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Electricity Generation Location and Benefits to Human Health: What health benefits can be attributed to RGGI in New Jersey, New York, and Pennsylvania?

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Abstract

This paper estimates the benefits, primarily from human health gains, from the longest running U.S. CO_2 control program. Further, it examines the patterns of electric generation to evaluate changes at regional and state levels, to better understand the potential of CO_2 leakage, which is CO_2 being emitted from generation that has moved from a regulated to a non-regulated state, and thus weakening the effects of the regulation.

This examination is achieved using a unique dataset of observed generation levels at fossil fuel plants from the year 2000 to 2013, in New Jersey, New York, and Pennsylvania. It is estimated that the Regional Greenhouse Gas Initiative (RGGI) has reduced CO_2 emissions in New York State and New Jersey by approximately 4.9 million short tons yearly on average, and has produced approximately $130 million worth of ancillary benefits from reduced SO_2, NO_X, $PM_{2.5}$, and PM_{10}, emissions yearly, while New Jersey participated. Just in New York, which has participated every year since the program inception in 2009, RGGI has produced approximately 3.5 million short tons and over $69 million worth of ancillary benefits yearly on average. Further, the study finds weak evidence that RGGI has altered generation between New York and Pennsylvania during the study period. However, it finds stronger evidence that there may have been leakage from Maryland and Delaware to Pennsylvania. There are indications that RGGI has contributed to significant changes in generation regionally in New Jersey and New York.

Electricity Generation Location and Benefits to Human Health: What health benefits can be attributed to RGGI in New Jersey, New York, and Pennsylvania?

by

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Chapter 1 Introduction

Burning fossil fuels for electricity generation creates CO_2 as a by-product. The amount of CO_2 emitted while generating a megawatt of electricity will vary depending on the fuel type used: coal will emit roughly twice as much CO_2 as gas will. CO_2 from electricity generation cannot economically be captured; when a CO_2 cap is imposed on electricity generation, the only way to reduce CO_2 emissions from fossil fuel generation, in the short run, is to change the mix of fuels being used to produce electricity. Changing the fuel mix will also change the levels of generation of conventional pollutants, such as SO_2 and NO_X, which can negatively impact human health. Since gas is favored over coal when CO_2 is capped and produces lower amounts of conventional pollutants, cap and trade programs for CO_2 create ancillary health benefits. There has been significant changes in the geographical distribution of electricity as can be seen in maps of actual fossil fuel generation from 2007 and 2013 (see map 1-1, and map 1-2), before and after RGGI was implemented.

RGGI is a cap and trade program, implemented in the Northeastern United States, which requires fossil fuel electric power generators over 25 megawatts (MW) to purchase allowances, at auction, for every ton of CO_2 emitted from their operations. It went into effect on January 1st, 2009. Currently, there are 9 states in RGGI: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont (see map 1-3). Pennsylvania has acted as an “observer” to RGGI, but has not joined. New Jersey was an original member of RGGI but withdrew from the program at the beginning of 2012. The initial cap for RGGI was set at 188 million short tons per year, with a reduction to 165 million short tons (150 metric tons) per year occurring over 2012 to 2014, and then additional yearly reductions of 2.5% through 2020. However, the program was updated in 2013 to lower the cap even further for 2014 to 91 million short tons (83 metric tons) and further reductions of 2.5% a year after that. Prices from the auctions have ranged from a low of $1.86 per allowance, 1 short ton of CO_2 emissions, to a recent high of $5.50 per allowance in June of 2015.

The debate over curbing CO_2 emission makes it important to understand what is gained by these actions, as understanding full benefits are important for informed policy decisions. Reducing CO_2 emissions will have ancillary benefits to society by reducing costs associated with pollution from burning fossil fuels. Examples of these are environmental damages such as those caused by acid rain, injured human health, infrastructure deterioration, and other economic damages. Risk assessments relating to human health have been used to assign values to changes in environmental quality that result in corresponding gains in human health. It is also important to understand how these benefits are distributed, and whether benefits in capped states lead to damages in uncapped states. These damages would occur if leakage, emissions occurring in uncapped regions that replace the observed reductions in the capped region, increased generation of electricity in states not participating in RGGI. Moreover, leakage is important because if there is a large amount of leakage from RGGI areas to non-RGGI areas, it would imply that the benefits from the program in terms of CO_2 are overstated

Further, the Environmental Protection Agency (EPA) recently proposed the Clean Power Plan, a rule for reducing CO_2 emissions from existing plants in the electric sector by approximately 30 percent relative to 2005 levels. It did so because electricity generation is the largest single source of carbon dioxide emissions and the sector accounts for about 33 percent of greenhouse gas emissions in the United States (EPA, 2015). The rule calls for these goals to be achieved at the state level and each state is given a specific emission rate target. States are allowed to submit joint plans under this rule and RGGI is singled out as an example of what such a joint program may look like, provided that the program meets the full level of reductions as required by the rule (EPA, 2014a, 34838).

The remainder of this dissertation is organized as follows. Chapter 2 introduces pertinent background to RGGI. It begins with a brief history, including some of the politics surrounding the program. Next, the original rules governing the program are presented, providing necessary background on the implementation of the program. RGGI was updated after the completion of the 2012 review. These updates give a further indication of the perception of how the program has functioned. Finally, the academic literature on RGGI is discussed.

Chapter 3 presents the relevant academic literature. It is relatively broad, including studies of RGGI but also works on other systems of pollution permits, on risk assessment, and on computing marginal health damages from air pollution. This literature is important for understanding both the theoretical basis for RGGI as well as the methods used here to determine its health benefits.

Chapter 4 then develops and introduces a sequence of theoretical models of the electric sector that form the basis for the statistical methods discussed later in the dissertation. The first set of models demonstrate how a program like RGGI can change regional patterns in generation. A second set of models is then used to understand how the program could cause emissions to leak from RGGI participants to neighboring states, and then to develop an approach for testing for such leakage.

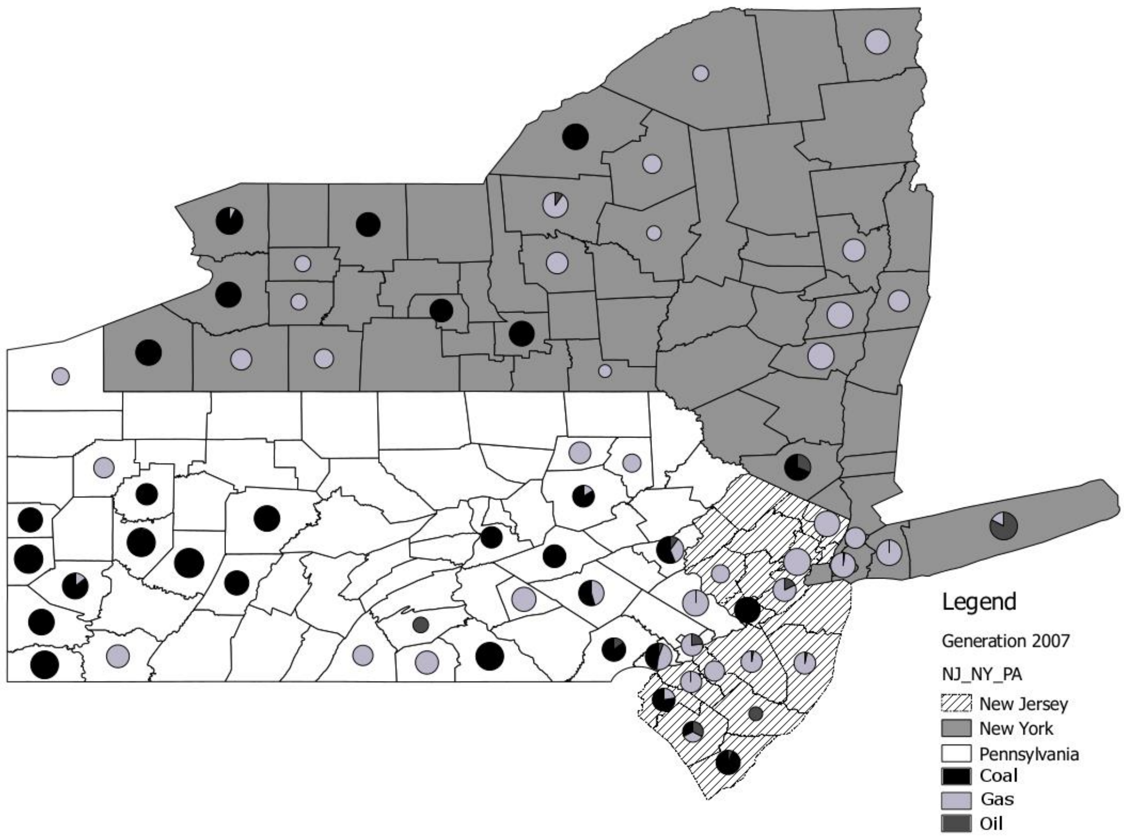
Chapter 5 presents the data sources used for the analysis and discusses the steps involved in constructing the dataset. A panel data set for the years 2000 to 2013 was created using data from a variety of sources, including the EPA, the National Oceanic and Atmospheric Administration (NOAA), the Energy Information Administration (EIA), and the Census. The primary data for this project was from the EPA's Air Markets Data Program (AMPD), which provides high frequency data for electricity generation at power plants with capacities greater than 25 MW.

Chapter 6 presents the methods used to estimate changes in generation induced by RGGI, and the health benefits that resulted. Taking into consideration the implications from the theory and the characteristics of the data, it develops and presents the necessary methodology for evaluating RGGI's ancillary benefits. The analysis was conducted using a random effects Tobit model. The results from that model were used to estimate the changes in air pollutants and to calculate changes in the health of downwind populations.

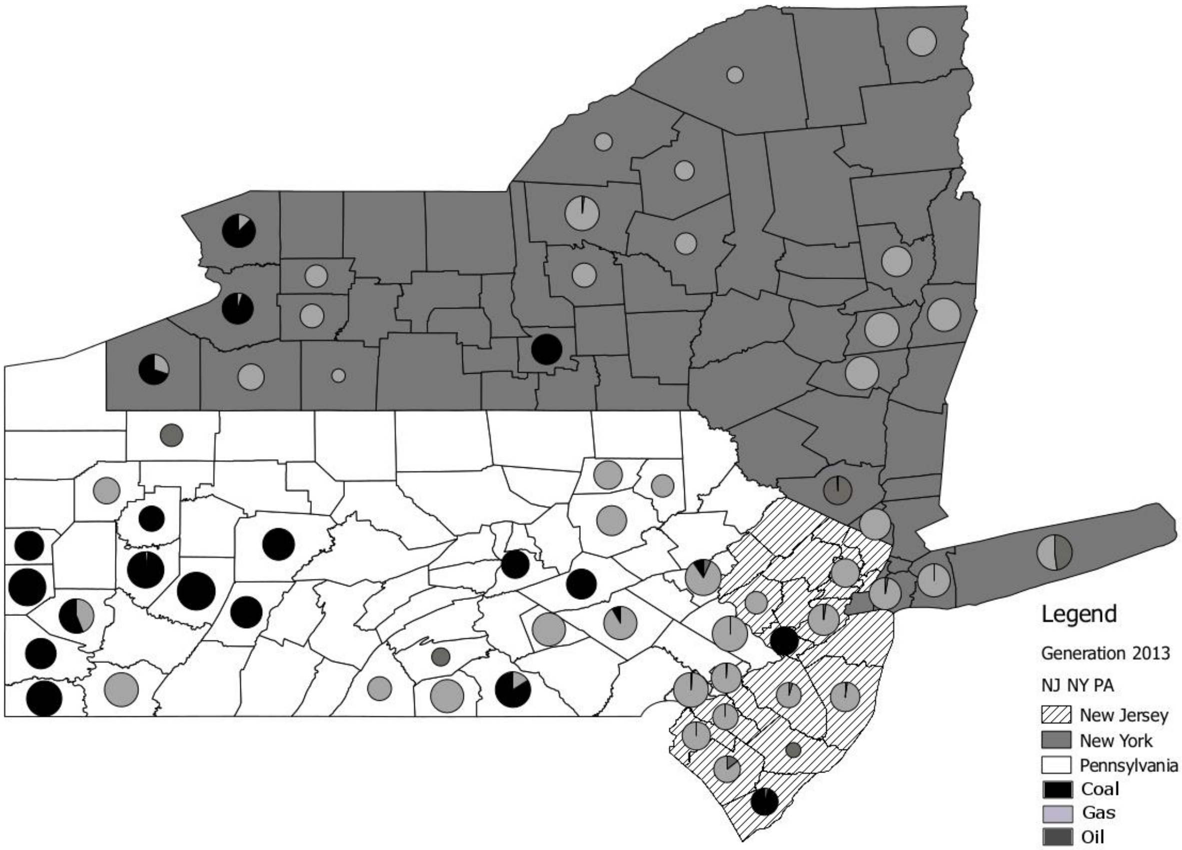
Chapter 7 tests for emissions leakage from RGGI through testing for additional generation in Pennyslvania. Leakage would cause generation that would have been generated in a capped region, is imported from a non-cap region instead. In this way the cap is not being effective and over counts emissions abatements, as the "leaked" emissions are not actually abated, instead they are shifted regionally. Specifically, it uses a Tobit model to test for leakage from New York to Pennsylvania. Further, if there is leakage present, the overall societal benefit of the program on human health would not be clear, as it would imply that there are or may be areas that have large negative impacts to human health.

Finally, Chapter 8 presents conclusions of the study regarding the overall benefits and likelihood of leakage. It also provides policy implications and directions for future research.

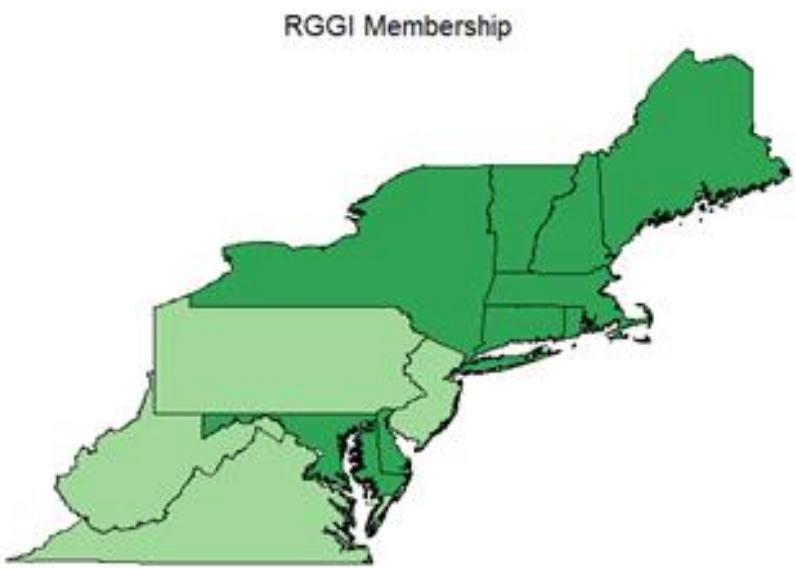
Map 1-1: Generation by Fuel for New Jersey, New York, and Pennsylvania 2007



Map 1-2: Generation by Fuel for New Jersey, New York, and Pennsylvania 2013



Map 1-3: RGGI Member States as of (2015)



Chapter 2 An Overview of RGGI

This chapter presents historical background on RGGI, including specifics on RGGI's completed auctions and a discussion of auction prices during the study period. It also includes a discussion of the official review of RGGI carried out in 2012 and a review of the relevant academic literature.

2.1 State Participation in the Agreement

As shown in Figure 2-1, which presents the history of RGGI as a timeline, RGGI was first discussed by governors from the Northeast in 2003 after Governor Pataki of New York proposed the program. The first official memorandum of understanding for RGGI was signed in December of 2005 by seven states: Connecticut, Delaware, Maine, New Hampshire, New Jersey, New York, and Vermont.

From the outset, RGGI has been controversial. It has been consistently criticized in multiple ways and member states have considered withdrawing from it. Some of the major themes of this criticism has been over electricity prices, fairness to those being regulated, and the effectiveness of the program. For example, Massachusetts and Rhode Island, both originally part of the discussion in 2003, decided not to participate "over concerns that controls would push up energy prices" (DePalma, December 21, 2005, New York Times). However, they did rejoin the program later, before trading began. There were others who criticized the program for being too lax and argued that "the emissions cap [was] too generous" (New York Times, Sept. 26, 2008). Lastly, before the program went into place, there were power companies that advocated for a national instead of a regional program (Barringer and Galbraith, 2008, p. 3 of 4).

There were also concerns about RGGI in Maryland, which was demonstrated by Maryland's cautious acceptance of RGGI. Maryland became the 8th member to adopt RGGI, through a state law, which was signed by Governor Ehrlich (Republican). However, the state law did not immediately make Maryland join RGGI and was written to allow Maryland to withdraw from RGGI after January 1, 2009, if concerns about electricity prices were not favorably resolved through a "comprehensive study of reliability and cost issues" (DePalma, April 7, 2006, New York Times). Maryland did not formerly sign onto RGGI until April 20, 2007, under Governor O'Malley (Democrat). Massachusetts entered RGGI in January 2007, when Governor Patrick (Democrat) came into office replacing Governor Romney (Republican) who had refused to sign; Rhode Island joined later that month when it's newly elected Governor Carcieri (Republican) signed onto the program. New Hampshire was the 11th state to join RGGI in 2008.

The debate over RGGI has not been limited to the beginning of RGGI. Governor Chris Christy (Republican) pulled New Jersey out of RGGI at the end of 2011. Governor Christy stated that RGGI was not effective as "allowances were never expensive enough to change behavior as they were intended to and ultimately fuel different choices." Further, the Governor stated, "RGGI does nothing more than tax electricity, tax our citizens, tax our businesses, with no discernible or measurable impact upon our environment" (Christy, May 26, 2011). Since, then the New Jersey Legislature has twice passed bills under which New Jersey would rejoin RGGI. Governor Christie vetoed both bills but legislative support for the bills has been close the threshold needed to override the vetoes (Martin, July 1, 2013, Bloomberg). Proposals to withdraw from RGGI have arisen in New Hampshire as well. After the New Hampshire Tea Party campaigned for the state to withdraw from RGGI, and a bill passed in the New Hampshire house (Davenport, May 29, 2011) and Senate, however the bill was vetoed by Governor Lynch and the override attempt failed.

2.2 Evolution of the Emissions Limit

The initial cap for RGGI was set at 188 million short tons per year, with a reduction to 165 million short tons per year occurring in 2012 to 2014, and then additional yearly reductions of 2.5% through 2018. However, in 2013 the RGGI rules were updated, this update slashed the cap in emissions to 91 million tons of CO_2, with a reduction of 2.5% in the cap each subsequent year until 2020 (see chart 2-2). This study's time period falls entirely under the original rule; hence the focus will be on the model rule, though the revisions will also be presented as they were based on a critique of the program during the study period.

The original model rule was developed by environmental staff members from the signature states and reflects significant stakeholder input, which included electric companies (RGGI, 2007). The process resulted in a model rule for each state to use for guidance in their individual legislation to adopt the trading program. There are key components of these laws that are important to understand for this study as they have the potential of affecting the behavior of power plants. These rules define an allowance as one short ton of CO_2 and allow for long compliance periods, safety valves, banking, and offsets. The goal was for the rules to take be able to address many potential problems.

The RGGI "control period," the time period that plants have to be in compliance to have enough allowances to cover their emissions, was set up to be over a three year period, but had contingencies, or "trigger events," included that would allow for a fourth year being added to the control period (RGGI, 2008, p. 13). If a plant's emissions over the control period exceed the allowances it holds at the end of the control period, then it is required to buy additional allowances equal to three times the excess emissions (RGGI, 2008, p. 56). Any excess allowances can be banked and saved to count against future emissions (RGGI, 2008, p. 58). The first control period ended on December 31, 2011, and plants had until March 1st to submit their allowances to RGGI (RGGI, 2008, pps. 8, 13).

Trigger events would have occurred if the price of RGGI allowances exceeded $7 for stage 1 and $10 for a stage 2 type trigger event, both indexed to 2005 dollars (RGGI, 2008, p. 17-18). Besides the potential to increase the compliance period by a year, trigger events have implications for the number of allowances. If trigger events had occurred they would have increased the number of offset allowances by 5 percent for a trigger one event, and 10 percent for a trigger two event (RGGI, 2008, p. 54).

2.3 Allowance Auctions and Prices

The RGGI auction was designed to have low costs, be "[p]ercieved as fair", be economically efficient, minimize collusion, minimize volatility of allowance prices, to raise revenue, and to work with existing market conditions (Holt et al., p. 5-6, 2007). The design was based on a literature review of previous programs, and on experiments for best designs. The program has a "uniform-price auction format, [where] the clearing price for the auction [is] the value of the highest rejected bid" (Holt et al, p. 6, 2007). Auctions are held quarterly. Two vintages of allowances, "future" and "current" were recommended to be auctioned off (Holt et al. p. 7, 2007). Current allowances could be used for compliance during the current three year control period (and were bankable for the second), and "future" permits which could be used in the second three year control period.

During the study period, emissions have been below the RGGI cap, as not all allowances have been sold. The RGGI allowance sale prices have ranged from a low of $1.86 to a high of $3.51 (nominal dollars) from 2009 to 2013. As shown in Chart 2-3, the price started near $3 per allowance, and then fell to the reserve price (originally $1.86 but adjusted up based on the CPI) before rebounding towards $3 per allowance in 2013Figure. This may have been in anticipation of the reduced cap announced for 2014. The number of "current" allowances sold have ranged from a high over 40.6 million in June 2010, to a low of 7,487,000 in the September 2011 auction (see Chart 2-4).

RGGI future allowance auctions (for the control period from 2012 to 2014) were first offered in the auction in March of 2009, and the last was future allowances were offered during the December 2011 auction. Sales of these permits started out matching the amount of allowances offered, as all of the first three "Future Auctions" were sold totaling 6,520,593 allowances (see Figure 2-5). However, the number of future allowances sold in the September and December 2011 auctions fell below the number offered. The "future allowance" prices started out at a high of $3.05 during the first future auction in March 2009 and then ultimately fell to the reserve price (see Figure 2-6).

2.4 Formal Review in 2012

While the formal review does not impact the time period considered in this analysis, it does provide important background information on RGGI. As called for at the time of the founding of RGGI, there was a comprehensive review of the program. This review had input from stakeholders, and starting in 2010 there were "over 12 stakeholder meetings, webinars and learning sessions" relating to RGGI (RGGI, undated, p.1). The review concluded that there was a surplus of available allowances, and, while never utilized, that the original "safety valve" mechanisms consisting of additional availability of offset allowances "would likely be ineffective" if they were needed (RGGI, undated, p.1).

To deal with the excess allowances, the report called for unsold allowances from 2012 and 2013 to be retired (RGGI, undated, p. 3). It also recommended significantly reducing annual allowances in 2014, as mentioned above, to 91 million tons (from 165 million), with subsequent reductions of 2.5% each year until 2020 (see Chart 2-2 above). The safety valve mechanism was enhanced by creating the cost containment reserve (CCR) "that creates a fixed additional supply of allowances that are only available for sale if CO_2 allowance prices exceed certain price levels" (RGGI, Feb. 7, 2013, p. 1). The price level was not to exceed $4 in 2014, rising by $2 per year until 2017 when it would be $10. After 2017 the price level would increase by 2.5% per year. This was predicted to "[r]esult in a modest increase in allowance prices, with allowances expected to be priced at approximately $4 ($2010) per allowance in 2014 and rising to approximately $10 ($2010) per allowance in 2020" (RGGI, Feb. 7, 2013, p. 2). The review did not expect significant changes in electricity bills to consumers—an increase of "less than 1 percent"--but also argued that these changes would result in over $2 billion in additional auction revenues (RGGI, Feb. 7, 2013. p.2).

The report called for some additional changes and further monitoring. First, the compliance period was changed to require generators to "hold allowances equal to at least 50 percent of their emissions in each of the first 2 years of the 3 year compliance period, in addition to demonstrating full compliance at the end of each 3 year compliance period" (RGGI, Feb. 7, 2013, p. 1). The justification for this change was "to reduce the impact of potential non-compliance" (RGGI, 2012). Further, the report calls for RGGI to continue to evaluate emissions, and "pursue additional legal research necessary, leading to a workable, practicable, and legal mechanism to address emissions associated with imported electricity" (RGGI, undated, p. 3).

2.5 A Survey of the Academic Literature

The academic literature on RGGI has focused on the design and impacts of the program. Work has been conducted on the auction design, the economic effects of the program, concerns on CO_2 leakage, and RGGI's effect on electricity generation, both in the overall amount and generation mix. Finally, among analysts there is still disagreement over how effective RGGI has been at reducing emissions (Legrand, 2013).

As mentioned above, Holt et al., (2007) conducted research to inform the design of the auction program, and utilized both literature review and experimental work. Subsequent work on RGGI's auction mechanisms includes Burtraw et al. (2009) which investigated the best way to structure markets to prevent collusion, and Burtraw et al. (2010) which, in part, describes early price discovery in RGGI and further explores auction market structuring.

Other work on RGGI has focused on its economic impacts. Hibbard and Tierney (2011) estimated that RGGI resulted in $1.6 billion of economic value added to state economies based on the state expenditures from the proceeds, consumer savings, and other benefits stemming from spending of the auction allowances. There are benefits from the spending of the allowance revenue by the states, also consumers benefits are approximately $1.1 billion due to energy efficiency programs, but electricity producers suffer net revenue losses of $1.6 billion (Hibbard and Tierney, 2011, p. 35). Paul et al. (2010) used three different models of the electricity market in Maryland to determine what impacts efficiency programs funded by revenue from RGGI proceeds would have on levels of electricity consumption. They found that Maryland's economy would benefit from lower electricity demand and hence lowered electricity bills, due to improvements in efficiency. However, the magnitude of this benefit would depend on how the state spent the proceeds from the auction. They estimated that if the state spent all of the auction proceeds on efficiency spending it would boost the state's economy by $150 million in 2010 (Paul, et al., 2010, p. 6828). Burtraw, Kahn, and Palmer (2006) analyzed the impacts of RGGI on the value of power plants. They found that there would likely be plants that increased in value and some that declined in value. Further, they determined that plants that were outside of the RGGI region would increase in value while those that were inside of RGGI would, in general, decrease in value. The impact on the value of firms depends on the secenario they used and the portfolio mix of emitting vs non-emitting plants (Burtraw, Kahn, and Palmer, 2006).

CO_2 leakage from RGGI states has also been studied. Chen (2009) found that "the amount of CO_2 leakage is positively associated with levels of CO_2 allowance prices but negatively when measured in percentage terms… and that NO_X and SO_2 emissions spillover … increases in commensurate with CO_2 costs both in amount and percentage terms" (p. 675). Another important observation found by Sauma and Chen (2010) was that, "when [a] transmission line is congested prior to the emissions trading in the direction of uncapped to capped region, there would be no pollution leakage effect since no surplus transmission capacity can support incremental exports" (p. 1). Kindle, Shawhan, and Swider (2011) also tested leakage resulting from RGGI between Pennsylvania and New York using historical data on the scheduled flows of electricity between the two states. Their study did not find evidence supporting CO_2 emissions leakage, and they argued that the allowance "price is too low to permit the empirical detection of inter-regional emissions leakage" (Kindle, Shawhan, and Swider, p. 19, 2011).

Lee (2014) investigated the linkage between RGGI permit prices and electricity prices. He found that they are not closely linked during the study period of 2009 and 2012, but still found that "RGGI has accelerated fuel switching" (Lee, 2014, p. 44).

Murray, Maniloff, and Murray (2014) utilized a yearly database from 1991 to 2011 for CO_2 emissions and electricity generation at the state level for the 48 continental states to estimate the effects of RGGI on electricity generation. Their analysis uses "a three-stage econometric model of electricity generation," with the first stage regression estimating state level generation

(Murray, Maniloff, and Murray, 2014, p. 13). It controls for electricity price, unemployment, heating degree days, cooling degree days, renewable portfolio standards (RPS), RGGI, and state fixed effects. The second stage regression estimates the power generated by each fuel type--coal, gas, and oil--and controls for fuel costs, carbon price, utilization rate, RPS, RGGI, and fixed effects. Finally, their third stage estimates CO_2 emissions from electricity generation, and controls for generation by fossil fuel, and fixed effects (Murray, Maniloff, and Murray, 2014, p. 14).

First, they argue that RGGI may increase power plant capacity utilization. However, they do not find significant effects of RGGI on the utilization rate of generation by fuel source, nor do they find the carbon price to be significant. The authors explain this apparent contradiction as due to "a modest decline in the scale of generation capacity under RGGI" (Murray, Maniloff, and Murray, 2014, p. 16-17).

The study goes on to use the coefficient estimates from their first two equations to produce six different scenario outcomes:

1. Full counterfactual defined by them as "Replace natural gas prices from 2009-2011 with those that existed in 2008, replace unemployment rates from 2007-2011 remained with 2007 levels, set RGGI program effect and price effect to zero, set RPS variable to zero."
2. Historical gas prices – "Replace natural gas prices from 2009-2011 with 2008 levels;"
3. No RGGI – "Set RGGI program effect and price effect to zero;"
4. No RPS (renewable Portfolio Standards) – "Set RPS variable to zero;
5. No RGGI program effect;
6. No RGGI price effect.

(Murray, Maniloff, and Murray, 2014, p. 19).

These scenarios "suggest that much of the decline [in emissions] is attributable to RGGI program effects" and there was a much lower decline in emissions in their no RGGI scenario (Murray, Maniloff, and Murray, 2014, p. 20). However, an important concern with this study is that the coefficients in the generation fuel source regressions were insignificant for RGGI so it is not clear how to interpret their results.

Murra, Maniloff, and Murray (2014) go on to test for leakage. They find some evidence suggesting that there was some leakage of emissions to Pennsylvania, and they call for further research on this topic (p. 24).

The study concludes that emissions have been reduced for RGGI states, but these reductions were due to a "combination of policy, natural gas market, and macroeconomic factors that emerged in the late 2000s" and that at least one third of these reductions can be attributed to natural gas prices and availability (Murray, Maniloff, and Murray, 2014, p. 25 – 26). Further, while they state that RGGI is "the dominate factor in emissions decline," they are not able to determine whether RGGI's impact is due to its carbon allowance prices or is due to other aspects of the policy that reduced electricity demand. Further, they find that "some or all of the reduction in RGGI emissions may be countered by generation and emissions leakage in surrounding states" (Murray, Maniloff, and Murray, 2014, p. 26).

Figure 2-1: RGGI Timeline

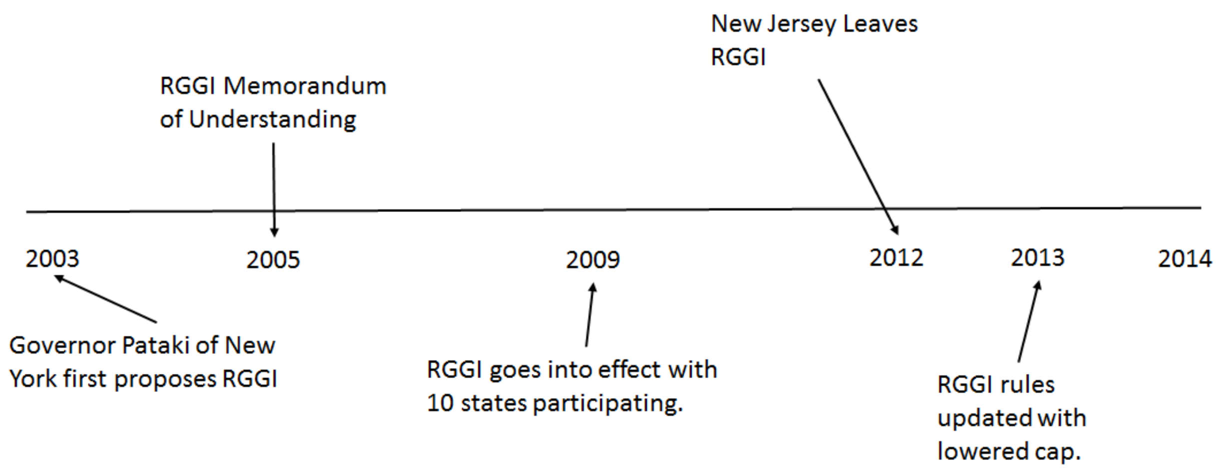


Chart 2-2: RGGI Permit Allowances Historical and Revised

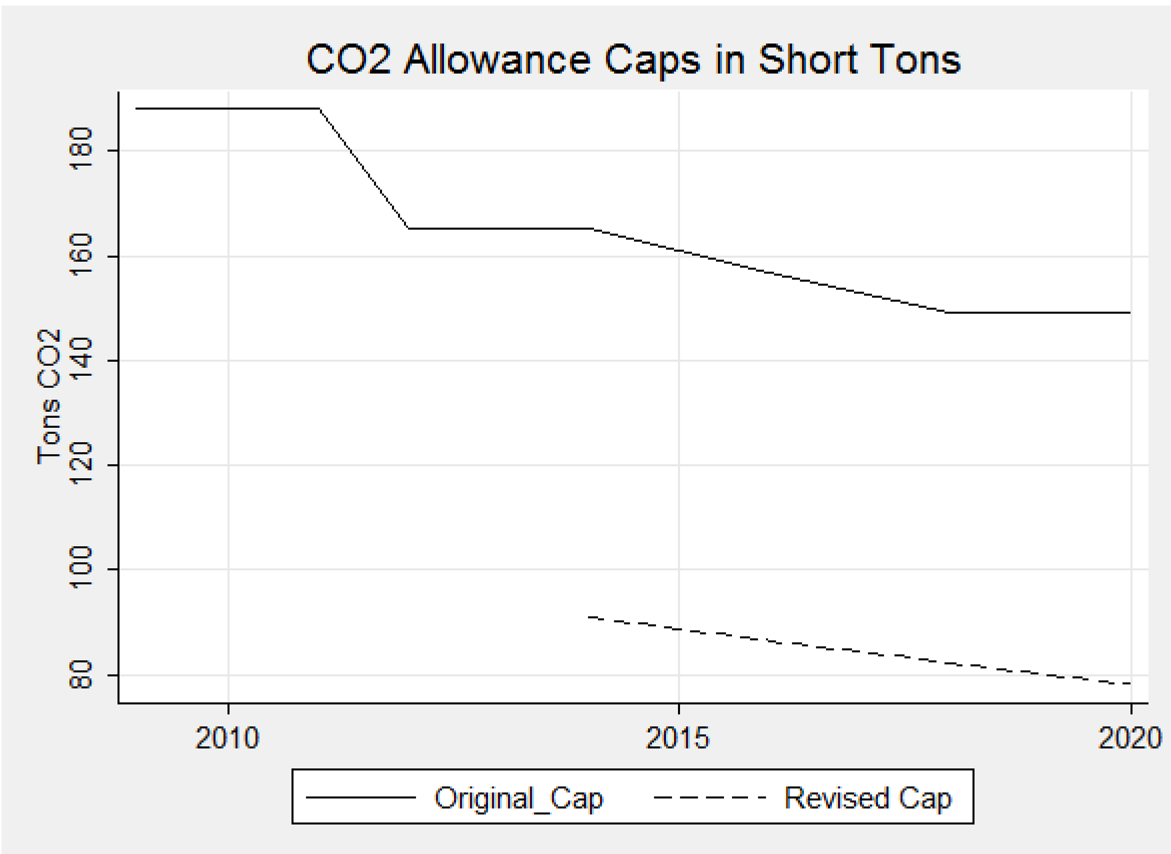


Chart 2-3: RGGI Permit "Current" Auction Million Allowances – Available and Sold

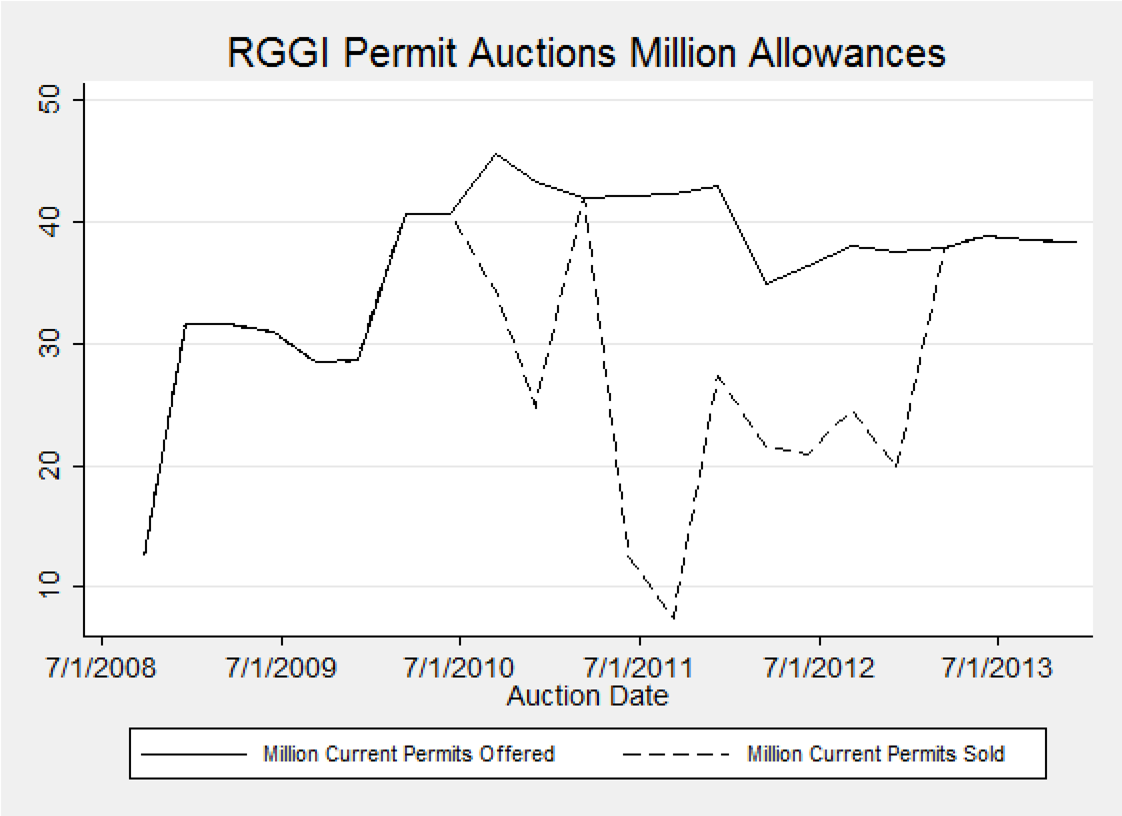


Chart 2-4: RGGI Permit "Current" Auction Prices 2008 to 2013

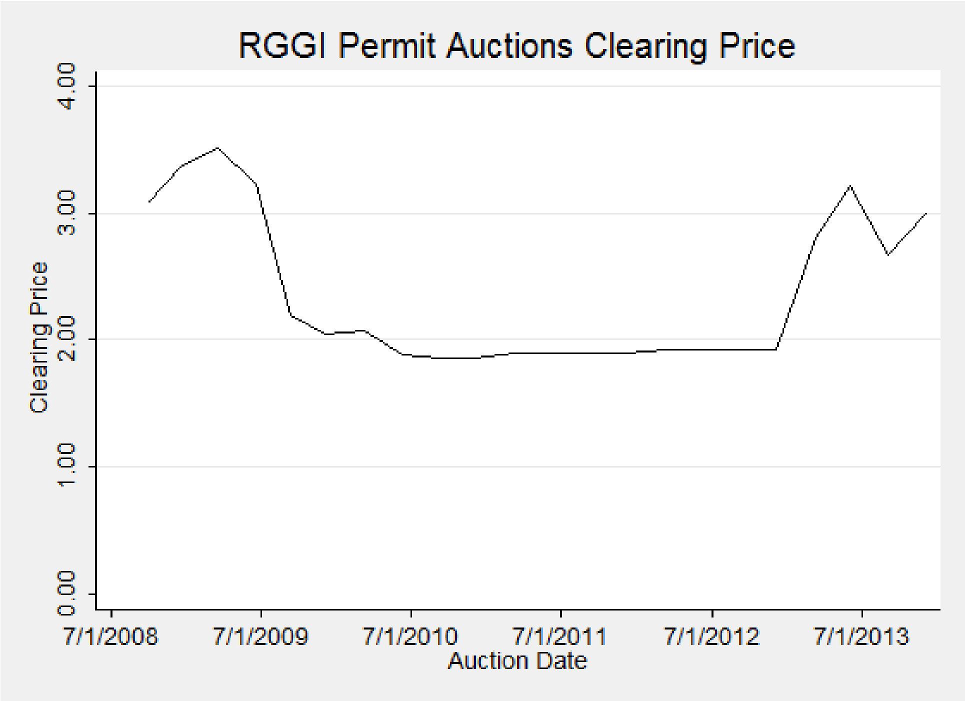


Chart 2-5: RGGI Permit "Future" Auction Allowances Offered and Sold

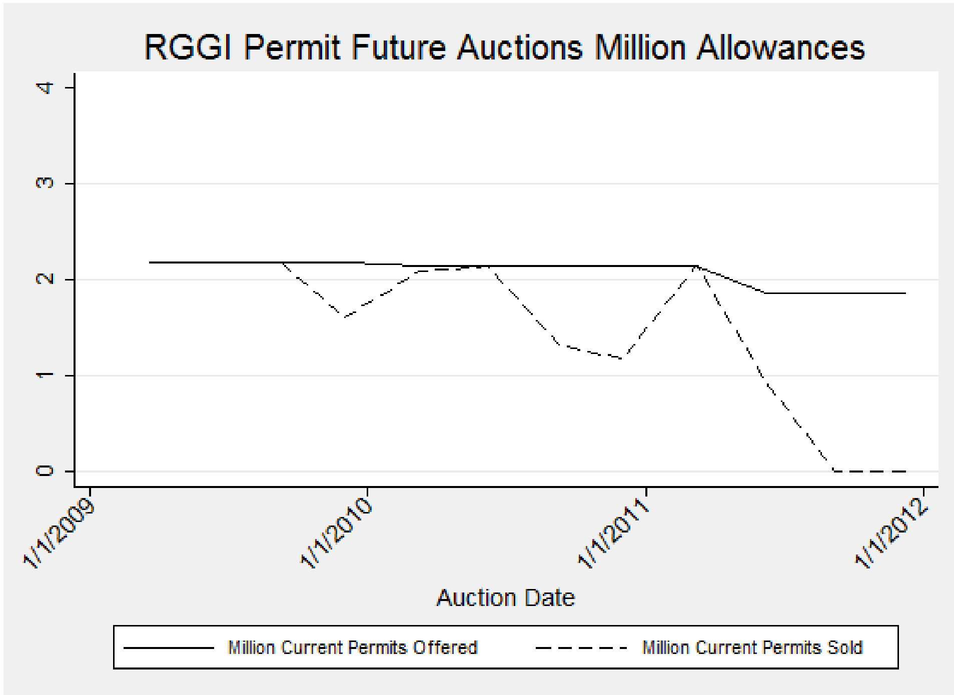
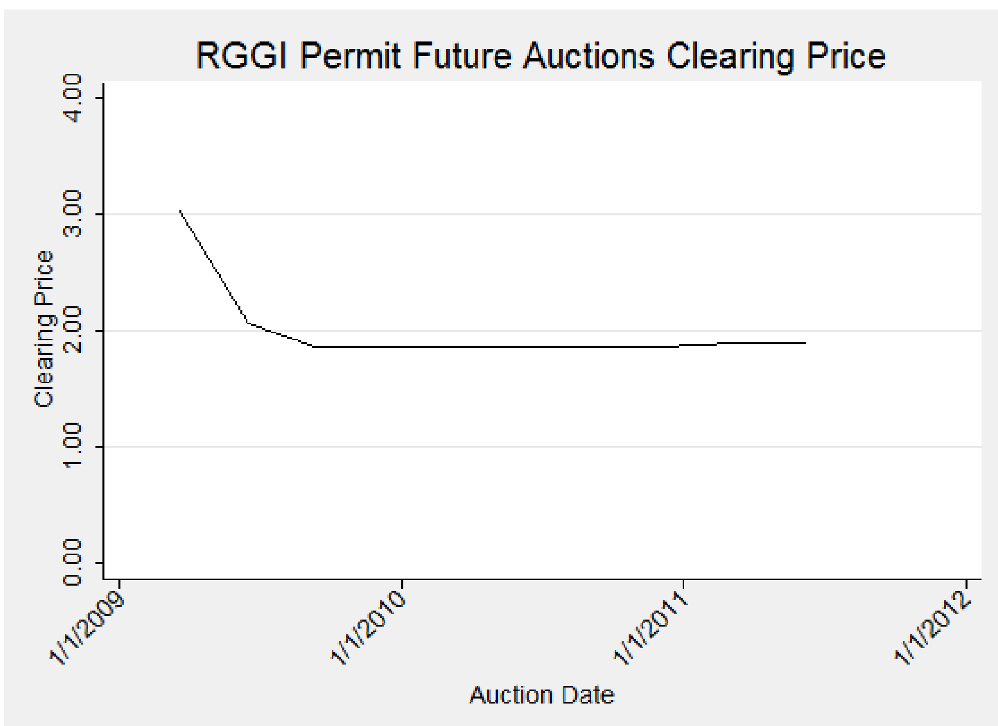


Chart 2-6: RGGI Permit "Future" Auction Prices



Chapter 3 Literature Review

3.1 Overview

This section reviews the literature that is not specific to the Regional Greenhouse Gas Initiative (RGGI), but still is important for this work. It consists of work on pollution permits, risk assessment, and work that has tied these two literatures together. The pollution permit work is important here because it provides important theoretical understanding of RGGI as an institution and the effects that RGGI has on electricity generation. Next, risk assessment is important to understand for the second portion of this study: the health benefits of RGGI. Lastly, it presents work from Muller and Mendelsohn, which builds on the works from the pollution permit and risk analysis sections, and estimates marginal damages from geographically dispersed pollution.

3.2 Pollution Permits

Many volumes could be filled with the literature on pollution permit programs. There are broad themes that can characterize much of this literature. Titenberg (2006) classifies broad themes in the literature as analysis of effects, spatial considerations, time considerations, determining how allocate allowances, market power, and monitoring and enforcement. For this research the literature on spatial considerations is most pertinent, and will be emphasized in this review.

Baumol and Oates (1971) advanced the idea of "pricing and standards" which had the idea of starting "with a predetermined set of standards for environmental quality and impos[ing] unit taxes (or subsidies) sufficient to achieve" them (p. 51). This work built upon that of Piguou who was the first to come up with subsidizing (taxing) external costs to make firms take them into account (Pigou, 1932). The advantage of these taxes is that they would result in plants achieving reductions in the least-cost manner, and by targeting a predetermined set of standards they would require less information on the part of the regulatory agency (1971, p. 51). Next, David Montgomery had two ideas for licenses for polluting activities. The first was a "pollution license" which "confers the right to emit pollutants at a rate which will cause no more than a specified increase in the level of pollution at a certain point" The second was an "emission license" which "confers a right to emit pollutants up to a certain rate" (1972, p. 396). One problem with "emission licenses" as defined by Montgomery, is that they are location-dependent and therefore not tradable "on a one-for-one basis" (1972, p .403). However, he demonstrates that a market system can have the effect of meeting standards at multiple locations when ambient concentrations are taken into account (Montgomery, 1972, p. 410). Tietenberg also developed an approach to deal with different levels of ambient pollution in different areas or zones. In his paper, tax levels would be tailored to the necessary rates to reach goals in each zone requiring different standards (1973, p. 202). His analysis is an expansion of Baumol and Oates' work, as their work can be considered a simplified version of Tietenberg's where there is only one pollution zone considered (1973, p. 202).

Atkinson and Tietenberg (1982) evaluated the costs and benefits of the two types of permit systems, ambient (Montgomery's "pollution license") and the emissions (Montgomery's "emission licenses"). They point out that ambient permit systems are complex, require lots of information, and could allow for total level increases (Atkinson and Tietenberg, 1982, p. 102). Emission permit systems, on the other hand, can still allow air quality standards to be violated or may require greater reductions to achieve the same goals, and conditions can change over time resulting in one area's actions causing another area to be out of compliance (Atkinson and Tietenberg, 1982, p. 103).

Krupnick, Oates, and Van De Verg (1983) analyzed different forms of marketable permit systems that took into account spatial differences in damages. In this paper they add to Montgomery's work to allow for an optimal solution under any initial allocation of emission allowances. Their analysis expanded the types of permits considered in Montgomery (1972) to include "pollution offsets." Under this approach "emission permits are subject to the restriction that the transfer does not result in violation of the air-quality standard at any receptor point" (p. 238). They also point out that for global pollutants or ones where there is "perfect mixing" the "market can take on a very simple structure," and point to the market then being developed for CFC's as potentially being a national market (p. 243). The more location matters in terms of concentrations the more expensive a program becomes. However, their approach nonetheless has the "capacity for realizing the least-cost pattern for abatement activity" (p. 247).

3.3 Risk Assessment Literature

Risk assessments can be used for public policies to calculate the likely costs from a variety of different sources of risk. The costs could be relating to human health, environmental damage, or other economic considerations that involve uncertainty. Risk assessments relating to human health can be used to assign values to improvements in environmental quality that result in corresponding gains in human health. At its simplest form human health risk assessment can be thought of as the health outcome obtained by a public policy, or:

$$\textbf{3.1}\quad HealthOutcomeObtained = \Delta EmissionRate \times \Delta HealthImpact \times TotalPopulation$$

Equation 3.1 shows that the health outcomes from a policy are simply the change in the emissions rate times the change in health impact relative from the change in emissions times the total population affected by the policy. Examples of the health outcomes could be reductions in hospital visits, asthmas attacks, heart attacks, death rates, etc. The health impact rates are determined through scientific studies on animal or human populations.

In general, though, risk assessments for environmental policies are more complex. First, the environmental outcome has to be understood. For example, a policy aimed at reducing pollution from electricity plants will not have a uniform effect on areas surrounding it as the distribution of the pollution will not be uniform. One tool that is often used to model the distribution of a plant's pollution over the surrounding area is the Community Multiscale Air Quality (CMAQ) model. Once the impacts pollution levels in the surrounding area are estimated, changes in health impacts can be calculated and the method described in Equation 3.1 can be used to determine the overall health effect of the policy. After the change in health outcomes is determined, monetary valuation can be added in through rates estimated in the economic literature. For example, if the health outcome is a reduction in mortality, the value of a statistical life (VSL), or value of mortality risk (VMR), can be used to monetize the benefits to society.

One example of risk assessment software in use today is EPA's BenMap. BenMAP utilizes geographical information on pollution and population data from the Census to perform benefit analysis with options for both health outcomes and valuation calculations. BenMAP has been used by the EPA for numerous studies on the impacts of reducing air pollution, and, notably, EPA recently utilized it for setting new air quality standards for particulate matter, $PM_{2.5}$. In this analysis the EPA recommended keeping the 24-hour standard at 35 $\mu g/m^3$, and recommended lowering the primary annual standard to 12 $\mu g/m^3$ from 15 $\mu g/m^3$ (EPA 2012). Another example of risk assessments is Levy, Greco, and Spengler (2002), where they analyzed predicted health benefits from introducing control technology to reduce particulate matter from 5 older fossil fuel plants within in 50 miles of Washington, D.C. They found that populations near the plants received greater benefits than the general population, with disproportionate mortality benefits for people with less than high school education and with reductions in childhood asthma rates for African Americans.

Uncertainty can come in every step of a risk assessment. First, there can be a level of uncertainty surrounding who benefits and in what amount from the policy based on complexities in the transport mechanisms, especially of airborne pollutants. Second, there is significant uncertainty relating to the health outcomes obtained based on the way that health impact rates are derived using dose-response functions. Lastly, there is uncertainty when monetizing the benefits of a policy using VSL methods. Uncertainty with the transport mechanisms will not be included here but uncertainty related to health outcomes and the VSL will be discussed.

The EPA identifies a number of factors that contribute to uncertainty in the dose response models. These include model uncertainty, parameter uncertainty, and human variation. Model uncertainties include: (1) the form of the model that is used to extrapolate to doses not observed, and (2) differences between the population sampled and the population that the inferences are being extended to, such as differences between children and adults (for example the information used below for the risk analysis was for adults ages 30 to 99), or between animal populations and humans. Statistical techniques used for estimating the parameters also are associated with uncertainty, such as random error and measurement errors. Lastly, human variation is simply that different people can have different biological responses to pollution (EPA 2005, p. 3-29 to 3-30).

There are also uncertainties surrounding calculations of the VSL when relating them to environmental policy decisions. First, environmental policies produce goods that are public in nature so it is not easy to identify the value of life from people's personal spending. In addition, the level of altruistic motivations affects the calculations (EPA 2010, p. 7). Altruism poses problems because how people feel about other's benefits may or may not matter in the calculation for the VSL. If a society has individuals making their decisions using a mix of altruistic and self-interested motivations, then the VSL will be higher than a society having individuals using only altruistic or self-interested motivations (Jones-Lee, 1992, p. 89). More recent work has included valuation based on more than one time period, avoidance of illness, and parents valuing a child's life (Gerking et al., 2014). Another difficulty is that studies on VSL are focused only on specific instances of people reducing their risks of mortality and morbidity. There are issues with generalizing people's overall valuation of life from past studies, there are questions as to whether there should be a cancer premium as studies show that people value not dying from cancer more than other deaths (EPA 2010, p. 7-9).

Due to the high level of information needed to perform a risk analysis, there are limits to what can be assessed using it. One major hurdle is that dose-response tests have to have been conducted to determine the toxicity of the chemical. There are many chemicals that have the potential to be toxic but have not been tested (Shute 2011). Further, there is often much uncertainty surrounding the dose-response at low levels of a chemical (for example, if high doses are used in laboratory settings and then the results are extrapolated to a low dose). There may be enough uncertainty in the calculation to make benefits statistically uncertain: that is, not necessarily different from zero.

3.4 The Marginal Damage Approach

Muller and Mendelsohn, in a series of articles from 2007 to 2014 (Muller and Mendelsohn 2007, Muller 2011, Muller and Mendelson 2012, Muller 2014), utilize risk analysis and mapping methods to estimate source-specific marginal damages from point sources across the United States. Their “Air Pollution Emission Experiments and Policy” model (APEEP) estimates marginal damages for “nearly 10,000 sources” in the United States (Muller, 2011, p. 2). Their work advocates using site-specific marginal damages from multiple pollutants in setting policies for dealing with pollution. Their approach is similar to the ambient permit approach in that it accounts for geographic variations in the damages from pollution but instead of measuring concentrations, emissions rates are set based on site-specific marginal damages from NH_3 (ammonia), PM 2.5 and PM10 (particulate matter), NO_X (nitrogen oxides), SO_2 (sulfur dioxide), and VOC (volatile organic compounds a precursor to ozone).

Muller and Mendelson find that urban emissions have much greater damages than rural emissions (2007, p. 13). They also argues that the SO_2 emissions trading program likely lowered social welfare, by increasing damages from emissions between $1.5 billion to $5.4 billion annually. Further, they argue that there is too much emphasis on regulation by tonnage, and that instead regulation should be based on the damages from air pollution (Muller and Mendelson, 2012, p. 138).

Muller’s work on marginal damage calculations in Muller (2014) provides a foundation for the calculations of total ancillary benefits from emissions reductions of SO_2, NO_X, $PM_{2.5}$, and PM_{10}, presented later in this analysis. Note that the majority (approximately 94%) of the damages come from adverse effects to human health, see Table 3-1, and 3-2 (Muller and Mendelsohn, 2007). However, the Muller numbers do include damages to agriculture, timber, visibility, materials and recreation. Specifics on how the marginal damage values are used will be provided in Chapter 6.

Table 3-1:Gross Annual Damages $billion/year from Muller and Mendelsohn, 2007

Pollutant	Mortality	Morbidity	Agriculture	Timber	Visibility	Materials	Recreation	Total
PM2.5	14.4	2.6	0	0	0.4	0	0	17.4
PM10	0	7.8	0	0	1.3	0	0	9.1
NOX	4.4	0.8	0.7	0.05	0.2	0	0.03	6.18
SO2	16.1	2.9	0	0	0.4	0.1	0	19.5
Total	34.9	14.1	0.7	0.05	2.3	0.1	0.03	52.18
Adapted from Muller & Mendelsohn, 2007, p. 8								

Figure 3-2:Percentage of Damages to Health and Other Causes

Pollutant	Health	Other
PM2.5	97.7%	2.3%
PM10	85.7%	14.3%
NOX	84.1%	15.9%
SO2	97.4%	2.6%
Total	93.9%	6.1%

Chapter 4 Models and Theory

This chapter presents the theoretical background for the study. It first presents a stylized economic model for two electricity markets connected by a transmission line. Next, a numerical example is presented of this model, to show how trade flows could occur. After this example, adding multiple time periods to the model is considered. Then the chapter presents issues surrounding the transport and fate of emissions, and presents a simplified example of valuing emissions changes. Lastly, the chapter presents a leakage model that builds on the economic and emissions model presented in the first part of the chapter but adds more markets and two distinct geographical jurisdictions. One of these jurisdictions is included in a cap-and-trade program and the other is not. The model demonstrates the conditions necessary for leakage to occur.

4.1 Previous Work

Previous work by Sauma and Chen (2010), found that transmission line congestion could impact trading between capped and uncapped regions, and prevent leakage of electricity generation from a capped region to an uncapped region. I will expand on the observations of their work by including multiple heterogeneous generators which are affected differently by a cap in this study. Moreover, there are two things relevant to this study that their model does not address. First, transmission costs can also impact how production will be distributed between power plants. Second, they do not consider that line congestion can prevent trading between plants that are included *within* a cap and trade region. This would impact the potential gains to society from such a program, and would allow for potentially large differences in prices in trading zones adjacent to each other. The large differences in prices have the potential to greatly impact the effectiveness of the program by impairing the ability of the market to shift generation to the lowest cost producers. Further, their research does not address the fate of conventional pollutants, and the impacts cap and trade programs aimed at global pollutants have on their distribution.

4.2 Electricity Markets and Emissions

To illustrate that transmission constraints can impact where electricity is generated by favoring plants with higher allowance costs, under a cap and trade program, a simple model with two regions connected by a single transmission line is constructed (see Figure 4-1). The model has two markets serving consumers in cities C1 and C2 and three power plants between the two. Further, the markets are connected by transmission line T1, which has a maximum capacity and is costly to use. Conventional emissions from local generation affect the airsheds indicated by the ovals surrounding the two different markets (see Figure 4-1).

Although it is highly stylized[1], the model provides insights on how a CO_2 cap will shift generation, and hence emission of CO_2 and conventional pollutants like SO_2, and NO_X, between the two markets depending on the characteristics of producers in each market and the condition of transmission line T1. For example, in Figure 4-1, suppose plant 1 burns coal and plants 2 and 3 burn gas, and that T1 is low-cost and unconstrained. The introduction of a modest carbon cap will sharply decrease generation by plant 1and increase generation by plants 2 and 3. Because conventional emissions are much higher for coal than gas, there will be large net reductions in conventional pollution in city 1 and small increases in conventional pollution in city 2. However, when trade is constrained by limits on T1, the effects could be quite different. There may be less scope for reductions in plant 1's output when additional electricity can't be imported from city 2. The result would be smaller improvements in the air quality in city 1. Moreover, air

[1] There are other factors that influence generation supply, demand, and distribution that are not included in this model, such as weather variables, economic conditions, and jurisdictional factors.

quality in city 2 might improve (rather than deteriorate) if gas generation is limited in city 1: achieving the emission cap might require reductions in emissions from plant 3. Thus, it is clear that transmission costs and constraints may shift the emissions of conventional pollutants and have the potential to exacerbate or ameliorate geographical hotspots in these pollutants. Understanding RGGI's effect on the distribution of conventional pollution will thus require detailed analysis of many geographically dispersed markets.

The model that I present in Figure 4-1 can be formalized to illustrate the different possibilities of cap and trade programs when transmission costs are included. For simplicity, I use linear willingness to pay (WTP) curves and assume three fuels: coal, gas, and higher cost gas. An example of higher cost gas is an older plant that utilizes a less efficient production method, for example an old steam generator versus a more modern combined cycle unit. The model starts in autarchy with no links between the markets and then the analysis proceeds through a series of steps to link the markets under constrained and unconstrained transmission capacity.

The demand equations for the markets are given by:

4.1 $WTP_z = A_z - q_z B_z$

4.2 $q_z^D = \frac{1}{B_z} \times (A_z - P)$.

where A_z and B_z are the intercept and slope, respectively, of the WTP curve in each market or zone, $z \in \{1, 2\}$. The inverse demand function is found in Equation (4.1), with q_z^D being the amount of electricity demanded in each zone z. Further, I assume that the demand function will not change, and that changes in demand will only be due to consumer's response to price changes[2].

[2] This is not completely accurate for RGGI, because part of the program uses proceeds from the allowance auctions for policies that are aimed at reducing demand.

The cost that each plant incurs to produce electricity is based on its technology (see Figure 4-2). I assume that the producers have a highly elastic marginal cost (MC) is based on fuel costs (FC) and unobservable non-fuel costs (MCNF), and also that output is constrained by the producer's maximum capacity so the amount of electricity produced by each fuel q_{fprod} is lower than the capacity restraint for each fuel $q_f cap$:

4.3 $MC_f = FC_f + MCNF$

4.4 $q_f prod \leq q_f cap$

where f$\in$*{coal, gas, high cost gas}*.

Combining the producers and the consumers allows us to find the market equilibrium and to start to understand the electricity market better (see Figure 4-3). First, we start out with a simple scenario with two electricity producers--gas and coal--and one consumer. Here equilibrium occurs when:

4.5 $WTP_1 = P_1 = MC_G$ and $MC_C < MC_G$

4.6 $Q^D = Q^S = q_{SC} + q_{SG} \leq q_C cap + q_G cap$ (note $Q^D > q_C cap$)

For this scenario, equilibrium between supply and demand will occur at Q^D, which corresponds to price P_1. Price P_1 is equal to the marginal cost of the highest-cost electricity producer in the market (in this case gas), and occurs at MC_G. When plants are subjected to a CO_2 allowance, the marginal cost curve increases based on the fuel type of the plant and the permit allowance cost associated with each fuel (PAC_f). With the simple market setup two scenarios are possible: the dispatch order can stay the same, i.e. the marginal cost of gas is greater than the marginal cost of coal, or it could switch. As a result we could see RGGI causing plants to drastically change the amount of electricity that they produce, and perhaps even stop producing electricity entirely.

When switching does not occur:

4.7 $WTP_1 = P_1 = MC_G+PAC_G$

4.8 $Q^{DR} = Q^{SR} = q_{SC} +q_{SG} \leq q_C cap+q_G cap$

Note that $Q^D > q_C cap$ and $Q^{DR} < Q^D$. When switching does occur, equation (4.7) becomes:

4.9 $WTP_1 = P_1 = MC_C+PAC_C$

The simple case demonstrates that the costs of an allowance system could cause a change in production. However, due to congestion and transmission costs the electric grid is much more complex than a simple one zone market.

Introducing trade into the model, we now have two markets linked by a transmission line that has transmission cost TC. When trading occurs, the prices in both markets will move towards equalization, as electricity will be sent from the low cost market to the higher cost market (see Figure 4-5). Trade between markets, with electricity production in both, can be seen in the following example. Here RGGI has also been introduced, which raises each cost curve by PAC_f, which is the RGGI allowance cost associated with each fuel.

At equilibrium we now get:

4.10 $WTP_1 = P_1 = MC_{HG}+PAC_{HG}-TC$
4.11 $WTP_2 = P_2 = MC_2 = MC_{HG}+PAC_{HG}$
4.12 $Q^{DR} = Q^{DR1} + Q^{DR2} = Q^{S1+} Q^{S2} = q_{SC} +q_{SG}+q_{SHG}$; $qs_{HG} < Q^{S2}$
4.13 $WTP_1 = A_1 – q_1B_1 + A_2-q_2B_2$
4.14 $WTP_2 = A_2-q_2B_2$

Here market 1 and market 2 are linked. At the clearing price between the two markets, electricity is imported into market 2 from market 1. As a result the prices in both markets are tied together and are based on the cost of the highest marginal cost producer, with market 1 paying the difference between the clearing price in market 2 of $MC_{HG}+PAC_{HG}$ less the transmission cost TC. Here market 2 produces enough electricity to fill in the remaining demand that imports from market 1 are not able to satisfy.

RGGI's effect on the market is not immediately clear, and will depend on: the allowance cost per unit of CO_2, the relative prices of different types of fuels, the distribution of electricity producers, and the transmission costs between the two markets. As discussed above, RGGI could cause shifts in the dispatch order, which could contribute to changes in imports and exports between the markets. RGGI could also cause a shift away from production in market 2 entirely if the demand for electricity can be met by imports from market 1 and the marginal cost of high-cost gas plus the allowance cost is higher than the cost of the energy being imported from market 1 (see Figure 4-6).

4.15 WTP1 = P1 = MCG+PACG
4.16 WTP2 = P2 = MC2 = MCG+PACG+TC
4.17 If QDR < qgcap +qccap, and TC < MCHG+FACHG
4.18 QDR = QDR1 + QDR2 = QS
4.19 QS = qSRC +qSRG +qSRHG ≤ qCcap+qGcap+qHGcap
(note QDR > qCcap+qGcap, QDR< QD, QDR1< QD1, QDR2< QD2)

RGGI can have many effects on local electricity markets. As the examples here show, these effects are going to depend on the differences in demand between markets, which can vary by time of day, the amount of production in each market, and the relative costs of electricity production the different markets. Note that if equation 4.17 holds, then we will see that the quantity of electricity supplied by the high cost gas plant will be 0.

Air sheds for conventional pollutants, such as SO_2, NO_X, and PM[3], are included in the model as ovals surrounding the two different markets. Currently, uniform mixing and identical transport functions for each pollutant are assumed. I consider three scenarios with this model, with varying constraints on trade and costs of transmission on TC1. The economic model, (Figure 4-1), determines how electricity generation shifts between two markets via T1, and the

[3] Particulate matter is currently not included in the analysis, and will be obtained from the National Emissions Inventory NEI database for the analysis.

air sheds demonstrate where resulting emissions of conventional pollutants in the two markets will be experienced. This allows for insights to be made on how a CO_2 cap will shift generation, and hence emission levels of the conventional pollutants, between the two markets depending on the characteristics of producers in each market.

4.2.1 A Note about Time Periods

The production model above applies at every period of time. These time periods could be as a short as an hour. Note at the hourly level there are likely some interesting properties due to potential changes in behavior associated with different start-up costs for different types of generators, and different transmission costs occurring at different times during the day. However, this study will focus on monthly totals. It is important to note that due to changes in relative costs to generate electricity from different fuels, from month to month, or season to season, the relationships between plants, in terms of the possible outcomes in the model scenarios can change. Whereas in one month there may be no trading due to TC being too high, in another month the relative prices of coal versus gas could change, and perhaps make trading occur.

4.3 A Model of Emissions Leakage Between Jurisdictions

Another simple model was developed to better understand whether electricity markets cause leakage of CO_2 from RGGI to non-RGGI states through changes in electricity generation. This model is developed with 4 connected markets, served by 4 different power plants as shown in Figure 4-11. These plants can be thought of as running on the same fuels, and using the same technologies, as the plants considered in section 4.1. Further, assuming that each of the 4 plants has the same marginal cost (MC) curve, and each market has the same demand function for electricity, in autarky each market will have the structure shown in Figure 4-12. However, each market is actually connected to the others and has transmission cost T to send electricity to an adjacent market. Four cases are developed that demonstrate the relationship between permit allowance costs and transmissions costs, and provide insight as to how this relationship will affect trading between two areas when one area has cap-and-trade permits and the other does not.

Each market has identical costs and enough capacity to meet its own local demand. So in autarky each plant generates enough energy for its own market. No trading will occur due to the positive transmission costs between each market and the identical marginal costs for each plant. From here, a permit system is introduced to the model in markets 1 and 2, so now the plants in those markets produce at their marginal cost plus the permit allowance cost (MC + PAC), while the plants in markets 3 and 4 will continue to produce at marginal cost MC.

In the first case, suppose the transmission cost T is greater than the permit allowance cost PAC. If so, there will not be any trading between the markets. We will also see a divergence in price between the markets under the cap (1 and 2), and those that are not under the cap (3 and 4). In markets 1 and 2 prices will rise to the marginal cost plus the permit allowance cost (MC+PAC), and in markets 3 and 4 the price of electricity will remain equal to MC (see Figure 4-13). The amount of electricity generated in markets 1 and 2 will fall from Q^D to Q^{Dcap}. No trading will occur because markets 3 and 4 would need to sell the electricity at below marginal cost for it to match the price in the capped markets. The price sellers in 3 and 4 would have to receive would be MC+PAC, but it would cost them MC+T to supply markets 1 and 2. Since PAC >, T they would be selling electricity at a loss under this scenario. As such, the amount of generation in markets 3 and 4 will remain Q^D.

In the second case, suppose the permit allowance cost is greater than the transmission cost but not greater than twice the transmission cost (T < PAC < 2T). In this case we will see trade between markets 2 and 3 but markets 1 and 4 will stay isolated from the others (see Figure 4-14). Market 2 will now import Q^{traded} from market 3, and the power plant in market 2 will now produce Q^{Dcap} - Q^{traded}. Market 3 will have its demand function expanded from D to D' with the extra demand added in from market 2. Market 3's price will move up from its marginal cost by the difference between the permit allowance cost and the transmission cost to MC+PAC-T. Market 2's price will stay at the marginal cost plus the permit allowance cost.

In the third case, suppose the permit allowance cost is greater than 2T but less than 3T. This will create trade between markets 2, 3, and 4 (see Figure 4-15). Even after including the transmission cost, markets 3 and 4 will be able to generate and transport electricity to market 2 at a lower cost than market 2 power plants will be able to produce it. Market 1 will remain isolated as in case 2: although sellers in market 2 could send electricity to market 1 and still make a profit on the sale, there would be a larger profit from selling in their own market. Market 3 will also send electricity to market 2, as even after the transmission cost of 2T the delivered cost will be lower than the cost of electricity produced in market 2 (MC + PAC).

In the fourth case, suppose the permit cost is now greater than 3T (see Figure 4-16). Also, assume that there is enough extra capacity in markets 3 and 4 to entirely meet the demand for electricity in market 2. In this case, local production market 2 will cease and the market will be entirely served by importing electricity from markets 3 and 4. Market 1 will also receive some imported electricity from markets 3 and 4. Market 1 will have a price of MC+PAC, and will still import lower cost electricity from market 3 or 4. Market 2 will have a price of MC+PAC-T. Market 3 will have a price of MC+PAC-2T, and market 4 will be at MC+PAC-3T.

As mentioned above, these scenarios are not exhaustive. There are many variations which could be considered, and there are ways that market 3 could actually receive imports from market 2, even under an allowance permit. For example, if there are no constraints, a low transmission cost, and a very high price in market 3, due to an old inefficient plant, relative to the rest of the markets, then you could in theory see power sent from market 2 to market 3.

This model is very simple but it does imply that if leakage is going to happen it is most likely to affect generation at the border between RGGI and non-RGGI states first. As one moves farther away from the border, the cost of transmission relative to the cost of permit allowances is going increase and, other things equal, trading will be less likely. The counties closest to the border between New York and Pennsylvania are hence the most likely to have leakage impact them.

4.4 Modeling Transport and Fate of Pollutants

In addition to modeling electricity markets, to evaluate the health impacts of RGGI it was also necessary to model the fate and transport of pollutants. To understand the health benefits of policies that reduce pollution two steps are required. First, it is necessary to understand what areas are receiving the benefits of reduced pollution. Second, it is necessary to understand how people in those areas are affected by reductions in pollution. Both of these steps are rather complex but fortunately there are software tools supported by the EPA to address both steps. Further, recent work by Muller (2014) also helps with this step. However, it is still necessary to understand the basic logic that goes into this calculation.

The location of pollution concentration reductions is dependent on atmospheric transport, which involves complex chemical pathways that dictate how far contaminants travel and what species of chemical will arrive at different locations. Wind speed, time of day, temperature, and other weather considerations will determine the speed of transport and chemical reactions that will occur. These chemical reactions will determine the level of different types of pollutants.

For example, SO_2 and NO_X can be transformed into secondary particulate matter. Air transport models, such as CMAQ (EPA 2014) and CALPUFF (Exponent 2014), have been developed to deal with these complexities when it comes to the policy making process. These models take into account atmospheric conditions, weather, and chemical and physical properties of pollutants to determine where pollutants are transported.

4.5 An Example Risk Assessment

Turning next to methods for evaluating the impact of pollution abatement on health, consider an illustrative risk analysis for the Buffalo, New York, metropolitan statistical area (MSA), for a 25% reduction in particulate matter ($PM_{2.5}$). Particulate matter is used as it has a relatively short transport distance and hence its fate is easier to estimate. The Buffalo MSA is in Western New York, and consists of Erie and Niagara Counties, which have populations of 919,040, and 216,469 according to the 2010 U.S. Census (Census 2013). To perform this analysis, information for the two counties was also collected on the concentration of $PM_{2.5}$ (from the EPA) and on mortality rates (from the CDC). The concentrations of $PM_{2.5}$ were obtained for four locations in the MSA daily for 2012 from the EPA. As a first order approximation for use in the risk analysis, the average daily concentration was calculated as 9.49 $\mu g/m^3$. All-cause mortality rates were obtained from the CDC's Wonder database for 2010. There were 21,914, and 5,716 all-cause deaths, for Erie and Niagara Counties respectively, corresponding to 0.024 and 0.026 mortality incidence rates (CDC Wonder).

There are multiple studies that give dose-response relationships for $PM_{2.5}$. For this analysis, Pope et al. (2002) was used because: (1) EPA has calculated coefficients from it to use in its formula for calculating changes in incidence rates, and (2) "Pope et al., 2002, may be the most generalizable [of PM studies] because it had the largest sample size (approximately 500,000)"

(Casper, 2008, p. 2). Pope et al. (2002) uses a log-linear model so the incidence rate given by the EPA (2012b, p. 44) is:

4.20 $\Delta y = y_0 \times \left(1 - \frac{1}{\exp(\beta \times \Delta PM)}\right)$

Where Δy is the change in incidence rate for all-cause mortality (this is the health impact rate in equation 4-20, y_0 is the base rate of all-cause mortality, and ΔPM is the change in the concentration of $PM_{2.5}$ in μg/m^3. Lastly, β is the coefficient from the Pope et al. study, and is given by the EPA as .005827 (EPA 2012, p. 75).

Equation (4-20) can be used to calculate the change in mortality, Δy, for each county. The result is then multiplied by the population of the county to produce the predicted change in overall mortality. This gives estimates of approximately 302 and 77 deaths avoided for Erie and Niagara Counties, respectively, for a 25 percent reduction in $PM_{2.5}$.

Further research could improve the estimate in several respects. First, the concentrations of $PM_{2.5}$ could be better split up between the two counties in the research area and, ideally, the city of Buffalo would be split out of the overall MSA to better understand the differences in local jurisdictions. Next, mortality rates could be broken down so that the types of deaths could be better estimated, as Pope et al. gives mortality risks for cardiopulmonary causes and lung cancer as well as all-cause mortality. Further, it could be expanded to include additional health outcomes such as asthma attacks and hospital admittance. Moreover, with a more sophisticated air model with greater geographic resolution, the benefits distribution could be estimated by demographic and regional groups. Lastly, maximum concentrations in a 24 hour time period as well as average concentrations could be analyzed to further understand benefits of improvements in air quality.

Figure 4-1: Electricity Markets and Emission areas

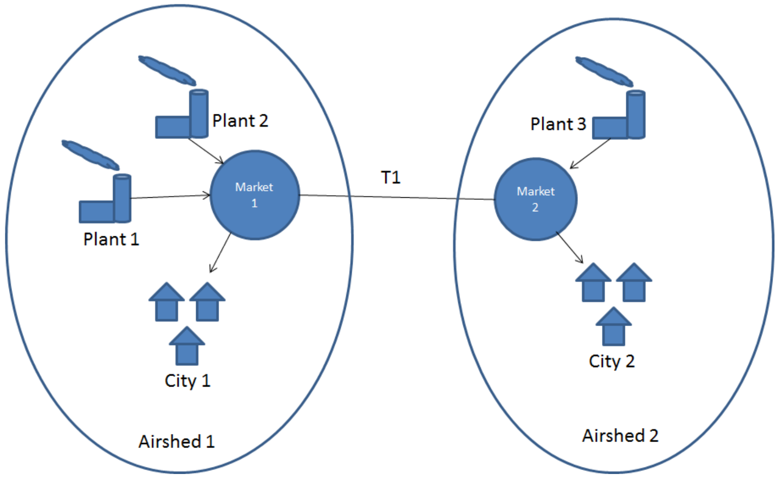
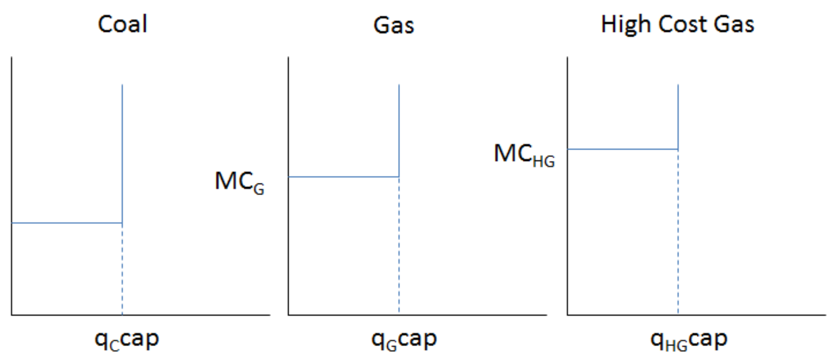


Figure 4-2: Electricity Producers Cost Curves



$MC_f = f(FC_f)$; $f \in \{C, G, HG\}$
$FC_f \equiv$ fuel cost by fuel

Figure 4-3: One Market with Gas and Coal

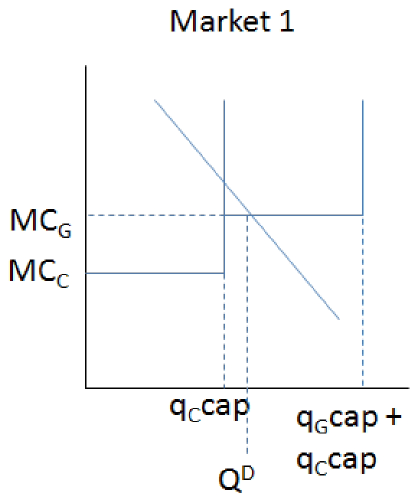


Figure 4-4: Two Scenarios for Market under RGGI

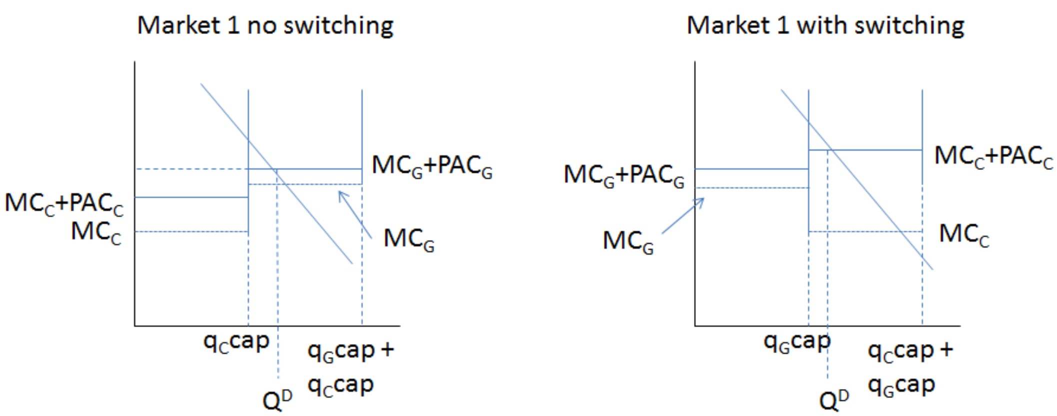


Figure 4-5: Trade with RGGI

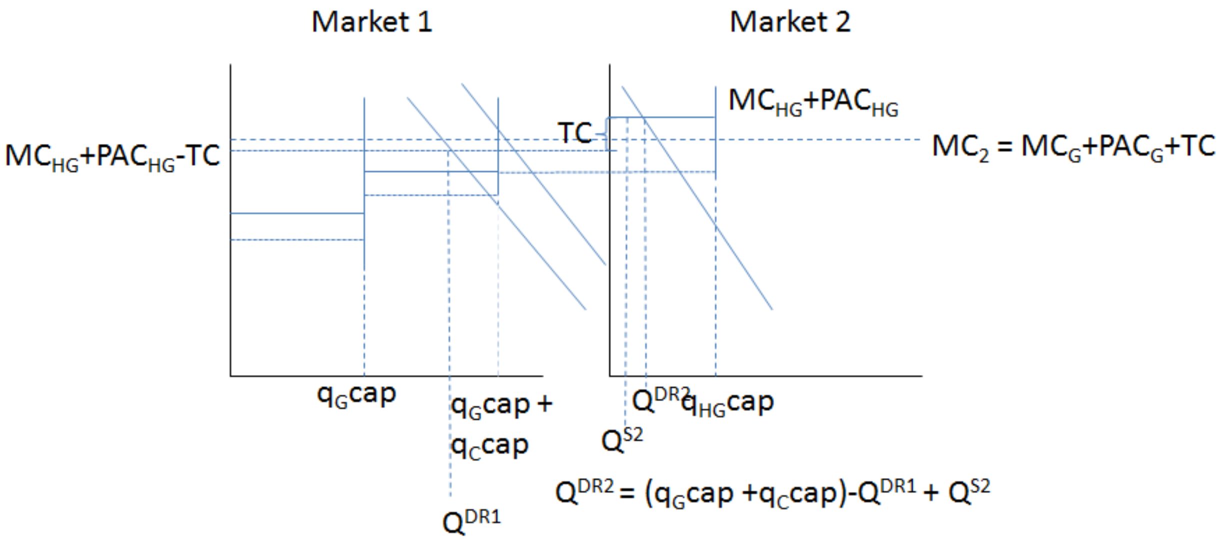


Figure 4-6: Trade with RGGI, market 2 shuts down

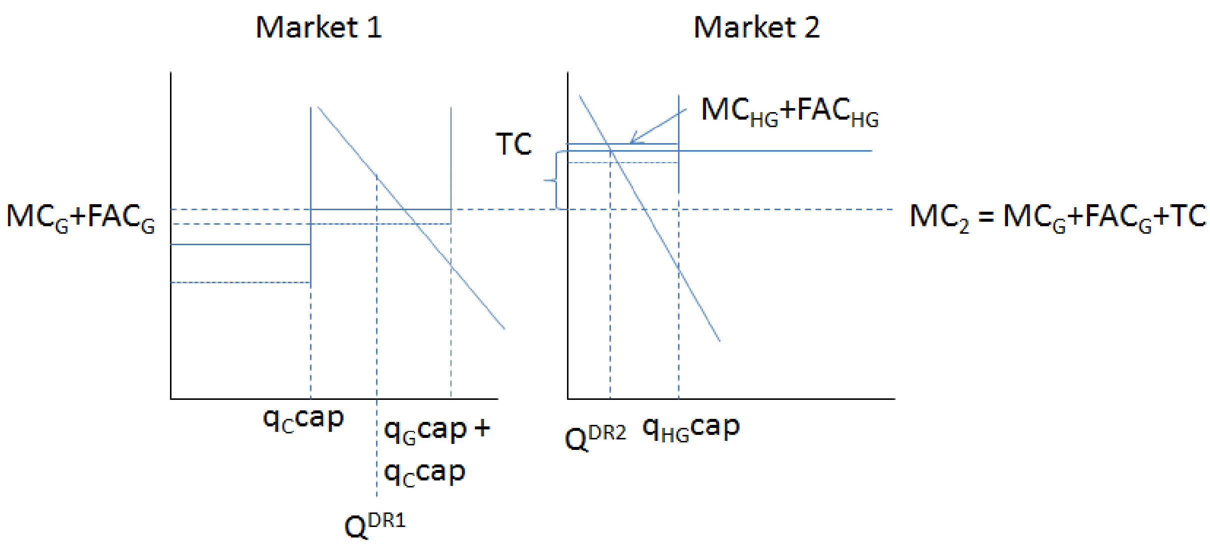


Figure 4-7: Leakage Model

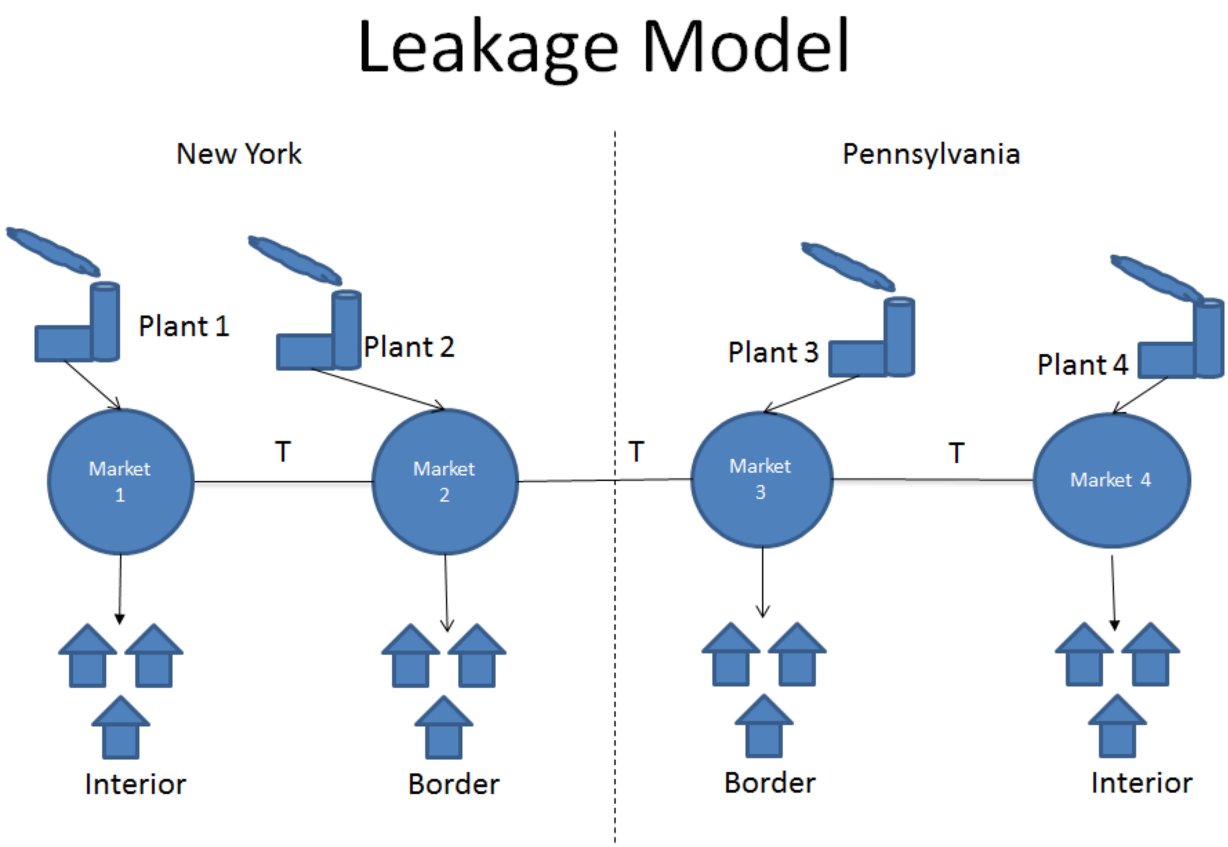


Figure 4-8: Each Market in Autarky

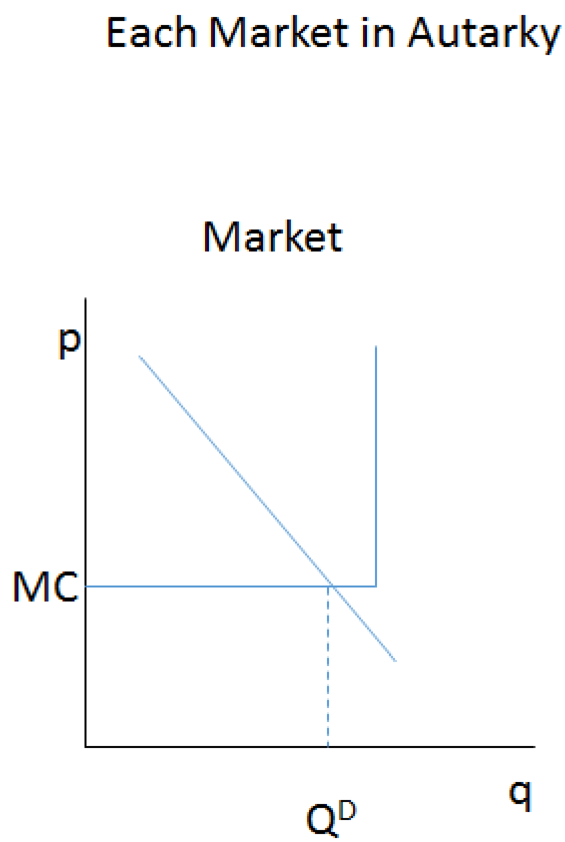


Figure 4-9:Case 1 Transmission Costs greater than Permit Allowance Costs

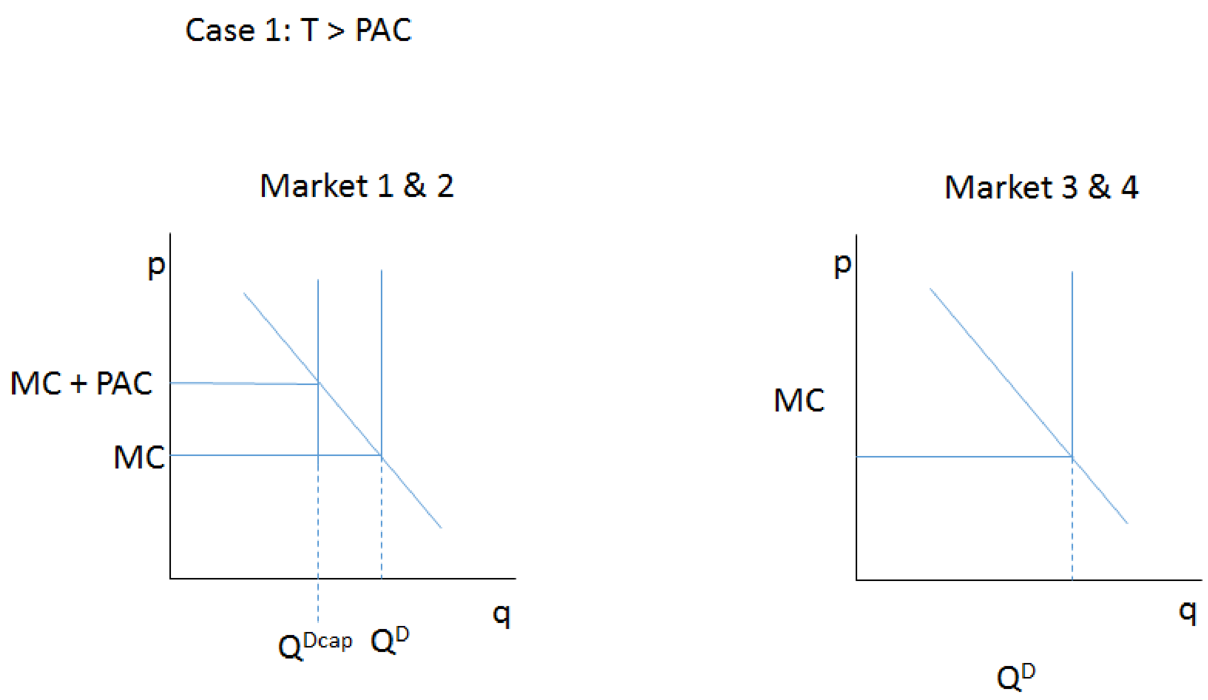


Figure 4-10: Case 2 Trading Between Markets 2 and 3

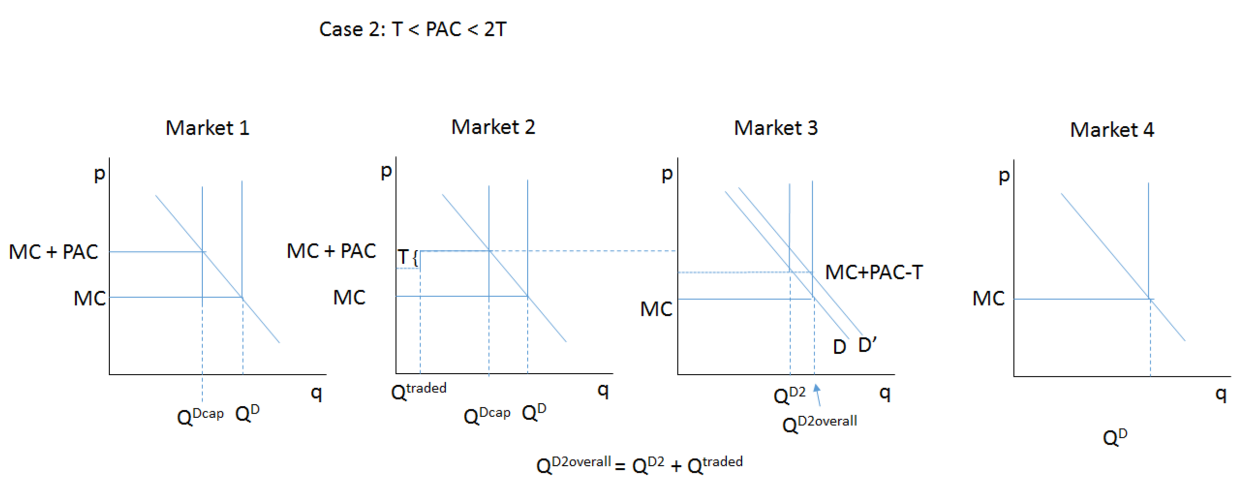


Figure 4-11: Case 3 Trading Between Markets 2, 3, and 4

Case 3: 2*T > PAC, 3*T < PAC

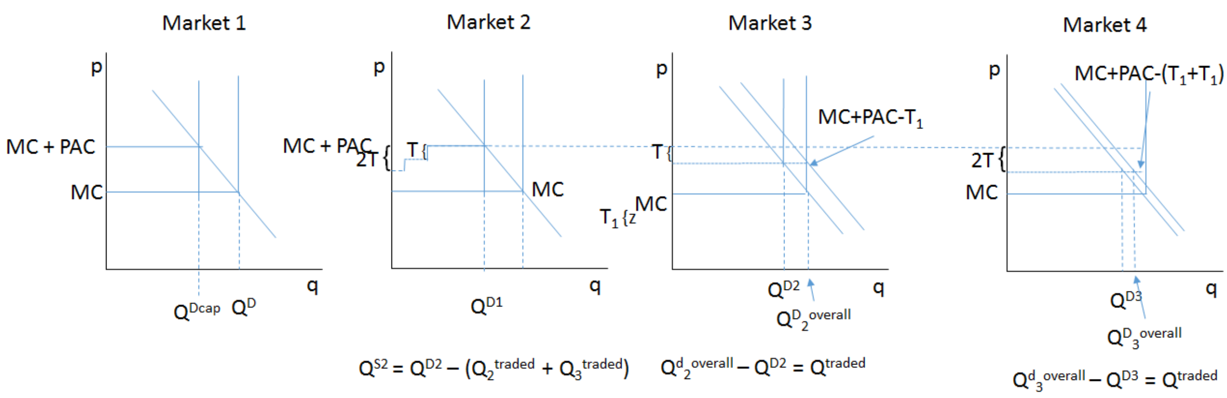
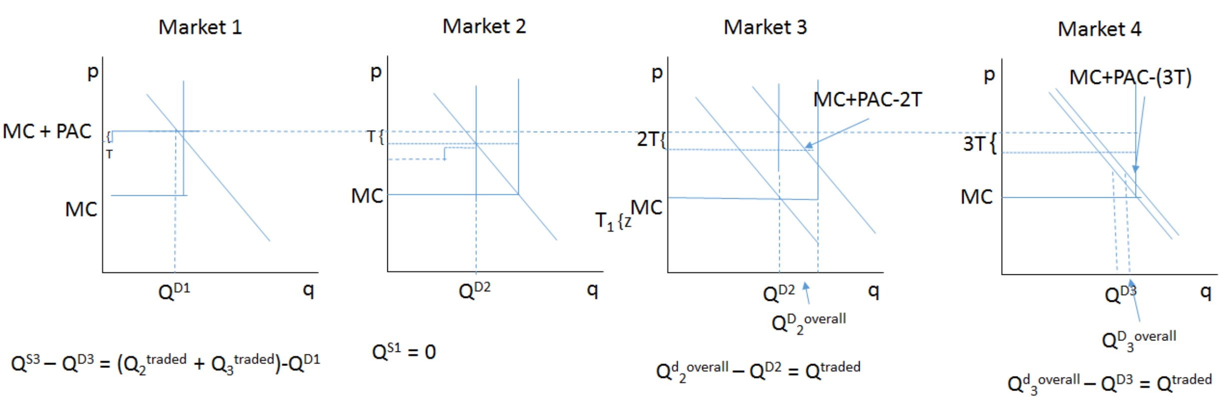


Figure 4-12: Case 4 Trading Between All Markets

Case 4: 3T < PAC



Chapter 5 Constructing the Dataset

To determine the effect of RGGI on the generation at the plant level this analysis utilizes a panel data set. The panel nature of the data set, with multiple states, counties, and plants help to control for fixed effects, and will allow for estimation of RGGI's effect on generation by fuel type. The states selected are interesting due to the fact that New Jersey's participation in the program changes during the time period of the study, as New Jersey withdrew from the program at the end of 2011 after being an original participant in the program in 2009. New York has always been a member of the program, and Pennsylvania never joined. Both states are also relatively large generators regionally. The dataset for the analysis starts at the beginning of the year 2000 and runs to the end of 2013. I use a variety of sources for the information in the database, including the EPA, NOAA, the U.S. Energy Information Administration (EIA), and the U.S. Census.

5.1 EPA's AMPD Dataset

The most important data for this project comes from the EPA's Air Markets Program Data (AMPD), which has hourly reports from power plants across the country. In general, power plants burning fossil fuels are required to report to the EPA if they have generating capacity greater than 25 megawatts under the Acid Rain Program (ARP) (EPA, 2009, p. 2). Plants in the ARP program are required to report year round. Other plants can be required to either report year round or only during specific seasons depending on if the plant is subject to the annual CAIR SO_2 and NO_X or the seasonal CAIR NO_x program (EPA, 2009, p. 68). Data from the ARP exists dating back to 1995, when it was first collected. However, at that time not all plants were required to report: only 110 facilities, nationwide, were originally affected. Starting in 2000, the current ARP rules for reporting were put into place. In general, these plants report hourly their electricity generation, heat input, SO_2, NO_X, and CO_2 emissions. The data set also has plant demographic information at the yearly level. Map 5-1 shows the distribution of these plants in 2007. As noted in Chapter 1, the location of plants reporting does vary year to year.

An example of this data can be seen for plant for plant 6082. This plant is a coal plant in Niagara County, New York. Figure 5-2 shows hourly observations of heat input in mmBtu plotted against the generation in MWh for 2009 for this plant. It is interesting to note that at the hourly level this plant shows a start-up cost in terms of needing to apply about 1000 mmBtu's of heat before electricity generation begins.

5.1.1 AMPD Data Processing

AMPD data comes in zipped csv monthly files at hourly resolution for each state. To be able to work with this data it is necessary to process it. A series of Stata "do" files were created to process the data to make it ready to be merged with other data sets, and ultimately for analysis. The files contain hourly data for units.

The first do file, reads in the .csv files from AMPD, and processes the observations to make them in uniform formats for merging. For example, in some plants the unit identifier for plants are numeric, and in others they are alpha numeric, resulting in two different variable types and preventing a successful merge later on. The output of this "program" is two files; the first is a plant key file, and the other contains the observations. Both files contain a key "code" to be able to combine again later. The second do file goes through each year and merges individual state by month files into monthly files of all plants in the identified states, still at the hourly resolution here.

The third do file goes through each year and merges the individual state and local monthly files into one large Stata database. It also creates a unique code for each plant, "orispl_unit_12", by ORISPL code (Office of Regulatory Information Systems Plant Location code, which is each facility's unique identifier) and generation unit id. It accomplishes this by adding leading zeros to plants with ORISPL codes and unit identification codes containing less than six characters. This is necessary to create unique identifiers, as it would be possible to have two plants having the same code if the ORISPL code and unit id were combined without this additional step. The program also makes sure that all variable names are identified consistently by year, as in some cases the variable names changed between different source data files. For example, generation load, given in MWh, was identified in different files as "gload" and "gloadmw." The more descriptive variable name was retained, so in this case gloadmw was retained since it indicates that the generation load of each plant is in megawatts.

After the observations are merged it is necessary to merge the key files, which has the demographic data (plant and state name), so that it will be in a compatible format with the observations. The information in this file was moved into its own system to save on processing time due to the size of the data set. The next processing step for the raw AMPD data is to merge the above files back together. First, the yearly demographic data for each plant is merged with the two files above to create the full AMPD data set. Only plants reporting a generation level are retained. Next, the data set is aggregated to monthly values. This is done by summing values for generation, SO_2, NO_X and CO_2, and by averaging.

AMPD gives very detailed fuel definitions, sometimes including multiple fuel types that a plant may burn. These fuel types are mapped to three main categories, coal, oil, and gas[4]. For example, some plants have a primary fuel source described as "Diesel Oil, Pipeline Natural Gas" these are mapped to being oil for this analysis. For a full listing of fuel types in the data set and

[4] Note that there are some plants that burn wood and biomass, however these are not considered for this analysis.

the mapping please see Table 5-3. Secondary fuel sources are given by AMPD. However, there is no way to determine whether any observation is being run with the primary or secondary fuel, therefore it is assumed that the primary fuel source is the fuel source for all observations for each year that it is reported.

A “plant runs” dummy variable is created and set to 1 if the plant was observed to run to at least 300 MWh during a month. Since the data is censored and, in general, only contains observations where the plant was observed to run, the data was “filled-in” with observations that included no generation. When plants had not been built yet, these zero generation observations were removed from the dataset. When a plant was not observed to run, or had too low of generation to be counted as run (as defined above) the log of the generation was set to 0. Otherwise, the log of the generation was created for each observation. An example of plants not always running can be seen with plant 2549 unit 66. This unit is a coal generator located in Erie County, New York. The plant reports running for 9 out of 12 months (see Figure 5-4). Plants are required to continuously report, and the EPA does have procedures to replace missing observations with “conservatively high” values (EPA 2009, p. 87) so missing data is assumed due to plants not actively generating electricity.

Additional information is needed to create the final dataset, to control for electricity supply and demand. Data form NOAA was obtained with temperatures (daily max and min) which was averaged for each month and county in New York and Pennsylvania (see below for how this file was created). Monthly data from the EIA for fuel costs for generating electricity from coal, gas, and oil was also added to the data, based on the fuel used at each unit (see below for description). Census data is also added to the data set. Each county’s population (yearly) is merged onto the data.

5.1.2 AMPD Plant Demographics

The "Facility Attributes" for all plants from 2000 to 2013 were downloaded from the EPA's Air Markets Data website, using the EPA's query tool. AMPD collects data on more than just electricity producers, as such it is necessary to trim down the facilities reported in the dataset, for example cement manufacturers are included in the downloaded data set. This trimming is accomplished by keeping only those plants that are identified by the EPA as having a "source category" of cogeneration, electric utility, and small power producer. The EPA defines "source category" as: "Description of a facility that classifies it in terms of the primary business the facility conducts" (EPA, 2014).

For the three states in the data set, only Pennsylvania had plants listed as being in the category of "small power producer." Four different plants were labeled this way. These producers had reported capacities in mmBtu/hr of between 450 and 1300. At 450 mmBtu/hr using estimates of power from EIA this would correspond to a roughly 42 MWh plant. Since RGGI applies to plants over 25 MWh, these plants are retained in the data set.

There are 72 missing primary fuel type indicators over 7 plants. The ORISPL codes for these plants are 3096, 3099, 3130, 7314, 50358, 55298, and 55690. Forty-two of these missing fuel types are at plant 3099 in Pennsylvania, but the file indicates that this plant has been retired, so this plant is dropped from the data set.

Plant 3096 had 12 missing observations. Six of these came from the three units identified as 1A, 1B, and 1C. All three of these missing observations for 2000 and 2001, but have observations for 2002 that are labeled "Diesel oil." As such the missing observations are filled in as Diesel oil. The plant is also missing 2000 and 2001 from units labeled 2A, 2B, and 3. For each of these units the fuel type is listed as "Pipeline Natural Gas" for 2002 to 2013, so the missing observations are filled in as "Pipeline Natural Gas."

Plant 3130 was also missing 12 observations for fuel type for its units. This plant was missing observations on fuel type for three out of five units from 2004 to 2006, and for 2009. All the observed fuel types at the plant are either for "Coal Refuse," or "Coal" as such the missing observations were mapped to being "Coal" as coal refuse is mapped to coal in this study in the next step.

Plant 7314 was missing one observation for primary fuel type, in 2000. Since the primary fuel for all of the other observations were "Pipeline Natural Gas," the missing observation was coded the same.

Plant 50358 was missing three primary fuel observations. This is a cogeneration plant in Pennsylvania that has incomplete data for 2000 to 2002. It does not have any reported primary fuel. Therefore it was dropped from the dataset. It is also missing heat input capacity data for all three years.

Plant 55298 was also missing 1 observation. It is missing the primary fuel type for one unit in 2002, and there observations for the plant from 2000 to 2013, and all of them are "Pipeline Natural Gas." Therefore, the missing observation was coded as "Pipeline Natural Gas."

Plant 55690 is missing 1 observation for one unit of fuel type. Just like above all other units are coded as "Pipeline Natural Gas," so this is filled in as the missing unit's designation.

The plant demographic data was also missing 1286 input capacity observations at the unit level, out of a total possible 7076 observations. The vast majority of these missing observations are in 2000 (609 missing) and 2001 (633 missing). To address these missing data points, a unique identifier was created using the orispl code and the unit id. Then I used Stata's time series functions to fill in missing variables from those in the time periods immediately following. I did this twice, so that many of the 2001 missing points could be moved to 2000 also. No additional observations were recovered with a third iteration of this procedure. That left a total of 55 unit capacity in mmBtu/hr yearly observations still missing. These missing observations were at four plants.

Many of these missing observations occurred at plant number 2529. This plant burned coal and is indicated to have retired on 5/1/2007. The plant has 4 units, which have heat capacity numbers for the year 2000, but not for subsequent years. As such the values 445 for units 1 and 2 and 475 for units 3 and 4 are used to fill in for the subsequent years by unit.

Plant 2404 had 16 missing observations. Three units at this plant had 5 missing observations each, 5001, 7001, and 11001. The unit 9001 had one missing observation. None these units had any observations that were filled in, and all of them had a commercial operation date of 5/4/1973. Since no other units at the plant were listed with this operation date, these observations were not recoded effectively keeping them out of the analysis.

Six of the observations occur at plant 2526, which is a coal plant in Broome County, NY. The missing observations occur when the plant is indicated as having the status of "Long-term Cold Storage" and "Retired." As such these observations are not filled in.

The last missing observation comes from plant 55298. It has one missing capacity for year 2002, but the operating status of the unit in that year is labeled as "Future" and the plant does not have any observations until 2004, so it appears it should be missing, and is, also, left alone.

5.1.3 AMPD Data Description

The generation mix has changed over time in all three states. Each has had a general downward trend in the number of coal units generating electricity each month (Figure 5-5). Pennsylvania has the most coal producing units during the observation period. New York has the second most, however this number drops and is very similar to the number of units reporting in New Jersey by the end.

The number of gas units generating electricity each month has had a clear upward trend in all three states (Figure 5-6). At the beginning of the sample New York and New Jersey had similar numbers of gas generators running monthly. However, by the end of the New York has clearly more gas units running in any given month. Pennsylvania's gas generation starts close to zero at the beginning of the data set. It steadily rises throughout the data and reaches just below the generation in New Jersey from gas units by the end of the observation period.

Oil generation has declined over time (from a high in early 2000s, but appears to have mostly stabilized after that with a slight downward trend (Figure 5-7). New York has the most oil units running of all three states. New Jersey and Pennsylvania have similar numbers of units running, to the point where there is significant overlap on the graph.

All three types of fuels show seasonality. Further, each state shows overall trends and changes in their fuel mixes (more on that below). This generation in the three states is not uniformly distributed as was seen in Map 5-1 above. For example in general gas units are more dispersed than the coal generation units. This means that shifts in the generation mix will lead to changes in the location of generation.

The total number of observations for generation, SO_2, NO_X, and CO_2 varies. There are a significant number of observations that have generation but do not have pollutant observations. The data set has 65,352 observed data points for generation, 64,954 NO_X observations, 45,080 SO_2 observations, and 45,088 observations reported for CO_2. The limitations of the observations for pollutants will be taken into account in the latter stages of this research. There are more observations missing for pollutants in the early years for the dataset. For example, in the year

2000, there are 4,104 monthly generation observations. However, the pollutant observations are significantly lower for this year; there are 4,027 NO_X, 1,753 CO_2, and 1,760 SO_2 observations.

Average rates of pollution per MWh of electricity generated vary greatly in the data. Average rates of pollution vary by state, fuel, year, and generation level. For example, the rate of lbs of SO2 per MWh of electricity for coal varies from a low in New York of 10.149 lbs/MWh to a high of 12.9 lbs/MWh in Pennsylvania. Pennsylvania also has the highest rate of SO_2 emissions for Oil, but the lowest for gas generation. For NO_X, New York has the lowest rate of emissions, and New Jersey is the highest (by over 1 lbs/MWh). Lastly, CO_2 rates do vary but not as significantly as the other pollutant rates do, the highest CO_2 emission for coal occur in New Jersey (see Table 5-8).

Total fossil fuel generation by fuel for each state over the entire data set can be seen in Figure 5-9. Trends in total fossil fuel generation are difficult to generalize for all of the states in the sample, and overall have been reasonably flat but with some volatility from year to year. All of the states have had different years for their maximum level of total fossil generation. The highest total fossil generation for New Jersey occurred in 2010 with over 22.6 TWh of generation (during New Jersey's participation in RGGI), in New York it occurred in 2005 with over 78.1 TWh of generation, and in Pennsylvania it occurred in 2001 at over 137.1 TWh of electricity.

Breaking the generation out by fuel type in the bar graphs below for 2008, 2011, and 2013 (Figure 5-10) we can see that since 2008 there has been a general downward trend in coal generation, and an upward trend in gas generation in all three states.

As mentioned above this data is combined with extra sources of data to create the final database. However, EIA plant data was planned to be used, but it turned out to be incompatible with the EPA AMPD information described here. While, in theory EIA and AMPD should line up, some plants in the two data sets have widely varying reported generation capacity between what would seemingly be the same units. Further, since different boilers can service different generators, mapping between the two definitions is not trivial and many units inside of plants do not have a clear link between EPA's AMPD and EIA data. As a result AMPD demographic data for capacity (given in mmBtu/hr) is used instead of EIA capacity data per plant[5].

Average fuel price was obtained from EIA's Monthly Energy Review, Table 9.9 "Cost of fossil-fuel receipts at electric generating plants." This provides prices in dollars per million BTU, including taxes for coal, oil, gas, and other fossil fuels. For oil, the variable "Total Petroleum Receipts" was used to approximate the cost to plants. Fuel prices have behaved differently for each fuel per million BTU in the data set from 2000 to 2013. As can be seen in Figure 5-11, below, coal prices have remained relatively stable over time, with a slight increase. The cost of gas and oil roughly followed each other until approximately 2009, when the cost of gas fell and the cost of oil increased. Even with the falling price of gas, it is still relatively more expensive per mmBtu than coal.

5.1.4 Linear Relationship Between Generation and Fuel Use

In general, at the monthly level the generation from the plants plotted against the heat input shows linear patterns. Different units have different efficiency rates; these rates will vary by fuel and other variables. For this reason, the pattern of generation to heat input will be described for each fuel type. There are some times when this relationship does not hold, especially around 0 MWh of output, this is likely due to extra fuel needed at start-up and for times when the plant is

[5] Note that these generation numbers are different then EIA numbers. EPA presumably calculates these numbers by observing the generation from individual plants.

on standby and generation is not active, though the plants are still burning fuel. Since the pattern seems most difficult to see in gas, and easiest to see in oil, gas will be presented first, and oil last.

Looking at all of the gas generation on aggregate does not show a clear pattern (see Figure 5-12). It does appear that there may be multiple linear patterns present. To see these patterns it is helpful to look at the data at the plant and unit level. A couple of plants have been selected to demonstrate the general linear patterns in the data.

The first plant selected was plant 50006. This plant demonstrates a few of the potential issues with the data. Looking at the overall production of the plant (upper left hand corner of Figure 5-13) we can see three potential linear patterns. There are a total of 6 generation units reported in AMPD for this plant, which are shown separated out (two at a time) in the other plots of Figure 5-13. We can see responses for each unit that appear to have multiple linear patterns that can be traced from the origin. We can explain this phenomenon by looking at the EIA data on the boiler and generator associations. The EIA maintains a list of boilers (where combustion takes place) and the generator, which is where electricity generation takes place. Boilers can be arranged in either a one-to-one or boilers can be tied to multiple generators. In Table 5-14, we can see that there are multiple connections between boilers and generators for plant 50006. As such it would be logical to potentially see the bands of patterns as generation changes based not only on the amount of fuel being used, but on the relative efficiencies of different boilers and combinations of boilers.[6] Taking this into consideration and looking at the break down generation by unit id, we can justify a linear relationship for this plant between heat input and electricity generation.

[6] Note as mentioned in the Data chapter Boiler and Generator id's do not match between EIA and EPA's AMPD dataset. This plant illustrates the difference between the two files. AMPD shows 6 different units, however, in this case EIA shows 3 generators and 5 boilers.

Coal follows a similar overall pattern to gas in that it appears to have more than one potential linear projection. When we look at all coal generation we get a graph that appears like it may have roughly two different linear clusters on it (see Figure 5-15). Again to understand the pattern we split out plants to see different behavior at the unit level. Three plants were selected 3179, 54634, and 6082.

Plant 3179's observations occur on the lower left hand corner of the overall coal observations in Figure 5-16. Looking at Figure 5 we can see that in general there appears to be a linear relationship for all three units. There are a few observations roughly 3 for unit 3, and 3 for unit 1 that fall outside of the band of most observations for the plant. However, the vast majority of the observations follow a general linear pattern, and outliers are not entirely unexpected due to variances in fuel and differences in efficiency at start up and when plants are running but not actively generating due to demand fluctuations.

Plant 54634 has only one unit. Its observations show up at the higher linear projection (less efficient) from the majority of the coal observations. This plant does still show an overall linear relationship seen in Figure 5-17.

Plant 6032, also, has only one unit. Its observations are clustered with the majority of the coal observations, and also contains some of the outliers at the less efficient side of the overall grouping. Still besides the few outliers, the pattern of generation to heat input clearly shows a linear pattern as can be seen in Figure 5-18.

For plants that generate using oil as a primary fuel source, there does not appear to be as much variation in the relationship of heat to generation as the other two fuel types. As can be seen in Figure 5-19 below, the relationship between heat input and generation is roughly linear for all oil plants in the data set, with less variance from the pattern than either coal or gas.

Plant 2516 was pulled out as Unit 3 in this plant contains two of the outliers on the overall oil plot (see Figure 5-20). These outliers occur at 4 million mmBtu and roughly 200 GWh, and at .5 million mmBtu and just over 150 GWh. Breaking the plants generation out, and down by unit still display an overall approximately linear project.

Looking at the overall heat input to generation relationships for each fuel, and individual plants for each fuel it can be demonstrated that a linear approximation is appropriate for this relationship. Approximately linear relationships held for each fuel type, at multiple different plants that represented different ratios for these fuel types.

5.2 National Emission Inventory PM Data

Particulate Matter data is not included in the AMPD data set, and as such to be able to get an estimate EPA's National Emission Inventory data is used (EPA 2008, EPA 2011). Data for PM_{10} (filt + Cond) and $PM_{2.5}$ (Filt+Cond) for New Jersey, New York, and Pennsylvania for Fuel Combustion, Coal, Oil, and Natural Gas was downloaded for both 2008 and 2011. Next, the PM data was processed and combined with the generation data for both 2008 and 2011. There were 13 counties each year that did not have either emissions data from NEI or generation data from the AMPD data set. The list of counties was not identical each year. Most of the counties with missing PM data are from gas generation and can be seen in Table 5-21 below, note the yearly generation number indicates the generation in the year that observations are missing in NEI from that year. There were also 80 counties that had PM reported as being from the electric industry that were in NEI but not in the AMPD dataset for 2008, and 82 for 2011. For 2011 the average pm 2.5 for these counties is significantly lower than the average for the counties that matched between the two data sets. For the NEI only counties the average $PM_{2.5}$ level was 2.86 short tons per year, while for the matching counties that average was 118.45 short tons per year.

Using the combined data, described above, for 2008 and 2011 $PM_{2.5}$ and PM_{10} (with $PM_{2.5}$ subtracted) rates were determined for each state in the analysis As can be seen in table Y, there is large variation between rates in different states for each fuel source. New York has the lowest average $PM_{2.5}$ rate for coal but the highest PM_{10} rate for coal. New Jersey's PM_{10} rate is much lower than the other state rates. For gas all of the states look reasonably similar for $PM_{2.5}$. Here again, New Jersey's PM10 rate is an order of magnitude less than the other state rates. Lastly, for oil New York has much lower rates, but also is the only state with significant generation from oil.

Due to New York's rates being significantly lower compared to the other states, and New York generating much more electricity than New Jersey, New York's rates are used for the calculations in this study, as they should provide more conservative estimates, see Table 5-22.

5.3 NOAA Data Processing

Daily Temperature data was obtained from NOAA's National Climatic Data Center (NOAA undated). All weather stations in New Jersey, New York, and Pennsylvania were collected for the observation period of the study (See Map 5-23). ArcGIS was used with county shapefiles from the U.S. Census to match stations to counties based on the coordinates that were given with the data from NOAA. The maximum temperature and minimum temperatures are given in this data set in the tenths of degrees Celsius. Temperatures were averaged by month for each county in New Jersey, New York, and Pennsylvania with available information.

For merging county names using ArcGIS all weather station observations with latitude and longitude listed as "unknown" are dropped as they cannot be mapped. There are stations where the weather station identification codes appear to "move." For example the station coded GHCND:USC00286979 appears for both Pennsylvania and New Jersey. In New Jersey the code reports weather from 2004 to 2007, and in Pennsylvania 2009 to 2013. For this station due to the data management technique used, this station will be counted for the counties in both states in their respective years.

However, the other two stations are from counties that border each other in Pennsylvania, and hence are not as easily dealt with, due to the processing procedure for these files. As a result these stations are assigned to one of the two counties. Station GHCND:USC00363758 shows up in both Pike and Wayne County in Pennsylvania, but is named the Hawley station which is in Wayne County. As a result all of these are assigned to Wayne County. Also, there are observations from Wayne from 2000 to 2007 which is a longer time period than for Pike, which has observations reported from 2009 to 2013. Station GHCND:USC00367732 is reported as being in both Lancaster and York Counties in Pennsylvania. It is only reported as being in Lancaster 2002 and York every year after, and it is located at the Safe Harbor Dam, which is on the Susquehanna River which is the border between the two counties. All of these observations are assigned to York County.

This approach matched most of the weather data observations with counties. There were 1,392,101 daily observations at the weather station level in Pennsylvania, New Jersey, and New York matched this way. Only 30,805 of these observations were not able to be matched due to missing location data for the weather station. When aggregated to the monthly level, these observations reduced down to 21,989 observations by county for the three states. These were not evenly distributed by state, which due to size differences in the states is expected. There were 3,132 monthly observations in New Jersey, 9,382 in New York, and 9,475 in Pennsylvania. The counties with weather observation do not match up one-to-one with those for the counties where generation occurs.

Not all counties that have power plants have a weather station. All three states were missing weather data, with 6,884 missing weather observations, and 58,468 generation observations were matched with weather data. Of the missing the data points, 985 missing observations were in New Jersey, 3,643 in New York, and 2,256 in Pennsylvania. In New Jersey the missing data comes from 5 counties, Camden (102 missing temperature observations), Gloucester (247), Hudson (103), Ocean (98), and Salem (435). In New York there are 6 counties missing data, Bronx (66 missing temperature observations), Genessee (1), Kings (1,869), Nassau (657), Richmond (490), and Rockland (560). In Pennsylvania there are 10 counties with missing data, Greene (6 missing temperature observations), Indiana (18), Lackawanna (155), Lawrence (28), Montour (324), Northhampton (1,089), Northumberland (63), Schuykill (288), Venango (118), and Wyoming (167).

To reduce the number of missing observations in the data set, temperature observations from nearby counties are used to fill in missing data points. The basic logic is to use an adjacent county with a complete set of observations which is in the same NOAA Climate Divisions[7]. For example, Richmond County, NY (Staten Island) Queens was selected as it was the nearest jurisdiction with complete observations for the time period that is in the same Climate Division, 4. Also in New York, Westchester County was used to substitute for Rockland County, as they are adjacent to each and both in Division 5. Lackawanna County is in Climate Division 1, and was replaced by observations from Luzerne County. Montour County is in Climate Division 5, and was replaced by Lycoming County, as it was the only adjacent county with observations in all time periods. Wyoming County in Climate Division 6, was replaced by observations from

[7] The maps for New York and Pennsylvania Climate Divisions are available in the appendix, and from NOAA's website at:
http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/states_counties_climate-divisions.shtml

Sullivan County, as before, this was the only adjacent county with observations in all time periods. In New Jersey 4 of the five missing counties were located in the southern part of the state and are in Climate division 2. All of these counties have been assigned to Burlington County to replace their missing temperature observations.

The additional counties were mapped in the same manner. In almost all cases an adjacent county in the same climate division was found (please see the Appendix for the full list of mappings, and for NOAA maps with climate divisions). However, there were a few counties in New York that were an exception to this rule. Lewis County is located in Division 3, but there are no counties in that division with full observations. As such, Oneida County, which borders Lewis County, but is in Division 6 was used to fill in missing data points. For Tompkins County there were no adjacent counties with all observations available. As such Ontario County, which located in Division 10, same as Tompkins, is used for missing data points.

This procedure brought most missing observations back into the sample. However, there remained 1 observations that this procedure did not reconcile. It did not bring one observation for Wyoming County, Pennsylvania into the analysis.

5.4 Census Data Processing

The U.S. Census Fact Finder tool was used to obtain yearly census estimates for each county in New Jersey, New York, and Pennsylvania. The data for the populations for each state came in two separate files. The first file gave all of the populations from 2000 to 2010, and the second gave data for 2010 to 2013. A Stata do file was written to process the file. The population number in the second file was used for the 2010 observation.

All three states have in general had a slight increase in population. New Jersey's population has gone from 8.43 million people in 2000 to 8.9 million in 2013. Over that same period, New

York's population has gone from about 19 million to 19.65 million, and Pennsylvania's population has expanded from 12.28 million people to 12.77 million. Population varies significantly in each state at the county level though (see map 5-22). For example, for 2013 New York, has both the lowest and highest population counties. Hamilton County New York, in the Adirondack Forest Preserve had a population reported of 4,773. While, Kings County one of the five boroughs of New York City, had a population of nearly 2.6 million people. In map 5-24 we can see that the darker areas are more populated, while the lighter ones have very low population.

Map 5-1: Generation by County Log of Total Generation for 2007, by Fossil Fuel

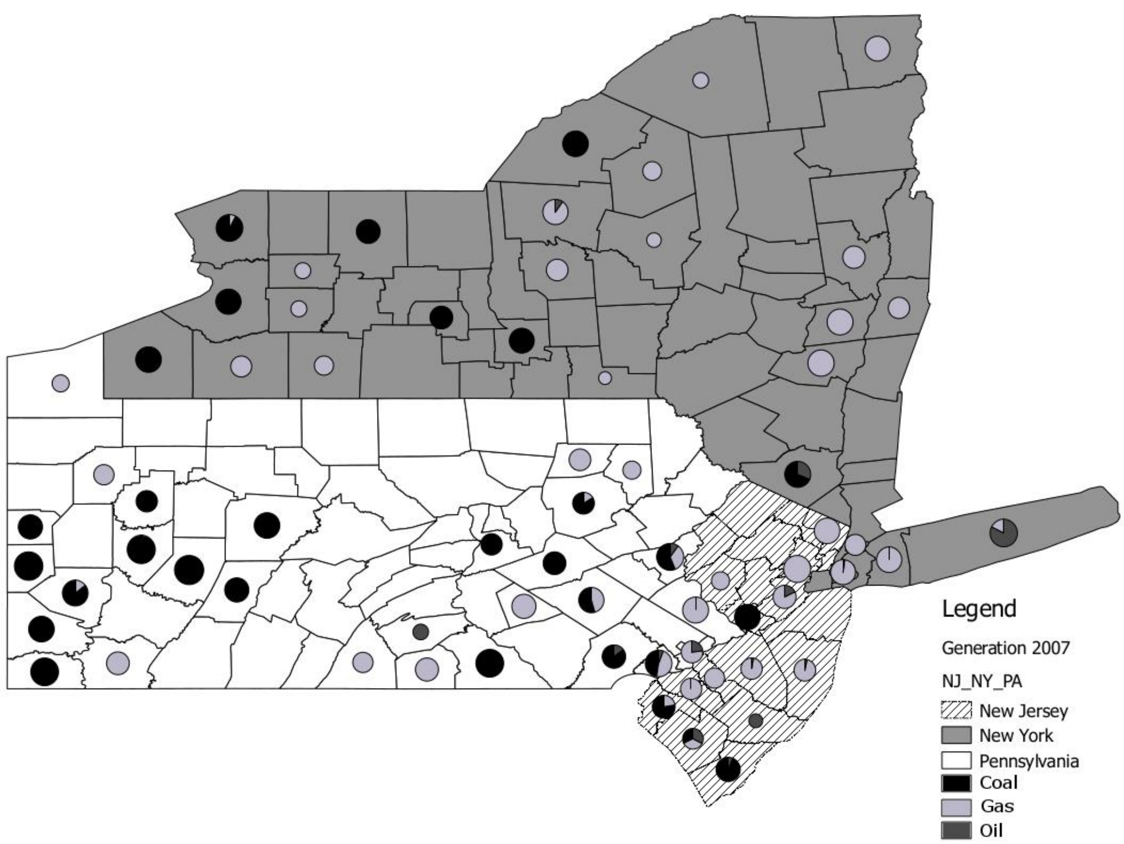


Chart 5-2: Hourly Generation (MWh) to Heat Input (mmBtu) for plant 6082

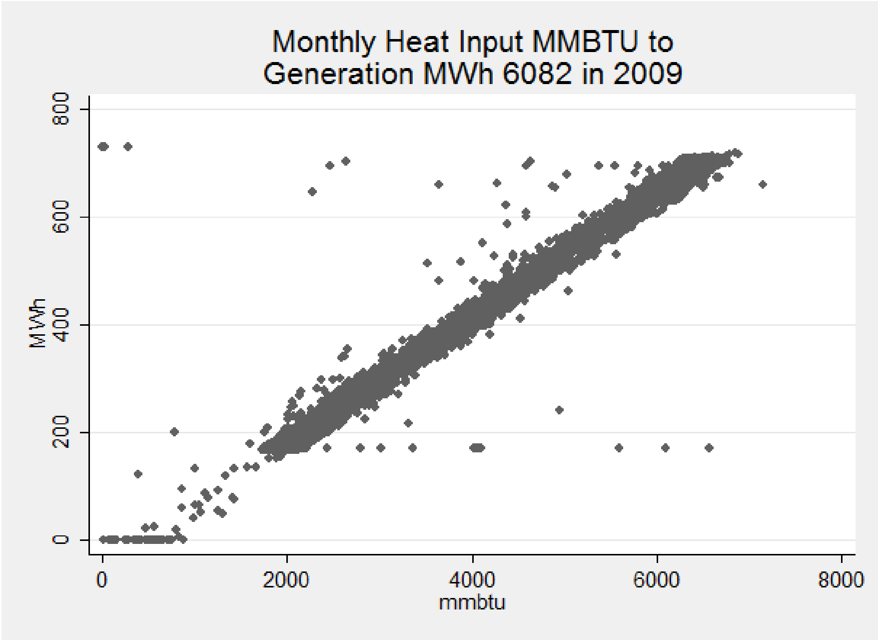


Table 5-3: Fuel Mappings

Primary Fuel Description	Mapped Fuel
Pipeline Natural Gas	Gas
Residual Oil	Oil
Coal	Coal
Diesel Oil, Pipeline Natural Gas	Oil
Diesel Oil	Oil
Diesel Oil, Other Oil	Oil
Other Oil	Oil
Natural Gas	Gas
Coal, Wood	Coal
Wood	NA
Diesel Oil, Residual Oil	Oil
Natural Gas, Pipeline Natural Gas	Gas
Other Gas	Gas
Process Gas	Gas
Coal, Coal Refuse	Coal
Coal Refuse	Coal

Chart 5-4: Plant 2549 Observations Running for 2006

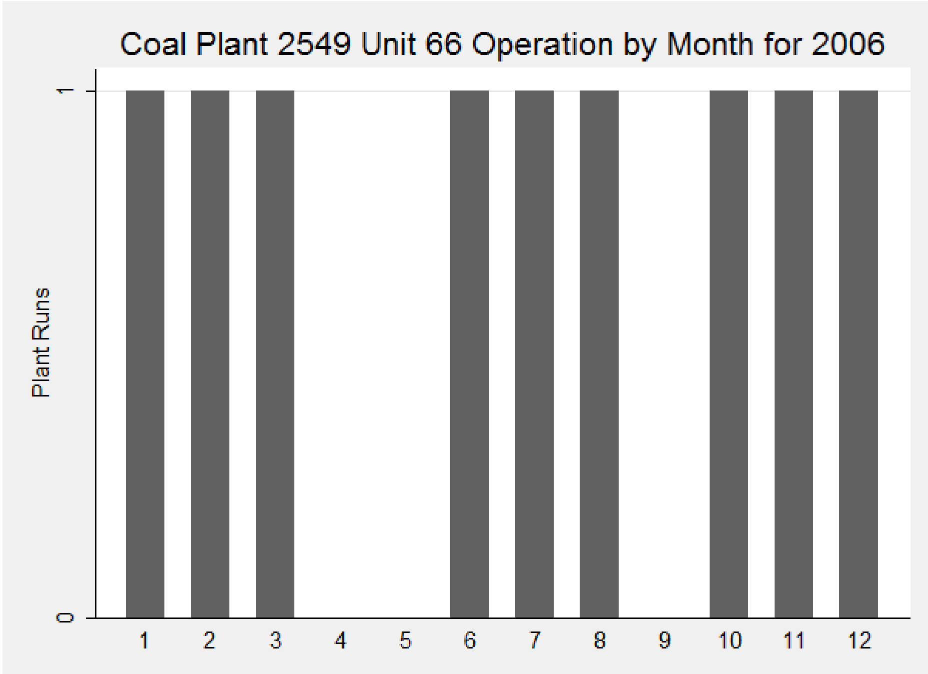


Chart 5-5:Coal Units Reported Running by State by Month.

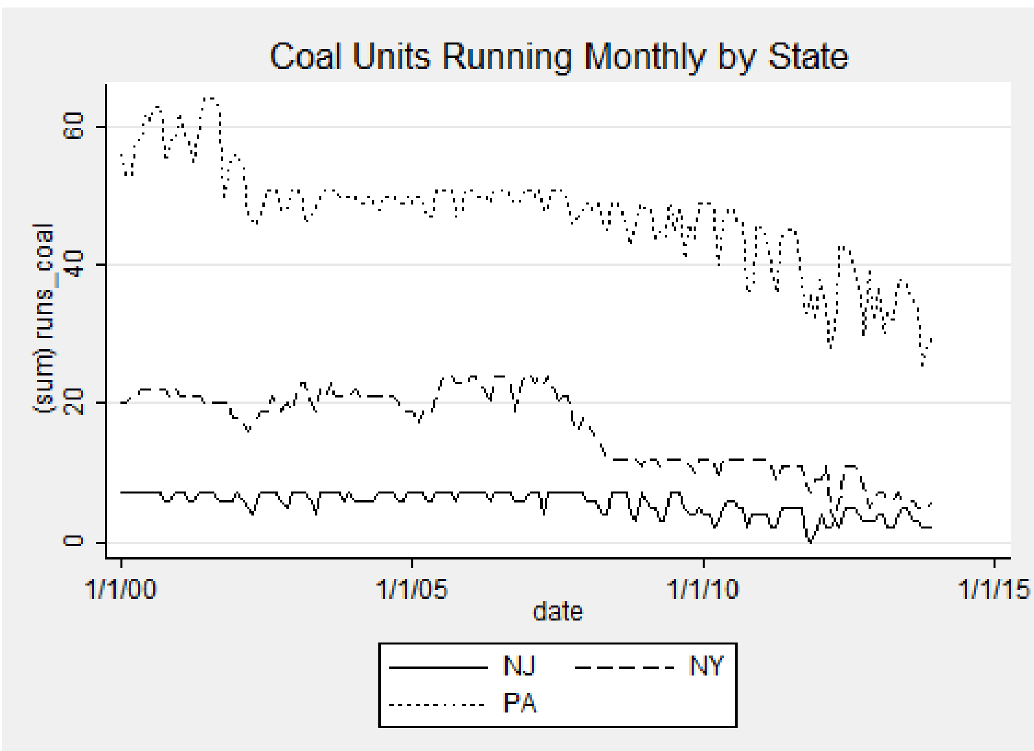


Chart 5-6:Gas Units Reported Running by State by Month

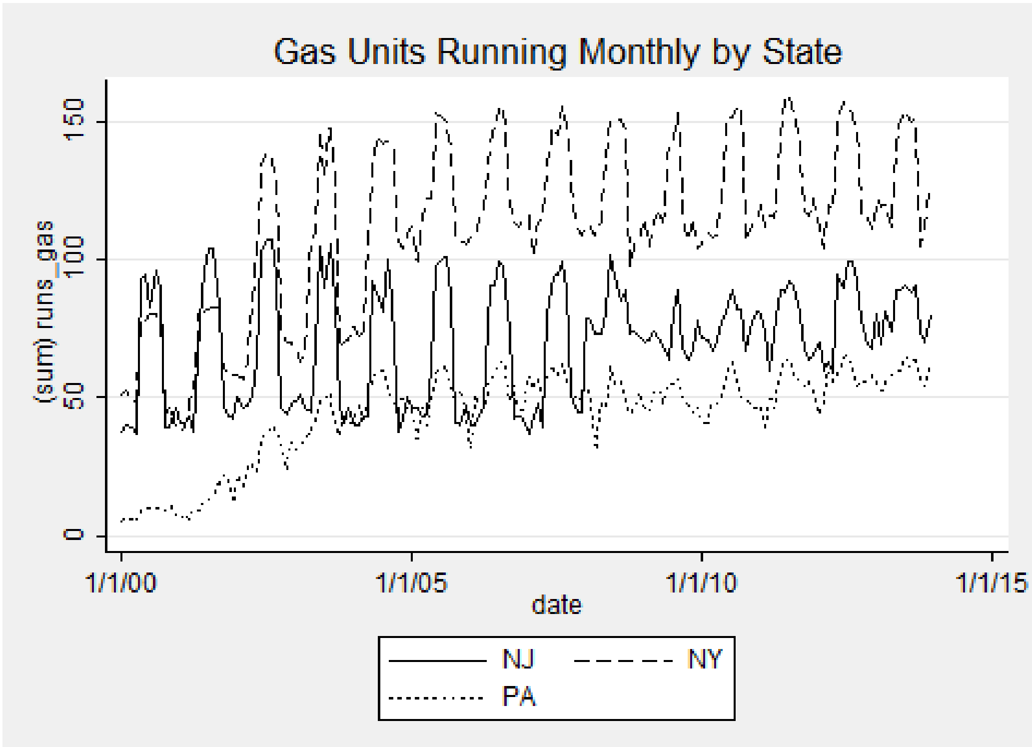


Chart 5-7:Oil Units Reported Running by State by Month

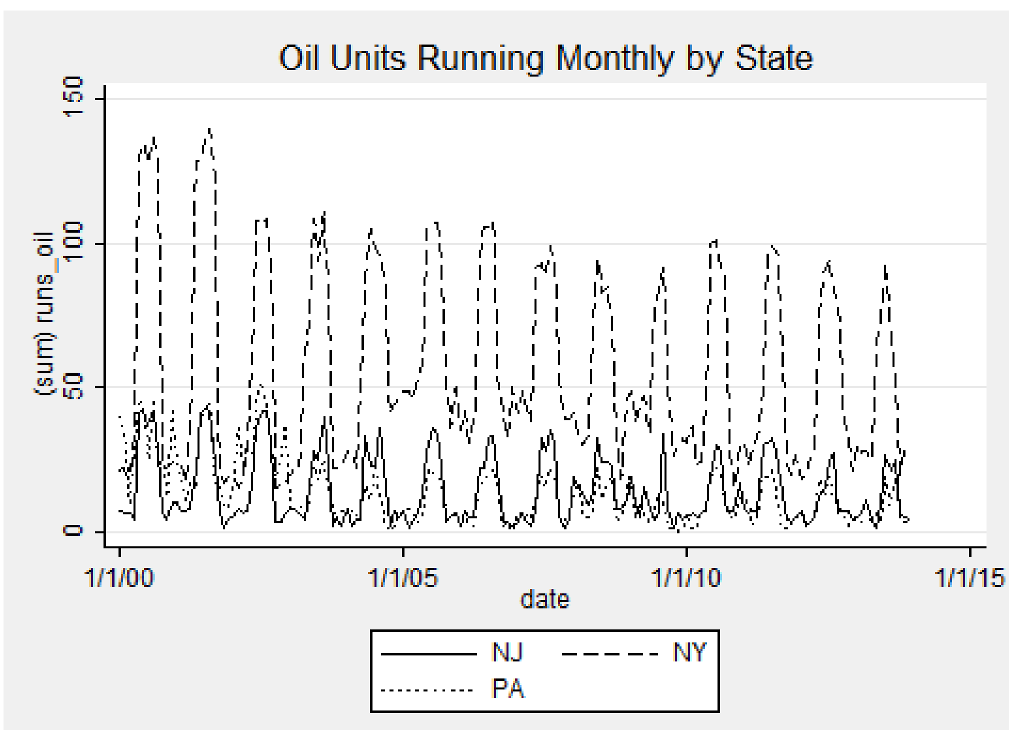


Table 5-8:Pollution Rates per MWh of Electricity Generation

State	Fuel	SO_2/Gen (lbs/MWh)	NO_X/Gen (lbs/MWh)	CO_2/gen (tons/MWh)
NJ	Coal	10.981	4.002	1.113
NJ	Gas	0.021	0.448	0.534
NJ	Oil	4.549	2.676	0.957
NY	Coal	10.149	2.528	0.984
NY	Gas	0.068	0.392	0.599
NY	Oil	6.076	1.687	1.191
PA	Coal	12.900	2.697	0.981
PA	Gas	0.008	0.172	0.527
PA	Oil	7.664	3.002	1.637

Chart 5-9:Total Generation in TWh by State

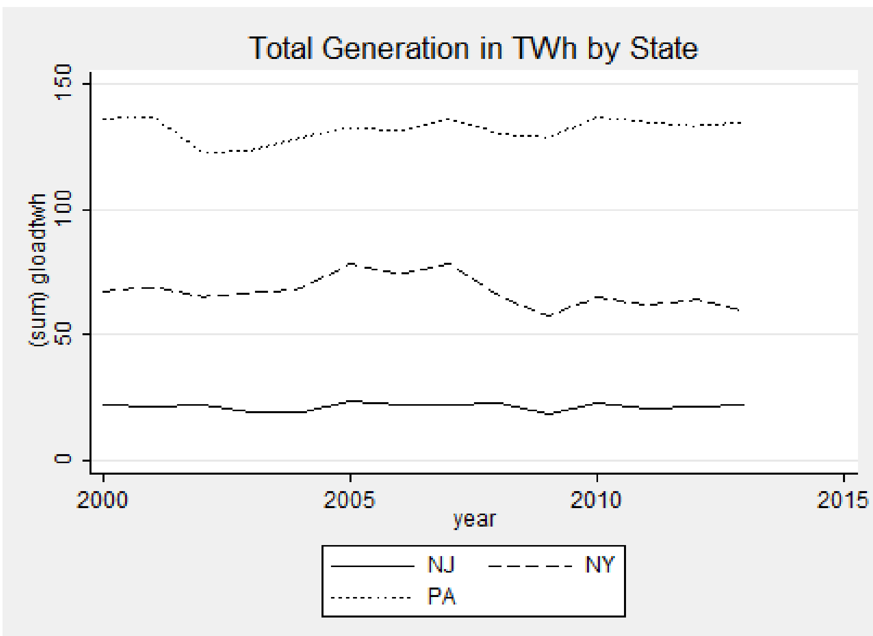


Chart 5-10:Fossil Generation by Fuel across states

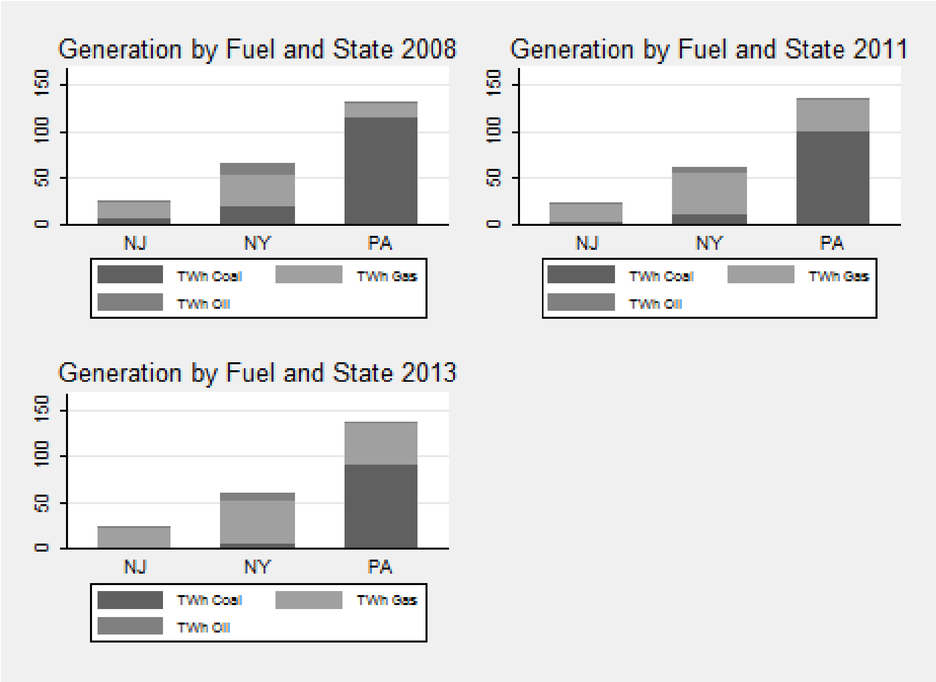


Chart 5-11:Fuel Prices mmBtu for Coal, Gas, and Oil

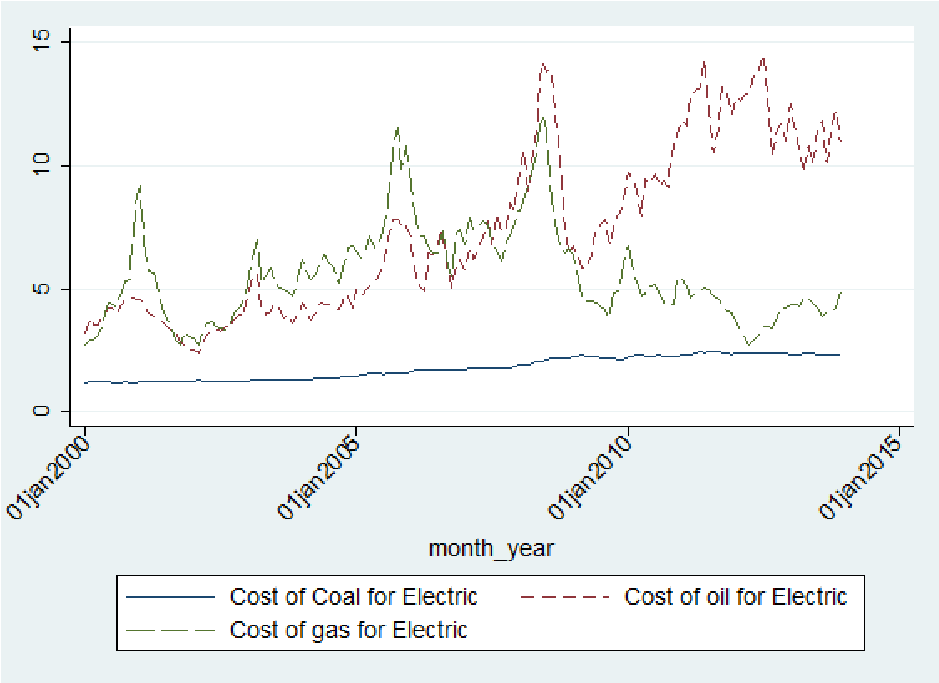


Chart 5-12:Monthly Heat Input million mmBtu to GWh

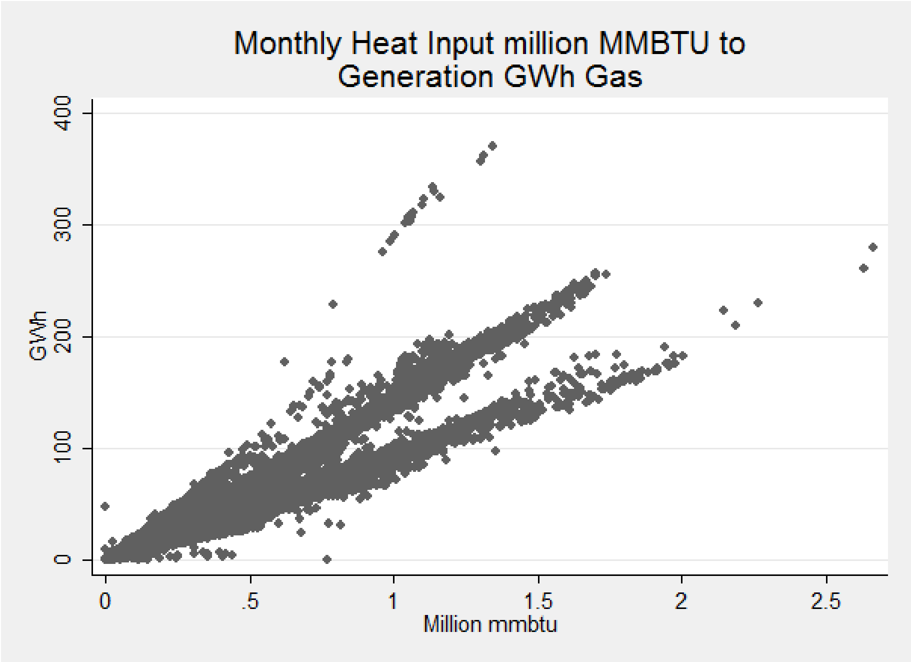


Chart 5-13: Monthly Heat Input to GWh for Plant 50006

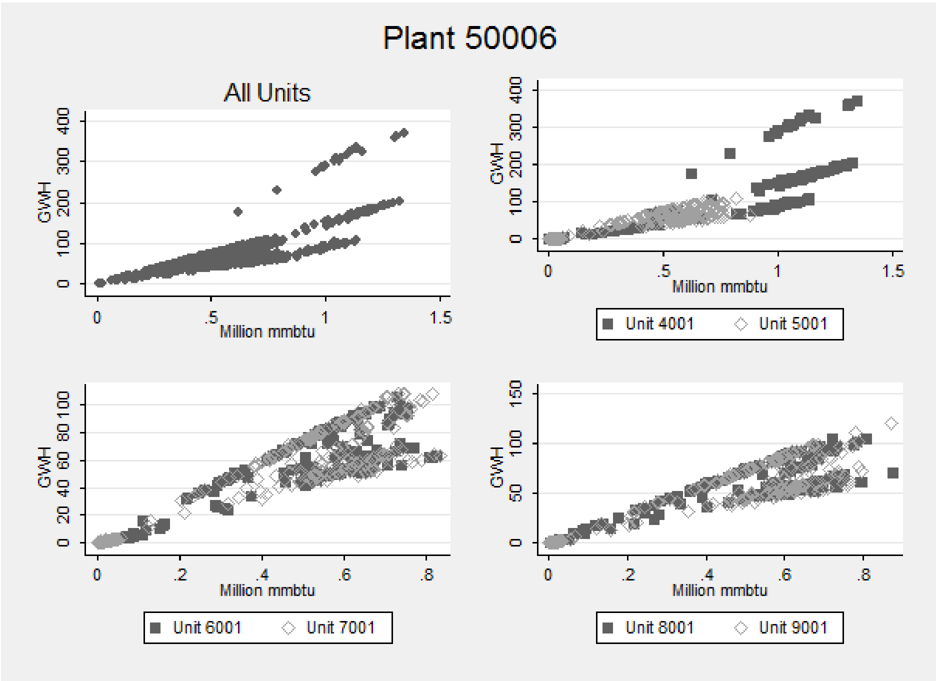


Table 5-14: EIA Data Boiler to Generator Association data for Plant 50006

2011 Form EIA-860 Data - Schedule 6, 'Boiler / Generator Associations'

UTILITY_ID	PLANT_CODE	BOILER_ID	GENERATOR_ID	GENERATOR_ASSOCIATION
3890	50006	HRSG1	STG1	A
3890	50006	HRSG1	STG2	A
3890	50006	HRSG1	STG3	A
3890	50006	HRSG2	STG1	A
3890	50006	HRSG2	STG2	A
3890	50006	HRSG2	STG3	A
3890	50006	HRSG3	STG1	A
3890	50006	HRSG3	STG2	A
3890	50006	HRSG3	STG3	A
3890	50006	HRSG4	STG1	A
3890	50006	HRSG4	STG2	A
3890	50006	HRSG4	STG3	A
3890	50006	HRSG5	STG1	A
3890	50006	HRSG5	STG2	A
3890	50006	HRSG5	STG3	A

Chart 5-15: Monthly Heat Input million mmBtu to GWh for all Coal Plants

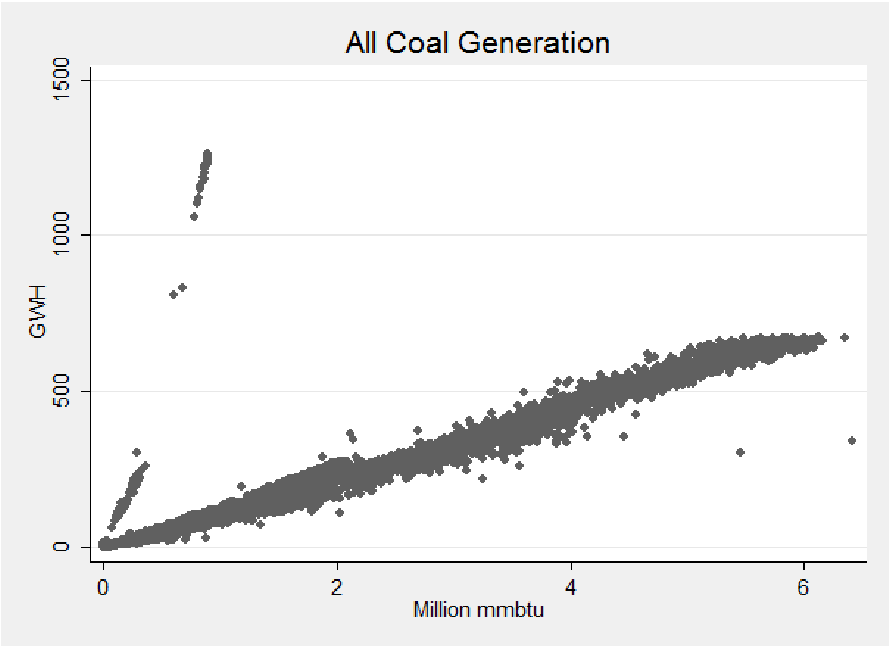


Chart 5-16: Monthly Heat Input million mmBtu to GWh for 3179

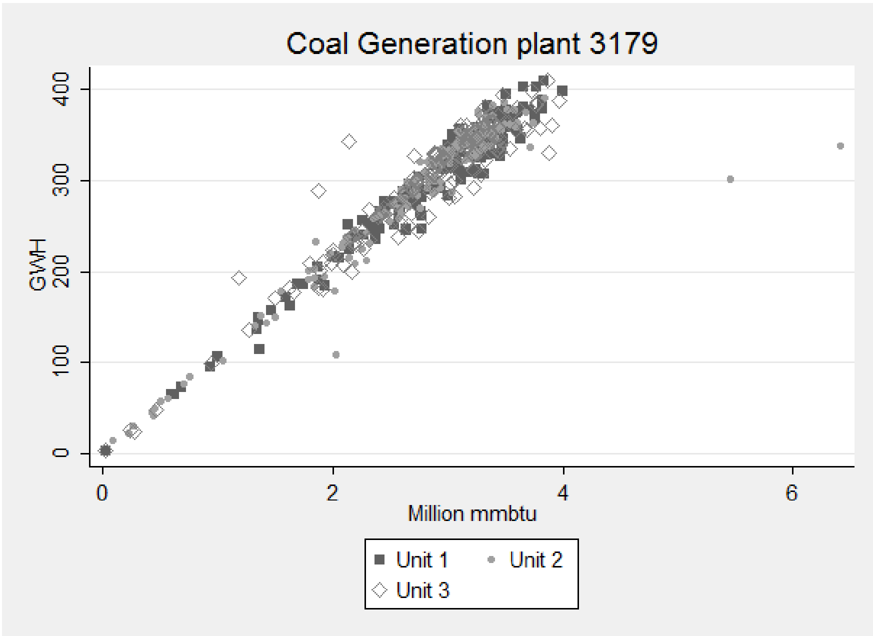


Chart 5-17: Monthly Heat Input million mmBtu to GWh for 54634

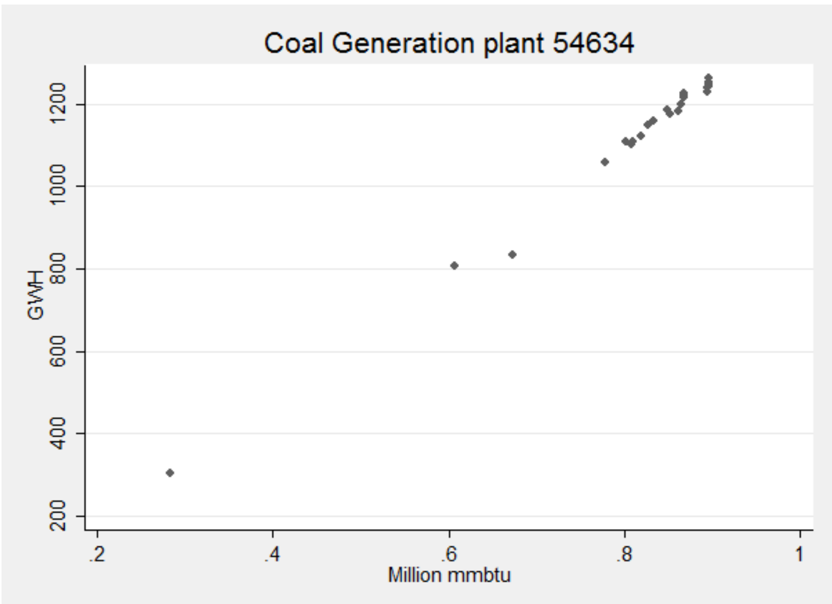


Chart 5-18: Monthly Heat Input million mmBtu to GWh for 6082

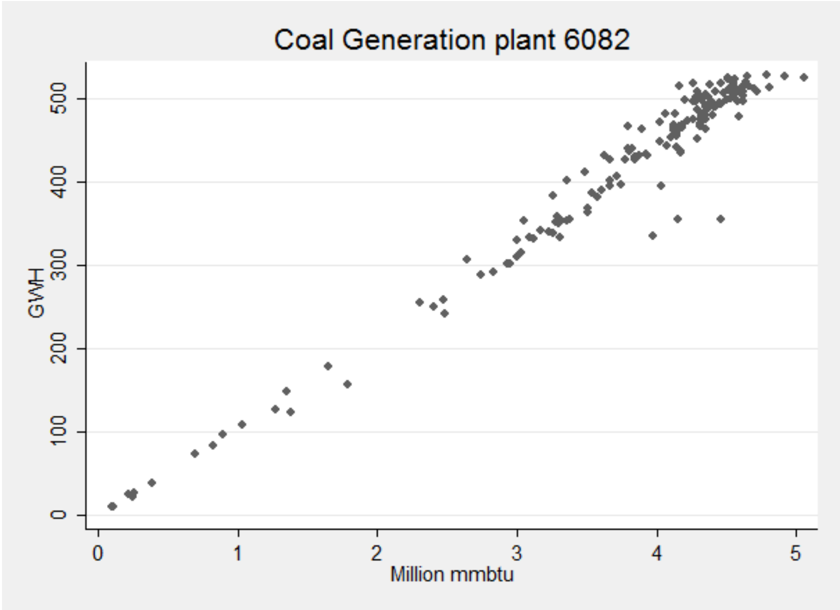


Chart 5-19: Monthly Heat Input million mmBtu to GWh for Oil

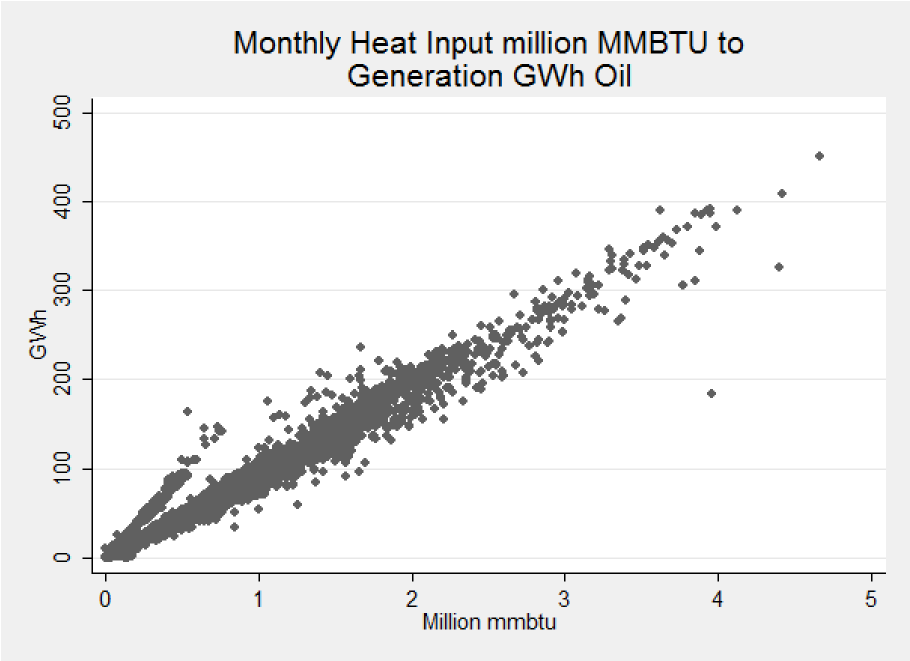


Chart 5-20: Monthly Heat Input million mmBtu to GWh for 2516

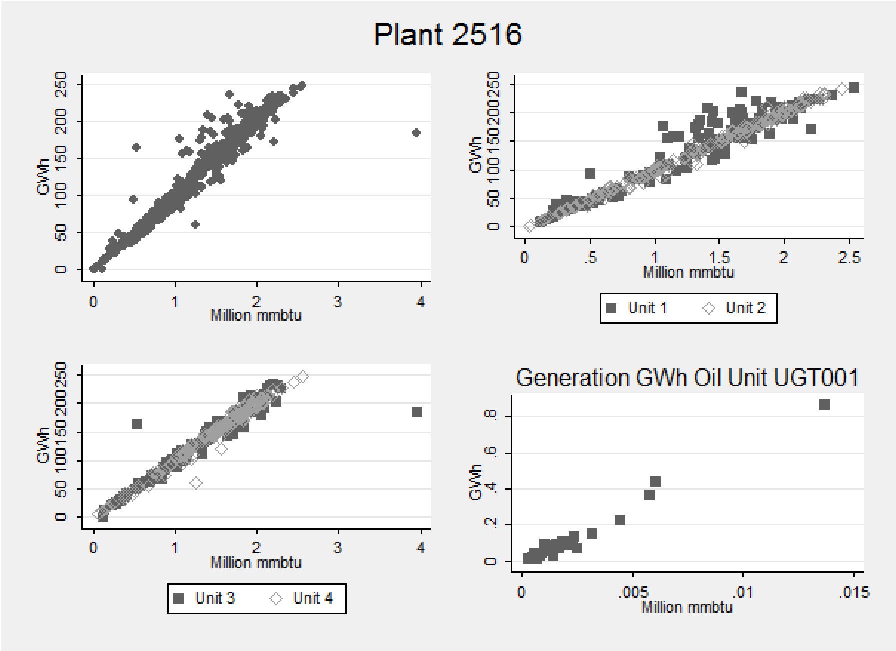


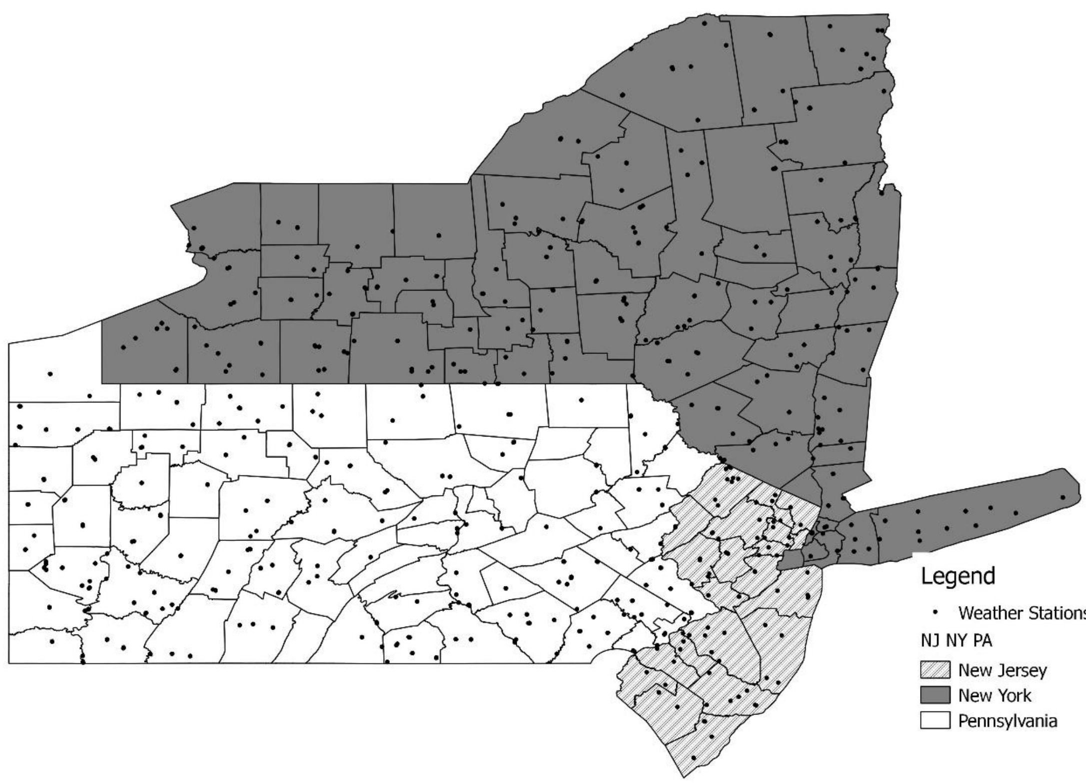
Table 5-21: Counties with Generation from AMPD not Matching NEI

County	FIPS	Fuel	Generation MWh 2008	Generation MWh 2011
Cattaraugus, NY	36009	gas	285,245	148,031
Clinton, NY	36019	gas	2,100,000	392,227
Genesee, NY	36037	gas	4,048	56,615
Hudson, NJ	34017	coal	2,400,000	NA
Jefferson, NY	36045	gas	5,207	7,119
Lebanon, PA	42075	gas	1,100,000	3,200,000
Lewis, NY	36049	gas	10,568	2,389
Niagara, NY	36063	gas	NA	54,861
Northumberland, PA	42097	coal	277,415	273,958
Oneida, NY	36065	gas	2,630	3,163
Saint Lawrence, NY	36089	gas	2,397	2,424
Saratoga, NY	36091	gas	782,576	906,106
Wyoming, PA	42131	gas	269,746	14,227
Wyoming, NY	36121	gas	6,985	386,397

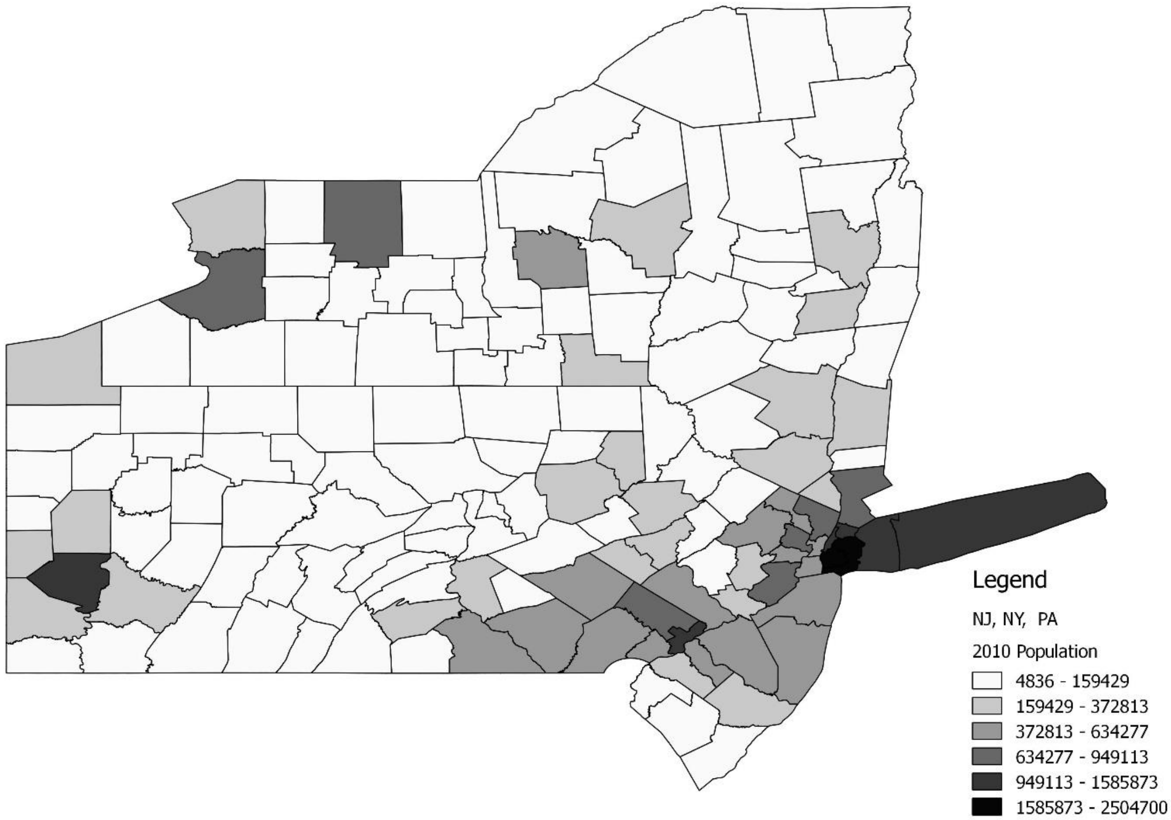
Table 5-22: Average 2008 and 2011 Generation and Yearly PM2.5 and PM10

State	Fuel	2008 and 2011 Generation GWh	2008 and 2011 PM2.5 tons	PM10 minus PM2.5 (tons)	PM2.5 lbs/GWh	PM10 lbs/GWh
NJ	coal	9,400	2,147	31	458.63	6.57
NY	coal	28,000	1,048	2,694	74.09	190.52
PA	coal	210,000	63,625	9,977	596.96	93.61
NJ	gas	33,000	1,179	4	70.82	0.25
NY	gas	79,000	2,408	115	60.96	2.92
PA	gas	51,000	1,431	125	56.34	4.93
NJ	oil	382	112	14	587.75	75.83
NY	oil	20,000	875	223	89.67	22.85
PA	oil	1,500	253	78	329.10	101.88

Map 5-23: Weather Stations in New Jersey, New York, and Pennsylvania from 2000 to 2013



Map 5-24: Population by County for New Jersey, New York, and Pennsylvania in 2010



Chapter 6 RGGI's Effects on Health

To be able to assess the health effects of RGGI a series of methodological steps must be made. First, it is necessary to estimate the effects on generation. There are two ways that RGGI can affect the behavior of power plants: by changing their decisions on when to produce electricity, and by changing the overall level of electricity generated. This analysis utilizes a Tobit random effects model for making estimates. The coefficients from this method are used to determine the effects of RGGI on generation at the county level. Following discussion of the generation calculations, the method for aggregating and valuing RGGI's health effects is presented. This step aggregates the changes in generation by plant and fuel and applies emissions coefficients to estimate overall changes in SO_2, NO_X, PM_{25}, and PM_{10} by county. These changes are then monetized using marginal damage estimates from Muller (2014). Total observed reductions are also calculated and presented, to better understand what has actually happened to generation in the states in the study.

6.1 Estimating the Effect of RGGI on Generation

The data set was split into two seasons, and the regressions were run separately on those sets. The two seasons were summer and all other months (not summer). These time periods were selected because: (1) there are practical reasons why the generation equations would be different due to different levels of demand and (2) at the national level there are seasonal programs to control ozone, which is not as much of a concern in the cooler months. Also, a Chow test showed that the coefficients for fuel price and generation from gas were different for the two regressions at a 5 percent confidence level, and that the coefficient for generation from coal was different for the two regressions at a 10 percent level.

6.1.1 Tobit Random Effects Model

The decision to run a power plant on a given day is complex, depending on the fuel used, time of year, anticipated demand, and characteristics of the individual plants such as age and technology. There are fixed costs of bringing a generator online so firms will only do it when the unit's generation is expected to exceed a threshold. Vella (1998) provides a survey of methods for correcting for selection bias. He reviews parametric, semi-parametric, and non-parametric methods. Two parametric methods that are often considered are the Tobit and Heckman (or Heckit) models.

Heckman (1976, 1979) corrects for selection bias by first creating a term to estimate the likelihood that an observation occurs in the sample. His approach uses the inverse Mill's ratio (λ_i) which Heckman points out has "several interesting properties" which are:

(1) Its denominator is the probability that observation *i* has data for Y_i.

(2) The lower the probability that an observation has data on Y_i the greater the value of $\lambda_{[i]}$ for that observation (1976, p. 479).

Probit can be used to obtain a consistent estimation of the inverse Mill's ratio (Heckman 1976, p. 481). However, one drawback of the Heckman approach is that it relies on normality and produces inconsistent estimators if this assumption fails (Vella, 1998, p. 131). Also, the Heckman approach requires variables that can be included in the selection equation that are not included in the effects model, but "there are frequently few candidates" in terms of variables that can be excluded from the effects model (Vella, 1998, p. 135).

There are other parametric, semi-parametric, and non-parametric approaches to estimating selection bias. For example Wooldridge (1995) and Semykina and Wooldridge (2010) have presented adaptations of the Heckman approach to be used with panel datasets with fixed effects. However, this type of approach required large amounts of computing power to employ.

There are potential problems with Tobit approach also. "Theoretically the standard Tobit model is applicable only if the underlying dependent variable contains negative values that have been censored to zero in the empirical realization of the variable" (Sigelman, and Zeng, p. 167, 1999). Ideally a fixed effects approach would be used to be able to control for estimations in this analysis. However, the Tobit model has problems because it uses a maximum likelihood estimator approach, and these suffer from bias when utilizing fixed effects. As Greene states, "The MLE/FEs of the slopes in the Tobit model seem not to be biased in either direction. However, the MLE/FE of the variance parameter in the Tobit model seems to be biased downward" (Greene, 2004, p. 127). The Heckman fixed effect approach also had problems in that when the fixed effects are added the regression for the summer fails to converge after 100 iterations.

Ultimately, a number of factors influenced which model was selected for this study. Besides the considerations given above, the data has a large amount of observations clustered at zero as can be seen in the histogram of the PDF see chart 6-1. Also, using the Heckman approach has proved to be infeasible due to problems with the model converging when capacity was controlled for in the effects equation as well as the selection equation. Due to these reasons, it was determined that the best approach to use was the Tobit model controlling for Random Effects at the county level.

The Tobit selection model describing a county's generation takes the form of:

6.1 $y_{i,t} = \alpha X_{i,t} + \beta V_i + \gamma T_t + u_{i,t},$ if $y_{i,t} > 2000$.

$y_{i,t}$ = 0 otherwise

The regressors vary based on different dimensions, and as such are broken up into three different vectors. The **X** vector contains the variables that change over both time and geography. Specifically, it contains variables for temperature (maximum and minimum), county population, the fuel dummies for coal and gas, and the RGGI interaction dummies. There are three variables for testing the interaction of RGGI with the three fuel types in the analysis, RGGI coal, RGGI, gas, and RGGI oil. The **V** vector contains the variables that vary by geography, but are set in time. These geography varying variables are the county dummies, and the average plant age in a county for each fuel source. For this analysis the plant age is set based on how old a plant was in 2014. The **T** vector consists of variables that change over time. Specifically, this vector contains the monthly fuel price for coal, gas, and oil, and year dummies for 2001 to 2013.

6.2 Results for Summer

The parameter estimates for the Tobit random effects equation for summer are shown in Table 6-2. In the summer regression, neither the maximum or minimum temperature coefficients are statistically significant. However, both coefficients are positive as would be expected. The population coefficient is positive and significant at the 5 percent level, and indicates that for every million people in a county, there is likely to be over 380,000 MWh of greater generation. For each year older the average age of units in a county are, the predicted generation falls by over 2,700 MWh, and is significant at the 1 percent level. Higher fuel price are also associated with lower generation for a fuel at the county level. For each dollar per mmBtu in price that a fuel rises, the model predicts a fall in generation of over 15,000 MWh, and is significant at the 1 percent level. Lastly, as the capacity of generation increases, generation will increase. The capacity in mmBtu shows that for every mmBtu of generation capacity, there will be an increase of about 35MWh in generation, which is significant at the 1 percent level.

The fuel coefficients are the most interesting ones for this study, as they allow us to understand the effects of RGGI. For the fuel variables both coal and gas are statistically significant at the 1 percent and 5 percent levels respectively. Both fuels generate more electricity compared to oil, coal producing nearly 230,000 MWh more than oil, and gas producing approximately 78,000 MWh more than oil. When RGGI is introduced both coal and oil generation fall, by over 88,000 and 89,000 MWh in a county respectively. Both variables are significant at the 1 percent level. RGGI has a different impact on gas generation, while not statically significant, the coefficient for gas is positive. During the summer months, RGGI has a large negative impact on coal and oil generation, which is not seen for gas generation. The overall, Sigma u, and panel-level variance, Sigma e, components indicate that about 40 percent of the variance is panel-level.

6.3 Results for Other Seasons

The parameter estimates for the Tobit random effects equation for non-summer months are shown in Table 6-3. In the non-summer regression, unlike above, both the maximum or minimum temperature coefficients are statistically significant at the 1 percent level. For the maximum temperature the model shows a negative correlation with generation, as the temperature goes up $1/10^{th}$ of a degrees centigrade, there is a reduction in generation by about 450 MWh, and generation goes up by the same amount for the minimum temperature variable. The population coefficient, like above, is positive and significant at the 5 percent level, and indicates that for every million people in a county, there is likely to be over 245,000 MWh more generation. For each year older the average age of units in a county are, the predicted generation falls by over 3,500 MWh, more than during the summer, and is significant at the 1 percent level. Again, higher fuel price are also associated with lower generation for a fuel at the county level. For each dollar per mmBtu in price that a fuel rises, the model predicts a fall in generation of over 18,000 MWh, and is significant at the 1 percent level. Further, as the capacity of generation increases, generation will increase. The capacity in mmBtu shows that for every mmBtu of generation capacity, there will be an increase of about 31 MWh in generation, and this variable is again significant at the 1 percent level.

The fuel coefficients are qualitatively similar to those for the summer months. For the fuel variables both coal and gas are statistically significant at the 1 percent level. Both fuels generate more electricity compared to oil, coal producing over 309,000 MWh more than oil, and gas producing over 111,000 MWh more than oil. When RGGI is introduced both coal and oil generation fall, by over 105,000 and 88,000 MWh respectively. Both variables are significant at the 1 percent level. For the non-summer months, the RGGI impact on gas is significant at the 10 percent level, and shows that gas generation will increase by over 10,000 MWh a month. The coefficients again demonstrate that when RGGI is introduced there will be a shifting in electricity generation away from coal and oil, and towards gas. The overall, Sigma u, and panel-level variance, Sigma e, components indicate that about a third of the variance is panel-level.

6.4 Linking Changes in Generation to Effects on Health

RGGI's effects on health were calculated for each of the models above using a four-step process. First, fitted values for generation at each location were compared with counterfactual values obtained by setting the RGGI variables in each equation to zero. Second, these changes were aggregated to the county level (not necessary for the county-level model). Third, county-level changes in generation were used to compute changes in emissions of NO_X, SO_2, $PM_{2.5}$ and

PM_{10}. Finally, these changes were monetized using county-specific marginal damages taken from Muller (2014). This section presents the steps in detail.

Let expected generation by unit *i* in county *c* using fuel *f* at time *t* be $y^*_{i,c,f,t}$. Aggregating to the county level by summing over by unit, and time period gives overall fitted county generation:

6.5 $CG^*{}_{c,f} = \sum_{i,t} y^*{}_{i,c,f,t}$

Next, the counter-factual generation, y^{*CF}, was calculated by setting the RGGI fuel interaction dummy variables, RGGI_Coal, RGGI_Gas, and RGGI_Oil, to 0 and predicting generation levels again. Again these values were aggregated to the county level, giving us the counterfactual county generation:

6.6 $CG^{*CF}{}_{c,f} = \sum_{i,t} y^{*CF}{}_{i,c,f,t}$

For each county the RGGI effect by fuel is thus:

6.7 $RGGI\_Generation\_Effect_{c,f} = CG^{*CF}{}_{c,f} - CG^*{}_{c,f}$

As shown in Equation 6.8, changes in emissions are calculated by multiplying RGGI's generation effect by the average CO_2, NO_X, and SO_2 emissions rates for each fuel using the average EPA emissions coefficients presented in Chapter 5, in sections 5.1.3. This approach was used rather than unit-specific emissions rates because no data was available on units that did not run. The rates are similar to overall estimates from the EPA (see Table 6-4). Section 5.2 shows the emission rates used for $PM_{2.5}$ and PM_{10} (Table 6-5)

6.8 $\text{Emissions}_{f,c} = \text{RGGI\_Generation\_Effect}_{f,c} * \text{Emission\_Rate}_f$

Changes in emissions were then converted to monetized changes in health using location-specific damages from Muller's (2014) APEEP, or AP2, model[8]. This approach is used due to the thoroughness of his model, and because it has marginal damages available at the county level. Muller's model makes use of highly detailed information about specific pollutant sources: "nearly 10,000 individual and grouped sources are attributed a unique marginal damage" (Muller, 2014, p. 472) and uses air transport modeling to predict changes in ambient concentrations of pollutants resulting from emissions in different counties. Muller then uses "[c]ounty-level inventories of people, agricultural crops and commercial timber" with these ambient concentration levels to predict exposure rates (2014, p. 473). These rates are then used to estimate the change in morbidity and mortality rates resulting from exposure to these pollutants, as well as the other relatively minor damages mentioned above. Finally, the changes in rates are monetized, giving a marginal damage cost for each county of each of the following pollutants: NH_3 (ammonia), PM 2.5 and PM10, NO_X, SO_2, and VOC (volatile organic compounds, a precursor to ozone) (Muller, 2014). Table 6-6 presents the top 20 counties in terms of SO_2 marginal damages, and Table 6-7 has the top 20 counties in terms of NO_X marginal damages, as estimated by Muller (2014). As can be seen in in Tables 6-6 and 6-7, the damages are most severe in urban areas where there is high population density.

To calculate the net health benefits, *B*, for county *c*, the county's emissions are summed over fuel types *f* and then multiplied by Muller's marginal damages for the county (referred to here as Muller's Marginal Damages or MMD).

6.9 $B_c = \sum_f Emissions_{f,c} * MMD_c$

[8] APEEP model information is available from Nick Muller's webpage: https://sites.google.com/site/nickmullershomepage/home/ap2-apeep-model-2 and allows for replication of Muller 2014.

6.5 Historical Change Effects on Health

To get a sense of how RGGI fits into the overall changes, comparing generation and pollution for periods both before and after RGGI for the states in the study is helpful. A three-year period before RGGI, 2005 to 2007, is compared with a three-year period with RGGI in effect, 2011 to 2013. This comparison is made by two different approaches. The first approach aggregates generation by fuel type for each state over both periods, and presents the generation differences and pollution estimates for each state. The second approach estimates potential changes due to individual plant changes in generation and in frequency of operation. The results are presented for summer and non-summer months to be more comparable to the results from the regressions presented in this chapter.

6.5.1 Historical Changes in the Summer

As shown in Table 6-8, historical average summer changes between these two periods show that there were large differences in generation for these states. As discussed in the data construction chapter, this was not unexpected. The changes in Table 6-8 show each state had large reductions in the average amount of generation, and associated pollution, during the summer. New York's overall reduction in fossil fuel generation was over ten times as much as Pennsylvania's even though Pennsylvania generates much more electricity with fossil fuels than New York. In Table 6-9 we can see that the changes vary by fuel. In New Jersey the generation falls for each fuel class considered in the analysis, while for both New York and Pennsylvania coal and oil generation falls while gas generation increases. As a result, all of the states in the analysis see a large decrease in CO_2, NO_X, SO_2, PM_{10}, and $PM_{2.5}$ emitted.

The second way of analyzing the changes for each state is to decompose total changes in generation into two components. The first component is the "intensity" change, or the change due to raising or lowering a running plant's output. The second component is the "switching" change, which is the change in generation due to a plant switching on or off.

These components are derived by defining the total generation, Q, for a time period as:

6.10 $Q_i = n_i \times A_i$

Where n is the number of months that the plant runs in the time period and A is the average monthly generation in MWh. With some simple algebra it can be shown that the change in generation, ΔQ, between the two periods can be decomposed as follows:

6.11 $\Delta Q = n_2 \times A_2 - n_1 \times A_1$

6.12 $\Delta Q = n_2 \times A_2 - n_1 \times A_1 + (n_2 \times A_1 - n_2 \times A_1)$

6.13 $\Delta Q = n_2 \times \Delta A + \Delta n \times A_1$

Where $n_2 * \Delta A$ is the change in intensity for plants running in period 2, and $\Delta n * A_1$ is the switching part of the change for plants running in period 1. The results of these calculations for the summer can be found in Table 6-10 below. As can be seen in the table, there were significant decreases for coal and oil in all three states in the analysis. Also, while the overall change in gas was positive for all three states, there were differences in the mix of intensity and switching changes. For New Jersey and New York both the switching and intensity components of the changes were positive, while for Pennsylvania the switching component was negative while the intensity change was positive.

6.5.2 Historical Changes in Other Months

For the non-summer months there have also been large reductions in overall generation for all three states (see Table 6-11). Again, the largest overall reduction came in New York. In all three states there were reductions in generation from coal and oil, and increases in generation from gas. All states saw large reductions in emissions of CO_2, SO2, NO_X, PM_{10}, and $PM_{2.5}$. While Pennsylvania saw growth in overall generation, it was due to the increases in gas out pacing the decreases in oil and coal, which can be seen in Table 6-12.

As with the summer data, each state's generation change was also broken down into components due to switching and intensity changes. These components have a slightly different pattern than seen above for the summer. Both components of generation change for coal and oil are negative for all states (see Table 6-13). Also, all states have positive components for gas.

6.5.3 Total Value of Historical Changes

These changes in generation and pollution result in significant improvements in terms of health effects for all three states in the study. All three states had positive overall effects. The largest overall value gain occurred in New York, which is estimated to have over $1.189 billion worth of positive health impacts yearly. Pennsylvania is estimated to have over $741 million worth of positive health impacts, and New Jersey is estimated to have nearly $267 million. Most of the value comes from reductions in SO_2 compared to NO_X, PM_{10}, or $PM_{2.5}$ (see Table 6-14).

The monetary value of the health changes that result from these changes in pollution levels vary by location and can be negative as well as positive. The largest negative value occurs in Bucks County, Pennsylvania, which had over $7 million worth of damages. While the largest value occurs in Queens which saw a large amount of oil generation go off line with over $759 million worth of benefits. Results for all three states are presented in Tables 6-15, 6-16, and 6-17 below. New Jersey and New York are of particular interest as the changes they experienced place an upper bound on the effect of RGGI. As mentioned above, this provides a check on the benefits estimated in this study.

6.6 Conclusion Regarding RGGI's Health Effects

The Tobit model described above in section 6.1.1 with the results presented in sections 6.2 and 6.3, was used also linked with health benefits using the method described in section 6.4. Overall, the model predicts over $60 million in annual benefits in New Jersey, and nearly $70 million in benefits in New York from RGGI. Between New Jersey and New York, the total estimated RGGI benefits under the county-level Tobit model account for approximately 9% of the benefits from the total change for those two states. The benefits were not evenly distributed within the two states (see Tables 6-18 and 6-19). While some counties have large benefits there are some counties that suffer damages due to RGGI, due to increased gas generation occurring in their boundaries. Not all counties benefit from RGGI, as can be seen in table 6-18, the largest damages occur in Bergen County New Jersey, which has over $600,000 worth damages. However, the overall benefits greatly outweigh the damages.

Mercer County in New Jersey had the largest overall value from changes due to RGGI at over $29 million worth of estimated benefits, the overall average yearly change in this time period was approximately $95 million. Queens is predicted to have the largest total benefit in New York, approximately $20 million. This is due to the large reductions in generation from oil which occurred there. The total change in value of health damages for Queens during this time is estimated at over $700 million, so this is feasible. Overall, the benefits outside those two counties are largely concentrated in the western counties of New York, south central New York, and near New York City (which are largely from Queens). Most of New Jersey's benefits occur in Mercer and Hudson, and most benefits occur in the central and southern part of the state. Map 6-20 also demonstrates that the vast majority of benefits come for SO_2 reductions, as opposed to the other pollutants.

In summary, an important side effect of programs to reduce CO_2 emissions is the ancillary benefits the produce as a result of reductions in coal and oil combustion. Previously, Burtraw, et al. estimated that ancillary health benefits from a $25 per ton carbon tax would be approximately $8 per metric ton of carbon for reductions in NO_X abated (1997 dollars) though their model did not predict aggregate reductions in SO_2 (p. 651, 2003). The present study estimates benefits of approximately $26 per short ton ($29 per metric ton) of carbon avoided in benefits from NO_X, SO_2, $PM_{2.5}$, and PM_{10} reductions. Most of the benefits coming from reductions in SO_2, which accounted for approximately $24 per short ton of benefits. The benefits are large despite the much lower auction prices of RGGI allowances, which had a maximum value of less than $4 over the study period. However, while the Muller marginal damages are mostly due to negative health impacts, they do include more than just the health effects used in Burtraw et al., and are also specific to an area that is likely to have higher than average damages due to its high population density.

Chart 6-1: Probability Distribution Function of Generation Data

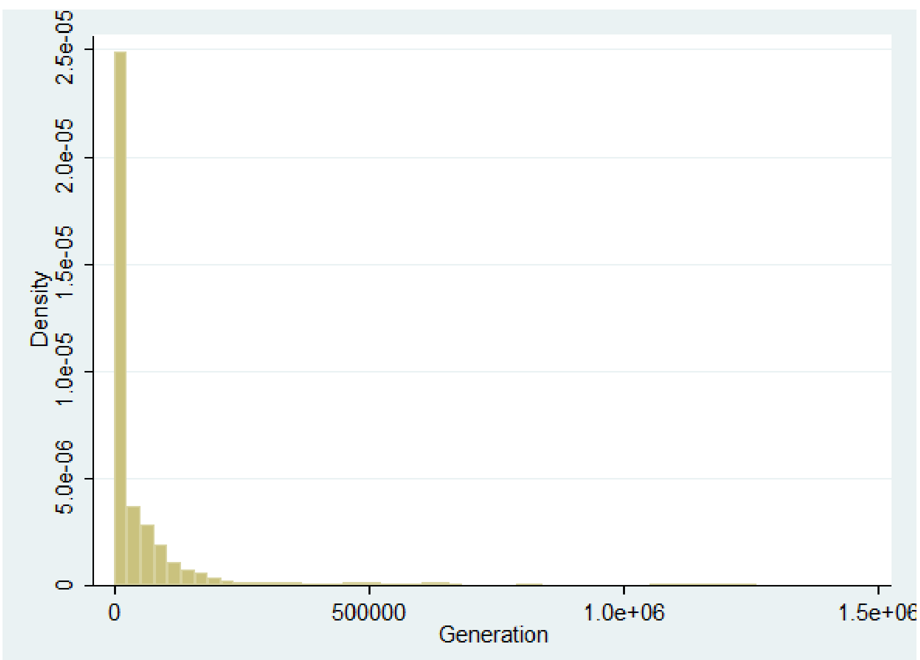


Table 6-2: Tobit Random Effects County Summer Months

Number of observations = 5050 Number of groups = 123		
Wald chi2(105) = 3245.00 Prob > Chi2 = 0.000		
Log Likelihood = -50919.293		
	Coefficient	Standard Error
Temp Max	37.98	172.52
Temp Min	64.67	193.17
Population	384667.6**	156118.20
Coal	229063.39***	33411.46
Gas	77726.39**	36824.53
RGGI Coal	-88148.15***	12176.56
RGGI Gas	6071.98	8476.68
RGGI Oil	-89554.05***	14400.28
Age	-2734.61**	1123.99
Fuel Price	-15718.01***	1282.20
Capacity (mmBtu)	35.82***	1.21
sigma u	91151.94***	6191.70
sigma e	111603.63***	1294.63
Rho	0.400	0.033

* p<0.10, ** p<0.05, *** p<0.01

NOTE: Yearly and county dummy variables not shown.

Table 6-3: Tobit Random Effects for Non-Summer Months

Number of observations = 15079 Number of groups = 123		
Wald chi2(105) = 4110.82 Prob > Chi2 = 0.000		
Log Likelihood = -126133.36		
	Coefficient	Standard Error
Temp Max	-447.248***	83.474
Temp Min	458.887***	96.378
Population	245461.3**	115349.4
Coal	309062.8***	33707.33
Gas	111592.8***	35348.96
RGGI Coal	-105218.1***	8650.804
RGGI Gas	10635.84*	6088.894
RGGI Oil	-88767.9***	11857.94
Age	-3531.642***	982.663
Fuel Price	-18313.7***	958.336
Capacity (mmBtu)	31.045***	0.940
sigma u	93422.02***	6191.70
sigma e	131217.0***	1294.63
Rho	0.336	968.3724

* p<0.10, ** p<0.05, *** p<0.01

NOTE: Yearly and county dummy variables not shown.

Table 6-4: Emissions Rates for SO2, NOX, and CO2

State	Fuel	SO_2 lbs/Mwh	NO_X lbs/MWh	CO2 tons/MWh
NJ	coal	10.98	4.00	1.11
NJ	gas	0.02	0.45	0.53
NJ	oil	4.55	2.68	0.96
NY	coal	10.15	2.53	0.98
NY	gas	0.07	0.39	0.60
NY	oil	6.08	1.69	1.19

State	Fuel	SO_2 lbs/MWh	NO_X lbs/MWh	CO_2 tons/MWh
PA	coal	12.90	2.70	0.98
PA	gas	0.01	0.17	0.53
PA	oil	7.66	3.00	1.64
EPA	coal	13.00	6.00	1.12
EPA	gas	0.10	1.70	0.57
EPA	oil	12.00	4.00	0.84

Table 6-5: Emission Rates for PM2.5 and PM10

State	Fuel	$PM_{2.5}$ lbs/GWh	PM_{10} lbs/GWh
NJ	coal	458.63	6.57
NY	coal	74.09	190.52
PA	coal	596.96	93.61
NJ	gas	70.82	0.25
NY	gas	60.96	2.92
PA	gas	56.34	4.93
NJ	oil	587.75	75.83
NY	oil	89.67	22.85
PA	oil	329.10	101.88

Table 6-6: Top 20 Marginal Damage Counties for SO2 (from Muller 2014)

State	County	NOX	SO2
California	Los Angeles County	$109	$43,344
New York	Queens County	$3,855	$22,109
New York	Kings County	$3,422	$17,878
New Jersey	Bergen County	$3,516	$17,359
California	San Diego County	$120	$14,459
New Jersey	Essex County	$2,311	$12,372
New York	Nassau County	$1,910	$12,337
New Jersey	Hudson County	$2,450	$12,281
California	Orange County	-$204	$11,905
California	Contra Costa County	$556	$10,157
New Jersey	Union County	$1,742	$10,128
New York	New York County	$1,461	$9,888
District of Columbia	District of Columbia	$96	$9,814
California	Riverside County	$181	$9,183
New Jersey	Passaic County	$1,531	$8,849
California	Santa Clara County	$220	$8,513
California	San Francisco County	$308	$8,305
New Jersey	Morris County	$1,283	$8,304
New York	Bronx County	$1,099	$8,258

Table 6-7: Top 20 Marginal Damage Counties for NOX (from Muller 2014)

State	County	NOX	SO2
New York	Queens County	$3,855	$22,109
Minnesota	Anoka County	$3,582	$6,653
New Jersey	Bergen County	$3,516	$17,359
Minnesota	Hennepin County	$3,477	$6,644
New York	Kings County	$3,422	$17,878
Minnesota	Wright County	$2,714	$5,074
Minnesota	Ramsey County	$2,578	$5,167
New Jersey	Hudson County	$2,450	$12,281
Minnesota	Dakota County	$2,408	$4,784
New Jersey	Essex County	$2,311	$12,372
Minnesota	Washington County	$2,269	$4,568
Missouri	Perry County	$2,197	$4,284
Illinois	Randolph County	$2,095	$4,095
Texas	Fort Bend County	$1,971	$6,201
New York	Nassau County	$1,910	$12,337
Missouri	Jackson County	$1,869	$1,309
Missouri	St. Louis County	$1,858	$3,913
Missouri	Clay County	$1,846	$1,269
New Jersey	Union County	$1,742	$10,128

Table 6-8: Average Yearly Generation and Pollution Change for Summer Months State Totals

State	Change in Generation	Change in CO_2	Change in SO_2	Change in NO_X	Change in PM_{10}	Change in $PM_{2.5}$
NJ	-553,486	-1,137,384	-10,250	-3,703	-133	-29
NY	-4,652,997	-6,280,744	-53,500	-18,500	-487	-227
PA	-419,989	-3,775,175	-42,550	-14,200	-590	-59
Total	-5,626,472	-11,193,303	-106,300	-36,403	-1,211	-315

Note: Generation in MWh, CO_2, SO_2, NO_X, PM_{10}, and PM_{25} are all given in short tons.

Table 6-9: Average Yearly Generation and Pollution Change for Summer Months by Fuel and State

State	Fuel	Change in Generation	Change in CO_2	Change in SO_2	Change in NO_X	Change in PM_{10}	Change in $PM_{2.5}$
NJ	coal	-1,391,154	-1,558,093	-9,050	-4,173	-133	-51
NJ	gas	1,047,897	597,302	52	891	2	32
NJ	oil	-210,230	-176,593	-1,261	-420	-2	-9
NY	coal	-4,714,499	-5,280,239	-30,650	-14,150	-449	-174
NY	gas	3,896,912	2,221,240	195	3,312	6	119
NY	oil	-3,835,410	-3,221,744	-23,000	-7,650	-44	-172
PA	coal	-6,243,366	-6,992,570	-40,600	-18,750	-595	-231
PA	gas	6,200,896	3,534,510	310	5,250	9	189
PA	oil	-377,518	-317,115	-2,265	-755	-4	-17

Note: Generation in MWh, CO_2, SO_2, NO_X, PM_{10}, and PM_{25} are all given in short tons.

Table 6-10: Average Yearly Generation Switch and Intensity Changes

State	Fuel	Total Change in Generation (MWh)	Generation Switch Change	Generation Intensity Change
NJ	coal	-1,391,154	-287,154	-1,104,000
NJ	gas	1,047,897	41,866	1,006,031
NJ	oil	-210,230	-76,816	-133,414
NY	coal	-4,714,499	-2,781,874	-1,932,626
NY	gas	3,896,912	195,320	3,701,592
NY	oil	-3,835,410	-2,190,923	-1,644,487
PA	coal	-6,243,366	-2,481,471	-3,761,894
PA	gas	6,200,896	-30,648	6,231,544
PA	oil	-377,518	-121,237	-256,281
	Total	-5,626,472	-7,732,937	2,106,465

Figure 6-11: Average Yearly Generation and Pollution Change for Non-Summer Months State Totals

State	Change in Generation	Change in CO_2	Change in SO_2	Change in NO_X	Change in PM_{10}	Change in $PM_{2.5}$
NJ	-516,649	-2,922,039	-31,150	-10,700	-445	-48
NY	-10,626,245	-15,700,000	-137,000	-47,350	-1,345	-533
PA	1,373,062	-11,000,000	-139,500	-45,050	-1,995	-103
Total	-9,769,832	-29,622,039	-307,650	-103,100	-3,785	-683

Note: Generation in MWh, CO_2, SO_2, NO_X, PM_{10}, and PM_{25} are all given in short tons.

Table 6-12: Average Yearly Generation and Pollution Change for Non-Summer Months Fuel by State

State	Fuel	Change in Generation	Change in CO_2	Change in SO_2	Change in NO_X	Change in PM_{10}	Change in $PM_{2.5}$
NJ	coal	-4,726,322	-5,293,480	-30,700	-14,200	-450	-175
NJ	gas	4,313,644	2,458,777	216	3,667	6	132
NJ	oil	-103,971	-87,336	-624	-208	-1	-5
NY	coal	-13,256,968	-14,800,000	-86,000	-39,750	-1,263	-491
NY	gas	11,182,374	6,373,953	559	9,500	16	341
NY	oil	-8,551,651	-7,183,387	-51,500	-17,100	-97	-383
PA	coal	-21,235,240	-23,800,000	-138,000	-63,500	-2,024	-786
PA	gas	23,082,771	13,200,000	1,154	19,600	34	704
PA	oil	-474,468	-398,553	-2,847	-949	-5	-21

Note: Generation in MWh, CO_2, SO_2, NO_X, PM_{10}, and PM_{25} are all given in short tons.

Table 6-13: Average Yearly Generation Switch and Intensity Changes

State	Fuel	Total Change in Generation	Generation Switch	Generation Intensity
NJ	coal	-4,726,322	-2,312,618	-2,413,703
NJ	gas	4,313,644	441,285	3,872,358
NJ	oil	-103,971	-74,212	-29,759
NY	coal	-13,256,968	-8,171,759	-5,085,209
NY	gas	11,182,374	1,214,080	9,968,294
NY	oil	-8,551,651	-5,079,630	-3,472,021
PA	coal	-21,235,240	-8,608,379	-12,626,861
PA	gas	23,082,771	477,373	22,605,398
PA	oil	-474,468	-89,983	-384,485
	Total	-9,769,831	-22,203,843	12,434,012

Table 6-14: Average Yearly Value of SO2 and NOX Changes

State	SO_2	NO_X	PM_{10}	PM_{25}	Total
NJ	$258,500,000	$8,989,000	$1,321,000	-$1,831,000	$266,978,000
NY	$1,139,000,000	$39,300,000	$1,462,000	$10,216,000	$1,189,978,000
PA	$722,000,000	$18,460,000	$2,074,000	-$1,531,000	$741,003,000
Total	$2,119,500,000	$66,748,000	$4,858,000	$6,853,000	$2,197,959,000

Table 6-15: Average Yearly Monetary Value of Changes by County for New Jersey

State	County	SO_2	NO_X	PM_{10}	$PM_{2.5}$	Total
NJ	Atlantic	$40,586	$1,261	$16	$752	$42,615
NJ	Bergen	-$986,870	-$3,398,316	-$11,694	-$2,507,962	-$6,904,843
NJ	Burlington	$294,176	$51,968	$403	$75,120	$421,668
NJ	Camden	-$68,214	-$83,501	-$687	-$165,810	-$318,212
NJ	Cape May	$22,020,590	$978,378	$51,587	$266,038	$23,316,593
NJ	Cumberland	$1,898,853	$66,295	$3,941	$14,994	$1,984,084
NJ	Essex	-$228,309	-$725,133	-$2,738	-$604,440	-$1,560,620
NJ	Gloucester	$26,170	$34,472	$194	$46,885	$107,720
NJ	Hudson	$126,600,000	$10,472,092	$874,450	$2,230,851	$140,177,393
NJ	Hunterdon	$17,004	$36,766	$130	$30,246	$84,146
NJ	Mercer	$89,200,000	$4,474,216	$365,703	$1,621,798	$95,661,717
NJ	Middlesex	$7,858,732	-$638,908	$1,496	-$635,082	$6,586,237
NJ	Ocean	$316,296	-$74,945	-$186	-$79,916	$161,250
NJ	Salem	$12,510,242	$455,137	$48,736	$121,783	$13,135,898
NJ	Union	-$910,299	-$2,661,005	-$10,021	-$2,246,923	-$5,828,249
	Total	$258,588,956	$8,988,778	$1,321,329	-$1,831,664	$267,067,399

Table 6-16: Average Yearly Monetary Value of Changes by County for New York

State	County	SO_2	NO_X	PM_{10}	$PM_{2.5}$	Total
NY	Albany	-$42,797	-$85,740	-$714	-$189,055	-$318,306
NY	Allegany	$2,400	$4,002	$9	$2,178	$8,589
NY	Bronx	$31,426	$71,095	$388	$82,472	$185,381
NY	Broome	$963	$1,336	$5	$1,211	$3,515
NY	Cattaraugus	$390	$498	$2	$502	$1,392
NY	Chautauqua	$30,665,403	$1,348,047	$52,170	$245,095	$32,310,716
NY	Clinton	$62,096	$93,100	$260	$61,282	$216,738
NY	Erie	$26,040,674	$960,708	$75,473	$380,223	$27,457,079
NY	Genesee	-$2,611	-$6,744	-$13	-$3,241	-$12,609
NY	Greene	-$40,625	-$35,196	-$245	-$61,675	-$137,739
NY	Herkimer	$886	$1,031	$4	$987	$2,908
NY	Jefferson	$25,641,902	$1,015,411	$46,709	$213,334	$26,917,357
NY	Kings	$9,745,837	$1,149,087	$10,957	$813,852	$11,719,732
NY	Lewis	$1,370	$1,689	$5	$1,292	$4,355
NY	Monroe	$14,792,083	$605,878	$45,079	$217,727	$15,660,768
NY	Nassau	$963,716	$703,281	$3,657	$692,553	$2,363,207
NY	New York	-$125,288	-$540,640	-$2,755	-$553,065	-$1,221,748
NY	Niagara	$34,498,948	$1,683,059	$77,704	$420,704	$36,680,415
NY	Oneida	$108	$139	$0	$123	$372
NY	Onondaga	$32,634	$41,174	$178	$45,586	$119,573
NY	Orange	$88,800,000	$4,734,868	$206,103	$1,527,568	$95,268,539
NY	Oswego	$4,325,054	-$169,703	$394	-$213,961	$3,941,784
NY	Queens	$733,000,000	$21,033,603	$588,029	$4,812,888	$759,434,520
NY	Rensselaer	-$299,555	-$270,524	-$1,890	-$474,421	-$1,046,390
NY	Richmond	-$98,323	-$231,993	-$1,077	-$233,681	-$565,075
NY	Rockland	$84,400,000	$5,453,862	$273,240	$1,308,243	$91,435,345
NY	Saint Lawrence	$1,984	$3,013	$6	$1,373	$6,375
NY	Saratoga	-$14,189	-$14,546	-$81	-$20,025	-$48,841
NY	Suffolk	$59,400,000	$488,659	$27,924	$852,858	$60,769,441
NY	Tompkins	$19,007,892	$747,407	$43,442	$200,559	$19,999,300
NY	Wyoming	$1,732	$3,556	$7	$1,870	$7,165
NY	Yates	$7,655,334	$425,161	$17,193	$80,492	$8,178,180
	Total	$1,138,449,445	$39,214,578	$1,462,163	$10,215,849	$1,189,342,035

Table 6-17: Average Yearly Monetary Value of Changes by County for Pennsylvania

State	County	SO_2	NO_X	PM_{10}	$PM_{2.5}$	Total
PA	Adams	-$375,266	-$791,341	-$1,934	-$489,745	-$1,658,286
PA	Allegheny	$6,373,797	-$112,692	$19,014	-$578,062	$5,702,057
PA	Armstrong	$55,100,000	$2,227,946	$113,622	$559,410	$58,000,977
PA	Beaver	$8,560,634	$363,090	$21,821	$114,337	$9,059,882
PA	Berks	$31,678,003	$835,932	$90,443	-$214,788	$32,389,590
PA	Bucks	-$1,555,689	-$2,091,217	-$14,193	-$3,496,875	-$7,157,975
PA	Cambria	-$1,822,659	-$69,695	-$4,142	-$21,630	-$1,918,126
PA	Chester	$29,899,654	$1,093,358	$86,814	$509,861	$31,589,686
PA	Clarion	$1,145,338	$48,426	$2,271	$11,333	$1,207,368
PA	Clearfield	$33,777,758	$1,410,771	$58,976	$286,429	$35,533,934
PA	Cumberland	$58,531	$2,591	$19	$910	$62,051
PA	Delaware	$110,800,000	$2,202,223	$490,142	$327,647	$113,820,012
PA	Erie	$2,910	$5,018	$12	$3,303	$11,243
PA	Fayette	-$476,269	-$701,466	-$1,900	-$523,169	-$1,702,804
PA	Franklin	$12,086	$25,173	$52	$13,184	$50,495
PA	Greene	-$3,688,779	-$142,974	-$7,815	-$39,801	-$3,879,369
PA	Indiana	$130,300,000	$3,830,219	$317,448	$1,688,017	$136,135,684
PA	Lackawanna	$1,307	$2,550	$7	$1,830	$5,694
PA	Lawrence	$17,204,198	$858,979	$38,956	$204,260	$18,306,393
PA	Lebanon	-$355,398	-$798,669	-$2,043	-$534,147	-$1,690,258
PA	Luzerne	$6,133,874	$163,783	$15,750	-$3,187	$6,310,221
PA	Montour	$49,742,701	$3,265,514	$129,908	$666,661	$53,804,784
PA	Northampton	$89,500,000	$1,222,304	$294,691	-$1,391,559	$89,625,436
PA	Northumberland	$476,788	$27,757	$1,133	$5,589	$511,266
PA	Philadelphia	$3,387,002	-$81,119	$798	-$370,605	$2,936,077
PA	Schuylkill	$61,262	$3,468	$167	$820	$65,716
PA	Venango	$230	$381	$1	$239	$852
PA	Warren	-$139,271	-$4,811	-$29	-$1,405	-$145,516
PA	Washington	$87,100,000	$1,794,329	$243,427	$1,309,338	$90,447,093
PA	Wyoming	-$7,451	-$14,077	-$36	-$8,972	-$30,536
PA	York	$69,500,000	$3,915,329	$181,059	$439,519	$74,035,907
	Total	$722,395,288	$18,491,081	$2,074,438	-$1,531,261	$741,429,545

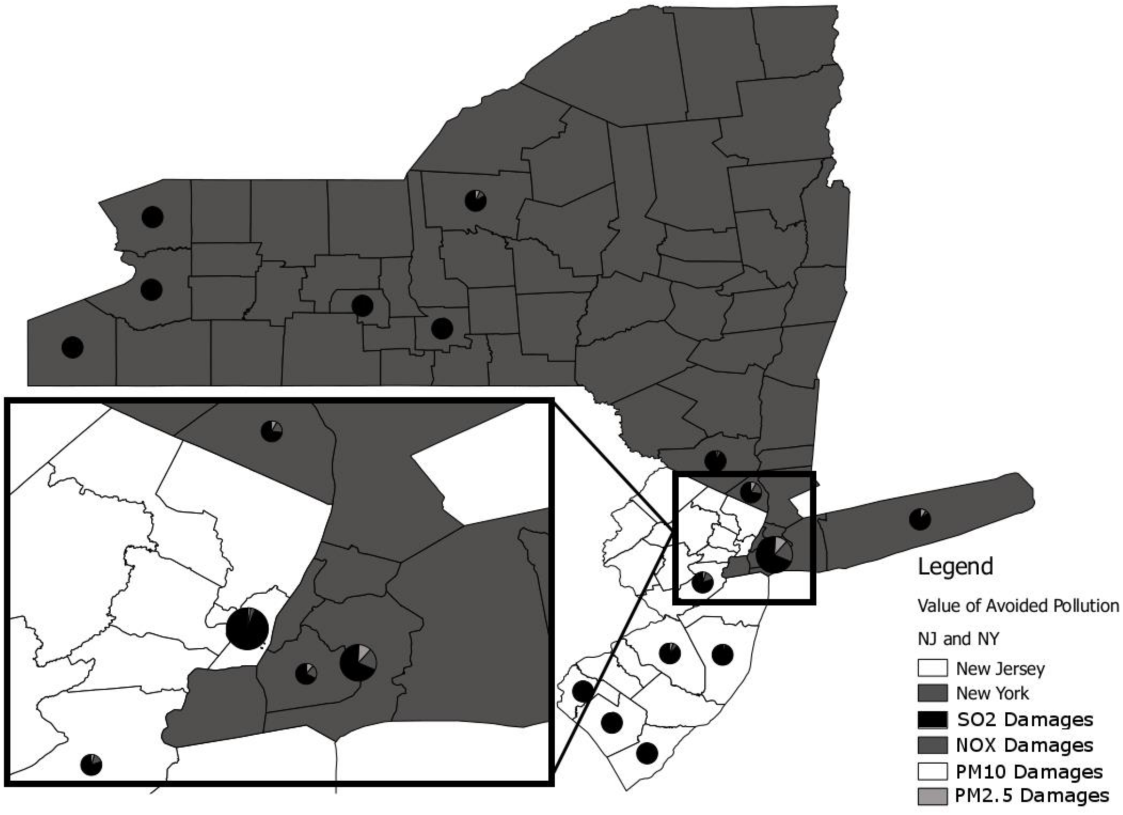
Table 6-18: Average Estimated Yearly Value of Changes by County for New Jersey using Tobit County Model

State	County	SO_2	NO_X	$PM_{2.5}$	PM_{10}	Total
NJ	Bergen	-$44,309	-$320,851	-$240,853	-$1,123	-$607,135
NJ	Burlington	$39,019	-$3,170	-$8,129	$51	$27,771
NJ	Camden	-$5,624	-$14,477	-$29,242	-$121	-$49,465
NJ	Cape May	$7,132,193	$144,867	$75,763	$15,381	$7,368,204
NJ	Cumberland	$411,266	$6,414	$2,626	$975	$421,280
NJ	Essex	-$18,962	-$126,643	-$107,376	-$487	-$253,468
NJ	Gloucester	-$3,912	-$11,480	-$15,890	-$66	-$31,348
NJ	Hudson	$19,980,942	$730,360	$387,926	$119,305	$21,218,533
NJ	Hunterdon	-$943	-$4,289	-$3,589	-$16	-$8,837
NJ	Mercer	$27,929,295	$605,801	$441,188	$99,485	$29,075,769
NJ	Middlesex	$173,014	-$9,304	-$23,957	$356	$140,109
NJ	Ocean	$19,367	-$7,797	-$9,483	$0	$2,087
NJ	Salem	$2,900,821	$51,409	$41,707	$9,831	$3,003,768
NJ	Union	-$13,487	-$82,910	-$71,211	-$318	-$167,926
		$58,498,678	$957,930	$439,479	$243,255	$60,139,343

Table 6-19: Average Estimated Yearly Value of Changes by County for New York using Tobit County Model

State	County	SO_2	NO_X	$PM_{2.5}$	PM_{10}	Total
NY	Albany	-$1,958	-$3,282	-$7,327	-$29	-$12,595
NY	Allegany	-$832	-$2,917	-$1,615	-$6	-$5,371
NY	Bronx	-$9,506	-$45,225	-$53,364	-$251	-$108,347
NY	Broome	-$3	-$9	-$9	$0	-$21
NY	Cattaraugus	-$2,666	-$7,156	-$7,342	-$27	-$17,190
NY	Chautauqua	$7,293,456	$138,820	$52,108	$10,765	$7,495,149
NY	Clinton	-$1,411	-$4,450	-$2,979	-$13	-$8,853
NY	Erie	$9,086,573	$144,434	$115,441	$22,816	$9,369,264
NY	Genesee	-$414	-$2,248	-$1,098	-$5	-$3,765
NY	Greene	-$4,764	-$8,680	-$15,471	-$62	-$28,976
NY	Jefferson	-$31	-$98	-$61	$0	-$190
NY	Kings	$1,967,751	$543,645	$260,435	$8,354	$2,780,184
NY	Lewis	-$43	-$111	-$87	$0	-$241
NY	Nassau	-$16,006	-$88,579	-$90,498	-$418	-$195,501
NY	New York	-$23,495	-$124,117	-$128,744	-$656	-$277,012
NY	Niagara	$6,907,606	$137,195	$63,800	$13,468	$7,122,070
NY	Oneida	-$179	-$486	-$437	-$1	-$1,104
NY	Onondaga	-$1,570	-$4,166	-$4,691	-$19	-$10,446
NY	Orange	$6,478,530	$316,816	$152,010	$19,352	$6,966,709
NY	Oswego	$741,301	$90,257	$53,030	$1,196	$885,785
NY	Queens	$13,944,874	$3,898,917	$2,253,767	$63,316	$20,160,874
NY	Rensselaer	-$3,547	-$6,736	-$12,015	-$48	-$22,345
NY	Richmond	-$12,832	-$63,664	-$65,229	-$301	-$142,026
NY	Rockland	$181,093	$45,101	$17,878	$453	$244,525
NY	Saint Lawrence	-$16	-$52	-$24	$0	-$92
NY	Saratoga	-$884	-$1,905	-$2,668	-$11	-$5,468
NY	Suffolk	$1,466,828	$76,375	$156,164	$3,578	$1,702,945
NY	Tompkins	$10,190,978	$172,946	$93,242	$20,197	$10,477,363
NY	Wyoming	-$473	-$2,041	-$1,092	-$4	-$3,609
NY	Yates	$3,276,032	$78,532	$29,872	$6,380	$3,390,817
	Total	$61,454,392	$5,277,118	$2,852,996	$168,026	$69,752,533

Map 6-20: Distribution of Benefits from RGGI New York Area Inset



Chapter 7 Testing for Emissions Leakage

One concern about RGGI and other regional cap-and-trade programs is that emissions-generating activities can move beyond the program's borders, a phenomenon known as "leakage". Under RGGI, leakage occurs if electricity that would otherwise have been generated in the capped region is imported from a non-capped region instead. This means that reductions in CO_2 may be counted as having occurred in the capped region even though in actuality the reductions were not realized because they happen in the uncapped region instead.

Testing for leakage—in this case, from New York to Pennsylvania—is very similar to the approach for testing for health effects presented in Chapter 6. Since the approach is parallel, this chapter will rely on Chapter 6 and discuss only a few adjustments to the model. In Chapter 6 it was argued that the best method to use for the analysis was the Tobit model at the county level. As such, this is model utilized to test for leakage. This model is run on both summer and non-summer months as they were in Chapter 6, and the results from these models are discussed.

7.1 Tobit Leakage Effects Model

The Tobit selection model used for testing leakage takes the form of:

7.1 $y_{i,t} = \alpha X_{i,t} + \beta V_i + \gamma T_t + u_{i,t}$, if $y_{i,t} > 2000$.

$y_{i,t} = 0$ otherwise

Equation 7.1 is very similar to equation 6.1, but with the RGGI regressors changed. As above, the regressors vary based on different dimensions, and as such are broken up into three different vectors. The **X** vector contains the variables that change over both time and geography. Specifically, it contains variables for temperature (maximum and minimum), county population, the fuel dummies for coal and gas, and the RGGI leakage dummies. The RGGI leakage dummies are based on county location geographically in a state. There are 5 county dummies used: New York inside counties, New York border counties, Pennsylvania border counties with New York, Pennsylvania inside counties, and Pennsylvania border counties with Maryland (see map 7-1). The **V** vector, is the same as in equation 6.1, and contains the variables that vary by geography, but are set in time. These geography varying variables are the county dummies, and the average plant age in a county for each fuel source. For this analysis the plant age is set based on how old a plant was in 2014. Lastly, as above, the **T** vector consists of variables that change over time. Specifically, this vector contains the monthly fuel price for coal, gas, and oil, and year dummies for 2001 to 2013.

7.2 Tobit Leakage Results Summer

The results of the Tobit random effects leakage regression for summer months can be seen in Table 7-2. Three of the control variables, maximum and minimum temperature, and population are not significant in this model. The coefficient for age is statistically significant at the 5 percent level, and indicates that for every year older a plant is it will produce approximately 3,000 MWh less electricity. The coefficient for fuel price indicates that for each dollar per mmBtu in price that a fuel rises, generation will fall about 22,000 MWh. Fuel price is significant at the 1 percent level. The capacity coefficient is also significant at the 1 percent level and indicates that for every mmBtu of generation capacity, there will be an increase of about 36MWh in generation. The fuel coefficients coal and gas are significant at the 1 percent and 5 percent levels respectively. If there is coal generation in a county, the model predicts that generate over 220,000 MWh, and gas will generate over 98,000 MWh more electricity than oil.

The RGGI variables for leakage present conflicting stories between New York and Maryland. For New York, the RGGI border variable indicates a reduction in generation of nearly 33,000

MWh and is significant at the 10 percent level. The RGGI New York inside variable is also significant at 10 percent level, and indicates only about 18,000 MWh in reduced generation. However, the Pennsylvania border variable with New York is not significant and indicates a reduction in generation, compared to the Pennsylvania inside county variable, which indicates an increase in generation of over 22,000 MWh and is significant at the 5 percent level. This does not lend strong support for RGGI having caused leakage from New York to Pennsylvania. However, for Maryland there does appear to be potential for there to have been leakage from Maryland to Pennsylvania, though this study is not fully able to determine if it has happened. The RGGI Pennsylvania border counties with Maryland saw an increase of over 46,000 MWh, which was significant at the 1 percent level, compared to the RGGI inside variable, which was mentioned above was only an increase of 22,000 MWh. This would be consistent with leakage from Maryland to Pennsylvania.

7.3 Tobit Leakage Results Non-Summer

The results of the Tobit random effects leakage regression for the non-summer months are presented in Table 7-3. For the non-summer months all of the control variables are significant. Both of the temperature variables are significant at the 1 percent level, with the maximum temperature being associated with a drop in approximately 500 MWh of generation for each tenth of a degree Centigrade of increased temperature, and the minimum associated with an increase of approximately 500 MWh per tenth of a degree of increase. The population variable is significant at the 5 percent level, and is associated with an increase of over 244,000 MWh of generation. The age coefficient indicates that for every year older a plant is it will produce approximately 4,500 MWh less electricity, and fuel price variable indicates that for each dollar per mmBtu in price that a fuel rises, generation will fall about 24,000 MWh. Both age and fuel price are significant at the 1 percent level. The capacity coefficient is also significant at the 1 percent level and indicates that for every mmBtu of generation capacity, there will be an increase of about 31 MWh in generation. The fuel coefficients coal and gas are significant at the 1 percent and 5 percent levels respectively. If there is coal generation in a county, the model predicts that generate over 313,000 MWh, and gas will generate over 132,000 MWh more electricity than oil.

As above for the summer months, the RGGI variables for leakage present conflicting stories between New York and Maryland. For New York, neither the border variable, nor the inside county variable are significant, and both show reductions in generation. The Pennsylvania border variable with New York also is not significant while the Pennsylvania inside county variable indicates an increase in generation of over 34,000 MWh and is significant at the 1 percent level. This does not support RGGI having caused leakage from New York to Pennsylvania. However, again there is some evidence that there may have been leakage from Maryland to Pennsylvania. The Pennsylvania border with Maryland variable indicates an increase of over 52,000 MWh and is significant at the 1 percent level. Compared to the inside Pennsylvania counties, this would be consistent with leakage from Maryland to Pennsylvania.

7.4 Erie County, PA

Gas generation in Erie County, Pennsylvania ceased in 2008, just before RGGI started. To understand the cause of the negative coefficient on generation for the Pennsylvania border counties, Erie County was dropped from the data set, and the Tobit Random Effects regressions were repeated. Besides the coefficient for the Pennsylvania Counties on the New York border, the results for both regressions were qualitatively the same. As a result the conversation below focuses only the RGGI variables for New York and Pennsylvania and their impacts on estimations regarding leakage.

The results of the Tobit random effects leakage regression, with Erie dropped, for summer months can be seen in Table 7-4. The main difference between these results and the ones presented in Table 7-2 is that the RGGI PA border with New York coefficient is now positive, but still statistically insignificant.

The results of the Tobit random effects leakage regression, with Erie dropped, for non-summer months can be seen in Table 7-5. Now the main difference between these results and the ones presented in Table 7-3 is that the RGGI Pennsylvania border with New York variable is now larger and significantly significant at the 5 percent level. Importantly, the coefficient for the RGGI Pennsylvania border is larger than that for the Pennsylvania inside counties. This is consistent with leakage. However, the New York RGGI coefficients are both not significantly different from zero, which is not strongly consistent with leakage.

7.5 Conclusions Regarding Leakage

For the summer months, there is not strong support that there has been leakage from New York to Pennsylvania. However, for the non-summer months, the Pennsylvania border and inside county variables do show evidence of leakage. There is stronger evidence from the Pennsylvania counties that suggests that Maryland may have had leakage to Pennsylvania, which will be explored in future work.

Map 7-1: Border and Internal County Groups for New York and Pennsylvania

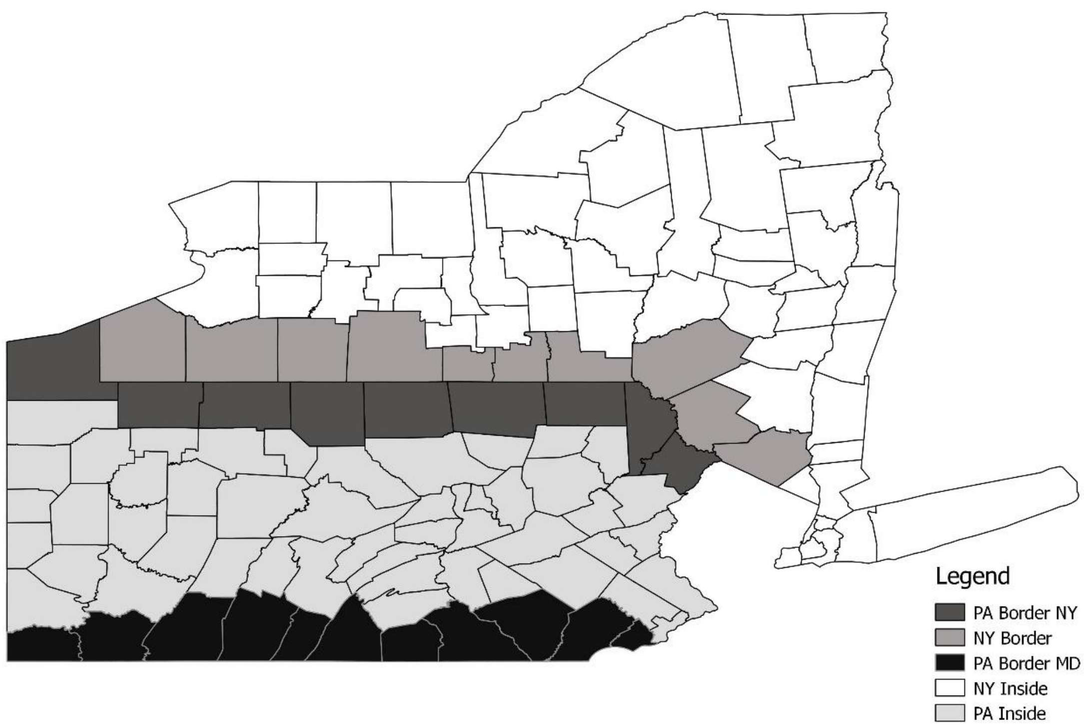


Table 7-2: Leakage Model for RGGI Summer Months

Number of observations = 5008 Number of groups = 122		
Wald chi2(105) = 2998.13 Prob > Chi2 = 0.000		
Log Likelihood = -49017.34		
	Coefficient	Standard Error
Temp Max	-27.43	181.51
Temp Min	142.07	202.87
Population	237,555.4	166,121.4
Age	-3,254.59**	1,178.52
Fuel Price	-22,006.7***	1,215.73
Capacity (mmBtu)	36.43***	1.25
Coal	221,164.3***	35,174.28
Gas	98,041.27**	38,766.25
RGGI PA Border (NY)	-65,9790.22	47,821.93
RGGI PA Inside	22,233.12**	11,160.64
RGGI PA Border (MD)	46,182.17***	14,648.38
RGGI NY Border	-32,923.62*	16,976.85
RGGI NY Inside	-18,273.83*	10,750.66
sigma u	96196.58***	6570.28
sigma e	114204.6***	1352.34
Rho	0.415	0.336

* p<0.10, ** p<0.05, *** p<0.01

NOTE: Yearly and county dummy variables not shown.

Table7-3: Leakage Model for RGGI Non-Summer Months

Number of observations = 14955 Number of groups = 122		
Wald chi2(105) = 3802.45 Prob > Chi2 = 0.000		
Log Likelihood = -121969.18		
	Coefficient	Standard Error
Temp Max	-519.32***	87.07
Temp Min	536.10***	100.56
Population	244,469.4**	121,198.9
Age	-4,502.77***	1,042.11
Fuel Price	-24,194.02***	899.73
Capacity (mmBtu)	31.90***	0.98
Coal	313,791.0***	35,174.48
Gas	132,849.9**	38,766.61
RGGI PA Border (NY)	26,1430.79	47,821.69
RGGI PA Inside	34,276.51***	11,160.36
RGGI PA Border (MD)	52,385.31***	14,648.34
RGGI NY Border	-7,191.07	16,976.14
RGGI NY Inside	-9,191.96	10,750.48
sigma u	99102.88***	6806.21
sigma e	134371.5***	1010.81
Rho	0.352	0.031

* p<0.10, ** p<0.05, *** p<0.01

NOTE: Yearly and county dummy variables not shown.

Table 7-4: Leakage Model for RGGI Summer Months with Erie County, PA Excluded

Number of observations = 4966 Number of groups = 121		
Wald chi2(105) = 2971.21 Prob > Chi2 = 0.000		
Log Likelihood = -48819.27		
	Coefficient	Standard Error
Temp Max	-27.43	182.02
Temp Min	141.62	202.87
Population	243,601.0	166,448.4
Age	-3,266.69**	1,182.74
Fuel Price	-22,199.35***	1,221.35
Capacity (mmBtu)	36.45***	1.26
Coal	220,132.0***	35,338.73
Gas	97,545.14**	38,928.0
RGGI PA Border (NY)	27,620.36	53,519.21
RGGI PA Inside	22,360.62**	11,180.52
RGGI PA Border (MD)	46,283.61***	14,674.54
RGGI NY Border	-32,819.28*	17,004.07
RGGI NY Inside	-18,324.83*	10,769.65
sigma u	96,664.563***	6,626.69
sigma e	114,392.7***	1,357.22
Rho	0.417	0.338

* p<0.10, ** p<0.05, *** p<0.01

NOTE: Yearly and county dummy variables not shown.

Table 7-5: Leakage Model for RGGI Non-Summer Months

Number of observations = 14829 Number of groups = 121		
Wald chi2(105) = 3780.75 Prob > Chi2 = 0.000		
Log Likelihood = -121821.88		
	Coefficient	Standard Error
Temp Max	-516.07***	87.18
Temp Min	533.65***	100.7
Population	247,485.6**	121,255.4
Age	-4,524.60***	1,044.69
Fuel Price	-24,275.82***	901.51
Capacity (mmBtu)	31.90***	0.98
Coal	313,663.3***	36,102.95
Gas	132,449.9**	37,888.32
RGGI PA Border (NY)	61,770.65**	30,984.92
RGGI PA Inside	34,369.95***	8,235.87
RGGI PA Border (MD)	52,438.09***	10,688.0
RGGI NY Border	-7,059.89	12,736.4
RGGI NY Inside	-9,174.79	7,994.74
sigma u	99,573.88***	6806.21
sigma e	134,417.0***	1011.67
Rho	0.354	0.032

* p<0.10, ** p<0.05, *** p<0.01

NOTE: Yearly and county dummy variables not shown.

Chapter 8 Conclusion

This study uses a unique data set of observed electric generation to estimate benefits from RGGI that arise through reductions in conventional pollutants. It provides a method for estimating benefits from other cap-and-trade programs for CO_2, and could be used for better estimating potential benefits of any new programs that might be developed in response to the EPA's proposed Clean Power Plan for existing power plants. The benefits found in this study were more approximately $130 million per year and result from reduced SO_2 and NO_X emissions in New York and New Jersey. Further, a test for leakage of generation and emissions to Pennsylvania found little evidence of significant changes due to RGGI.

RGGI provides large ancillary benefits to New York and, while it participated, New Jersey, through reductions in NO_X, SO_2, $PM_{2.5}$, and PM_{10} emissions. These benefits are not uniformly distributed and counties in the western, south central, and south eastern area of New York benefit the most. In New York, Queens County received a disproportionate share of the benefits while in New Jersey, Hudson County received the largest share of benefits. Many counties in both states had very little benefit (or occasionally increased costs). County benefits vary strongly due to differences in location-specific marginal damages estimated by Muller. As shown in Chapter 6, Tables 6-14 and 6-15, at the national level counties that have high marginal damage values are situated in different areas of the country: they are scattered across seven different states and the District of Columbia. As such, the approach used here—which distinguishes between emissions at different geographic locations—would be important to many other states as they consider programs that would reduce CO_2 emissions.

Leakage has been a concern of previous studies and has complicated the estimation of benefits from RGGI in the past. This analysis shows that, for the time period analyzed, there is weak support for leakage occurring from New York to Pennsylvania. However, as the leakage model presented in Chapter 4 demonstrates, leakage could become more of a problem as the allowance prices for CO_2 under RGGI increases. This would change the ratio between transmission costs and the allowance price and could thus result in large amounts of leakage even though it appears little has occurred at current prices. In the long term, however, leakage may not be an issue if the EPA's Clean Power Plant rules are implemented and neighboring states are also constrained.

There is still much future research to be done that can be supported with this data. This future works revolves around the resolution of the data, geographical considerations, different statistical techniques that could be utilized and, as discussed below, the analysis could be expanded to address related policy questions. This research would allow for greater understanding of RGGI and cap and trade programs in general.

First, work will be done to increase the frequency of observations to better understand the behavior and response of power plants to cap and trade programs, and to understand dynamics between generation and demand at different times of day when a cap is present. As mentioned in the model section, different fuels have different fixed costs associated with bringing generators on line. Spatial methods could be utilized to account for potential spatial auto-correlation. This would likely mean that switching a power plant off for short periods is infeasible, and could change patterns of generation that are not observable with the current data set. It would also be interesting to compare the patterns of RGGI effects observed versus a hypothetical relocation of same reductions but being carried out at the highest marginal damage areas first. It would also be interesting to analyze benefits from programs at the per capita level, as this would change the apparent geographic distribution of the benefits. The number of observations could also be increased by adding more states into the analysis. The leakage analysis, in particular, could benefit from that since there are other possible places where RGGI could experience leakage. It was shown that the Pennsylvania border with Delaware and Maryland showed changes consistent with leakage occurring. Delaware, Maryland, and the surrounding states should also be tested to definitively determine if leakage has occurred.

Second, future work should consider increasing the number of equations used to model generation, moving beyond the summer and non-summer structure used in this study. Also, while there is covariance between electric generation using different fuel types, there is also some evidence that generating units using different fossil fuels behave differently and hence should be treated as separate equations. There should also be further work on investigating the role of size differences between units, and whether large and small units should be modeled differently. Also, there are interactions between fuel types, different size plants, and seasonal time periods that should be tested.

Lastly, work could be done to expand this analysis and to answer related policy questions. There are likely to be water quality benefits from the changes in fuel usage patterns demonstrated in this study. Also, by adding prices of electricity into the analysis a number of other research topics could be addressed. First, it could be estimated how much RGGI has cost consumers in higher prices, and supply and demand for electricity could likely be estimated through simultaneous equation methods.

From a policy standpoint it is clear that trading programs for global pollutants from fossil fuels, will produce local benefits and damages. However, the benefits will be much larger in magnitude than the damages. Further, investing in lower transmissions costs would likely allow for greater trade between regions, and would allow for generation to occur in areas with lower marginal damages. Due to the differences in marginal damages, and the association of high damages with urban areas, the ancillary benefits from EPA's CPP program is likely to disproportionately flow to urban areas.

Appendix A: NOAA Data Supplement

NOAA Data Processing:

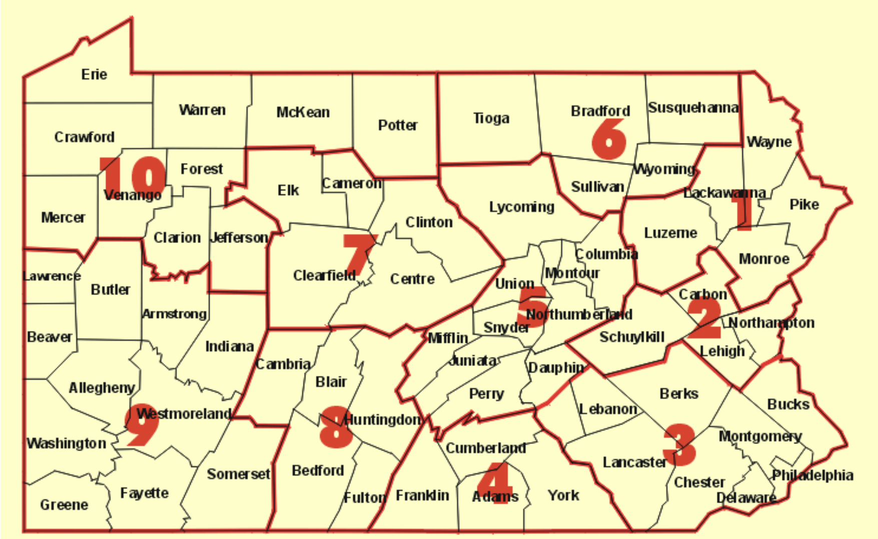
State	County	Mapped to	State	County	Mapped to
NY	Bronx	Queens	**PA**	Greene	Fayette
NY	Genesee	Erie	**PA**	Indiana	Westmoreland
NY	Kings	Queens	**PA**	Lackawanna	Luzerne
NY	Nassau	Queens	**PA**	Lawrence	Butler
NY	Richmond	Queens	**PA**	Montour	Lycoming
NY	Rockland	Westchester	**PA**	Northampton	Lehigh
NJ	Camden	Burlington	**PA**	Northumberland	Snyder
NJ	Gloucester	Burlington	**PA**	Schuykill	Lehigh
NJ	Hudson	Union	**PA**	Venango	Crawford
NJ	Ocean	Burlington	**PA**	Wyoming	Sullivan
NJ	Salem	Burlington			

NOAA Climatic Divisions Maps.[9]

[9] Available from: http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/states_counties_climate-divisions.shtml

New York

Pennsylvania



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