts, can be used in comparing scenarios that differ significantly with respect to ramping or start-ups, such as a high-wind-penetration scenario and a low-wind-penetration scenario. The emission functions are applied to simulation data of five scenarios differing in wind penetration from the Electric Reliability Council of Texas (ERCOT). In this way CO_2, NO_x, and SO_2 emissions are forecasted and compared across the scenarios to determine how emissions change as the level of wind penetration increases.

5.2 Literature Review

Some research has been done exploring the relationship between wind penetration and generation operation on emissions. Two studies show that generation operation will change with increasing wind penetration. Simulations run by General Electric (GE) show that 20 to 30 percent renewables penetration in the Western Electricity Coordinating Council (WECC) would result in a significant increase in ramping of generation units, including those fueled by coal (GE Energy, 2010). Analysis of power spectrum density plots of wind variability has found that the relatively large amplitude of low frequency fluctuations of wind output (in the range of hours), compared to high frequency fluctuations (minutes or seconds), highlights the importance of using slow ramping generation, such as coal or natural gas fired units, to back up variable wind generation (Apt, Fertig, & Katzenstein, 2012). Increased instances of ramping, or increases in the magnitude of ramping could increase emissions above the rate at which they occur when at a steady state of constant generation. These higher emission rates could then increase overall emissions, potentially offsetting gains from wind power.

Several studies have tried to determine the impact on generator or system emissions from changes in wind penetration with different results. Increases in wind penetration in Ireland are modeled and determined to be an effective means of reducing CO_2 emissions on the system but not to reduce NO_x and SO_2 emissions (Denny & O'Malley, 2006). They find that applying an emission tax or similar regulation in combination with wind power does reduce NO_x and SO_2 emissions. This is likely just due to the regulation changing dispatch order however.

Two studies use displacement analysis to determine the extent of emissions reductions under different amounts of wind generation. Displacement analysis considers expected emission reductions to be proportional to the displaced fossil fueled generation by wind. Katzenstein and Apt (2009) use regression analysis to model emissions of NO_x and CO_2 for two types of fast-ramping natural gas generators and apply the results to a small 2 gas, 1 wind, 1 solar unit system. Their results show that actual CO_2 emissions reductions are 75-80% of what the reductions would be using a constant emission rate. For NO_x, depending on emissions controls emissions reductions range from 30-50% of constant emission rate reductions to an increase of 2-4 times the constant emission rate reductions. Fripp (2011) finds that using gas operating reserves will undo 6% of the emission reductions that are expected from wind power. This comes from inefficiency in the system which runs excess combined cycle and simple cycle generators, and uses simple cycle generators because they can start quickly instead of more efficient options. These two studies place importance on the use of fossil fuel operating reserves to back up wind has been shown to offset at least some of the emissions reductions from wind and solar power (Katzenstein & Apt, 2009) (Fripp, 2011).

Estimates of the effects of wind energy on coal unit ramping and emissions have been similarly disparate. Bentek energy released a report in April 2010 saying that wind energy causes increases in SO_2 and NO_x emissions in both PSCO (Colorado) and ERCOT (Texas) and increases in CO_2 emissions in PSCO. Colorado's Xcel energy later refuted this report saying that their large additions in wind energy have resulted in an overall decline in emissions (Prager, 2010). Finally, a study by Lew et al. found insignificant impacts on emissions from ramping but significant impacts on emissions from partial load operation and from starting up, for both coal and gas plants (Lew, et al.).

Two studies analyze the impact of wind penetration in Texas. The first study estimates the marginal impact of adding wind generation to the system. Cullen (2013) uses a reduced form econometric model to determine the marginal change to generation caused by wind. After estimating the marginal change to generation for each individual generator, average emission rates are applied to determine the impact on emissions. Cullen (2013) estimates that SO_2 emissions are offset by 3.15 lbs/MWh wind, NO_x

emissions by 1.05 lbs/MWh wind, and CO_2 emissions by 0.71 tons/MWh wind. This estimation method is limited because it assumes constant emission rates and only estimates the change in generation caused by wind.

Kaffine et al. (2013) expand on Cullen by using a similar model, but instead of estimating the marginal impact of wind on generation, estimate the marginal impact of wind on emissions for each generator. They do this by regressing, for each generator, its reported emissions on control variables and a variable consisting of total wind generation on the system in each hour. This results in an hourly estimate of the marginal impact of total system wind generation on a generator's emissions. They find that SO_2 emissions are offset by 1.277 lbs/MWh wind, NO_x emissions by 0.710 lbs/MWh wind, and CO_2 emissions by 0.523 tons/MWh wind. Since their model does not structurally estimate the direct impact of an individual generator's elecitricity generation on emissions, out-of-sample forecasts under scenarios where wind capacity is different from their dataset cannot be accurately done. The small changes in wind generation that may occur under the current system are not comparable in their impacts on generation operation to the much larger changes that may occur with higher levels of wind penetration. This paper can capture the impacts on large changes in generation operation and accurately determines the resulting emission impacts by using dynamic emission functions.

Such large differences in results points to the need for further research on this topic. This paper aims to improve on these studies by using a method which will accurately estimate emissions from fuel-fired generators and apply them to realistic wind penetration scenarios. Since the emissions functions used accurately forecast emissions during periods of ramping, startup, and shutdown, they are particularly well fitted for analyzing different wind penetration scenarios. This will allow for a careful analysis of the impact of wind penetration on emissions and provide robust results to a question that has had many answers.

5.3 Research Method

To estimate the emissions impacts of wind penetration the following procedure is used. The procedure consists of two components which are estimating emission functions and then applying them to data from simulations of the ERCOT power system under different wind penetration scenarios to estimate emissions. Historically reported data is used to estimate the emission functions. This allows for the creation of equations which will accurately predict emissions given a generator's hourly electricity output. The emission functions are then applied to simulated wind penetration scenarios in Texas. By applying the functions, hourly emissions are forecasted under each scenario and can be added up to produce forecasted total emissions in the system. The forecasted emissions are compared across all the scenarios in order to determine the wind penetration impact.

Emissions are forecasted for 5 wind penetration scenarios in Texas. Texas provides a self-contained electricity system to research. This is because it is, for the most part, not electrically connected to anywhere else. With 5 scenarios the analysis will attempt to determine if the changes in emissions across the levels of wind differ greatly. The following emission function is estimated for generator *i* and emission type *e*. Description of methods for estimation and all the variables are found in Section 3.4 of Chapter 3 and Table 3.2.

$$E_{iet} = \omega_1 \mathrm{GenOn}_{it} + \sum_{a=1}^{23} g_a \mathit{HourlyInteraction}_{it} + \sum_{aa=1}^{11} h_{aa}\mathrm{MonthlyInteraction}_{it} + \alpha_1 \mathit{GLOAD}_{it} + \alpha_2(\mathit{GLOAD}_{it})^2 + \sum_b^z \beta_b \mathit{Upramp}_{i(t-b)} + \sum_c^y \gamma_c(\mathit{Upramp}_{i(t-c)})^2 + \sum_d^x \delta_d(\mathit{Upramp}_{i(t-d)} * \mathit{GLOAD}_{i(t-d)}) + \sum_e^w \epsilon_e \mathit{Downramp}_{i(t-e)} + \sum_f^v \zeta_f(\mathit{Downramp}_{i(t-f)})^2 + \sum_g^u \eta_g(\mathit{Downramp}_{i(t-g)} * \mathit{GLOAD}_{i(t-g)}) + \sum_{h=}^T \kappa_h \mathit{Startup}_{i(t-h)} + \sum_j^S \lambda_j \mathit{Warmstart}_{i(t+j)} + \sum_k^r \mu_k \mathit{Coldstart}_{i(t+k)} + \sum_l^q \xi_l \mathit{Shutdown}_{i(t+l)} + \sum_m^p \pi_{m\to\rho}\mathrm{CalibrationVars} + \sum_n^o \rho_{n\to o}\mathrm{MODCVars} + v_t$$

$$v_t = \sum_{n=1}^{p} \phi_n E_{ie(t-n)} + \sum_m^q \theta_m \epsilon_{t-m}$$

This function, and the appropriate lag length for each variable, is estimated for each generator in Texas. This is done by an iterative method which intiially adds variables with a large number of lags. The lags are reduced until the largest numbered lag is significant at a 0.05 significance level. Once the lags of each vaiable are chosen, the function is estimated with each combination of AR and MA terms from (0,0) to (3,3). The combination which produces the lowest AIC value is then chosen as the ARMA portion of the emission function. This process is shown in chapter 3 to produce accurate out of sample forecasts for all types of generators and emissions. The out of sample forecasts are accurate for total yearly emissions and for hours of ramping, startup, and shutdown. After estimating the function for each generator STATA software is used to forecast emissions over the simulation data. The simulation data contains hourly generation output and therefore can be used to create all the necessary variables for the forecast.

In order to ensure that all the forecasts for simulation emissions were realistic all results were examined. This was done by checking to see if the average heat rate and emission rate for each generator was realistic. The average heat rate and emission rate are calculated for each generator from the 2010 CEMS data and for the simulation forecasts. The standard deviation of each generator type, coal, gas steam turbine, combined cycle, and simple cycle, were calculated from the 2010 CEMS heat and emission rates. If a generator's average heat rate or emission rate in the simulation forecasts is calculated as being greater than 3 times the standard deviation for that unit's generator type, it was considered to be unrealistic. This was the case for 5 of the generators. For these 5 generators the base function described in Chapter 3 was used to forecast emissions. This base model is a simplified version of the full model where ramping is included linearly and all variables have no lags and leads. The forecasting results in Chapter 3 indicate that this function still forecasts well, although not as well as the fully estimated function. Forecasted heat rates and emission rates for the simulation data, using the base model for these 5 generators, were again checked and found to be realistic.

5.4 Simulation Data

ERCOT simulated hourly operation of their system for one year using PROMOD software. PROMOD is an electric market simulation software which runs unit commitment and economic dispatch, with transmission grid topology and constraints, and with ramping constraints for units. Five simulations were run using five different wind penetration scenarios. The five scenarios consist of 3,500, 10,000, 16,500, 23,000, and 29,500 MW of wind capacity. For reference, the 2010 Texas system had 10,000 MW of installed wind capacity. All scenarios are run with 2012 load conditions, and the projected 2016 transmission system which has wind-oriented expansions. The reason for using the 2016 transmission system is that under all but the lowest wind penetration scenario, the current transmission system must curtail or spill wind to stay within transmmission constraints. Under the 2016 transmission system there is enough transmission capacity to handle the maximum amount of wind generation that can occur under the 10,000 MW to 29,500 MW wind capacity scenarios.

To estimate emissions from the scenarios, the generators from the ERCOT data are matched with generators from the EPA and EIA data sets using generator characteristics such as unit name, fuel type, latitude, longitude, and capacity. The estimated emission functions are then applied to each generator's simulated hourly output under each scenario to produce hourly estimated emissions. For natural gas fired generation, SO_2 emissions are ignored due to their low magnitude.

It is important that the characteristics of the simulation data are realistic in order to use the emission functions to forecast emissions based upon the simulation data. The reason for this is that if generators do not ramp, startup, shutdown, and have the same capacity limits as the CEMS data, forecasts will become inaccurate. If a generator in the CEMS data never undergoes a 300 MW ramp, and in the simulation data it does, then the 300 MW ramp will have an estimated impact based upon the smaller ramps it actually did in the CEMS data. Since the ramp variables are non-linear this could quickly lead to inaccurate results. In order to ensure the simulation data does not do this, the PROMOD model was run with realistic assumptions regarding generator operation. The average operating assumptions for each generator type used in the simulation are provided in Table 5.1, below.

The forced outage rate denotes the probability that the unit will not be available to generate electricity when dispatched. The forced outage duration is the length the unit is assumed to be unavailable if there is a forced outage. Minimum downtime is the minimum number of hours the generator must be off until it can startup again. The minimum runtime is the minimum number of hours the generator must be on until it can shutdown. The maximum ramp rate gives the maximum rate at which a generator can ramp up or down as a percentage of its maximum capacity. Simple cycle units are fast ramping and are assumed to be capable of ramping their entire generation capacity in one hour. The slowest ramping units are the coal generators which can only ramp 15.7%

of their capacity in an hour. The installed capacity indicates that most of the generation on the system is natural gas fired with most of that being combined cycle generators.

Table 5.1: Operating Assumptions in PROMOD Simulation

	Coal	Gas Steam Turbine	Combined Cycle	Simple Cycle
Forced Outage Rate (%)	7.92	3.11	5.08	3.12
Forced Outage Duration (Hours)	50.0	26.0	43.8	26.5
Minimum Downtime (Hours)	12.1	8.00	4.27	1.25
Minimum Runtime (Hours)	24.0	8.00	5.87	1.10
Max Ramp Rate (% of Max Generation/Hour)	15.7	32.5	39.0	100
Installed Capacity (MW)	19,812	12,356	35,238	3,853

It is the case that combined cycle units in the simulation data have much higher maximum generator outputs than the same combined cycle generators in the CEMS data. The reason for this is that the CEMS data only includes the generator output from the combustion turbine portion of a combined cycle unit. Any generation from the steam turbine portion is not reported since no emissions are generated by it. The solution to this mismatch is to calculate the maximum observed generation from the CEMS data and use it to modify all the generator output values of the simulation combined cycles. This changes the simulation data for combined cycle generators, which includes both their combustion turbine and steam turbine, into an approximation of what only the combustion turbine would produce. In this way the emission functions from the CEMS data can be applied with the least error.

5.5 Simulation and Emission Results by Generator Type

The impact of increasing wind penetration is different for each of the four generator types. This is the case for both the operation of the generators in each wind penetration scenario, and the emission forecasts in each scenario. The results by individual generator type are important to consider because system results may be biased by the emission rates of different fuels and generator types. For example a system of entirely coal generators would find larger reductions in CO_2 emissions compared to reductions in total generation than a system with half coal and half gas, where only the gas generators reduce generation. This means that the aggregate results for Texas cannot be generalized to other systems with different generation mixes. The results by generator type are more generalizable since the coal, gas steam turbine, combined cycle, and simple cycles in Texas are unlikely to be much different from those in other states. Still, depending on the wind penetration scenario, and how it impacts generator operations, the emission impacts are still case dependent. Since the differences between aggregated and generator type results are important, this section reports results for each type of generator seperately, and then aggregate results across the entire system.

For each generator type, the first set of results reported come from the simulation data. They analyze the characteristics of generation operation under the different wind penetration scenarios. One of the main assumptions made is that increasing wind penetration will increase the number of instance generators are required to ramp, startup, and shutdown. The changes in these across the wind penetration scenarios is therefore reported first. From these results an operating profile can be given of the various generator types and better inform the emission results. The impacts on emissions from the many changes across the different types of generators are also reported.The emission functions show the ability to forecast ramps, startups, and shutdowns accurately. They are better suited than other simpler functions for forecasting scenarios like the ones presented here. This is because of the large changes for each of the different types of generators in ramp, startup, and shutdown operations across the different scenarios.

Table 5.2, below, reports the basic profile of wind generation in each of the scenarios. It is clear from the table that although there is a constant increase in wind capacity of 6,500 MW between the wind penetration scenarios, the resulting wind generation does not increase proportionally. Therefore care must be taken in interpreting results between scenarios.

Table 5.2: Wind Penetration Scenarios: Wind Characteristics

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Wind Capacity (MW)	3,500	10,000	16,500	23,000	29,500
Wind Generation (MWh)	14,415,000	35,431,000	63,215,000	92,590,000	113,145,000

5.5.1 Coal Results

This is especially important for coal units since they are not designed for rapidly changing operation and are the least efficient during these operations. Table 5.3 provides the simulation results for coal generator operation. Reported are the total amount of generation in each wind penetration scenario, the number of upramps, downramps, startups, and shutdowns, and the average size of upramps and downramps as well as their standard deviations. Startups and shutdowns have the same number of instances for every generator and in total so they are reported in the same row.

Table 5.3: Coal Generators in Simulation

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
Total Generation (MWh)	129,371,386	127,774,000 (-1.2%) [-1.2%]	123,716,000 (-3.2%) [-4.4%]	116,433,000 (-5.9%) [-10%]	106,982,000 (-8.3%) [-17%]
Average Upramp Size (MW)	71.49	71.56 (0.001%) [0.001%]	74.48 (4.1%) [4.2%]	76.55 (2.8%) [7.1%]	76.84 (0.3%) [7.5%]
Upramp Instances	5,964	10,327 (73%) [73%]	18,016 (74%) [202%]	25,603 (42%) [329%]	28,694 (12%) [381%]
Upramp Standard Deviation (MW)	32.24	32.29 (0.1%) [0.1%]	31.58 (-2.2%) [-2.0%]	30.81 (-2.4%) [-4.4%]	30.34 (-1.5%) [-5.9%]
Average Downramp Size (MW)	52.15	66.85 (28%) [28%]	75.28 (13%) [44%]	77.48 (2.9%) [49%]	77.33 (-0.2%) [48%]

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
Downramp Instances	4,294	8,532 (99%) [99%]	16,245 (90%) [278%]	24,113 (48%) [462%]	27,551 (14%) [542%]
Downramp Standard Deviation (MW)	30.81	31.93 (3.6%) [3.6%]	30.90 (-3.2%) [0.2%]	29.90 (-3.2%) [-2.9%]	29.50 (-1.3%) [-4.3%]
Startup/Shutdown Instances	429	429 (0%) [0%]	433 (0.9%) [0.9%]	486 (12%) [13%]	574 (18%) [34%]

From the results in Table 5.3 it can be seen that coal generation consistently decreases as wind capacity increases. It decreases in total by 17% from the lowest wind scenario to the highest one. This is significant because it means that coal generation, which typically runs as base load in Texas, is being replaced by wind generation. This has a large impact on the operation of the coal generators who in the 3500 MW wind scenario have 429 startups, 5,964 upramps, and 4,294 downramps across all generators during the year and an average upramp size of 71 MWh and average downramp size of 52 MWh. All of these operation types increase rapidly as wind penetration increases. Upramp instance increase the most, by 73%, from 3500 MW to 10,000 MW of wind capacity. From the lowest wind penetration scenario to the highest they increase by 381%. Similarly, downramps increase across the same scenarios by 542%. The average ramp sizes also increase for upramps and downramps by 7.5% and 48% respectively from the lowest wind scenario to the highest. Startup and shutdown instances do not change much from the 3500 MW wind scenario to the 10000 MW one, only increasing in frequency by 0.9%. They increase by 12% to the next highest scenario and 18% after that for a grand total of 34% from the lowest to highest scenario.

All of these results are expected as wind penetration increases. Coal becomes less of a consistent base load generator due to the reduced demand for coal generation when there is a large amount of wind on the system. Coal must decrease generation when wind is high enough to reduce all generation higher than coal on the bid stack. The change in emissions due to these changes in coal generation operation are reported in Table 5.4.

Table 5.4: Coal Emission Results

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 Emissions (Tons)	128,858,000	127,345,000 (-1.2%) [-1.2%]	123,540,000 (-3.0%) [-4.2%]	116,652,000 (-5.6%) [-9.5%]	107,518,000 (-7.8%) [-17%]
NO_x Emissions (lbs)	154,734,000	151,965,000 (-1.8%) [-1.8%]	145,952,000 (-4.0%) [-5.7%]	135,910,000 (-6.9%) [-12%]	122,595,000 (-9.8%) [-21%]
SO_2 Emissions (lbs)	687,351,000	678,176,000 (-1.3%) [-1.3%]	653,570,000 (-3.6%) [-4.9%]	609,918,000 (-6.7%) [-11%]	556,377,000 (-8.8%) [-19%]
Total Generation (MWh)	129,371,386	127,774,000 (-1.2%) [-1.2%]	123,716,000 (-3.2%) [-4.4%]	116,433,000 (-5.89%) [-10%]	106,982,000 (-8.3%) [-17%]
Total Wind Generation (MWh)	14,415,000	35,431,000 (146%) [146%]	63,215,000 (78%) [389%]	92,590,000 (46%) [542%]	113,145,000 (22%) [685%]

Emissions from coal generators decrease across all the scenarios. Despite the changes in number of ramps, startups, and shutdowns from coal units, their emissions change in similar proportion to the changes in generation. CO_2 emissions decrease by almost exactly the same percentage as does coal-fueled generation, across the five scenarios. CO_2 emissions are reduced from the 3500 MW wind scenario to the 29,500 MW wind scenario by 17%, while total coal generation was reduced by 17% across the same scenarios. Both NO_x and SO_2 emissions actually decrease by more than the decrease in generation. From the lowest penetration scenario to the highest, NO_x emissions decrease by 21%, while SO_2 emissions decrease by 19%. The chart in Figure 5.1 graphically represents the results from Table 5.4. Each cluster of bars shows the percentage change for each emission type and for generation from the 3500 MW wind penetration scenario to the large scenarios. These are the percentage changes found in brackets in Table 5.4.

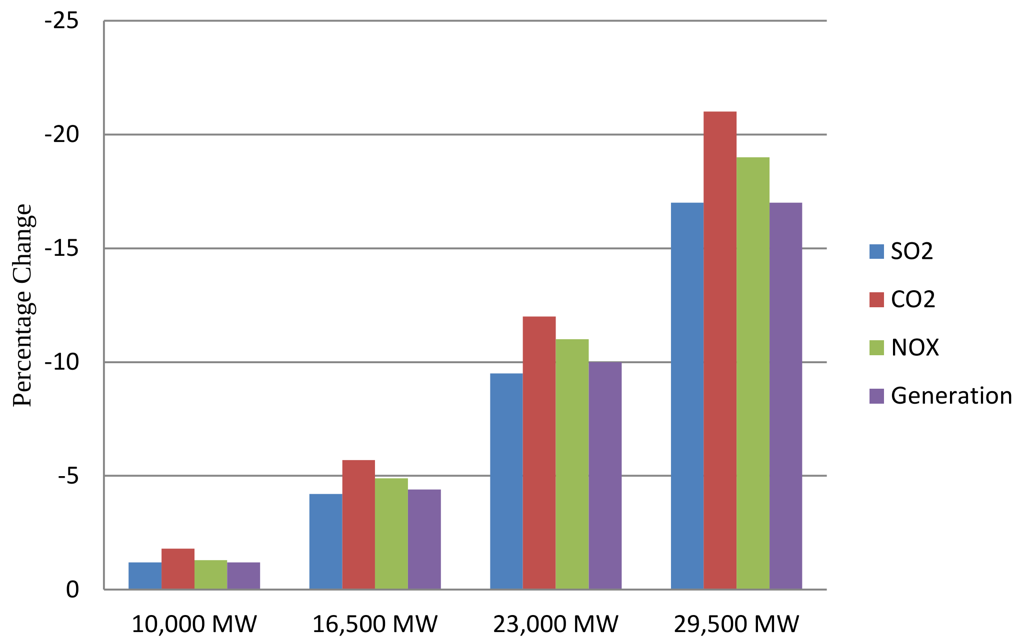

Figure 5.1: Percentage Change from 3500 MW Wind Penetration Scenario - Coal

In each scenario it is clear that CO_2 and NO_x emissions decrease by more than the decrease in coal generation from the 3500 MW wind penetration scenario to each larger scenario. The difference between changes in SO_2 emissions and generation is very small with SO_2 emissions decreasing by slightly more than decreases in generation. NO_x emissions may decrease by more than SO_2 emissions because as coal units reduce their generation they may be operating at lower heat levels, which would reduce thermal NO_x emissions.

Due to the non-proportional change in wind generation from scenario to scenario another metric to analyze the change in emissions is to calculate the marginal impact of wind generation on emissions. This is the metric used in Kaffine et al. (2013) and Cullen (2013). It is calculated with the following formula:

$$(\text{Emissions}_{i+1} - \text{Emissions}_i) / (\text{Wind Generation}_{i+1} - \text{Wind Generation}_i)$$

This is calculated for each i+1 scenario where i=0 is the lowest wind penetration scenario and i=4 is the highest wind penetration scenario. The resulting calculated metrics are shown in Table 5.5.

Table 5.5: Emission Impacts per MWh of Wind Generation

	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 tons/MWh Wind	-0.07	-0.14	-0.23	-0.44
NO_x lbs/MWh Wind	-0.13	-0.22	-0.34	-0.65
SO_2 lbs/MWh Wind	-0.44	-0.89	-1.49	-2.60
Coal Generation MWh/MWh Wind	-0.08	-0.15	-0.25	-0.46

These results are interpretable as the average change in emissions from a marginal increase in wind generation from one scenario to another. CO_2 emissions decrease, on average, by 0.07 tons per MWh of wind generation added between the 3,500 and 10,000 MW wind capacity scenarios. These average marginal changes increase in magnitude as wind penetration increases. From the 23,000 MW wind capacity scenario to the 29,500 MW wind capacity scenario, CO_2 emissions decrease, on average, by 0.44 tons per MWh of wind generation added. The decrease in NO_x emissions also increases in magnitude as wind penetration increases with the largest wind penetration scenario having the largest per MWh of wind generation decrease in NO_x emissions. SO_2 emissions show the same pattern. They decrease on average by 0.44 lbs per MWh of added wind generation from the 3,500 MW scenario to the 10,000 MW scenario compared to a decrease of 2.60 lbs per MWh of added wind generation from the 23,000 MW scenario to the 29,500 MW scenario. This means that all three types of emissions benefit, where benefit assumes reducing emissions is good, from increasing wind penetration. These results are not directly to Kaffine et al. (2013) and Cullen's (2013) estimates because they estimated system wind marginal changes and not by fuel or generator type.

5.5.2 Gas Steam Turbine Results

Natural gas fired steam turbine results are discussed next. Their operation profile and changes from scenario to scenario are presented in Table 5.6.

Table 5.6: Gas Steam Turbine Generators in Simulation

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
Total Generation (MWh)	1,729,000	1,244,000 (-28%) [-28%]	735,000 (-41%) [-57%]	509,000 (-31%) [-71%]	354,000 (-30%) [-80%]
Average Upramp Size (MW)	76.22	77.39 (1.5%) [1.5%]	72.48 (-6.3%) [-4.9%]	76.82 (6.0%) [0.1%]	81.10 (5.6%) [6.4%]
Upramp Instances	1161	771 (-34%) [-34%]	422 (-45%) [-64%]	279 (-34%) [-76%]	194 (-30%) [-83%]
Upramp Standard Deviation (MW)	25.78	24.69 (-4.2%) [-4.2%]	26.15 (5.9%) [1.4%]	21.98 (-16%) [-15%]	21.09 (-4%) [-18%]
Average Downramp Size (MW)	76.69	76.36 (-0.4%) [-0.4%]	71.72 (-6.1%) [-6.5%]	77.07 (7.5%) [0.5%]	82.62 (7.2%) [7.7%]
Downramp Instances	1156	778 (-33%) [-33%]	422 (-46%) [-63%]	286 (-32%) [-75%]	203 (-29%) [-82%]
Downramp Standard Deviation (MW)	25.53	26.02 (1.9%) [1.9%]	24.95 (4.1%) [-2.3%]	22.43 (-10%) [-223%]	18.81 (-16%) [-26%]
Startup/Shutdown Instances	1333	1010 (-24%) [-24%]	633 (-37%) [-53%]	459 (-27%) [-66%]	331 (-28%) [-75%]

The characteristics of steam turbine operation change differently from the coal generators in the simulations. They show large decreases in their generation output as wind penetration increases. The 29,500 MW wind capacity scenario results in gas steam turbine generators producing 80% less power than in the lowest wind penetration scenario. In connection with this many of the operating statistics decrease across the scenarios. Ramping instances, startups, and shutdowns decrease across all the scenarios. This is a result of the steam turbines being used so much less as more wind penetration increases. With the large reduction in generation, upramp, startup, and shutdown instances, it is likely that emissions will decrease by as least as much as generation.

Table 5.7: Gas Steam Turbine Emission Results

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 Emissions (Tons)	1,122,000	786,000 (-30%) [-30%]	456,000 (-42%) [-59%]	297,000 (-35%) [-73%]	191,000 (-36%) [-83%]
NO_x Emissions (lbs)	1,854,000	1,253,000 (-32%) [-32%]	685,000 (-45%) [-63%]	441,000 (-36%) [-76%]	320,000 (-27%) [-83%]
Total Generation (MWh)	1,729,000	1,244,000 (-28%) [-28%]	735,000 (-41%) [-57%]	509,000 (-31%) [-71%]	354,000 (-30%) [-80%]
Total Wind Generation (MWh)	14,415,000	35,431,000 (146%) [146%]	63,215,000 (78%) [389%]	92,590,000 (46%) [542%]	113,145,000 (22%) [685%]

The results for gas steam turbine generator emissions are consistent with the coal generation results. The decrease in CO_2 and NO_x emissions across the wind penetrations scenarios closely follows the decrease in generation as wind penetration increases. For both CO_2 and NO_x emissions the percentage decrease is 3% larger in magnitude than the percentage generation decrease. Generation from gas steam turbines decreased by 80% from the lowest to highest wind penetration scenario and emissions of CO_2 and NO_x emissions decreased by 83% each. The only difference of note is that NO_x emissions only decreased by 27% from the 23,000 MW wind capacity scenario to the 29,500 MW capacity scenario compared to a 36% decrease in CO_2 emissions and 30% decrease in MWh generation. The results for steam turbines indicate the importance of capturing all the operating changes of the generator in estimating emissions. Different conclusions regarding the impact of wind penetration on emissions could be made by looking at the different results. Looking at the lowest penetration scenario to the highest, it could be concluded that CO_2 and NO_x emissions will decrease by more than the decrease in generation. If only the 23,000 MW wind capacity to 29,500 MW wind capacity scenario were analyzed, it would look like emissions decrease by less than the decrease in generation. In reality it depends on the behavior of the generators in each case. Conclusions on the impact of wind penetration likely need to be drawn on a case by case basis. Figure 5.2 graphically presents the emissions and generation change from the 3500 MW wind capacity scenario.

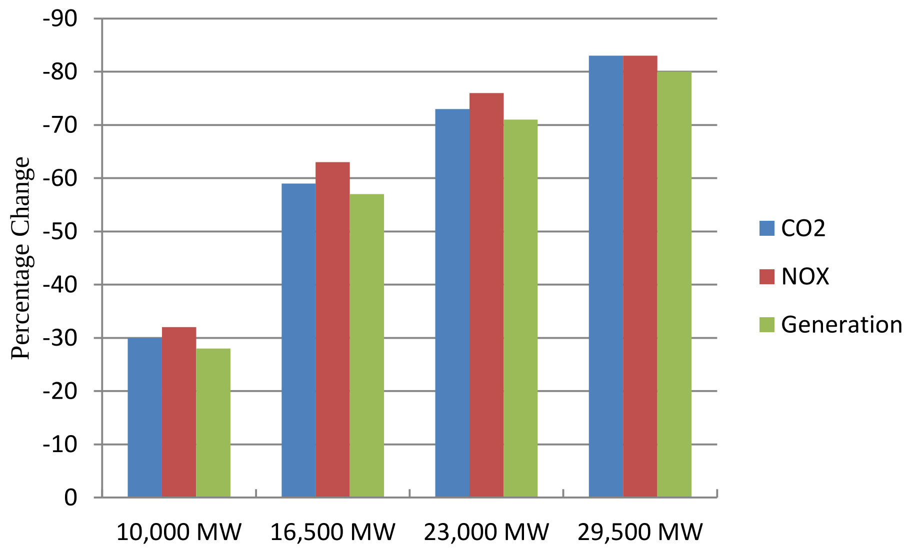

Figure 5.2: Percentage Change from 3500 MW Wind Penetration Scenario - Gas Steam Turbines

The bar chart provides a visual representation of the bracket percentage values from Table 5.7. It is clear from this visual representation the similarity in changes between emissions and generation. Using the 3500 MW wind capacity as a comparison base, each larger wind penetration scenario shows that both CO_2 and NO_x emissions decrease by more than the decrease in generation. These results are consistent with the results for the coal generators which also had larger decreases in emissions than generation. Table 5.8, below, reports the average change in emissions from a marginal increase in wind generation from one scenario to another. These values are calculated using the same formula used for Table 5.5 which is displayed again for the i wind penetration scenario where 0 is the lowest wind penetration scenario and 4 is the highest wind penetration scenario:

$$(\text{Emissions}_{i+1} - \text{Emissions}_i) / (\text{Wind Generation}_{i+1} - \text{Wind Generation}_i)$$

This is calculated for each i+1 scenario where i=0 is the lowest wind penetration scenario and i=4 is the highest wind penetration scenario.

Table 5.8: Emissions Change from Marginal Increase in Wind Generation – Gas Steam Turbines

	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 tons/MWh Wind	-0.016	-0.012	-0.005	-0.005
NO_x lbs/MWh Wind	-0.029	-0.020	-0.008	-0.006
Gas ST Generation MWh/MWh Wind	-0.023	-0.018	-0.008	-0.008

The emission impact per MWh of wind generation for steam turbine generators is much smaller than the results for coal generators. This is partly because there is much less generation from gas steam turbines on the system and also because they have lower emission rates. These units show a decreasing emission impact per MWh of wind generation as more wind generation is added to the system. This is due to the steady displacement of steam turbine generators by wind generation and other generation as described from the results in Table 5.6.

5.5.3 Combined Cycle Results

The simulation and emission estimation results for combined cycle generators are discussed next. The changes in operation under each wind capacity scenario are presented below in Table 5.9.

Table 5.9: Combined Cycle Generators in Simulation

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
Total Generation (MWh)	112,615,000	95,686,000 (-15%) [-15%]	77,059,000 (-19%) [-32%]	63,801,000 (-17%) [-43%]	54,278,000 (-15%) [-52%]

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
Average Upramp Size (MW)	112.4	109.5 (-2.6%) [-2.6%]	109.4 (-0.1%) [-2.7%]	111.5 (1.9%) [-0.8%]	112.7 (1.1%) [0.2%]
Upramp Instances	25252	28805 (14%) [14%]	26678 (-7.4%) [5.6%]	24069 (-9.8%) [-4.7%]	21743 (-9.7%) [-14%]
Upramp Standard Deviation (MW)	52.97	52.92 (-0.1%) [-0.1%]	52.70 (-0.4%) [-0.5%]	52.68 (0%) [-0.5%]	52.77 (0.1%) [-0.3%]
Average Downramp Size (MW)	110.8	107.0 (-3.4%) [-3.4%]	105.6 (-1.3%) [-4.7%]	107.1 (1.4%) [-3.3%]	107.2 (0.1%) [-3.2%]
Downramp Instances	25827	29988 (16%) [16%]	28433 (-5.2%) [10%]	26064 (-8.3%) [1.0%]	23763 (-8.8%) [-8.0%]
Downramp Standard Deviation (MW)	52.25	51.66 (-1.1%) [-1.1%]	50.92 (-1.4%) [-2.5%]	50.64 (-0.5%) [-3.0%]	50.53 (-0.2%) [-3.3%]
Startup/Shutdown Instances	3813	5011 (31%) [31%]	5870 (17%) [54%]	6109 (4.1%) [60%]	5872 (-3.9%) [54%]

Combined cycle units have consistently reduced generation as the wind capacity on the system increases. Changes in generation operation are a bit inconsistent. Upramp and downramp instances increase from the lowest wind penetration scenario to the 10,000 MW wind capacity scenario. They decrease from there. Average ramp sizes vary. They decrease from the 3,000 MW capacity scenario through the 23,000 MW capacity scenario for upramps. Upramps then increase into the largest wind penetration scenario. Downramps decrease through the 16,500 MW capacity scenario and increase into the largest two scenarios. Startup and shutdown instances increase going from the lowest wind capacity scenario to the second highest and then decrease from the second highest to the last. These results are indicative of there being less need for combined cycle on the system as more wind generation is added. Although upramp isntance decrease in the larger two wind penetration scenarios the inctrease in ramp size may be due to larger swings in wind generation. Startup instance increase from the lowest scenario and are also indicative of the combined cycle units being used to backup wind power.

Table 5.10: Combined Cycle Emission Results

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 Emissions (Tons)	45,702,000	39,559,000 (-13%) [-13%]	31,527,000 (-20%) [-31%]	25,105,000 (-20%) [-45%]	20,944,000 (-17%) [-54%]
NO_x Emissions (lbs)	62,442,000	47,874,000 (-23%) [-23%]	30,674,000 (-36%) [-51%]	21,336,000 (-30%) [-66%]	13,582,000 (-36%) [-78%]
Total Generation (MWh)	112,614,883	95,686,000 (-15%) [-15%]	77,059,000 (-19%) [-32%]	63,801,000 (-17%) [-43%]	54,278,000 (-15%) [-52%]
Total Wind Generation (MWh)	14,415,000	35,431,000 (146%) [146%]	63,215,000 (78%) [389%]	92,590,000 (46%) [542%]	113,145,000 (22%) [685%]

Table 5.10 reports the emissions results for combined cycle generators. Despite the large number of increases in ramps, startups, shutdowns between the 3,500 MW wind capacity scenario and the 10,000 MW wind capacity scenario, NO_x emissions decrease by a larger magnitude percentage than total generation. Total generation drops by 15% between the two scenarios and NO_x emissions fall by 23%. CO_2 emissions on the other hand decrease by only 13%. From the lowest wind penetration scenario to the highest, CO_2 emissions decrease by 54% and NO_x emissions by 78% compared to a decrease in generation by 52%. The results for NO_x and CO_2 emissions are consistent between each wind penetration scenario. That is, the percentage decrease in emissions between each scenario is always larger in magnitude than the percentage decrease in generation. Figure 5.3 graphically presents the emissions and generation changes from the 3500 MW wind capacity scenario to the higher wind capacity scenarios.

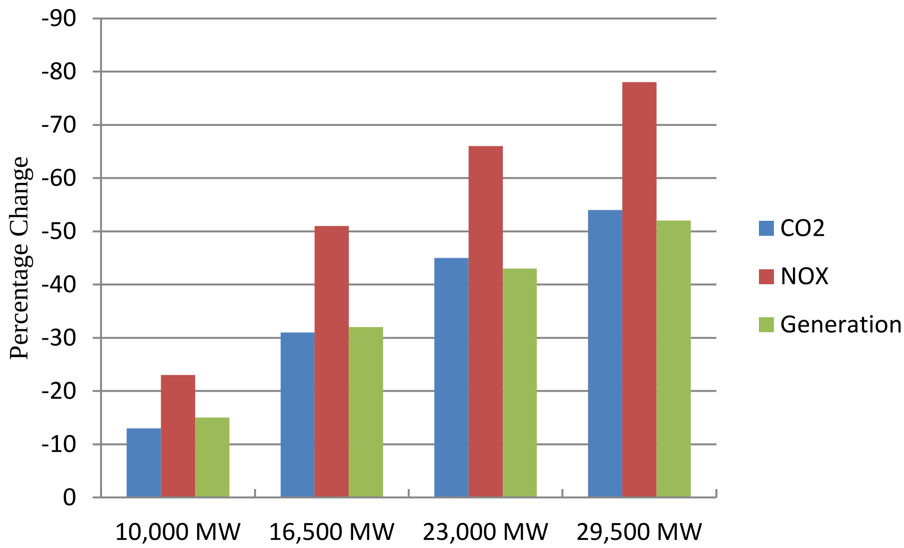

Figure 5.3: Percentage Change from 3500 MW Wind Penetration Scenario - Combined Cycle

The bar chart in Figure 5.3 illustrates the large relative change in NO_x emissions compared to generation. Each wind capacity scenario shows that NO_x emissions decrease by much more than the percentage decrease in generation from the 3500 MW wind penetration scenario. CO_2 emissions on the other hand decrease by a little less than generation from the 3500 MW scenario to the 10,000 MW and 16,500 MW scenarios and decrease by a little more than generation in the largest two scenarios. Table 5.11, below, estimates the emissions impact per MWh of wind generation using the 3500 MW wind capacity scenario as a baseline. These values are calculated using the same formula used for Table 5.5 which is displayed again for the i wind penetration scenario where 0 is the lowest wind penetration scenario and 4 is the highest wind penetration scenario:

$$(\text{Emissions}_{i+1} - \text{Emissions}_{i}) / (\text{Wind Generation}_{i+1} - \text{Wind Generation}_{i})$$

This is calculated for each i+1 scenario where i=0 is the lowest wind penetration scenario and i=4 is the highest wind penetration scenario.

Table 5.11: Emissions Change from Marginal Increase in Wind Generation – Combined Cycle

	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 tons/MWh Wind	-0.29	-0.29	-0.22	-0.20
NO_x lbs/MWh Wind	-0.69	-0.62	-0.32	-0.38
Combined Cycle Generation MWh/MWh Wind	-0.81	-0.67	-0.45	-0.46

The emission impact per MWh of wind generation for combined cycle generators is much larger than the steam turbine impacts. This is because they make up a much larger portion of the generation in Texas. The impact of increasing wind generation on CO_2 emissions decreases in magnitude by a small amount in each scenario with marginal increases in wind leading to an average reduction in CO_2 by 0.29 tons in the 10,000 MW capacity scenario and 0.20 tons in the 29,500 MW wind capacity scenario. The average change in NO_x emissions from a marginal increase in wind generation from the 3,500 MW scenario to the 10,000 MW scenario is a decrease by 0.69 lbs. The average change for NO_x emissions from the 23,000 MW scenario to the 29,500 MW scenario is -0.38 lbs per MWh of wind generation added. Both of these results indicate that increases in wind generation in ERCOT will have diminishing benefit, where benefits are considered to be emission reductions, for combined cycle generators.

5.5.4 Simple Cycle Generation

The simulation and emission estimation results for simple cycle generators are discussed next. The changes in operation under each wind capacity scenario are presented below in Table 5.12.

Table 5.12: Simple Cycle Generators in Simulation

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
Total Generation (MWh)	1,842,000	1,348,000 (-27%) [-27%]	906,000 -(33%) [-51%]	942,000 (3.0%) [-49%)	1,046,000 (10.1%) [-43%]
Average Upramp Size (MW)	36.67	37.19 (1.4%) [1.4%]	36.84 (-0.9%) [0.5%]	36.18 (-1.8%) [-1.3%]	36.31 (0.3%) [-0.9%]
Upramp Instances	4347	3272 (-25%) [-25%]	2260 (-31%) [-48%]	2347 (4.9%) [-46%]	2667 (14%) [-39%]
Upramp Standard Deviation (MW)	7.41	6.53 (-12%) [-12%]	6.73 (3.1%) [-9.2%]	7.20 (7.0%) [-2.8%]	7.39 (2.6%) [-0.3%]
Average Downramp Size (MW)	37.06	36.96 (-0.3%) [-0.3%]	36.65 (-0.1%) [-1.1%]	36.91 (0.7%) [-0.4%]	36.59 (-0.8%) [-1.3%]
Downramp Instances	5335	4108 (-23%) [-23%]	2827 (-31%) [-47%]	2877 (1.8%) [-46%]	3020 (5.0%) [-43%]
Downramp Standard Deviation (MW)	6.99	6.80 (-2.7%) [-2.7%]	6.77 (-0.4%) [-3.1%]	6.42 (-5.2%) [-8.2%]	7.48 (17%) [7.0%]
Startup/Shutdown Instances	5748	4977 (-13%) [-13%]	3619 (-27%) [-37%]	2797 (-23%) [-51%]	2381 (-15%) [-59%]

The generation output of simple cycle generators initially decreases as wind capacity increases. However, when wind capacity increases from 16,500 MW to 23,000 MW, simple cycle generation increases. Generation also increases again from the 23,000 MW wind capacity scenario to the 29,500 MW wind capacity scenario. The number of upramp and downramp instances also increase in the larger two scenarios. Simple cycle units are likely being dispatched to back up the large amount of wind generation on the system. Ramping up when wind power decreases and ramping down when it increases.

With their fast ramping capabilities they have the best ability to do this and therefore are seeing increases in total generation.

Table 5.13: Simple Cycle Emission Results

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 Emissions (Tons)	1,335,000	917,000 (-31%) [-31%]	608,000 (-34%) [-54%]	589,000 (-3.2%) [-56%]	622,000 (5.5%) [-53%]
NO_x Emissions (lbs)	6,094,000	3,993,000 (-34%) [-34%]	2,368,000 (-41%) [-61%]	1,707,000 (-28%) [-72%]	1,137,000 (-33%) [-81%]
Total Generation (MWh)	1,842,674	1,347,996 (-27%) [-27%]	905,930 -(33%) [-51%]	941,864 (3.0%) [-49%]	1,046,671 (10.1%) [-43%]
Total Wind Generation (MWh)	14,415,000	35,431,000 (146%) [146%]	63,215,000 (78%) [389%]	92,590,000 (46%) [542%]	113,145,000 (22%) [685%]

The emissions results for simple cycles in Table 5.13 show that emissions reductions are larger than the reductions in generation output. In the case of CO_2 emissions the difference is small with percentage decreases across each wind penetration scenario only slightly large in magnitude than the percentage decreases in generation across the scenarios. The largest change is from the 23,500 MW scenario to the 29,500 MW scenario where there is an increase in generation of 10.1%, yet CO_2 emissions only increase by 5.5%. NO_x emissions decrease across all the scenarios despite the increase in generation between the last two. NO_x emissions also decrease in each case by larger than the corresponding change in generation. This again provides more evidence against previous results which have found increase in emissions or reductions in emissions not as large in magnitude as generation reductions. These results are presented graphically in Figure 5.4.

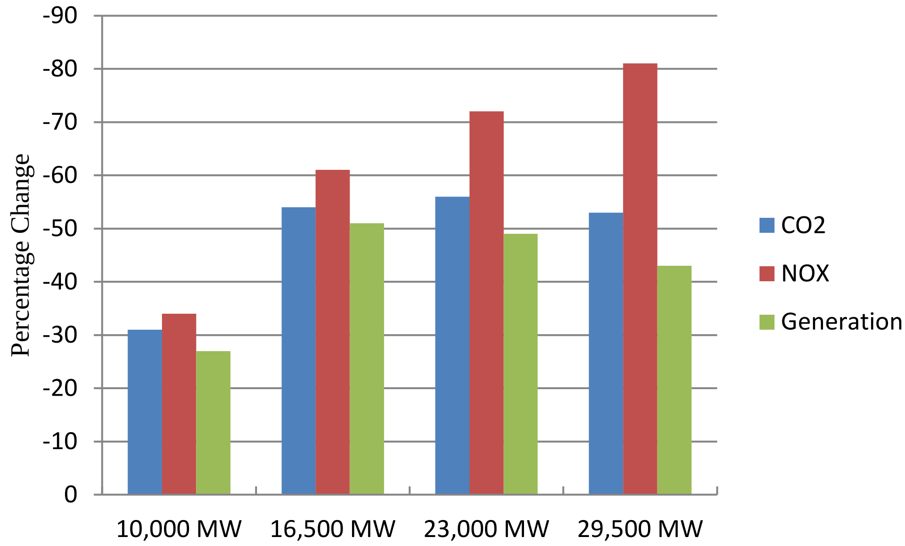

Figure 5.4: Percentage Change from 3500 MW Wind Penetration Scenario - Simple Cycle

The bar chart in Figure 5.4 is interesting because although percentage change in generation from the 3500 MW scenario begins to get smaller in the 23,000 and 29,500 MW scenarios, the percentage decrease in NO_x emissions continues to get larger. The percentage change in CO_2 emissions on the other hand levels out some. The most likely explanation for this phenomenon is the decrease in startups in the largest two wind penetration scenarios. This is because upramp and downramp instances, as well as total generation, both increase in the largest two wind penetration scenarios from the 16,500 MW scenario. Table 5.14, below estimates the emissions impact per MWh of wind generation using the 3500 MW wind capacity scenario as a baseline. These values are calculated using the same formula used for Table 5.5 which is displayed again for the i wind penetration scenario where 0 is the lowest wind penetration scenario and 4 is the highest wind penetration scenario:

$$(\text{Emissions}_{i+1} - \text{Emissions}_i) / (\text{Wind Generation}_{i+1} - \text{Wind Generation}_i)$$

This is calculated for each i+1 scenario where i=0 is the lowest wind penetration scenario and i=4 is the highest wind penetration scenario.

Table 5.14: Emissions Change from Marginal Increase in Wind Generation – Simple Cycle

Table 13. Emissions Change from Marginal Increase in Wind Generation – Simple Cycle				
	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 tons/MWh Wind	-0.020	-0.011	-0.001	0.002
NO_x lbs/MWh Wind	-0.100	-0.058	-0.023	-0.028
Combined Cycle Generation MWh/MWh Wind	-0.024	-0.016	0.001	0.005

The results in Table 5.14 for simple cycle generators indicate very small decreases in emissions per MWh of wind generation. As with gas steam turbines this is mostly due to the small amount of simple cycle generation in ERCOT compared to other forms. For simple cycle generators in ERCOT the average impact on CO_2 emissions from marginal increases in wind generation are actually positive when going increasing wind penetration from the 23,000 MW to 29,500 MW scenario. This is because as discussed before, generation actually increases between these two scenarios. NO_x emissions face decreasing benefit from increases in wind penetration.

5.6 Simulation and Emission Results Aggregated

Aggregated reesults for the entire Texas system are reported below in Table 5.15. For SO_2 emissions, the results are only for coal generators due to the extremely low SO_2 emissions from natural gas fired generators and the inability of the functions to estimate SO_2 emissions for them. The results for CO_2 emissions show that the percentage decrease in total fossil fuel generation is larger in magnitude than the percentage decrease in emissions from the lowest wind penetration scenario to the highest one. On the system level this result is due to the larger decrease in combined cycle generation than coal generation. These two types of generators make up the majority of fossil fuel fired generation, and coal generation emits a higher level of CO_2 emissions. Therefore, the percentage reduction in CO_2 emissions is not as large as the percentage reduction in generation. Between each wind penetration scenario the percentage reductions in CO_2

emissions gradually get larger in magnitude. Emissions decrease from the 3,500 MW wind capacity scenario to the 10,000 MW wind capacity scenario by 4.8% and from the 23,000 MW wind capacity scenario to the 29,500 MW wind capacity scenario by 9.3%.

Table 5.15: ERCOT System Results

(Percent change from previous scenario in parantheses) [Percent change from 3500 MW scenario in brackets]					
	3500 MW Wind Capacity	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 Emissions (Tons)	177,017,000	168,607,000 (-4.8%) [-4.8%]	156,131,000 (-7.4%) [-12%]	142,643,000 (-8.6%) [-19%]	129,275,000 (-9.3%) [-27%]
NO_x Emissions (lbs)	225,124,000	205,086,000 (-8.9%) [-8.9%]	179,680,000 (-12%) [-20%]	159,394,000 (-11%) [-29%]	137,634,000 (-14%) [-39%]
SO_2 Emissions (lbs) – Coal only	687,351,000	678,176,000 (-1.3%) [-1.3%]	653,570,000 (-3.6%) [-4.9%]	609,918,000 (-6.7%) [-11%]	556,377,000 (-8.8%) [-19%]
Total Generation (MWh)	245,558,000	226,052,000 (-7.9%) [-7.9%]	202,417,000 (-10%) [-17%]	181,685,000 (-10%) [-26%]	162,661,000 (-10%) [-34%]
Total Wind Generation (MWh)	14,415,000	35,431,000	63,215,000	92,590,00	113,145,000

The changes in NO_x emissions across the wind penetration scenarios are larger than the generation changes. NO_x emissions decrease by 39% from the lowest wind penetrations scenario to the highest wind penetration scenario and total generation decreases by 34%. As with the individual generator types this result is counter-factual to most of the literature which finds either increases in NO_x emissions or decreases in NO_x emissions which are smaller in magnitude than the reductions in generation.

The SO_2 emissions reductions are smaller in magnitude than the percentage change decreases in total generation. This is due to the fact that we only include SO_2 emissions for coal generation which do not decrease total generation as much as the other three unit types. Since natural gas units have such low SO_2 emissions this result is still accurate as a system wide estimate. This means that on a system with a generation mix like Texas, SO_2 emissions are likely to decrease by a smaller magnitude than the decrease in total system generation under increasing wind penetration scenarios. This comes more from changes in what generators are being dispatched as opposed to changes from generation operation.

The changes across scenarios described in the previous paragraphs are graphically represented in Figure 5.5 below. Each cluster of bars represents the percentage change from the 3500 MW wind penetration scenario. It is clearer from the chart that NO_x emissions decrease by more than the decrease in generation from the 3500 MW wind penetration scenario to each of the larger scenarios. CO_2 emissions decrease by less than the decrease in generation from the 3500 MW wind penetration to each of the larger scenarios and SO_2 emissions decrease by even less.

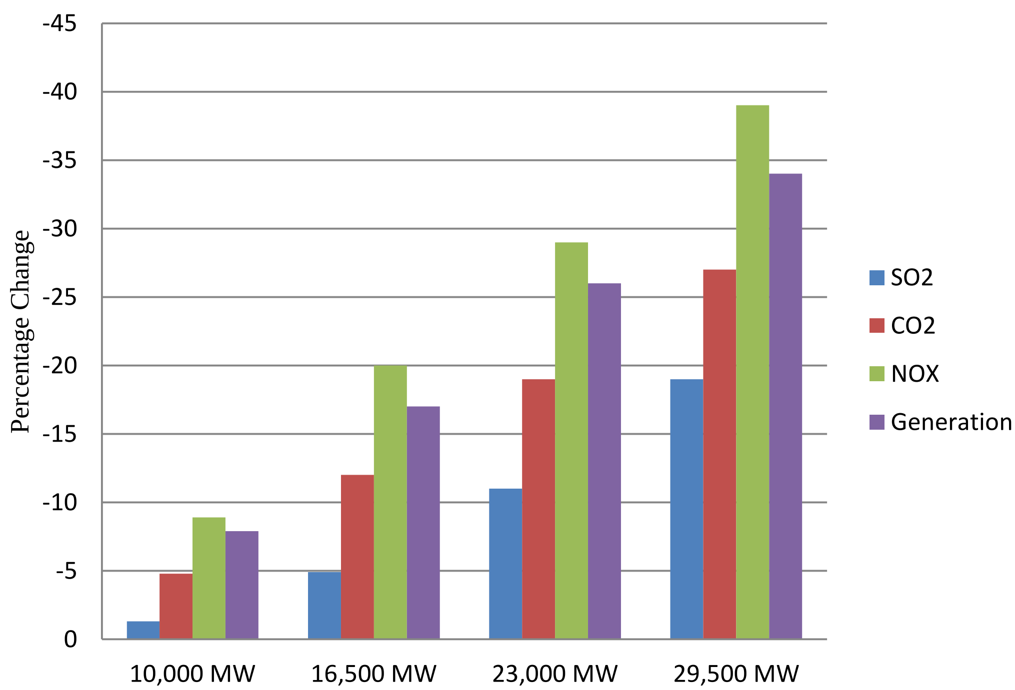

Figure 5.5: Percentage Change from 3500 MW Wind Penetration Scenario - ERCOT

The calculation of the emission impact per MWh of wind generation can allow for a direct comparison to the results from Cullen (2013) and Kaffine et al. (2013). The system results from this analysis are presented in Table 5.16. These values are calculated using the same formula used for Table 5.5 which is displayed again for the i wind penetration scenario where 0 is the lowest wind penetration scenario and 4 is the highest wind penetration scenario:

$$(\text{Emissions}_{i+1} - \text{Emissions}_i) / (\text{Wind Generation}_{i+1} - \text{Wind Generation}_i)$$

This is calculated for each i+1 scenario where i=0 is the lowest wind penetration scenario and i=4 is the highest wind penetration scenario.

Table 5.16: Emissions Change from Marginal Increase in Wind Generation – ERCOT

	10000 MW Wind Capacity	16500 MW Wind Capacity	23000 MW Wind Capacity	29500 MW Wind Capacity
CO_2 tons/MWh Wind	-0.40	-0.45	-0.46	-0.65
NO_x lbs/MWh Wind	-0.95	-0.91	-0.69	-1.06
SO_2 lbs/MWh Wind	-0.44	-0.89	-1.49	-2.60
Fossil Fuel Generation MWh/MWh Wind	-0.93	-0.85	-0.71	-0.93

Average CO_2 reductions per MWh of wind generation increase in magnitude between each wind penetration scenario, from 0.40 to 0.65 tons per MWh of added wind generation. NO_x emissions initially decrease in magnitude between the first four wind penetration scenarios. NO_x emissions decrease an average of 0.95 lbs per MWh of wind generation added between the 3,500 MW and 10,000 MW wind penetration scenario. This value becomes 0.69 between the 16,500 and 23,000 MW scenarios. It then increases from magnitude to 1.06 between the 23,000 MW and 29,500 MW scenarios. Finally, SO_2 emission reductions increase in magnitude as wind penetration increases from 0.44 lbs per MWh of wind generation added to 2.60 lbs per MWh of wind generation added.

These results can be compared to the Cullen (2013) and Kaffine et al. (2013) result. The most direct comparison comes from the results calculated between the 3,500 MW scenario and the 10,000 MW scenario. This is because they both use older datasets which cover time spans where ERCOT had less wind capacity. Cullen uses a time span of 2005 to 2007 and Kaffine et al. 2007 to 2009. Wind capacity during 2007 to 2009 ranged from 2,800 MW to 9,000 MW (Nicholson, Rogers, & Porter, 2010). This is similar to the wind capacity between the lower two wind penetration scenarios. The values presented here for those scenarios for coal SO_2 emissions are 0.44 lbs/MWh wind generation, for NO_x emissions 0.95 lbs/MWh wind generation, and for CO_2 emissions 0.40 tons/MWh wind generation. Cullen found that SO_2 emissions are offset by wind generation at a rate of 3.15 lbs/MWh wind, NO_x emissions by 1.05 lbs/MWh wind, and CO_2 emissions by 0.71 tons/MWh wind. Kaffine et al. found that lower results with SO_2 emissions being offset by wind generation at a rate of 1.277 lbs/MWh wind, NO_x emissions by 0.710 lbs/MWh wind, and CO_2 emissions by 0.523 tons/MWh wind. Kaffine et al. explain that their results are lower than the Cullen results because their model better captures the impacts of cycling generators on emissions. The reason the results from this chapter are lower than Kaffine et al. is likely the same reason. While Kaffine et al. use a non-structural model to indirectly determine the impact on emissions from wind generation, the functions used here can directly forecast emissions given generation inputs. This results in accurate forecasts of emissions under all the different generator operations. The result is lower estimated reductions in emissions.

5.7 Conclusion

Several studies have found that an increase in wind penetration can cause increases in emissions or reductions in emissions that are smaller in magnitude than associated generation reductions. Many of these studies use simplistic analyses or unrrealistic assumptions. Through the use of emission functions that take into account the imapcts on emissions from ramping, startup, and shutdown of generators, this study can accurately predict emissions under scenarios where generators operate differently. ERCOT provides five simulated wind penetrations scenarios with 3,500, 10,000, 16,500, 23,000, and 29,500 MW of wind capacity. Applying each generator's estimated function to that generator's simulation results provides a forecast of emissions. The simulation results find that the operation of coal generators at higher levels of wind penetration results in significantly more ramping, startups, and shutdowns. The three natural gas fired units all find reductions in instances of ramping, startup, and shutdown as well as generation. The only exception is simple cycle units in the largest two wind penetration scenarios where they increase generation from the 16,500 MW wind capacity scenario and have increased instances of ramping.

The emissions impacts of these changes in operation are analyzed for each generator type and on aggregate for the entire Texas system. Coal generators find percentage reductions in CO_2 emissions which are the same as the percentage reductions in coal generation. NO_x and SO_2 emissions from coal generation decrease by a larger magnitude than the decrease in total coal generation. Gas steam turbines find decreases in CO_2 emissions that are larger in magnitude than the decrease in gas steam turbine generation. Their NO_x emissions decrease by a lesser magnitude than the decrease in generation. Combined cycle units shows decreases in both CO_2 and NO_x emissions that are much larger than their decrease in generation. Finally, simple cycle units report emissions reductions for CO_2 and NO_x emissions that are larger than their decrease in generation. Additionally NO_x emissions decrease across all scenarios despite increases in generation from the 16000 MW wind capacity scenario to the largest two scenarios.

Aggregate system results find that both CO_2 and SO_2 emissions are reduced by less than the reduction in total generation from the smallest to largest wind penetration scenario. This is mostly due to the fact that combined cycle units, which are less emitting, have a larger reduction in generation than more emitting coal generators. System wide NO_x emissions on the other hand, decrease by more than the reduction in total generation. The difference in results between the individual generators and the aggregated system shows the importance in analyzing the impacts of wind penetration on a system level and by generator type.

The system wide results are comparable to the emission impact per MWh of wind estimates in Cullen (2013) and Kaffine et al. (2013). This paper estimated average CO_2 emissions offsets of between 0.40 and 0.65 tons/MWh of wind generation. Average NO_x emission offsets are estimated to be between 0.69 and 1.06 lbs/MWh of wind generation. Finally, SO_2 emission offsets are estimated to be between 0.44 and 2.60 lbs/MWh of wind generation. This wide range in estimates is due to the large reductions in coal generation that occur at the higher wind penetration scenarios. The impacts estimated here show that for CO_2 and SO_2 emissions, there are increasing returns to wind generation. The CO_2 and SO_2 emission reductions per MWh of wind generation steadily increase as wind generation increases. For NO_x emissions the reductions in emissions per MWh of wind generation initially decrease in magnitude as wind generation increases. The estimated emission reductions per MWh of wind generation only increase in magnitude in the largest wind penetration scenario.

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6. Conclusion

The work presented in this dissertation provides information and support for economic policy analysis and researchers studying emissions and their relation to the power system. To properly address climate change policies addressing emissions, especially CO_2 are going to become more common at least regionally if not nationally. Due to the economics of the power system, costs imposed on generators that would reduce their generation or change their operation may have impacts that cannot be predicted using simple models. Economic theory and simple models can predict that a CO_2 cap and trade program will cause significant emissions leakage, or that wind power will simply replace emitting generator's electricity production and there will be a corresponding drop in emissions.

The first chapter of research looks at the question of emissions leakage with respect to the Regional Greenhouse Gas Initiative. This cap and trade program for CO_2 emissions requires generators in New York and other states to hold allowances for each ton of CO_2 they emit. This increase in cost puts them at a competitive disadvantage compared to neighboring emitting generation in Pennsylvania not under the program. Economic theory says that power will be imported from Pennsylvania instead of using the more expensive generation in New York. The findings presented here indicate that the RGGI allowance price has not resulted in a statistically significant increase in electricity imports from Pennsylvania. Several potential reasons are theorized for this. Leakage may be mitigated by transmission limits between New York and Pennsylvania. Demand for imports may be limited by transmission constraints across New York, or by reliability rules of the NYISO. Different scheduling and other rules that differ between PJM and the NYISO may also play a role. The biggest two factors are likely the very low price of the CO_2 allowances in RGGI and the fact that imports seem to not follow price signals. These findings on RGGI leakage and the potential mitigating factors are interesting especially for researchers looking to study emissions leakage in electricity systems elsewhere, or looking to design cap and trade policies in other regional systems.

The other main topic covered by the dissertation is the need for detailed emission functions in order to be able to properly analyze emissions under scenarios where the dispatch of generators changes their traditional operating profile. Generators which have different emission rates during times of startup, shutdown, and ramping periods are most affected by this Simple models do not forecast well during these types of operational hours and these are the hours most likely to change in frequency under scenarios where there is more stochastic renewable generation. These scenarios are likely to occur under any policy which may impose costs on emitting generators or support renewable energy through subsidies, tax breaks, or other policies. It is important in designing these policies to recognize that they may result in higher than expected costs or lower emission reductions if the emissions from changing generator operation are not accounted for.

The research in chapter 3 presents a highly detailed emission function which can be applied and customized to specific generators automatically. This emission function takes into account the major generator operations of startup, shutdown, and ramping and by doing so produces highly accurate within sample predictions and out of sample predictions. These forecasts often outperform simpler models in all hours and when they do not, the forecasts are more accurate in ramping, startup, and shutdown hours specifically. These functions are good for analyzing any scenario where the ramping, startup, and shutdown of units are important considerations. These functions also prevent measurement bias which may be inherent in the continuous emission monitoring systems data. By including variables capturing whether a generator is reporting actually measured or calculated emissions, and variable indicating the hour during which a generator calibrates its CEMS equipment, the model can better estimate emissions during both normal operating hours and hours when CEMS measurement is not occurring.

Chapter 4 uses the fact that the emission functions can estimate the impact of calibration to try and determine if generators are using a calibration exemption to under report emissions. Generators once per 26 hours are required to calibrate their CEMS equipment. During the hour they calibrate they only need to report measured emissions averaged over the portion of the hour when calibration is not occurring. By calibrating during portions of an hour with higher emissions rates, such as during ramping, startup, or shutdown hours, generators may be able to under report emissions. We find that coal generators may be doing this by calibrating the majority of the time in hours of upramp. Additionally the upramp hours they calibrate in tend to be larger than average upramps.

Using the estimates on calibration from the emission functions we find that for coal generators, emissions during calibration hours are lower than other hours. The results are more mixed across hours for other types of units. By applying the calibration variables to 2010 yearly data to find that only coal units show lower reported emissions across the entire year in calibration hours compared to other hours. The under reporting of emissions by these coal units is not very large and saves a negligible amount of money in avoided NO_x and SO_2 allowances. Coal generators may be engaging in the practice as a holdover from higher NO_x and SO_2 allowance prices.

The final chapter of research, chapter 5, uses the estimated functions for all Texas generators to analyze five wind penetration scenarios. This is done because previous literature has found that wind generation can cause emissions decreases that are less than the decreases expected using constant emission rates. Emission functions that can estimate emissions under all generator operating conditions forecast emissions under 5 simulated wind penetration scenarios. These scenarios differ in the amount of installed wind capacity and wind generation in ERCOT. After forecasting emissions under all scenarios the results are analyzed to find that increasing wind penetration in ERCOT results in consistently larger in magnitude decreases in CO_2 and SO_2 emissions. The average decrease in NO_x emissions from additional marginal wind generation decreases in magnitude as wind penetration increases.

The research from this dissertation has shown the importance of interdisciplinary analysis when researching emissions from the electricity system. It is important to take into account both the economics and physical constraints which drive generation dispatch and operation. These types of analyses hope to provoke future research to carefully consider both aspects of the power system in order to do the important analysis and policy designed to address emissions related issues like climate change.