DOES CAP AND TRADE WORK?
ASSESSING THE IMPACT OF THE REGIONAL GREENHOUSE GAS INITIATIVE

A Thesis
submitted to the Faculty of the
Graduate School of Arts and Sciences
of Georgetown University
in partial fulfillment of the requirements for the
degree of
Master of Public Policy
in Public Policy

By

Rachel C. Erlebacher, B.S.

Washington, DC
April 9, 2020

I would like to express my gratitude to Adam Thomas for his invaluable wisdom and support throughout this entire process. A special thanks to Raphael Calel for his subject matter expertise.

Many thanks,
Rachel C. Erlebacher

DOES CAP AND TRADE WORK?
ASSESSING THE IMPACT OF THE REGIONAL GREENHOUSE GAS INITIATIVE

Rachel C. Erlebacher, B.S.

Thesis Advisor: Adam Thomas, Ph.D.

ABSTRACT

There is substantial evidence of an association between greenhouse gas emissions and the warming of the global climate. A warming planet has implications for human health, agriculture, and economic growth. Several policy strategies may help to reduce greenhouse gas emissions. One potential solution is a cap and trade system, which is a market-based instrument that sets an upper limit on emissions and allocates to participating firms a certain number of permits to pollute, which they can trade with other firms. The Regional Greenhouse Gas Initiative (RGGI), agreed to among participating states in the northeastern United States in 2005 and implemented in 2009, was the first mandatory cap and trade program in the United States designed to mitigate greenhouse gas emissions, specifically within the electricity sector. This paper attempts to determine whether RGGI has been effective in reducing greenhouse gas emissions from affected power plants. I use annual power-plant-level emissions data from the EPA's eGRID database to estimate a difference in differences model that compares changes in carbon dioxide emissions between plants in participating states and plants in non-participating states from 1996 to 2016. I find some suggestive evidence that emissions declined at a faster rate among plants in RGGI states than among plants in non-RGGI states, although my results are not conclusive.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Scientists find substantial evidence of a strong association between increased greenhouse gas emissions and a warming global climate (IPCC, 2014). While greenhouse gases (GHGs) are necessary to keep the planet warm enough for the survival of life, the exponential increase in GHGs, beginning at the time of the Industrial Revolution, has become a cause for concern (NASA, 2019b). Natural events, such as volcanic eruptions and changes in solar irradiance, can impact global temperatures (Crowley, 2000).[1] However, several studies have found that unforced climate variability has played a relatively small role in warming temperatures over the last 150 years, suggesting that climate forcing from anthropogenic sources is the primary cause (Crowley, 2000; Mann, Bradley, & Hughes, 1998).[2]

The primary GHG emitted from anthropogenic sources is carbon dioxide (CO_2) (EPA, 2019b). There are several anthropogenic GHG sources, such as industry, agriculture, transportation, and electricity generation (EPA, 2019b). While atmospheric carbon levels do fluctuate, for the 800,000 years before 1950 they had remained between 150 and 300 parts per million (ppm) (NASA, 2019a). Then, in 1950, carbon dioxide emissions levels began to increase steadily, and in 2013, they exceeded 400ppm for the first time in recorded history (Lindsey, 2019).

A warming planet has important implications. While it is difficult to attribute specific weather events to climate change, since 1901, the United States has seen a 1.8 Fahrenheit degree

---

[1] An increase in volcanic eruptions is associated with climate cooling and likely played a role in the last Little Ice Age (Crowley, 2000). Conversely, an increase in solar irradiance, or the sun's energy output, increases global temperatures (Crowley, 2000). Major changes in the land's surface (e.g. deforestation or large-scale glacial melting) are another source of unforced climate variability – i.e., natural changes in the earth's surface temperature (Crowley, 2000).

[2] Climate forcing is the difference between incoming radiation and outgoing radiation. If this difference is positive, the Earth will warm, and if this difference is negative the Earth will cool. Climate forcing can occur from natural atmospheric processes as well as anthropogenic drivers (NOAA, 2019). The term "anthropogenic" refers to change caused by human activity (NOAA, 2019).

increase in surface temperatures, which scientists have found to be correlated with increased carbon emissions (USGCRP, 2017). The Intergovernmental Panel on Climate Change (IPCC, 2014), a United Nations working group composed of thousands of scientists from around the world, finds strong evidence that in the wake of changes to the planet's climate the number of extreme cold days will decrease and that extreme heat days will increase, including more frequent and intense heat waves. The mid-latitude regions are likely to experience more intense precipitation events, including cyclone activity, and some regions will experience more severe drought (IPCC, 2014).[3] All of these predicted changes have implications for human health, agriculture, and GDP (IPCC, 2014; USGCRP, 2017).

The United States is currently the world's second largest emitter of GHGs (Friedrich, Ge, & Pickens, 2017). Moreover, according to the Environmental Protection Agency (EPA) (2019b), in 2017, electricity generation accounted for 18.3 percent of U.S. GHG emissions. Several policy strategies can reduce GHG emissions, including a cap and trade system, which is a market-based solution. Two studies have found that cap and trade programs are associated with greater reductions in environmental pollution and are less costly than command-and-control policies (Ellerman, 2006; Burtraw & Palmer, 2004).[4] Burtraw and Palmer (2004) use simulations of, and Ellerman (2006) reviews the relevant literature on, the sulfur dioxide cap and trade program (also known as the Acid Rain Program), which was established by the Clean Air Act in 1990. Both studies conclude that implementation of this cap and trade program was associated with reduced emissions. While no Federal mandatory climate mitigation program exists in the United States,

[3] The mid-latitude regions are between 30 and 60 degrees North and South and include over 50 percent of the world's population (Moon et al., 2017).
[4] Command-and-control policies require firms to meet set uniform standards, such as performance standards or an emissions ceiling (EPA, 2019a). Market-based instruments, in contrast, utilize economic tools to incentivize firms to reduce emissions (Haites, 2018).

two regional cap and trade programs in the U.S. currently regulate emissions from electricity generation. One of these programs is the Regional Greenhouse Gas Initiative (RGGI), a collaborative effort among nine northeastern states with the goal of reducing GHG emissions from the electricity sector.[5]

This paper attempts to determine whether RGGI has been effective in reducing GHG emissions in the electricity sector. I use annual power plant-level emissions data from the EPA's eGRID database to compare changes in carbon dioxide emissions between plants in participating states and plants in non-participating states from 1996 to 2016.

BACKGROUND

There are two primary policy mechanisms for reducing GHG emissions: command-and-control policies, such as performance standards or technology standards, and incentive-based solutions, such as carbon taxes or cap and trade programs.[6] In recent years, cap and trade programs have gained in popularity, promoted for their cost effectiveness and environmental effectiveness. Cap and trade programs set an upper limit on emissions. Participating firms are then allocated a certain number of permits (in units of pollution) to pollute, which they can sell to other firms depending on whether it is cheaper for them to abate and reduce emissions or buy additional permits to pollute.[7] In theory, this system should bring emissions down in the cheapest way.

RGGI, established in 2005 and implemented in 2009, was the first mandatory cap and trade program in the United States aimed at mitigating GHG emissions, specifically targeting the

[5] California established the other regional program in 2013 (Market-Based Strategies, 2017).
[6] Unless otherwise noted, all factual claims in this paragraph are attributed to Market-Based Strategies (2017).
[7] While this is the basic framework of a cap and trade program, many nuances render existing cap and trade programs very different from one another (Betsill & Hoffmann, 2011).

electricity sector (Regional Greenhouse Gas Initiative [RGGI], 2019). Nine states currently participate: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont. New Jersey participated until 2011 and rejoined on January 1, 2020, and Virginia plans to join in 2020 (Regional Greenhouse Gas Initiative [RGGI], 2019). Emission limits are set at the state-level, and all power plants in a participating state with a nameplate capacity greater than 25 megawatts (MW) are required to participate (Regional Greenhouse Gas Initiative [RGGI], 2019).[8]

In 2005, the Governors of Connecticut, Delaware, Maine, New Hampshire, New Jersey, New York, and Vermont signed a Memorandum of Understanding (MOU), which provided a framework for the program. Massachusetts, Maryland, and Rhode Island signed on to the MOU in 2007 (Ramseur, 2019). The MOU and the so-called "Model Rule," which was drafted, revised, and published between 2006-2008, provided a regulatory framework to implement the program.[9] However, each state was, and still is, responsible for drafting its own regulations based on state statutes (Program Design Archive, 2019).

RGGI operates in three-year control periods (2009-2011; 2012-2014; 2015-2017; 2018-2020) (Regional Greenhouse Gas Initiative [RGGI], 2019). As required by the MOU, the program is reviewed between control periods and then updated based on the recommendations provided during the review (Regional Greenhouse Gas Initiative [RGGI], 2019). During the first two control periods (until 2014), the overall emissions cap – i.e., the cap on emissions across all states – remained constant, and since 2015, it has declined 2.5 percent annually (Regional

[8] Any emissions produced by plants smaller than 25 MW do not count towards the emissions cap within which each state is restricted. Therefore, if total emissions from the electricity sector are calculated for a state, they may appear to exceed the state's cap. However, if this is the only reason that emissions are too high, a state would still be considered in compliance.
[9] The Model Rule is a regulation that was written and published collectively by participating states. It serves as a unified framework to provide consistency across states in the way that the program is implemented (Regional Greenhouse Gas Initiative MOU, 2005).

Greenhouse Gas Initiative MOU, 2005).[10] The MOU also provided the initial allocation of CO_2 emissions permits (or the state-wide emissions caps) among the participating states (see Table 1) (Regional Greenhouse Gas Initiative MOU, 2005).

Table 1. Annual Regional Greenhouse Gas Initiative state emissions permit allocations, 2009-2014, as established by the 2005 Memorandum of Understanding [a]

State	Initial Permit Allocations (short tons)
Connecticut	10,695,036
Delaware	7,559,787
Maine	5,948,902
New Hampshire	8,620,460
New Jersey	22,892,730
New York	64,310,805
Vermont	1,225,830
Massachusetts	26,660,204
Rhode Island	2,659,239
Maryland	36,503,983

[a] These are the annual allocated caps. They do not necessarily reflect the number of permits that were actually auctioned (and sold) each quarter.

Permits (or allowances) are auctioned on a quarterly basis.[11] The program allows plants to bank an unlimited number of permits for future use. It also includes an offset program under which, according to a Congressional Research Service (CRS) evaluation of RGGI, up to 3.3 percent of a plant's emissions can be offset by funding a project that reduces methane emissions from landfills, improves carbon sequestration through reforestation projects, and/or captures

[10] In an exception to the initial MOU, the total emissions cap across all states did decline in 2012 to reflect New Jersey's withdrawal from the program. The state-level caps did not change.
[11] Unless otherwise noted, all factual claims in the following paragraph are sourced from Ramseur (2019).

methane through better manure management practices. To date, the RGGI Board has approved only one offset project. In addition, in 2014, after the second program review, RGGI added a Cost Containment Reserve. With the goal of stabilizing prices, the Reserve constitutes a separate bank of permits that can be auctioned if permit prices rise above a certain threshold.[12] This threshold has been raised annually. The prices of permits to emit one short ton of carbon have fluctuated between $1.86 and $7.50, peaking in 2015 after the cap was significantly lowered.

In addition, the MOU stipulated that at least 25 percent of the revenue generated from the auctions had to be used by states for a "consumer benefit or strategic energy purpose," such as energy efficiency, promoting renewable energy, or stimulating research for new abatement technologies (Regional Greenhouse Gas Initiative MOU, 2005). Each state could decide how to spend the rest of the funds, but they had to be spent within an "eligible category" as defined by RGGI (Regional Greenhouse Gas Initiative MOU, 2005).

During the first control period, approximately 80 percent of allocated permits were sold at auctions, and emissions remained lower than the allowed emissions set by the overall cap (Ramseur, 2019). The cap was lowered in 2014 following the second program review to better align with actual emissions (Ramseur, 2019).

[12] The Cost Containment Reserve has been triggered twice since its creation – in 2014 and 2015 (Ramseur, 2019).

LITERATURE REVIEW

Several economic and regulatory mechanisms have been proposed to reduce GHG emissions. While a substantial body of literature outlines the economic theory behind each of these mechanisms, research on the effects of enacted policies on emissions is more limited. Among the studies that do attempt to measure program effectiveness, many rely on computer models that are built on assumptions that enable one to make projections, rather than on observed data that measure emissions reductions (e.g., Burtraw & Mansur, 1999; Ellerman, 2006; Haites, 2018). This feature of the literature presents a hurdle in determining causality. Furthermore, because other economic factors (e.g., changes in energy prices, the economic downturn in 2008) are also associated with changes in emissions, it is difficult to determine the degree to which these mechanisms truly account for such changes (Murray & Maniloff, 2015).

Command-and-Control vs. Market-Based Instruments

Economic solutions to environmental problems can be assigned to two categories: command-and-control policies and market-based instruments. Command-and-control policies require firms to operate according to set standards, such as performance standards or emissions ceilings (EPA, 2019a). Often, such standards are uniform across firms (Ellerman, 2006). Market-based instruments, in contrast, use economic tools to incentivize firms to reduce emissions (Haites, 2018).

While Federal policy has long favored command-and-control regulatory action, research suggests that market-based instruments are more cost effective and are thus preferable mechanisms for reducing emissions (Haites, 2018; Goulder & Parry, 2008; Stavins, 2008b). Command-and-control regulations force all firms to meet the same standards regardless of costs

(Goulder & Parry, 2008). Evaluations of existing command-and-control policies suggest that they are vulnerable to exemptions and loopholes, which can weaken the programs and delay their impacts (Stavins, 2008b). In contrast, economic models demonstrate that market-based policies provide flexibility: the regulator sets an economy-wide or industry-wide standard and forces firms to pay a price to pollute if they choose not to reduce emissions (Stavins, 2008b).

Ellerman (2006) suggested that in addition to their cost-effectiveness, market-based instruments are also better able to achieve intended environmental outcomes (i.e., reducing emissions). He based his conclusion on an analysis of the Regional Clean Air Incentives Market (RECLAIM), a cap and trade program in California aimed at reducing sulfur dioxide (SO_2) and nitrous oxides (NO_x) emissions that replaced a command-and-control plan. Predictive models of each showed that RECLAIM was expected to achieve the desired reductions seven years earlier and at a lower cost than the previous plan (Ellerman, 2006).

Additionally, prior to the implementation of the Acid Rain Program – a national cap and trade program aimed at reducing sulfur dioxide emissions – the New Source Performance Standards (NSPS) had attempted to accomplish the same objective as the Acid Rain Program (Burtraw & Palmer, 2004). But, the NSPS, a command-and-control approach, was less successful because power plants that existed prior to the program's implementation were not regulated (Burtraw & Palmer, 2004).

The two most common market-based instruments are carbon taxes and cap and trade programs. Economic theory suggests that, if implemented correctly, both achieve the same emissions reductions and are equally cost effective but are executed through different mechanisms.[13] Carbon taxes set a price on carbon, ideally at its marginal external cost. Firms can

[13] Unless otherwise noted, all factual claims in this paragraph are taken from Haites (2018).

choose to reduce emissions or pay the tax to pollute. Cap and trade programs set a maximum quantity, or cap, on the pollution that firms are allowed to emit. Unlike command-and-control regulations that establish firm-level limits, cap and trade programs set economy-wide or industry-wide caps on emissions. Firms are then provided permits that allow them to pollute up to a certain limit. If they pollute more than their permits allow, they can either reduce their emissions or buy additional permits from other firms that have excess allocations. The major difference between carbon taxes and cap and trade programs is that carbon taxes create a fixed price, allowing emissions to vary, whereas cap and trade programs create a fixed emissions cap and allow prices to vary (Stavins, 2008b; Goulder & Schein, 2013).

While, as noted, both carbon taxes and cap and trade programs should, in theory, achieve the same outcome at the same cost, economists and policymakers continue to debate which is the better option (Goulder & Schein, 2013; Stavins, 2008a; Stavins, 2008b; Haites, 2018). One of the biggest concerns with cap and trade programs is the risk of large price fluctuations that shock the market (Goulder & Schein, 2013).[14] In contrast, unlike a pure cap and trade model, a carbon tax reduces the likelihood of drastic price swings because the price of emissions is fixed (Stavins, 2008b). However, as is discussed below, several modifications to a pure cap and trade model can reduce the risk of price volatility.

Hybrid Cap and Trade Systems

In an assessment comparing a carbon tax, a pure cap and trade program, and a hybrid cap and trade program that adds price controls, Goulder and Schein (2013) find that a hybrid cap and trade program is associated with significant reductions in price volatility as compared to a pure

[14] In contrast, a carbon tax has less of an ability to control emissions reductions, since only the price is fixed by the program (Goulder & Schein, 2013).

cap and trade program. The authors claim that the hybrid system achieves this through several mechanisms, discussed below, all of which are employed in RGGI. Although few studies evaluate RGGI in particular, the literature on other cap and trade programs that share similar design features is more extensive.

The cap and trade system was first used in the 1980s to address acid rain, which is a by-product of high sulfur dioxide emissions (Betsill & Hoffmann, 2011). Many researchers recognize this as one of the most successful cap and trade programs (Burtraw & Mansur, 1999; Burtraw & Palmer, 2004; Ellerman, 2006; Stavins, 2018b). Unlike a pure cap and trade system, the Acid Rain Program allowed firms to bank unused permits, which could then be used in future years (Burtraw & Palmer, 2004). Banking allows firms to be more flexible in deciding when and how to reduce their emissions, which can help to reduce price volatility (Burtraw & Mansur, 1999).

A simulation model created by Burtraw and Mansur (1999) found that banking was a key factor in the success of the Acid Rain Program because it incentivized firms to reduce emissions at a faster rate than mandated. By comparing simulated emissions levels under a “business-as-usual” scenario to the observed emissions changes after program implementation, their model provides suggestive evidence that the observed emissions reductions would not have occurred without the trading and banking scheme (Burtraw & Mansur, 1999).[15] Supporting this claim, two other studies found that within the first year of implementation emissions fell 30 percent below 1980 levels, which was more than double the amount regulators expected during the first five years of the program (Ellerman, 2006; Burtraw & Palmer, 2004). Burtraw and Palmer (2004)

[15] The IPCC (2014) defines a “business-as-usual” scenario as one in which the program being studied was not implemented. Under this counterfactual, the level of greenhouse gas emissions is therefore the estimated level that would have occurred if no policy action had been taken.

note that “the ability to bank allowances for future use proved crucial to the success of the program. Once firms had built up a bank of unused allowances, they had a vested interest in maintaining the value of those banked credits, and thus in furthering the program itself” (p. 46).

In contrast, while the RECLAIM program in California was accompanied by a reduction in emissions, it was also accompanied by large price swings. This has been attributed to the absence of a banking program (Goulder & Schein, 2013; Stavins, 2008a). In addition to banking, to help minimize price volatility some cap and trade systems (RGGI included) also build in price floors and ceilings (Goulder & Schein, 2013).

Cap and trade was not seriously considered as a climate mitigation strategy until the 2007 Kyoto Protocol (Betsill & Hoffmann, 2011).[16] Since then, however, many countries and states have implemented cap and trade programs with varying levels of success. In Tokyo, evidence suggests that emissions may have increased after implementation of a cap and trade system, although Haites (2018) notes that many of Japan’s nuclear facilities shut down during the program’s implementation following a major earthquake in 2011.[17] On the other hand, simulation models suggest that under the EU’s Emissions Trading Scheme program emissions were 130-247 $MtCO_2$ (metric tons of carbon dioxide equivalent) lower than under a business-as-usual scenario (Haites, 2018). Similarly, Ellerman (2006) concludes that implementation of the RECLAIM program has been associated with a 40 percent reduction of NOx and SO_2 emissions since the start of the program. It should be noted, though, that these studies acknowledge the likelihood that other factors, such as changing energy prices, may have also contributed to

[16] The Acid Rain Program was targeting a pollutant, but sulfur dioxide is not a greenhouse gas. Sulfur dioxide creates acid rain, which pollutes water and kills trees, but it is not a major contributor to climate change (Betsill & Hoffmann, 2011; NASA, 2019b).
[17] Nuclear plants do not produce carbon dioxide emissions, and nuclear energy is considered to be a renewable energy source (Energy Information Administration, 2020).

declining emissions. It is difficult to isolate the effects of the aforementioned programs from the effects of these other contributing factors.

Initial Evaluations of the Regional Greenhouse Gas Initiative's Effects

While most studies of RGGI have focused on the program's economic benefits, a few have analyzed its environmental effectiveness. These studies find evidence of a negative association between implementation of the program and emissions in participating states (Ramseur, 2019; Murray & Maniloff, 2015; Abt Associates, 2017). However, several external technological and economic factors also may have contributed to participating states' decreased emissions. These factors include the Great Recession in 2008, the increased availability and decline in price of natural gas, and the complementary effects of other environmental programs such as renewable portfolio standards (Ramseur, 2019; Murray & Maniloff, 2015). Murray and Maniloff (2015) attempted to isolate the impact of RGGI using panel data from the period 1990-2012 for the contiguous United States. Controlling for confounding variables and for state fixed effects, they found a significant difference in emissions rates between states that did and did not participate in RGGI. They estimated that emissions in participating states would have been 24 percent higher, had the program not been implemented. Furthermore, emissions data collected by RGGI show that between 2005 and 2009, the period between the announcement of the program to the start of its implementation, emissions from the electricity sector declined by 30 percent (Murray & Maniloff, 2015). This suggests that emissions may have declined in anticipation of the program going into effect.

Haites (2018) notes that cap and trade mechanisms are also likely to have indirect effects. In the case of RGGI, a portion of the revenue generated by the auctioning of permits must be invested in renewable energy, which also likely accounted for a portion of the decreased emissions, albeit not as a direct result of the cap (Haites, 2018; Murray & Maniloff, 2015). A study on the health impacts of RGGI found that improvements to air quality during the implementation of the program were associated with $5.7 billion in health benefits (e.g. avoided lost days at work, avoided health care costs) and prevented illnesses (Abt, 2017).

The Present Study

Much of the existing literature on cap and trade programs is based on economic theory and simulation modeling, rather than on empirical analyses of programmatic effects. Of the studies that do assess existing programs, few focus specifically on RGGI. While some similarities in program design exist among cap and trade programs around the world, there are enough differences to make it difficult to extrapolate their results to RGGI. Studies that do analyze the impact of RGGI focus primarily on its economic benefits. While Murray and Maniloff (2015) attempted to estimate the environmental impact of RGGI, the authors' state-fixed effects analysis relied only on state-level data through 2012. My study contributes to the literature by estimating a differences-in-differences model using plant-level data through 2016 to better assess the extent to which RGGI contributed to emissions reductions.

CONCEPTUAL FRAMEWORK

Based on the literature discussed above, I hypothesize that power plants in the northeastern states that participate in RGGI have experienced a larger reduction in greenhouse gas emissions than power plants in states that do not participate in the program. As discussed in the literature review, several other factors may have also contributed to changes in emissions. My model accounts for economic and energy indicators, as well as for weather, demographic characteristics, and other environmental policies. These controls are displayed in Figure 1 and are discussed further below.

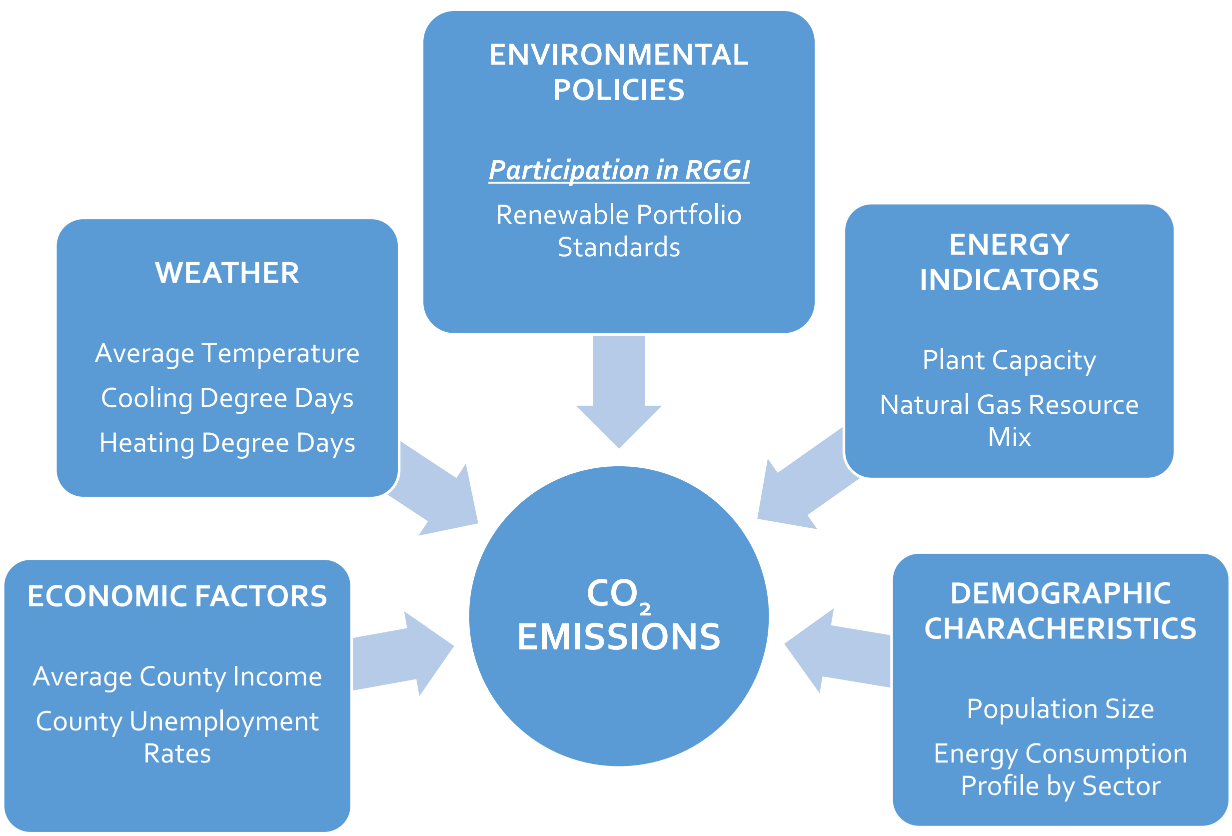

Figure 1. Factors impacting CO_2 emissions

Environmental Policies

Aside from RGGI, other state and Federal programs also encourage reductions in GHG emissions (Murray & Maniloff, 2015; Ramseur, 2019; Energy Information Administration, 2012). For example, several states have Renewable Portfolio Standards (RPS), which establish target dates by which a certain percentage of energy generation should be sourced from renewable energy (Energy Information Administration, 2012). My model accounts for whether the states where plants are located participate in these programs in order to distinguish their impact on GHG emissions from the impact of RGGI.

Weather-related Factors

The United States spans several climate regions, some of which tend to be much colder than others. These varying conditions require different levels of space heating and cooling. According to the Energy Information Administration (EIA), space heating and cooling account for over half of residential energy use (Berry, 2018; Mayclin, 2018). Additionally, the extent of reliance on electricity (vs. natural gas or oil) for heating varies geographically (Lawrence & Berry, 2017). I capture changes in energy demand to regulate outside temperatures by controlling for average temperature. To relate energy demand and temperature, I also include controls for heating and cooling degree days.[18] The latter two variables are used in Murray and Maniloff's (2015) model to account for differences in energy demand.

[18] The cooling degree days variable reflects the sum, across all days in the year in which the average temperature was above 65 degrees Fahrenheit, of the difference between the temperature outside and the temperature at which most people are thought to feel comfortable indoors (again, 65 degrees Fahrenheit). This variable serves as a proxy for energy demand for air conditioning and other sources of cooling (EPA, 2016; EIA, 2018b). Similarly, the heating degree days variable reflects the sum, across all days in the year in which the average temperature was below 65 degrees Fahrenheit, of the difference between the temperature outside and the above-mentioned temperature at which most people are thought to feel comfortable indoors. This variable serves as a proxy for energy demand for heating. Together these variables can be used as a proxy for the weather-related changes in energy demand. For

Energy Indicators

Both Ramseur (2019) and Murray and Maniloff (2015) speculate that some of the change in emissions after the implementation of RGGI may have been driven by long-term structural changes to the energy profile of the U.S. [19] The authors specifically note the increased availability and reduced price of natural gas in the wake of the fracking boom. To account for the changing energy market, Murray and Maniloff (2015) include both coal and natural gas prices. However, since these are measured at the national level, they cannot be included in my difference in differences model. Instead, I control for the natural gas resource mix for each plant. The natural gas resource mix captures the percentage of electricity generation that was sourced from natural gas. This is plausibly an important factor for which to control because natural gas exploration and discovery in the United States are dependent on where natural gas is found geographically. Thus, there may be regional variation in access to this energy source (EIA, 2018a).

Economic Factors

Several studies find evidence of a positive correlation between economic growth and energy use (Arora & Lieskovsky, 2014; Ramseur, 2019; Murray & Maniloff, 2015). Specifically,

---

example, a MWh/degree day measure can be calculated to understand how energy usage changed over time, while standardizing temperature (National Weather Service, 2019).

[19] I considered the inclusion of a variety of other indicators in my regression but opted to exclude them because they are plausibly endogenous. For instance, energy use per capita and plant net generation may have changed over time as result of RGGI being implemented and the consequent need to absorb increased compliance costs. On the other hand, however, these measures may have changed due to an exogenous shift in consumer demand, perhaps in response to the Great Recession. Similarly, the energy resource mix may have changed either because power plants turned to renewable energy sources or natural gas in order to comply with RGGI or because the energy market changed (e.g. the fracking boom). Given these concerns, I excluded most such variables from my regressions (when I included them in unreported sensitivity tests, the corresponding regressions' r-squared values were implausibly large). The only exception is my control for a plant's natural gas resource mix. I retained this variable in my final regressions because the natural gas fracking boom occurred in the early 2000s, right around the time that RGGI was implemented.

these studies find that electricity use decreases during economic downturns.[20] RGGI was implemented during the height of the Great Recession, so it is likely that the economy had an impact on emissions (Murray & Maniloff, 2015). To account for the impacts of the Great Recession and other changes to the economy, my model includes local average income and unemployment rates, both indicators of economic health (Murray & Maniloff, 2015).

Demographic Characteristics

In order to account for geographic variation in energy demand, I follow Murray and Maniloff's (2015) approach of controlling for population size. Additionally, states have different electricity consumption per sector. According to the EPA (2015), 35 percent of electricity is used by the commercial sector nationally, 37 percent is used by the residential sector, 27 percent is used by the industrial sector, and less than one percent is used by the transportation sector. Because each of these energy uses varies based on geographic region and time, I account for such variation in energy demand by controlling for sectoral differences in the composition of the market that each plant serves (EPA, 2015).

[20] Burke and Abayasekara (2017) find that demand for electricity is relatively price inelastic in the short-run but is more price elastic over the long-run.

DATA AND METHODS

My analyses use plant-level data gathered over a 13-year period for all electricity-generating power plants in the United States.[21] The data for my dependent variable, carbon dioxide emissions, were obtained from the Emissions and Generation Resource Integrated Database (eGRID), which is maintained and hosted by the EPA. Information on my key independent variable was derived from the RGGI MOU, which lists the states that chose to participate in the program and the times at which they joined (RGGI, 2005).[22]

As discussed previously, my analyses also control for other environmental policies designed to reduce emissions, energy indicators that may reflect changes in demand related to changes in the electricity resource mix in a given area, annual temperature trends that may impact electricity demand, and county economic and demographic characteristics that may affect electricity demand. Data on my control variables were obtained from several sources. Information on state enactment of and/or participation in other state environmental programs was obtained from the Energy Information Administration (EIA) and the Database of State Incentives for Renewables and Efficiency (DSIRE).[23] The energy indicators – specifically, the natural gas resource mix and plant capacity– were sourced from eGRID at the plant level. Data for county-level weather indicators were obtained from the National Oceanic and Atmospheric Administration's (NOAA) nClimDiv dataset. The Bureau of Labor Statistics (BLS) and the Bureau for Economic Analysis (BEA) provided the data for the county-level economic indicators. Finally, data for the demographic controls, including county population sizes and

---

[21] The dataset contains data from the following years: 1996; 1997; 1998; 1999; 2000; 2004; 2005; 2007; 2009; 2010; 2012; 2014; 2016.
[22] I obtained the date when New Jersey withdrew from the program for my independent variable from Ramseur (2019).
[23] Because Federal policies would presumably have been implemented similarly across states, my difference in differences model controls for them automatically.

state housing units, were collected by the Census Bureau, and data on state electricity customers and state energy profiles by sector were collected by the EIA.

It should be noted that several studies (Chen, 2009; Ramseur, 2019; Murray & Maniloff, 2015) find evidence that energy leakage – i.e., the increased import of fossil fuels from neighboring states – may reduce the effectiveness of RGGI. This is because plants in participating states can, in theory, buy electricity that is sourced from a cheaper fossil fuel from a neighboring state that does not participate in RGGI (Ramseur, 2019; Chen, 2009). This mechanism allows plants in participating states to keep costs down while technically staying under the cap (Chen, 2009). In order to account for this to some degree, I exclude from my control group plants located in states that do not participate in RGGI, but that share power markets with plants in RGGI states.[24]

To determine whether RGGI has reduced GHG emissions, I estimate a difference in differences regression model. My model compares the change in emissions for plants located in states that do and do not participate in RGGI. The time period for my analysis spans a period beginning prior to the implementation of RGGI and ending after the program's implementation. I estimate several variations of this model. In some specifications, I consider the "start date" of RGGI to be 2005, when the MOU was signed; in other specifications, I consider the program to have started in 2009, when the program was implemented. I estimate these specifications to test the sensitivity of my core results, given that Murray and Maniloff (2015) find evidence that some plants preemptively reduced emissions prior to a regulatory program being implemented.

[24] Power markets, otherwise known as Regional Transmission Organizations (RTOs), are "independent, member-based, non-profit organizations" that optimize sales of wholesale electricity (i.e., they make it easier to buy and sell electricity across state lines). They are regulated by the Federal Energy Regulatory Commission (FERC) and seek to increase competition and access to the electricity market. Electricity systems that not part of an RTO are managed by individual utilities (EIA, 2011). The RTOs that include plants in RGGI states also sometimes include plants in states that do not participate in RGGI. In order to minimize the unobserved impact of leakage, my regressions have excluded non-RGGI plants that share an RTO with RGGI plants.

Additionally, since RGGI evolved over each of its three-year control periods as a result of New Jersey exiting the program and previously discussed recommendations based on evaluations of the program, I vary the post-implementation date across specifications. I also estimate models with various state groupings. Thus, in some regressions, I exclude plants in California, which implemented its own cap and trade program in 2013. Specifically, in the regressions in which I assume 2014 and 2016 to be my post-implementation years, I do not measure regressions that include California. Also, since RGGI only requires plants larger than 25MW to participate, I estimate a triple differences model to compare differential emissions changes for treatment and control plants that are larger and smaller than 25MW (RGGI, 2005).

I thus estimate the following model using plant-level data:

$$CO2\_emissions_{i,t} = \beta_0 + \beta_1 RGGI_i + \beta_2 post\_implementation_t + \beta_3 RGGI*post\_implementation_{i,t} + \beta_4 RPS_{i,t} + \beta_5 plant\_capacity_{i,t} + \beta_6 natural\_gas\_mix_{i,t} + \beta_7 average\_temperature_{i,t} + \beta_8 cooling\_degree\_days_{i,t} + \beta_9 heating\_degree\_days_{i,t} + \beta_{10} county\_income_{i,t} + \beta_{11} county\_unemployment_{i,t} + \beta_{12} county\_population_{i,t} + \beta_{13} state\_housing\_units_{i,t} + \beta_{14} state\_electricity\_customers_{i,t} + \beta_{15} percent\_industry\_sales_{i,t} + e_{i,t},$$

where *i* is a plant index, *t* is a year index, $e_{i,t}$ is the error term, and β_3 is the coefficient of interest. My dependent variable measures carbon dioxide emissions in tons.[25] The sample size for my overall model is 64,860 observations (an average of 4,989 plant-level observations per year with 13 years of data, once missing data issues are addressed). Table 2 provides definitions and data sources for all of the variables included in my model.

[25] While nitrous oxide and methane are also greenhouse gases, carbon dioxide makes up most of the emissions from the electricity sector, which is why I use carbon dioxide emissions as my dependent variable (EPA, 2019c).

Table 2. Definitions of variables

Variable	**Definition**	**Source**
Dependent Variable		
CO_2 Emissions	A continuous variable measuring the annual carbon dioxide emissions in tons from each power plant.	EPA eGRID
Independent Variable		
RGGI	A dichotomous variable indicating whether or not the state in which a plant is located participates in RGGI (1=yes; 0=no). [a]	RGGI MOU
Post Implementation	A dichotomous variable indicating whether RGGI had been implemented for each plant-year observation (1=yes; 0=no).[a]	RGGI MOU
Environmental Policies		
Renewable Portfolio Standards (RPS)	A dichotomous variable indicating whether or not the state in which a plant is located has a Renewable Portfolio Standard in place (1=yes; 0=no).[b]	EIA DSIRE
Energy Indicators		
Plant Nameplate Capacity	A continuous variable measuring maximum plant output for each plant in MW.	EPA eGRID
Natural Gas Resource Mix	A continuous variable measuring the percentage of electricity produced by each plant from natural gas.	EPA eGRID
Weather Indicators		
Average Temperature	A continuous variable measuring average annual temperature in the county in which a plant is located.	NOAA nClimDiv
Cooling Degree Days	A continuous variable measuring the sum, across all days in the year in which the average temperature was above 65 degrees Fahrenheit, of the difference between the temperature outside and the temperature at which most people feel comfortable (i.e., 65 degrees Fahrenheit) in each county in which a plant is located.	NOAA nClimDiv
Heating Degree Days	A continuous variable measuring the sum, across all days in the year in which the average temperature was below 65 degrees Fahrenheit, of the difference between the temperature outside and this threshold in each county in which a plant is located.	NOAA nClimDiv

Table 2. (cont.)

Variable	Definition	Source
Economic Indicators		
Average County Income	A continuous variable measuring average annual income in 2016 dollars for each county in which a plant is located.	BEA Local Area Personal Income
County Unemployment Rates	A continuous variable measuring the average annual unemployment rates among a county's residence (specifically, the denominator for this variable reflects the size of the non-incarcerated population over the age of 16).	BLS Local Area Unemployment Statistics
Demographic Characteristics		
Population Size	A continuous variable measuring the annual population sizes for the county in which a plant is located.	Census Bureau County Intercensal Data
Housing Units	A continuous variable measuring the annual number of housing units in each state in which a plant is located.	Census Bureau Annual Estimates of Housing Units
Electricity Customers	A continuous variable measuring the annual number of electricity customers in each state in which a plant is located.	EPA/EIA Electric Power Annual Report
Industrial Energy Use	A continuous variable measuring the percentage of electricity retail sales for industry use in the state in which a plant is located.	EPA/EIA Electric Power Annual Report

[a] This is one of the variables whose definition varies based on model specification.
[b] I use a dichotomous variable to indicate the existence of a standard rather than the specifications of the standard because these programs have varying targets and set varying dates (often far into the future) by which those targets must be met. States with renewable portfolio goals (rather than standards) are flagged as "0" because they are voluntary programs.

DESCRIPTIVE STATISTICS

Table 3 provides descriptive statistics for all of the variables included in my regression, including controls, for the contiguous United States for the years 2004, 2010, 2012, 2014, and 2016.[26] All estimates are weighed by plant nameplate capacity. My results show that plants in the United States emitted an average of approximately three million tons of carbon dioxide annually. This measure varies widely across observations in my dataset, with a minimum value of 0 tons and a maximum value of 25,600,000 tons. Nine percent of my plant-year observations participated in RGGI. It is also worth noting that, while participation in RGGI is only required for plants larger than 25 MW, the weighted average plant nameplate capacity in my sample is 1,245 MW, with a standard deviation of 1,045, which is to say that the bulk of the plants in my weighted sample are larger than 25 MW and would thus be subject to RGGI if located in a participating state.

[26] There were 80 plant observations for which FIPS county codes were missing and nine plant observations for which there were no emissions or generation data. These observations were all dropped, since most were unlisted or were as-yet-unopened plants with no known production data. NOAA's climate and weather data source did not include information on Hawaii or the District of Columbia (DC), so Hawaii was dropped entirely from the model. For DC, I averaged temperature, heating degree days, and cooling degree days values (separately) for the surrounding counties for each year and assigned those average values to DC. Additionally, several variables were not available for Alaska, so that state was also excluded from the analysis. The eGRID data had some missing values for several of the variables used in the analysis. There were also some missing values from certain demographic controls. I used interpolation to fill in missing values for CO_2 emissions, plant nameplate capacity, natural gas resource mix, county income, county unemployment rates, population size, and the number of housing units. Household unit data were missing for all observations for 1999, but missing data for the other variables were more dispersed. Interpolation was only applied for observations with available data on either side of the year in question and resulted in 5,150 interpolated datapoints. Any remaining missing data for my dependent variables were left missing and those observations were subsequently dropped using listwise deletion. To address the remaining missing data for my control variables, I used single imputation, which was used to fill in missing values for county income, population, and housing units, resulting in 1,244 imputed datapoints. I dropped observations with any remaining missing values. After filling in missing values using the above-described steps, my final dataset contains 64,860 plant-year observations from the contiguous United States (out of a possible total of 75,194). Within my final dataset, 6,394 datapoints were interpolated or imputed, which constitutes 0.43 percent of the total number of datapoints in my analytic sample.

Table 3. Descriptive statistics for dependent, key independent, and control variables [a]

Variable	Mean	Min	Max	SD
Annual plant-level CO_2 emissions (tons)	2,918,876	0	25,600,000	4,586,290
Participation in RGGI	0.09	0	1	0.29
Year Indicator	0.83	0	1	0.38
Environmental Policies				
Renewable Portfolio Standard	0.62	0	1	0.48
Energy Indicators				
Plant nameplate capacity (MW)	1,244.82	0.2	6,809	1,045.37
Natural gas resource mix	40.76	0	100	47.56
Weather Indicators				
Average annual temperature	58.24	33.02	77.63	58.24
Average annual cooling degree days	134.45	0	407.50	85.30
Average annual heating degree days	337.02	11.92	970.58	173.74
Economic Indicators				
Per capita income ($ 2016)	41,355.49	18,395.03	224,366	10,385.67
Unemployment rate	7.26	1.1	28.8	2.76
Demographic Characteristics				
Percent of electricity sales to industry	27.12	1.69	60.66	10.43
Population	551,315.7	417	10,200,000	1,336,621
Housing Units	4,960,923	237,318	14,100,000	3,775,256
Electricity customers	5,442,400	228,233	15,300,000	4,111,357
N = 31,059				

[a] There are more housing units than members of the population because the former is measured at the state level, while the latter is measured at the county level.

Table 4 reports baseline (2004) descriptive statistics for plants in RGGI states and plants in non-RGGI states outside of the power markets impacted by RGGI. Carbon dioxide emissions are lower among plants in RGGI states than among plants in non-RGGI states. There are significant differences between the two groups for almost every control variable, suggesting that there are important differences between them beyond their participation in the program. Compared to their non-RGGI counterparts, RGGI states tend to be colder, less industrial, and wealthier, but with higher unemployment. Of note in particular, however, is the natural gas resource mix percentage, which is not significantly different between the two groups. This suggests that, while the fracking boom occurred in specific geographic regions of the United States where natural gas is found, the increase in natural gas usage was more universal. Figure 3 in Appendix A provides additional details on the ways in which each state changed its electricity resource mix over time.

Table 4. Subgroup analysis of key independent variable, 2004 [a]

Variable	(1) **48 States**	(2) **States Outside of Impacted Power Markets**	(3) **RGGI States**	(4) **Difference (3) – (2)**	(5) **Robust SE**
Annual plant-level CO_2 emissions (tons)	3,536,072	3,430,798	1,418,047	-2,012,751***	394,078.2
Participation in RGGI	0.11	0	1	N/A	N/A
Year Indicator	0	0	0	N/A	N/A
Environmental Policies					
Renewable Portfolio Standard	0.46	0.50	0.57	0.07	0.05
Energy Indicators					
Plant nameplate capacity (MW)	1,235.31	1,228.916	1,008.46	-220.45*	121.75
Natural gas resource mix	36.22	42.66	36.64	-6.02	4.48
Weather Indicators					
Average annual temperature	57.41	60.71	50.45	-10.26***	0.52
Average annual cooling degree days	117.17	149.91	54.40	-95.51***	4.82
Average annual heating degree days	344.73	277.11	493.60	216.49***	11.27
Economic Indicators					
Per capita income ($ 2016)	38,657.05	36,828.21	48,346.35	11,518.14***	1,129.67
Unemployment rate	5.88	5.94	6.00	-0.83***	0.12
Demographic Characteristics					
Percent of electricity sales to industry	29.10	28.42	18.44	-9.98***	0.75
Population	520,715.5	630,467.9	600,279.3	-30,188.56	91,928.21

Table 4. (cont.)

Variable	(1) **48 States**	(2) **States Outside of Impacted Power Markets**	(3) **RGGI States**	(4) **Difference (3) – (2)**	(5) **Robust SE**
Housing Units	4,550,123	4,851,171	4,231,952	-619,219**	302,974.1
Electricity customers	5,009,660	5,422,537	4,327,885	-1,094,652***	304,474.7
	N= 4,703	N= 2,956	N= 788		

* p < 0.1
** p < 0.05
*** p < 0.001

[a] The table assumes that New Jersey is part of RGGI even though it withdrew from the program in 2012. The implementation period for the primary regression is 2009, when the program was implemented, and included New Jersey at that time.

Table 5 displays the mean values for each variable at three different points in time: prior to the announcement (and implementation) of RGGI, between the announcement and implementation of RGGI, and after the implementation of RGGI.[27] Carbon dioxide emissions decreased across the United States over the 14-year period. Additionally, the number of state renewable portfolio standards increased, as did the use of natural gas, which also may contribute to changes in emissions. From 2007 to 2014, unemployment also increased, likely as a result of the Great Recession; and over the entire 14-year period, population sizes increased. All of these trends have implications for energy use and emissions and are controlled for in my regressions. Most of the other control variables remained fairly constant during the period of analysis.

[27] To illustrate changes over time, this table includes years that are not included in my primary regression specification.

Table 5. Time trends

Variable	2000	2007	2014
Annual plant-level CO_2 emissions (tons)	4,202,033	3,509,755	2,851,216
Participation in RGGI	0.12	0.11	0.08
Year Indicator	0	0	1
Environmental Policies			
Renewable Portfolio Standard	0.18	0.57	0.65
Energy Indicators			
Plant nameplate capacity (MW)	1,254.86	1,221.36	1,304.84
Natural gas resource mix	25.89	39.77	42.40
Weather Indicators			
Average annual temperature	56.77	58.04	56.79
Average annual cooling degree days	117.29	133.03	123.13
Average annual heating degree days	365.36	340.29	369.41
Economic Indicators			
Per capita income ($ 2016)	37,376.12	40,695.76	42,354.4
Unemployment rate	4.43	4.88	6.54
Demographic Characteristics			
Percent of electricity sales to industry	31.36	27.85	26.95
Population	496,268.5	523,135.5	568,347.1
Housing Units	4,255,936	4,759,326	5,064,967
Electricity customers	4,651,166	5,216,640	5,559,226
	N= 4,511	N= 5,029	N= 6,568

Emissions trends are also visualized in Figure 2, which shows changes in average carbon dioxide emissions over time for plants in RGGI states and plants in non-RGGI states outside of the impacted power markets. These two groups follow a similar pattern prior to the implementation of RGGI, suggesting that emissions trends for the two groups might have been the same after the implementation of RGGI if the program had not been implemented, thus supporting the identifying assumption for my difference in differences analyses.

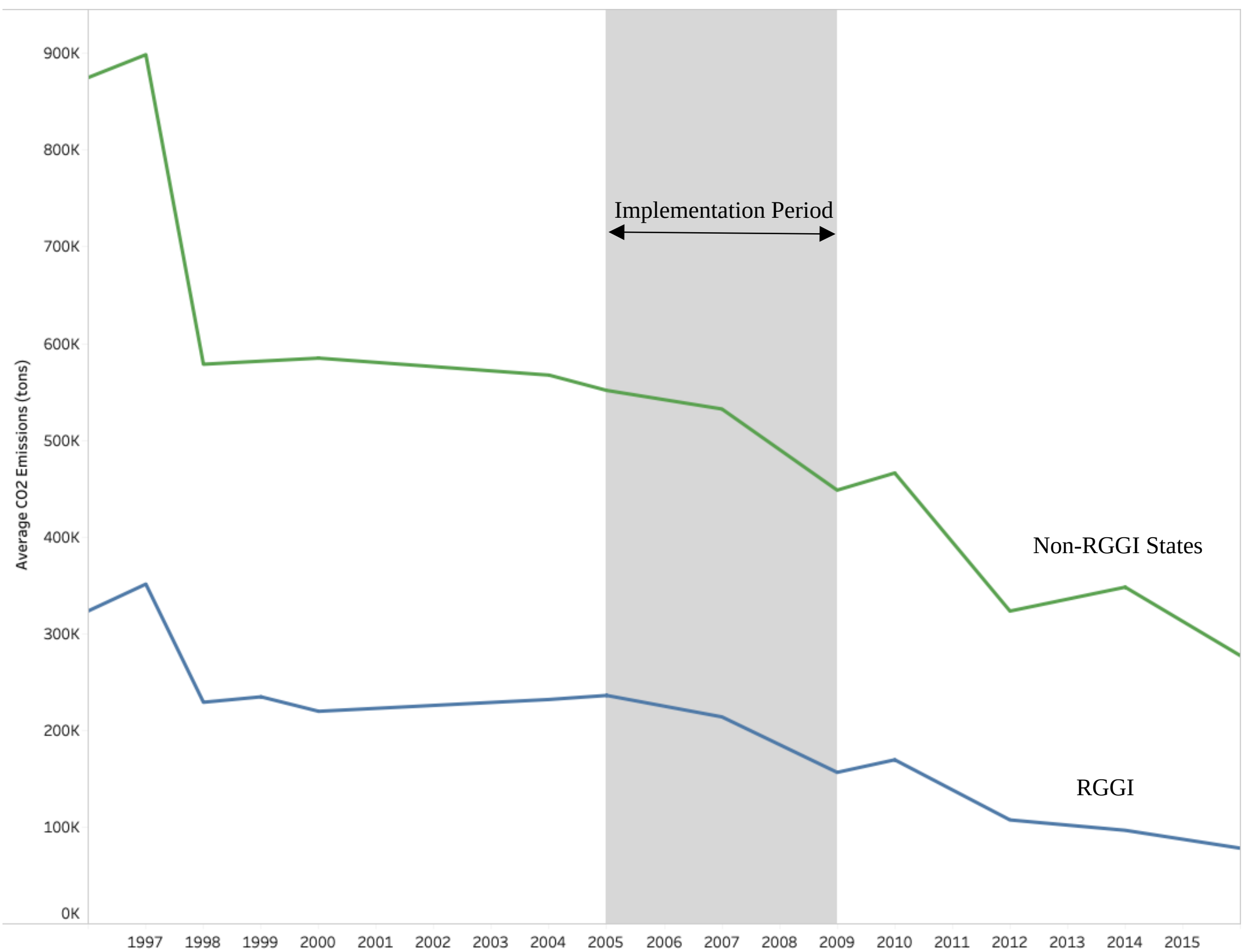

Figure 2. Average annual CO_2 emissions for RGGI states and non-RGGI states outside of impacted power markets

REGRESSION RESULTS

My regression results are summarized in Tables 6 and 7. The first table reports weighted and unweighted difference in differences model (DiD) estimates, and the second table separately reports the DiD estimates for my triple differences regressions that compare the differential changes of small and large treatment and control plants.[28] Each row of the tables presents results for a different variation of my regression in terms of the way in which I measure the pre- and post-treatment period. While the RGGI program began at the start of 2009, the MOU was signed at the end of 2005. As Murray and Maniloff (2015) noted in their study of RGGI, some plants may have started reducing their emissions in 2005 in anticipation of the program going into effect. The varying approaches to measuring the program's "pre-implementation years" attempt to tease out the potential effect of announcing the policy versus the effect of implementing it.

In order to capture the way in which emissions rates may have changed in different control periods as a result of programmatic changes to RGGI, I also estimate models with several different post-implementation year specifications. For example, the overall emissions cap during the first control period (2009-2011) was higher than actual overall emissions at the start of 2009, so I would not expect to see a large change in emissions during this period as a result of RGGI.[29]

For the models in which the "implementation year" is 2005, my pre-implementation data are taken from year 2004. For the models in which the "implementation year" is 2009, my pre-implementation data are taken from year 2007 because the dataset does not contain data from 2008. Data for the post-implementation years are taken from the years specified in the tables

[28] See Appendix B for a full set of regression results, including for my control variables.
[29] The overall cap remained constant through the first two control periods, until the start of 2015 (with the exception of adjusting for New Jersey's withdrawal). The overall cap was then readjusted in 2015 to fall below actual emissions at the time and has declined 2.5 percent annually since. Thus, I would expect the program to have a larger effect after 2014 as compared to the initial years.

(i.e., 2010, 2012, 2014, and 2016). Thus, the "implementation" period for a given model is assumed to begin at the start of the implementation period year specified (i.e., 2005 or 2009) and to end at the close of the year preceding the post-implementation year noted on the tables. For example, for the model in which the implementation year is 2005 and the post-implementation year is 2010, the implementation period is assumed to run from the beginning of 2005 through the end of 2009.

As discussed in previous sections, due to leakage concerns, the impact of RGGI may be misestimated if all non-RGGI states are included in the control group. In Table 6, models 1 and 3 attempt to address this concern by excluding all plants in non-RGGI states that share an RTO power market with plants in RGGI states. As previously discussed, models 2 and 4 also exclude California, since that state implemented its own cap and trade program in 2013. Thus, models 1 and 3 do not include regressions that specify post-implementation years 2014 or 2016 because, once California's program was implemented in 2013, the inclusion of data from plants in California in the control group would have been inappropriate. Similarly, in Table 7, model 1 excludes plants in states that are located in the impacted power market. Model 2 excludes California as well as the states that share the impacted RTO.[30]

Weighted vs. Unweighted Specifications

The first two columns in Table 6 report results for regressions weighted by plant nameplate capacity (in MW). By weighting my regressions, I focus on the overall regional change in emissions as a result of the implementation of RGGI, averaged over all of the plants in

[30] I also estimated regressions for all of these specifications without imputed data and found no meaningful differences in my results. While natural gas use may also be endogenous, the fracking boom occurred at about the same time that RGGI was implemented and may have had an effect on emissions (due to a shift away from coal), so it is included in my regressions.

my analytic sample. Here, I find that some of the DiD coefficients are statistically significant with a negative sign, specifically for the models for which 2005 is the implementation year (models 1a, 2a, 1c, 2c, and 2g). The model in which implementation begins in 2005 and post-implementation is measured in 2010, excluding California yields a significant and positive DiD coefficient (model 2b), but the rest of the estimates are not significant. For models with a negative and significant coefficient, the results suggest that the implementation of RGGI is associated with a 78 to 135 percent greater reduction rate in overall emissions compared to non-RGGI plants. This range seems implausible. While it is technically possible that some treatment plants would have experienced a reduction in emissions that is more than 100 percent of the reduction among control plants, this result is unlikely, as this would have required RGGI plants to reduce emissions (or at least slow their growth rate) by a large amount, with non-RGGI plants simultaneously increasing emissions.

The second two columns in Table 6 report results for the same regression specifications without weighting. The regressions measure the average change in emissions due to the implementation of RGGI for a typical power plant, without regard to annual energy production. Without weighting, some specifications yield a negative and significant DiD estimate. However, the DiD coefficients for the regressions with a 2009 implementation year are not significant except when 2016 is the post-implementation year (model 4h). Conversely, with the exception of model 4a, all of the specifications with a 2005 program start date yield a negative significant DiD estimate. The magnitudes of these estimates vary greatly, but generally increase as the post-implementation date moves forward in time. These results suggest that, with an assumed implementation period from the start of 2005 through the end of 2009, the implementation of RGGI is associated with an emissions reduction rate among treatment plants that is 57 percent larger than among non-RGGI plants (model 3a). With an implementation period beginning in 2005 through the end of 2015, the implementation of RGGI is associated with an emissions reduction rate among treatment plants that is 102 percent greater than among non-RGGI plants (model 4g). This supports my hypothesis that the more stringent caps during the later control periods had a larger impact on emissions reductions.

A few DiD coefficients are particularly worth noting. My results yield positive significant coefficients only when the program is assumed to begin in 2009 with 2010 as the post-implementation year (i.e., the implementation period is from the start of 2009 through the end of 2009, only one year). The MOU was signed in 2005 and set the overall caps for each state but did not specify how the program would operate. Perhaps plants responded to the signing of the MOU and lowered emissions without fully knowing the impact the program would have on their operations. Then, in 2009, when the program was actually implemented, plants realized that their emissions were already lower than the caps, and they could bank their permits without further reducing emissions, resulting in positive DiD coefficients.

While most of my results are somewhat consistent between the weighted and unweighted specifications, models 1c and 3c (implementation year 2005 and post-implementation year 2012) yield DiD coefficients with very different magnitudes. Both of these regressions include California. The California Cap and Trade Program was announced in 2011 and implemented in 2013. Similar to the RGGI announcement effect, perhaps plants in California responded to the announcement of the program in 2012 prior the actual implementation of the program. This could help to explain why these two models show such different magnitudes. The average plant size is larger in RGGI states than in California (130 MW vs. 91 MW), so I would expect that the rate of change would be larger for the weighted regression as compared to the unweighted regression.

Table 6. Weighted and Unweighted DiD Coefficients

Dependent Variable: Logged CO_2 Emissions				
	Weighted by Plant Capacity		**Unweighted**	
	(1) Non-RGGI States Outside Impacted Power Market	(2) Non-RGGI States Outside Impacted Power Market w/o CA	(3) Non-RGGI States Outside Impacted Power Market	(4) Non-RGGI States Outside Impacted Power Market w/o CA
Post-Implementation Year: 2010				
(a) Implementation Begins: 2005	-1.0629***	-0.7753**	-0.5713***	-0.1585
	(0.8187)	(0.8629)	(0.1308)	(0.1423)
	n = 8,082	*n = 6,666*	*n = 8,082*	*n = 6,666*
	r-squared = 0.1736	*r-squared = 0.1372*	*r-squared = 0.4864*	*r-squared = 0.4541*
(b) Implementation Begins: 2009	0.5158	0.6011*	0.2531**	0.3171***
	(0.3361)	(0.3318)	(0.1132)	(0.1151)
	n = 8,341	*n = 6,879*	*n = 8,341*	*n = 6,879*
	r-squared = 0.2145	*r-squared = 0.1777*	*r-squared = 0.5135*	*r-squared = 0.4859*
Post-Implementation Year: 2012				
(c) Implementation Begins: 2005	-1.1601**	-1.0635**	-0.6840***	-0.4446*
	(0.4962)	(0.5009)	(0.1658)	(0.1719)
	n = 9,402	*n = 7,592*	*n = 9,402*	*n = 7,592*
	r-squared = 0.2449	*r-squared = 0.1940*	*r-squared = 0.5213*	*r-squared = 0.4836*
(d) Implementation Begins: 2009	0.2337	0.2622	-0.145	-0.0585
	(0.3234)	(0.3324)	(0.1222)	(0.1246)
	n = 9,661	*n = 7,805*	*n = 9,661*	*n = 7,805*
	r-squared = 0.2869	*r-squared = 0.2385*	*r-squared = 0.5446*	*r-squared = 0.5129*
Post-Implementation Year: 2014				
(e) Implementation Begins: 2005		0.4538		-0.3763**
		(0.5269)		(0.1776)
		n = 7,272		*n = 7,272*
		r-squared = 0.1385		*r-squared = 0.4782*
(f) Implementation Begins: 2009		0.4614		-0.0203
		(0.4237)		(0.1587)
		n = 7,485		*n = 7,485*
		r-squared = 0.1686		*r-squared = 0.5061*
Post-Implementation Year: 2016				
(g) Implementation Begins: 2005		-1.3475**		-1.0175***
		(0.6313)		(0.2048)
		n = 7,629		*n = 7,629*
		r-squared = 0.1828		*r-squared = 0.5219*
(h) Implementation Begins: 2009		-0.0648		-0.8566***
		(0.4599)		(0.1690)
		n = 7,842		*n = 7,842*
		r-squared = 0.2253		*r-squared = 0.5483*

Robust standard errors, clustered at the plant level, in parentheses
*** p<0.01, ** P<0.05, * p<0.1

Subgroup Analysis: Small Plants vs. Large plants

Table 7 reports the results from triple differences (DDD) models that assess whether there is a significant difference between plants over and under 25 MW in terms of the differential rates of emissions change rates for treatment versus control plans.[31] Recall that RGGI only applies to plants larger than 25 MW. My triple differences estimates essentially compare difference in differences estimates for small plants – for which the policy should have had no effect – versus large plants, for which the policy could in theory have had an effect. None of the DDD coefficients are significant, suggesting that, in terms of the differential emissions change between treatment and control plants, there is no difference between those that were large enough to be required to participate in RGGI and those that were not.

These results suggest that one or more of the following is possible: 1) there is some other factor driving emissions changes among both small and large plants; 2) the program had no effect on large plants' emissions; or 3) for some reason, small plants reduced emissions in response to the program, just as large plants did. There is no plausible explanation of why small plants would have voluntarily complied with RGGI. Thus, these results suggest that the policy may not have been effective.

[31] In Table 7, I only report DDD coefficients, but I include a full set of control variables and two-way interactions in these regressions. For a full set of regression results, see Tables 12 and 13 in Appendix B.

Table 7. Triple Differences Coefficients

Dependent Variable: Logged CO_2 Emissions		
	Triple Differences	
	(1) Non-RGGI States Outside Impacted Power Market	(2) Non-RGGI States Outside Impacted Power Market w/o CA
Post-Implementation Year: 2010		
(a) Implementation Begins: 2005	-0.3054	-0.2706
	(0.2197)	(0.2265)
	n = 8,082	*n = 6,666*
	r-squared = 0.5304	*r-squared = 0.5068*
(b) Implementation Begins: 2009	0.0654	0.127
	(0.1609)	(0.1683)
	n = 8,341	*n = 6,879*
	r-squared = 0.5555	*r-squared = 0.3362*
Post-Implementation Year: 2012		
(c) Implementation Begins: 2005	-0.4048	-0.3089
	(0.2810)	(0.2872)
	n = 9,402	*n = 7,592*
	r-squared = 0.5534	*r-squared = 0.5220*
(d) Implementation Begins: 2009	-0.0982	-0.0087
	(0.2376)	(0.2448)
	n = 9,661	*n = 7,805*
	r-squared = 0.5752	*r-squared = 0.5484*
Post-Implementation Year: 2014		
(e) Implementation Begins: 2005		0.0938
		(0.3169)
		n = 7,272
		r-squared = 0.5288
(f) Implementation Begins: 2009		0.2365
		(0.2905)
		n = 7,485
		r-squared = 0.5515
Post-Implementation Year: 2016		
(g) Implementation Begins: 2005		0.0347
		(0.3268)
		n = 7,629
		r-squared = 0.5643
(h) Implementation Begins: 2009		0.3734
		(0.3021)
		n = 7,842
		r-squared = 0.5879
Robust standard errors, clustered at the plant level, in parentheses		
*** p<0.01, ** P<0.05, * p<0.1		

CONCLUSION

My analysis provides some suggestive evidence that plants in states that participated in RGGI may have reduced emissions in response to the policy. However, given that my regressions yielded mixed results, among other concerns, I cannot assert with certainty that this is the case. I found more conclusive results from specifications that considered the start of the program to be 2005, when the MOU was signed. This finding provides suggestive evidence that power plants may have responded to the need to reduce emissions in anticipation of RGGI going into effect. Murray and Maniloff (2015) found similar results in their analysis. In contrast, when I used 2009 as the implementation year, the results were more varied, less conclusive, and even produced some positive and statistically significant DiD coefficients. One plausible explanation is that plants responded by initially lowering emissions when the program was announced in 2005 but were then able to bank their permits once the program was actually implemented because their emissions were already lower than the initial caps.

My weighted analyses show larger initial emissions reduction rates for plants in RGGI states, compared to plants in non-RGGI states, hovering at around 100 percent, which is about double that of my unweighted analyses. Results with the magnitudes of my weighted estimates suggest that plants in RGGI states had large declines in emissions rates, while plants in non-RGGI states actually increased emissions rates. While this is certainly possible, it is unlikely that this is the case because the initial cap was higher than actual emissions at the time of implementation. Thus, there may be unaddressed bias in my regressions, and my results should be interpreted with caution. My unweighted analyses show a similar pattern in regard to which specifications showed that implementation of the program was associated with a reduction in emissions rates. However, the magnitudes of these coefficients were smaller than their weighted counterparts.

Triple differences regressions produced insignificant results, suggesting that there is no difference between small and large plants in terms of the differential reduction in emissions rates for treatment versus control plants. This dimension of my findings is interesting because only large plants (those with nameplate capacities greater than 25 MW) were required to comply with RGGI. So, either small plants voluntarily chose to comply, the policy did not have the intended effect, and/or there are unobserved sources of bias in my results.

Murray and Maniloff (2015) is the only other study to have assessed the environmental effectiveness of RGGI (as opposed to its economic benefits). These authors found that the implementation of RGGI was associated with a reduction in emissions. Thus, to at least some degree, my results stand in contrast to theirs. However, it is important to note that the unit of analysis in their study was the state-year, which may have yielded a less precise estimate than my analysis, which uses plant-year data. Additionally, because the authors included all states contiguous to RGGI states as controls in their models, their regressions did not account for potential leakage issues. Finally, their state fixed effect models produced r-squared values of 0.99, suggesting that their state fixed effects and state-specific time trends explain so much of the outcome that there may be little left to be explained by the other variables in their model, including the RGGI dummy. Thus, their results, like mine, should be interpreted cautiously.

Limitations of the Study

It is possible that the DiD identifying assumption may not hold for my analyses. While my DiD models account for many unobserved and potentially confounding factors, they exclude certain potentially important control variables – including net plant generation, renewable energy resource mix, and annual state electricity prices – because those controls were plausibly endogenous to the policy and outcome. While removal of these variables from my analysis was necessary, the variables are also likely to be partially confounding factors. Their omission could thus be biasing my estimates. Additionally, many of my control variables are measured at a higher unit of analysis (e.g., the state-year) than the level at which I measured emissions. Perhaps this consideration has rendered my control variables less effective.

Because RGGI only imposed emissions restrictions on power plants larger than 25 MW, and assuming that my regressions' identifying assumption holds, I would expect to see significant differences between the program's "effects" on small and large plants in my triple differences specifications. However, because none of my triple differences coefficients were statistically significant, there is evidence to suggest that my identifying assumption – that there would have been no difference between treatment and control plants in emissions rate changes had the policy not been implemented – may have been violated. Thus, there may be something else driving differential changes in emissions that is not accounted for in my regressions.

Because some of the states that share a power market with RGGI states do not participate in the program, such as Pennsylvania, power plants in RGGI states are likely to have purchased cheaper, but more carbon intensive, energy from non-RGGI states to keep their costs low while staying under the cap. I attempted to address this leakage issue by excluding power plants in states that share an RTO power market with plants in RGGI states. However, while the exclusion of these states from my analysis may have alleviated this problem, it likely produced other forms of bias because the plants in my control group are not as similar to the plants in my treatment group as compared with plants in non-RGGI states that are geographically closer to RGGI states.

Thus, in addressing the leakage issue, I have placed further strain on my identifying assumption. If I were able to account for leakage in a different way, it is possible that I would observe an even smaller relationship between the implementation of RGGI and emissions reductions. This is because, if I accurately captured the energy being sourced outside of RGGI states and imported into RGGI states, many plants would likely be much closer to, or even exceed, their allotted permits.

Policy Implications

Despite the limitations of my research, there is still much to be gleaned from it. There is strong theoretical evidence that cap and trade programs could be an effective strategy to reduce emissions at the lowest cost to firms (Stavins, 2008a; Stavins, 2008b; Goulder & Schein, 2013; Haites, 2018). Furthermore, the success of the Acid Rain Program and other carbon emissions reduction mechanisms – such as the EU Emissions Trading Scheme – provide additional evidence that cap and trade can be effective (Burtraw & Mansur, 1999; Burtraw & Palmer, 2004; Ellerman, 2006; Haites, 2018). However, there are key differences between these programs and RGGI – most importantly, that RGGI is a regional program. Because electricity is produced and sold based on power markets that cross state borders, a cap and trade program regulating the electricity sector is likely to be more successful if it is carried out nationally, or at least if it includes all plants within a power market. In other words, the best way to address the leakage problem and make a cap and trade program more effective (and to allow for more effective evaluation of such programs) is, at a minimum, to create a policy that affects all states within a power market equally. My results do not prove that RGGI is effective, but nor do they conclusively show that RGGI is not working. Because RGGI is a regional policy, and since the issues associated with leakage could potentially be alleviated if the program were scaled up nationally, it may be inappropriate to use these results to assess the potential effects of a national cap and trade program. This suggests that additional work is needed, perhaps a renewed research effort to address the leakage issue or policy experimentation to adjust the estimates that are used to set emissions caps.

APPENDIX A: ADDITIONAL FIGURE

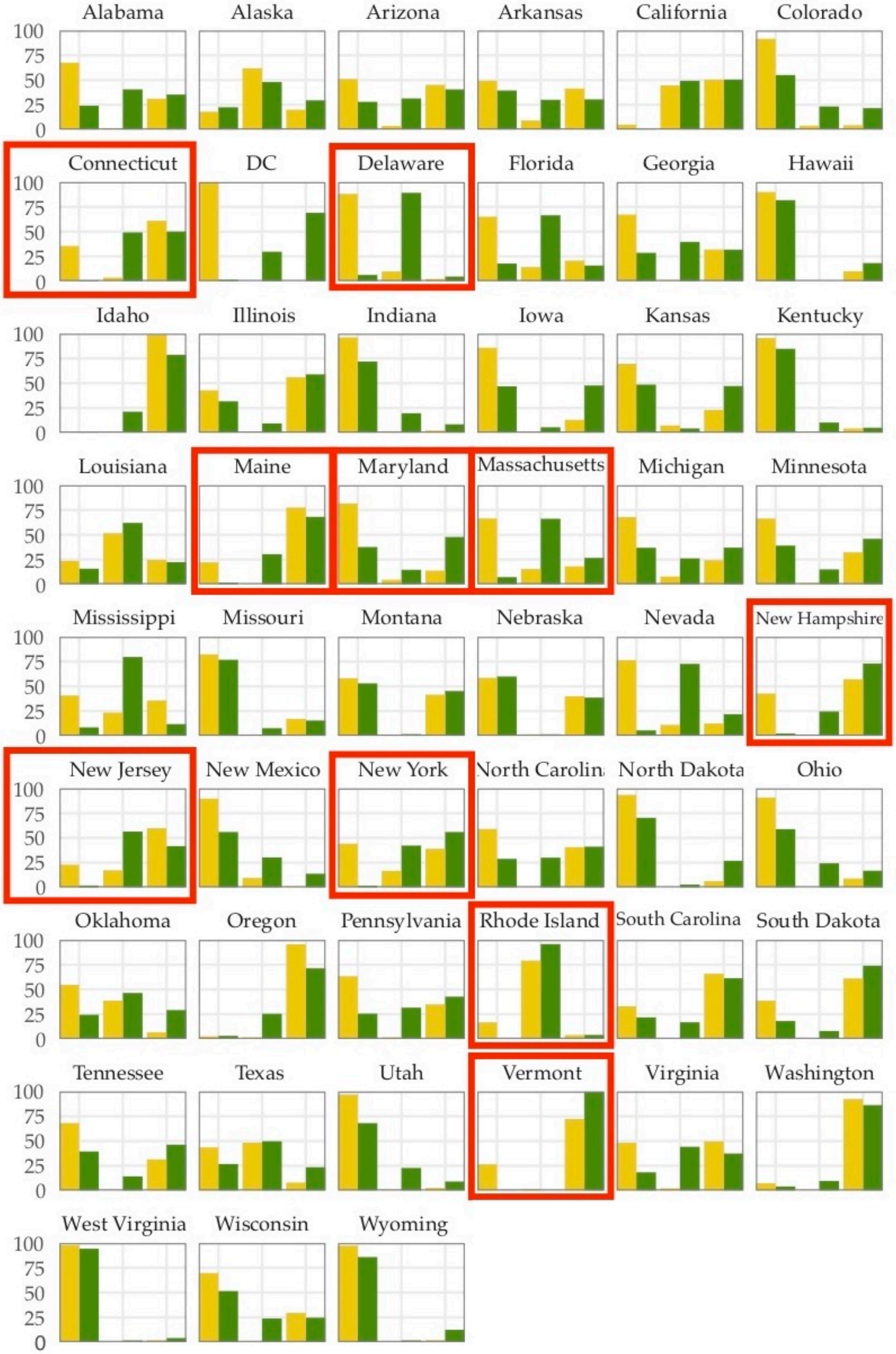

Figure 3. Change in resource mix by state, 1990-2016

APPENDIX B: FULL REGRESSION RESULTS

Table 8. Full Weighted Regressions, 2005

Dependent Variable: Logged CO_2 Emissions						
Implement. Year - 2005	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
RGGI Indicator	0.5156	0.0470	1.0047	0.2975	0.2491	0.4051
	(0.8861)	(0.9110)	(0.8733)	(0.8923)	(0.8998)	(0.8610)
Post-Implementation	0.1791	-0.2717	-0.4564	-0.6186*	-0.4642*	-0.7973**
	(0.4469)	(0.5394)	(0.2890)	(0.3517)	(0.2772)	(0.3553)
Interaction Term	-1.0629***	-0.7753**	-1.1601**	-1.0635**	0.4538	-1.3475**
	(0.8187)	(0.8629)	(0.4962)	(0.5009)	(0.5269)	(0.6313)
RPS	0.3565	0.6351	0.2140	0.5497	0.4264	0.4991
	(0.6235)	(0.5834)	(0.5653)	(0.5561)	(0.5433)	(0.5335)
Nameplate Capacity	0.0007	0.0006	0.0010*	0.0009	0.0007	0.0008
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)
Natural Gas Resource Mix	0.0419***	0.0347***	0.0581***	0.0513***	0.0381***	0.0443***
	(0.0047)	(0.0052)	(0.0040)	(0.0044)	(0.0046)	(0.0047)
Avg. Temperature	-14.5310*	-16.0366*	-11.5940	-12.6727	7.3693	-18.1949***
	(7.7831)	(8.2045)	(7.5804)	(8.2339)	(6.6503)	(6.7730)
Avg. Cooling Degree Days	0.4899*	0.5413**	0.3829	0.4111	-0.2437	0.6028***
	(0.2539)	(0.2686)	(0.2490)	(0.2724)	(0.2178)	(0.2225)
Avg. Heating Degree Days	-0.4773*	-0.5265*	-0.3844	-0.4234	0.2394	-0.6002***
	(0.2572)	(0.2707)	(0.2498)	(0.2705)	(0.2192)	(0.2236)
Annual Income	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 8. (cont.)

Implement. Year - 2005	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
Unemployment Rate	-0.1690**	-0.1358	-0.2711***	-0.2987**	-0.3657**	-0.3461**
	(0.0849)	(0.1068)	(0.0856)	(0.1231)	(0.1443)	(0.1536)
County Population	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
State Housing Units	-0.0000	0.0000	-0.0000	0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industrial Energy Use	-0.0060	-0.0039	0.0093	0.0117	0.0161	0.0117
	(0.0307)	(0.0309)	(0.0303)	(0.0304)	(0.0282)	(0.0266)
Electricity Customers	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	949.4914*	1,046.7165**	761.9044	834.0871	-467.0055	1,190.1010***
	(505.9568)	(533.1600)	(492.2601)	(534.2152)	(431.7537)	(440.1487)
Observations	8,082	6,666	9,402	7,592	7,272	7,629
R-squared	0.1736	0.1372	0.2449	0.1940	0.1385	0.1828

Robust standard errors, clustered at the plant level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Full Weighted Regressions, 2009

Dependent Variable: Logged CO_2 Emissions						
Implement. Year - 2009	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
RGGI Indicator	-1.1745	-1.1512	-1.0224	-1.2896	-0.1121	-1.1489
	(0.9010)	(1.0198)	(0.8999)	(0.9809)	(0.9842)	(0.9409)
Post-Implementation	0.8026*	0.5310	0.2580	0.2525	0.0723	0.4407
	(0.4517)	(0.5698)	(0.3211)	(0.4354)	(0.3441)	(0.3894)
Interaction Term	0.5158	0.6011*	0.2337	0.2622	0.4614	-0.0648
	(0.3361)	(0.3318)	(0.3234)	(0.3324)	(0.4237)	(0.4599)
RPS	0.0583	0.1155	0.1046	0.1666	-0.4532	0.1463
	(0.6720)	(0.6700)	(0.6385)	(0.6588)	(0.7027)	(0.6306)
Nameplate Capacity	0.0008	0.0007	0.0011*	0.0011*	0.0008	0.0009
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Natural Gas Resource Mix	0.0477***	0.0416***	0.0631***	0.0570***	0.0436***	0.0499***
	(0.0047)	(0.0052)	(0.0041)	(0.0045)	(0.0047)	(0.0045)
Avg. Temperature	-26.0720***	-25.3783***	-29.5457***	-30.4895***	-11.6853*	-28.1028***
	(6.5143)	(6.6523)	(6.9994)	(7.1787)	(5.9736)	(6.2586)
Avg. Cooling Degree Days	0.8655***	0.8457***	0.9709***	0.9992***	0.3862**	0.9264***
	(0.2122)	(0.2169)	(0.2285)	(0.2351)	(0.1947)	(0.2040)
Avg. Heating Degree Days	-0.8589***	-0.8350***	-0.9764***	-1.0087***	-0.3871*	-0.9271***
	(0.2156)	(0.2201)	(0.2318)	(0.2375)	(0.1976)	(0.2076)
Annual Income	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment Rate	-0.1549*	-0.1191	-0.2434***	-0.2462**	-0.2593*	-0.3291**
	(0.0842)	(0.1116)	(0.0816)	(0.1238)	(0.1562)	(0.1600)

Table 9. (cont.)

Implement Year - 2009	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
County Population	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
State Housing Units	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industrial Energy Use	-0.0180	-0.0153	-0.0021	-0.0035	-0.0181	0.0094
	(0.0337)	(0.0346)	(0.0317)	(0.0324)	(0.0310)	(0.0286)
Electricity Customers	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1,699.0402***	1,653.2038***	1,926.7271***	1,988.9139***	768.6735**	1,832.7339***
	(423.5025)	(432.4687)	(455.0122)	(466.5330)	(388.0874)	(407.1846)
Observations	8,341	6,879	9,661	7,805	7,485	7,842
R-squared	0.2145	0.1777	0.2869	0.2385	0.1686	0.2253

Robust standard errors, clustered at the plant level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Full Unweighted Regressions, 2005

Dependent Variable: Logged CO_2 Emissions						
Implement. Year - 2005	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
RGGI Indicator	0.6401**	0.3687	0.8718***	0.5549**	0.6186**	0.6620***
	(0.2586)	(0.2662)	(0.2383)	(0.2455)	(0.2538)	(0.2464)
Post-Implementation	-0.8070***	-1.3924***	-1.3430***	-1.6571***	-1.5054***	-1.7794***
	(0.1189)	(0.1573)	(0.0857)	(0.1056)	(0.1007)	(0.1281)
Interaction Term	-0.5713***	-0.1585	-0.6840***	-0.4446*	-0.3763**	-1.0175***
	(0.1308)	(0.1423)	(0.1658)	(0.1719)	(0.1776)	(0.2048)
RPS	0.8484***	0.9835***	0.5855***	0.7497***	0.6277***	0.7342***
	(0.1522)	(0.1532)	(0.1276)	(0.1345)	(0.1380)	(0.1278)
Nameplate Capacity	0.0039***	0.0040***	0.0038***	0.0040***	0.0040***	0.0040***
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Natural Gas Resource Mix	0.0649***	0.0583***	0.0730***	0.0674***	0.0658***	0.0694***
	(0.0014)	(0.0016)	(0.0012)	(0.0014)	(0.0015)	(0.0014)
Avg. Temperature	-6.4523***	-8.7199***	-2.5490	-5.4019**	-2.5682	-4.0502**
	(2.2264)	(2.4215)	(2.0882)	(2.3393)	(1.8016)	(1.9500)
Avg. Cooling Degree Days	0.2184***	0.2976***	0.0862	0.1795**	0.0908	0.1387**
	(0.0723)	(0.0787)	(0.0682)	(0.0766)	(0.0584)	(0.0635)
Avg. Heating Degree Days	-0.2149***	-0.2879***	-0.0866	-0.1809**	-0.0854	-0.1346**
	(0.0736)	(0.0800)	(0.0688)	(0.0771)	(0.0597)	(0.0644)
Annual Income	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment Rate	0.0361	0.0709**	0.0051	-0.0044	0.0146	0.0322
	(0.0229)	(0.0326)	(0.0196)	(0.0295)	(0.0370)	(0.0389)

Table 10. (cont.)

Implement. Year - 2005	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
County Population	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
State Housing Units	0.0000**	0.0000***	0.0000*	0.0000**	0.0000	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industrial Energy Use	0.0105	0.0074	0.0199**	0.0199**	0.0184*	0.0223***
	(0.0103)	(0.0104)	(0.0093)	(0.0093)	(0.0094)	(0.0086)
Electricity Customers	-0.0000***	-0.0000***	-0.0000**	-0.0000**	-0.0000*	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	420.2643***	566.3876***	167.5841	353.1944**	168.0630	264.0039**
	(144.7047)	(157.3845)	(135.6411)	(151.9225)	(117.1742)	(126.6995)
Observations	8,082	6,666	9,402	7,592	7,272	7,629
R-squared	0.4864	0.4541	0.5213	0.4836	0.4782	0.5219

Robust standard errors, clustered at the plant level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11. Full Unweighted Regressions, 2009

Dependent Variable: Logged CO_2 Emissions

Implement. Year - 2009	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
RGGI Indicator	-0.1976	-0.1050	-0.0457	-0.1183	0.2264	0.1041
	(0.2564)	(0.2708)	(0.2409)	(0.2503)	(0.2507)	(0.2506)
Post-Implementation	-0.3489***	-0.4398***	-0.9579***	-0.9288***	-0.9656***	-0.7576***
	(0.1211)	(0.1436)	(0.0885)	(0.1057)	(0.0935)	(0.1145)
Interaction Term	0.2531**	0.3171***	-0.145	-0.0585	-0.0203	-0.8566***
	(0.1132)	(0.1151)	(0.1222)	(0.1246)	(0.1587)	(0.1690)
RPS	0.8816***	0.8727***	0.6817***	0.6765***	0.4561***	0.6244***
	(0.1677)	(0.1731)	(0.1425)	(0.1496)	(0.1542)	(0.1384)
Nameplate Capacity	0.0038***	0.0039***	0.0038***	0.0039***	0.0040***	0.0039***
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Natural Gas Resource Mix	0.0669***	0.0621***	0.0748***	0.0706***	0.0688***	0.0727***
	(0.0014)	(0.0016)	(0.0012)	(0.0014)	(0.0014)	(0.0014)
Avg. Temperature	-16.2227***	-16.5317***	-15.1353***	-16.2700***	-12.6059***	-13.6445***
	(1.6627)	(1.8015)	(1.5862)	(1.6849)	(1.5805)	(1.5434)
Avg. Cooling Degree Days	0.5358***	0.5493***	0.4975***	0.5345***	0.4191***	0.4507***
	(0.0540)	(0.0581)	(0.0517)	(0.0547)	(0.0512)	(0.0500)
Avg. Heating Degree Days	-0.5387***	-0.5477***	-0.5024***	-0.5399***	-0.4173***	-0.4519***
	(0.0550)	(0.0597)	(0.0524)	(0.0557)	(0.0524)	(0.0511)
Annual Income	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment Rate	0.0470**	0.0612**	0.0257	0.0063	0.0428	0.0261
	(0.0223)	(0.0301)	(0.0192)	(0.0277)	(0.0379)	(0.0381)

Table 11. (cont.)

Implement Year - 2009	(1) Non-RGGI States Outside Impacted Power Market Post-Implement: 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Implement: 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Implement: 2016
County Population	0.0000	0.0000	-0.0000	-0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
State Housing Units	0.0000***	0.0000**	0.0000**	0.0000*	0.0000	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industrial Energy Use	0.0090	0.0084	0.0163*	0.0145	0.0136	0.0213**
	(0.0108)	(0.0109)	(0.0094)	(0.0096)	(0.0098)	(0.0086)
Electricity Customers	-0.0000***	-0.0000**	-0.0000***	-0.0000**	-0.0000	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1,055.2264***	1,074.5851***	984.8241***	1,058.8674***	819.9088***	887.2564***
	(108.1430)	(117.2408)	(103.1018)	(109.5723)	(102.8015)	(100.3995)
Observations	8,341	6,879	9,661	7,805	7,485	7,842
R-squared	0.5135	0.4859	0.5446	0.5129	0.5061	0.5483

Robust standard errors, clustered at the plant level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12. Full Triple Differences Regressions, 2005

Dependent Variable: Logged CO_2 Emissions						
Implement. Year - 2005	(1) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2016
RGGI Indicator	0.0768	-0.1634	0.3664	0.1312	0.1060	0.1562
	(0.2417)	(0.2508)	(0.2231)	(0.2309)	(0.2386)	(0.2329)
Post-Implementation	-0.7055***	-1.3052***	-0.9458***	-1.2228***	-1.3566***	-1.4081***
	(0.1190)	(0.1551)	(0.0932)	(0.1162)	(0.1085)	(0.1301)
DiD Interaction Term	-0.2849**	0.1961	-0.3746**	-0.1415	0.0261	-0.7074***
	(0.1362)	(0.1526)	(0.1627)	(0.1726)	(0.1736)	(0.2007)
Large Plants	2.4642***	2.7718***	2.3300***	2.6054***	2.7203***	2.6592***
	(0.1798)	(0.2149)	(0.1728)	(0.2080)	(0.2074)	(0.2035)
RGGI*DiD Interaction Term	1.4698***	1.4624***	1.4494***	1.3282***	1.4194***	1.3488***
	(0.3293)	(0.3471)	(0.3325)	(0.3479)	(0.3481)	(0.3487)
Post-Implement.*DiD Interact. Term	-0.1107	-0.2127*	-0.6229***	-0.7088***	-0.3171**	-0.5772***
	(0.1001)	(0.1185)	(0.1139)	(0.1334)	(0.1567)	(0.1593)
DDD Interaction Term	-0.3054	-0.2706	-0.4048	-0.3089	0.0938	0.0347
	(0.2197)	(0.2265)	(0.2810)	(0.2872)	(0.3169)	(0.3268)
RPS	0.7696***	0.8957***	0.5137***	0.6673***	0.5754***	0.6648***
	(0.1457)	(0.1464)	(0.1232)	(0.1297)	(0.1322)	(0.1236)
Nameplate Capacity	0.0029***	0.0029***	0.0029***	0.0030***	0.0030***	0.0030***
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
Natural Gas Resource Mix	0.0579***	0.0509***	0.0672***	0.0612***	0.0580***	0.0619***
	(0.0014)	(0.0016)	(0.0012)	(0.0014)	(0.0015)	(0.0014)
Avg. Temperature	-5.2801**	-7.5718***	-2.1635	-5.5297**	0.3673	-6.9270***
	(2.1396)	(2.3225)	(2.0189)	(2.2590)	(1.6940)	(1.9006)

Table 12. (cont.)

Implement. Year - 2005	(1) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2016
Avg. Cooling Degree Days	0.1803***	0.2624***	0.0737	0.1852**	-0.0042	0.2349***
	(0.0696)	(0.0756)	(0.0660)	(0.0740)	(0.0551)	(0.0620)
Avg. Heating Degree Days	-0.1751**	-0.2478***	-0.0730	-0.1836**	0.0128	-0.2276***
	(0.0707)	(0.0767)	(0.0665)	(0.0744)	(0.0561)	(0.0627)
Annual Income	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment Rate	0.0098	0.0425	-0.0138	-0.0216	-0.0184	0.0002
	(0.0222)	(0.0318)	(0.0192)	(0.0286)	(0.0355)	(0.0374)
County Population	0.0000*	-0.0000	0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
State Housing Units	0.0000**	0.0000**	0.0000	0.0000*	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industrial Energy Use	0.0100	0.0049	0.0178**	0.0165*	0.0125	0.0126
	(0.0099)	(0.0099)	(0.0089)	(0.0089)	(0.0089)	(0.0082)
Electricity Customers	-0.0000**	-0.0000**	-0.0000	-0.0000*	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	342.8934**	489.9963***	141.4448	359.9486**	-23.8918	449.2988***
	(139.0433)	(150.9143)	(131.1270)	(146.6840)	(110.1616)	(123.4814)
Observations	8,082	6,666	9,402	7,592	7,272	7,629
R-squared	0.5304	0.5068	0.5534	0.5220	0.5288	0.5643

Robust standard errors, clustered at the plant level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13. Full Triple Differences Regressions, 2009

Dependent Variable: Logged CO_2 Emissions						
Implement. Year - 2009	(1) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2016
RGGI Indicator	-0.5084**	-0.3298	-0.3584	-0.3424	-0.0671	-0.2259
	(0.2372)	(0.2467)	(0.2216)	(0.2277)	(0.2321)	(0.2308)
Post-Implementation	-0.1838	-0.2693**	-0.5220***	-0.4343***	-0.8694***	-0.2641**
	(0.1158)	(0.1353)	(0.0956)	(0.1146)	(0.0937)	(0.1264)
DiD Interaction Term	0.2955***	0.3819***	-0.0207	0.0550	0.1692	-0.6367***
	(0.1115)	(0.1141)	(0.1202)	(0.1258)	(0.1492)	(0.1644)
Large Plants	2.5788***	2.8469***	2.3821***	2.6292***	2.6008***	2.7116***
	(0.1721)	(0.2066)	(0.1643)	(0.1979)	(0.1936)	(0.1941)
RGGI*DiD Interaction Term	1.0593***	1.0365***	1.0844***	0.9801***	1.2295***	0.9737***
	(0.3182)	(0.3369)	(0.3222)	(0.3376)	(0.3350)	(0.3369)
Post-Implement.*DiD Interact. Term	-0.3128***	-0.4475***	-0.7052***	-0.8149***	-0.3021**	-0.7209***
	(0.0755)	(0.0937)	(0.0961)	(0.1139)	(0.1383)	(0.1464)
DDD Interaction Term	0.0654	0.127	-0.0982	-0.0087	0.2365	0.3734
	(0.1609)	(0.1683)	(0.2376)	(0.2448)	(0.2905)	(0.3021)
RPS	0.7682***	0.7332***	0.5914***	0.5660***	0.3466**	0.5101***
	(0.1622)	(0.1674)	(0.1384)	(0.1452)	(0.1496)	(0.1341)
Nameplate Capacity	0.0028***	0.0029***	0.0029***	0.0030***	0.0030***	0.0030***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Natural Gas Resource Mix	0.0596***	0.0544***	0.0686***	0.0641***	0.0608***	0.0649***
	(0.0014)	(0.0017)	(0.0012)	(0.0014)	(0.0015)	(0.0014)
Avg. Temperature	-16.0196***	-16.0126***	-15.4763***	-16.8641***	-11.2340***	-15.3797***
	(1.6089)	(1.7511)	(1.5446)	(1.6528)	(1.5050)	(1.5231)

Table 13. (cont.)

Implement. Year - 2009	(1) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2010	(2) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2010	(3) Non-RGGI States Outside Impacted Power Market Post-Impl. - 2012	(4) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2012	(5) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2014	(6) Non-RGGI States Outside Impacted Power Market w/o CA Post-Impl. - 2016
Avg. Cooling Degree Days	0.5297***	0.5350***	0.5090***	0.5557***	0.3758***	0.5092***
	(0.0523)	(0.0566)	(0.0504)	(0.0537)	(0.0488)	(0.0493)
Avg. Heating Degree Days	-0.5307***	-0.5281***	-0.5127***	-0.5578***	-0.3705***	-0.5075***
	(0.0532)	(0.0580)	(0.0510)	(0.0546)	(0.0499)	(0.0504)
Annual Income	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment Rate	0.0349	0.0502*	0.0154	0.0011	0.0343	0.0022
	(0.0217)	(0.0298)	(0.0188)	(0.0274)	(0.0368)	(0.0371)
County Population	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
State Housing Units	0.0000**	0.0000*	0.0000*	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industrial Energy Use	0.0080	0.0059	0.0139	0.0115	0.0076	0.0128
	(0.0103)	(0.0104)	(0.0090)	(0.0092)	(0.0093)	(0.0082)
Electricity Customers	-0.0000***	-0.0000*	-0.0000**	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1,040.5160***	1,038.6903***	1,005.6806***	1,095.6867***	729.2989***	998.3453***
	(104.6066)	(113.9106)	(100.3705)	(107.4524)	(97.8718)	(99.0491)
Observations	8,341	6,879	9,661	7,805	7,485	7,842
R-squared	0.5555	0.5342	0.5752	0.5484	0.5515	0.5879

Robust standard errors, clustered at the plant level, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

REFERENCES

Abt Associates. (2017). *Analysis of the public health impacts of the regional greenhouse gas initiative, 2009-2014.* Retrieved from https://www.abtassociates.com/sites/default/files/2018-06/Analysis%20of%20the%20public%20health%20impacts%20of%20regional%20greenhouse%20gas.pdf

Arora, V., & Lieskovsky, J. (2014). *Electricity use as an indicator of U.S. economic activity.* Washington, DC: Energy Information Administration. Retrieved from https://www.eia.gov/workingpapers/pdf/electricity_indicator.pdf

Berry, C. (2018). Space heating and water heating account for nearly two thirds of U.S. home energy use. Retrieved from https://www.eia.gov/todayinenergy/detail.php?id=37433

Betsill, M., & Hoffmann, M. J. (2011). The contours of 'cap and trade': The evolution of emissions trading systems for greenhouse gases. *Review of Policy Research, 28*(1), 83-106. doi:10.1111/j.1541-1338.2010.00480.x

Burke, P. J., & Abayasekara, A. (2017). *The price elasticity of electricity demand in the united states: A three-dimensional analysis.* (No. 2017-50). CAMA Working Papers.

Burtraw, D., & Palmer, K. (2004). SO2 cap-and-trade program in the united states: A "living legend" of market effectiveness. In W. Harrington, R. D. Morgenstern & T. Sterner (Eds.), *Harrington, Winston, Morgenstern, Richard D., and Sterner, Thomas. Choosing Environmental Policy Comparing Instruments and Outcomes in the United States and Europe* (pp. 41-66). Hoboken: Taylor and Francis.

Chen, Y. (2009). *Does a regional greenhouse gas policy make sense? A case study of carbon leakage and emissions spillover* doi:https://doi-org.proxy.library.georgetown.edu/10.1016/j.eneco.2009.02.003

Crowley, T. J. (2000). Causes of climate change over the past 1000 years. *Science*, *289*(5477), 270-277.

Ellerman, A.D. (2006). Are Cap and Trade programs more environmentally effective than conventional regulation? In J. Freeman, & C. D. Kolstad (Eds.), *Moving to markets in environmental regulation*. New York: Oxford University Press. doi:oso/9780195189650.003.0003. Retrieved from https://www.oxfordscholarship.com/10.1093/acprof:oso/9780195189650.001.0001/acprof-9780195189650-chapter-3

Energy Information Administration. (2011). About 60% of the U.S. electric power supply is managed by RTOs. Retrieved from https://www.eia.gov/todayinenergy/detail.php?id=790

Energy Information Administration. (2012). Most states have Renewable Portfolio Standards. Retrieved from https://www.eia.gov/todayinenergy/detail.php?id=4850

Energy Information Administration. (2018a). Natural gas explained: Where our natural gas comes from. Retrieved from https://www.eia.gov/energyexplained/natural-gas/where-our-natural-gas-comes-from.php

Energy Information Administration. (2018b). Units and calculators explained. Retrieved from https://www.eia.gov/energyexplained/units-and-calculators/degree-days.php

Energy Information Administration. (2020). Nuclear explained - nuclear power and the environment. Retrieved from https://www.eia.gov/energyexplained/nuclear/nuclear-power-and-the-environment.php

Environmental Protection Agency. (2016). Climate change indicators: Heating and cooling degree days. Retrieved from https://www.epa.gov/climate-indicators/climate-change-indicators-heating-and-cooling-degree-days

Environmental Protection Agency. (2015). Electricity customers. Retrieved from https://www.epa.gov/energy/electricity-customers

Environmental Protection Agency. (2019a). Economic incentives. Retrieved from https://www.epa.gov/environmental-economics/economic-incentives

Environmental Protection Agency. (2019b). Greenhouse gas inventory data explorer. Retrieved from https://cfpub.epa.gov/ghgdata/inventoryexplorer/#allsectors/allgas/econsect/all

Environmental Protection Agency. (2019c). Sources of greenhouse gas emissions. Retrieved from https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

Fickling, M. (2017). Per capita residential electricity sales in the U.S. have fallen since 2010. Retrieved from https://www.eia.gov/todayinenergy/detail.php?id=32212

Friedrich, J., Ge, M. & Pickens, A. (2017). This interactive chart explains world's top 10 emitters, and how they've changed. Retrieved from https://www.wri.org/blog/2017/04/interactive-chart-explains-worlds-top-10-emitters-and-how-theyve-changed

Goulder, L. H., & Parry, I. W. (2008). Instrument choice in environmental policy. *Review of Environmental Economics and Policy, 2*(2), 152-174.

Goulder, L. H., & Schein, A. R. (2013). Carbon taxes versus cap and trade: A critical review. *Climate Change Economics*, *4*(3), 1-28. Retrieved from http://www.jstor.org.proxy.library.georgetown.edu/stable/climchanecon.4.3.02

Haites, E. (2018). Carbon taxes and greenhouse gas emissions trading systems: What have we learned? *Climate Policy*, *18*(8), 955-966. doi:10.1080/14693062.2018.1492897

IPCC, 2014: *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Lawrence, C., & Berry, C. (2017). U.S. households' heating equipment choices are diverse and vary by climate region. Retrieved from https://www.eia.gov/todayinenergy/detail.php?id=30672

Lindsey, R. (2019, September 19). Climate change: Atmospheric carbon dioxide. Retrieved from https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide

Mann, M. E., Bradley, R. S., & Hughes, M. K. (1998). Global-scale temperature patterns and climate forcing over the past six centuries. *Nature*, *392*, 779-787.

Market-based strategies. (2017). Retrieved from https://www.c2es.org/content/market-based-strategies/

Moon J., Lee W. K., Song C., Lee S. G., Heo S. B., Shvidenko A., Kraxner F., Lamchin M., Lee E. J., Zhu Y., Kim D., Cui G. (2007). An introduction to mid-latitude ecotone: sustainability and environmental challenges. *Sibirskij Lesnoj Zurnal (Sib. J. For. Sci.)*, 6, 41–53.

Murray, B. C., & Maniloff, P. T. (2015). *Why have greenhouse emissions in RGGI states declined? An econometric attribution to economic, energy market, and policy factors* doi:https://doi-org.proxy.library.georgetown.edu/10.1016/j.eneco.2015.07.013

Mayclin, D. (2018). Air conditioning accounts for about 12% of U.S. home energy expenditures. Retrieved from https://www.eia.gov/todayinenergy/detail.php?id=36692

NASA. (2019a). Climate Change: How Do We Know?. Retrieved from https://climate.nasa.gov/evidence/

NASA. (2019b). The causes of climate change. Retrieved from https://climate.nasa.gov/causes

National Weather Service. (2019). What are heating and cooling degree days. Retrieved from https://www.weather.gov/key/climate_heat_cool

NOAA. (2019). Climate forcing. Retrieved from https://www.climate.gov/maps-data/primer/climate-forcing

Program design archive. (2019). Retrieved from https://www.rggi.org/program-overview-and-design/design-archive

Ramseur, J. L. (2019). *The Regional Greenhouse Gas Initiative: Background, impacts, and selected issues.* Congressional Research Service. Retrieved from https://fas.org/sgp/crs/misc/R41836.pdf

Regional Greenhouse Gas Initiative (RGGI). (2019). Retrieved from https://www.c2es.org/content/regional-greenhouse-gas-initiative-rggi/

Regional Greenhouse Gas Initiative Memorandum of Understanding. (2005). Retrieved from https://www.rggi.org/sites/default/files/Uploads/Design-Archive/MOU/MOU_12_20_05.pdf

Stavins, R. N. (2008a). Addressing climate change with a comprehensive US cap-and-trade system. *Oxford Review of Economic Policy, 24*(2), 298-321. Retrieved from http://www.jstor.org.proxy.library.georgetown.edu/stable/23606646

Stavins, R. N. (2008b). A meaningful U.S. cap-and-trade system to address climate change. *Harvard Environmental Law Review, 32*(2), 293-371. Retrieved from http://proxy.library.georgetown.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,uid&db=ofm&AN=502601697&site=ehost-live&scope=site

US Global Change Research Program (USGCRP). (2017). *Climate science special report: Fourth national climate assessment, volume I*. Washington, DC, USA: U.S. Global Change Research Program. doi:10.7930/J0J964J6. Retrieved from Climate Science Special Report: Fourth National Climate Assessment, Volume I.