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Missing Out on Going Green?

Economic and Health Outcomes of New Jersey's Leaving the Regional Greenhouse Gas Initiative

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
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Abstract

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This paper examines the impact that leaving the Regional Greenhouse Gas Initiative (RGGI) has had on electricity prices and asthma-related health outcomes in New Jersey. Specifying a variety of treatment dates and treatment effect timelines, this research finds that, with regard to either outcome of interest, there was no statistically significant treatment effect. New Jersey did not, as many predicted, experience lower residential electricity prices after leaving the program, nor did the state experience an increase in asthma symptoms or attacks. Results prescribe continued investigation of New Jersey's post-RGGI experience, as well as closer examination of the different ways that participation in the program has affected Maryland and Delaware.

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I. Introduction

Global climate change has increasingly become recognized as one of the definitive challenges of the twenty-first century. Many facets of this challenge are economic in nature, given that climate change has many economic causes and will bring with it a variety of economic consequences. Economists often refer to climate change as one of the world's largest market failures, given that climate change is a negative externality that results from individuals' use of products and processes that emit greenhouse gases. Many of the potential solutions to climate change thus call for pricing greenhouse gas emissions as a way of forcing individuals to take into account the negative externality of carbon pollution. Put simply by Otaviano Canuto, former Vice President of the World Bank, "the solution to climate change can be summarized in a single statement: 'get the prices right!'," which requires "taxing fossil fuels proportionately to the amount of carbon they release, in order to correct the problem that corresponding negative spillovers of their use are not reflected in their market prices."[1]

Beginning in 2009, ten northeast states created the Regional Greenhouse Gas Initiative (RGGI) in an attempt to decrease carbon dioxide emissions in the power generation sector. New Jersey announced its intent to leave the program in mid-2011 and officially withdrew at the end of 2011. As justification for leaving the program, New Jersey cited higher energy prices and a lack of noticeable benefits to consumers. Presently, over three years later, New Jersey remains the only state to have opted out of the regional trading initiative, despite continued attempts by the New Jersey Senate to rejoin the program (Baxton 2011; O'Malley 2014).

This paper examines empirically the economics and supposed benefits of regional carbon trading schemes, which have become increasingly important given the lack of national action to

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[1] Taken from a quote given to the Global Energy Initiative's "The Economist's Solution to Climate Change" piece (http://globalenergyinitiative.org/environment/139-the-economist-solution-to-climate-change.html).

mitigate climate change, but have remained relatively uninvestigated given the lack of programs currently in existence. This project seeks specifically to answer the following questions: (1) Has New Jersey's leaving the RGGI led to increased consumer benefits in the form of lower electricity prices? (2) Has New Jersey's leaving the RGGI harmed citizens by causing a reversion to pre-RGGI pollution within the state?

These questions are of particular interest to the overall debate concerning climate change mitigation strategies because they should either confirm or deny (to some extent) some of the claims made by opponents of carbon trading schemes. In this case, those claims are that such policies bring short-term costs (increased electricity prices) without any corresponding short-term benefits (decreased incidence of illness related to pollution). Given New Jersey's recent abandonment of the program, and the increased number of Republican politicians elected in the northeast United States in the 2014 elections, it may currently be more important to focus on the effects of *leaving* such programs more than the effects of joining them, lest more states abandon the program under incorrect pretenses. To answer these specific questions, I plan to perform difference-in-differences regressions to test whether New Jersey's leaving the RGGI has led to decreased residential electricity prices and increased asthma-related health problems for individuals living within the state.

II. Literature Review

a. Economics and Climate Change

Over the past several decades, a scientific consensus has begun to emerge regarding both the validity of climate change as an observable event as well as the primary role that manmade carbon dioxide emissions have played in that process (IPCC 2013). Climate change has been referred to as the most important market failure in history (Stern 2007), due to the magnitude of the phenomenon as well as several unique facets that distinguish it from most other instances of negative externalities. Unlike many other cases where market failure leads to immediate negative environmental externalities, the consequences of climate change will not be felt until much further in the future. Nor will these consequences be exclusively noneconomic: increased temperatures are expected to decrease labor productivity; extended droughts may significantly decrease agricultural yields; and extreme weather may destroy infrastructure and capital (Rhodium Group 2014). These are only a few of the future direct economic consequences expected to result from unmitigated climate change. Indirect economic consequences are also likely, as climate change leads to increased food insecurity (as a result of decreased agricultural productivity) and induced migration (as a result of extreme weather changes), each of which exacerbate violent conflict and political instability that undoubtedly affect economic output (IPCC 2013).

b. Environmental Regulation

The character and efficacy of environmental regulation is hardly a new or settled area of economic study. Many economists have called into question the original premise underlying regulation that government intervention is necessary to correct market inefficiencies and increase social welfare. Coase (1960) was one of the first to question this idea, arguing that regulation should not be viewed as inherently beneficial, given that the harm incurred from curtailing some productive processes may end up outweighing the actual harm incurred from the processes. Other research has questioned the motives behind environmental regulation, arguing that producers sometimes drive the push for regulation. Given the relatively larger per capita stakes that firms have in regulatory decisions, they are more likely to be able to overcome collective action problems and influence government policy (Peltzman 1976). Additionally, producer and environmentalist interests may actually align, especially when regulation may result in decreases in production that provide existing firms with cartel-like profit gains (Maloney and McCormick 1982). These and other papers provide theoretical reasons why firms may end up benefiting from regulation.

Various studies have found empirical evidence that environmental regulations can be instrumental in changing firm behavior and bringing about the desired environmental improvements. Weil (1996) found that even low levels of regulation by the Occupational Safety and Health Administration (OSHA) induced high levels of firm compliance that led to modest increases in worker safety. Relatively infrequent inspections appeared to be enough to induce changes in firm behavior. Shimshack and Ward (2008) connected increased regulations with over-compliance, especially in those industries where the daily extent of environmental discharge was stochastic or connected to the production of other regulated substances.

Other studies have found less encouraging results. Environmental regulations may end up being counterproductive if they lead to unexpected behavioral changes that negate the desired environmental or health goal. Davis (2008) found that restrictions on driving in Mexico City did not actually improve air quality, as consumers bought additional cars to bypass the regulations (which limited the days on which particular cars could be driven) despite relatively strict enforcement. Viscusi (1979) found that stringent pollution regulation succeeded in increasing firms' investments in safety systems, but that the effect of this increase on worker safety was largely negated by resulting decreases in worker attentiveness to safety hazards. Henderson (1996) found that regulations aimed at curtailing harmful ozone emissions in the United States were largely effective at inducing changes in firm behavior in non-attainment locations, but also may have reduced air quality in attainment areas, as firms moved from more polluted localities to less polluted ones. These articles illustrate that compliance may not necessarily be the best way to measure regulatory success, and suggest a focus on actual environmental outcomes.

c. Emissions Trading Schemes

Given this understanding of climate change as a market failure, one of the mechanisms most often suggested as a way to combat climate change is some form of emissions trading scheme that would put a price on harmful emissions. Distinct from an emissions tax, where firms pay a certain amount for every unit of pollution produced, emissions trading programs operate through the use of permits, which are auctioned off in a primary market organized by the government, and allow firms to emit a certain amount of greenhouse gases, commensurate to the number of permits purchased. Firms would be able to sell these permits amongst each other in secondary markets, allowing firms to regain some of the auction costs if they realize that they will not use all of their permits. This secondary mechanism has led some economists to dub emissions trading schemes as the most "efficient" market-based way to combat climate change (Bayon, Hawn, and Hamilton 2007). This claim is not without controversy. Pizer (2002) argued that auctions that set a predetermined quantity of auction permits are less efficient than those systems which simply set a price or tax on carbon, given uncertainties regarding auction prices.

Many trading schemes focus on one greenhouse gas in particular: carbon dioxide (CO_2), one of the most widespread manmade greenhouse gases. While these programs may be worth undertaking for their carbon reduction potential alone, it would be a mistake to overlook ancillary benefits that may accrue from reducing emissions other than carbon dioxide. Burtaw et al. (2003) modeled the ancillary benefits that would accrue from a $25 per ton carbon tax, finding near-term secondary reductions in the emissions of mono-nitrous oxides (NO_x). This ancillary benefit is just one example of how carbon-trading programs may lead to short-term aggregate health benefits.

The RGGI is an example of a regional carbon-trading program, where ten states in the northeast decided in 2009 to cap emissions from electricity generated by large power plants within their borders. States issue permits independently, which are then sold in regional quarterly auctions where firms can purchase CO_2 allowances. The proceeds of these auctions are then returned to the states where they are be used to fund other programs that would help offset emissions, including energy efficiency upgrades and renewable energy investment projects (RGGI 2012). Several states, including Massachusetts and New Hampshire, had already officially capped emissions, but believed that a regional program would be more effective than if they continued to act alone, given the highly integrated nature of the Northeast's electric grid (Rabe 2006).

The regionalization of the Northeast's efforts is both a strength and weakness of the program. Regional programs are inevitably incomplete solutions, given that they do no prevent emitters from simply moving to an adjacent area that has not capped carbon emissions, a phenomenon known as "emissions leakage" (OECD 2009). This problem may be particularly acute with regard to the RGGI, given that several of the original participators, specifically New Jersey, Delaware, and Maryland, operate within the same regional electric power market as the nonparticipating Pennsylvania (FERC 2014). Chen (2009) found a large risk that the regional initiative would indeed result in decreased carbon emissions in participating states, but mostly because these states would shift from electricity generated inside their borders to energy imported from nonparticipating states and regions. The issue of emissions leakage remains relatively unstudied from an empirical standpoint. As such, any research that finds potential instate benefits from regional carbon trading must keep in mind the potential negatives of emissions leakage.

Given that the efficacy of environmental regulations remains a point of debate in the literature, it is worth going more in-depth into the particulars of the RGGI. Under the RGGI, firms may be awarded extra permits (not bought through the auction process) if they undertake "offsets" projects. These projects would either focus on reducing other greenhouse gases (such as methane) or on sequestering carbon from the atmosphere in the long-term (such as via reforestation). Permits are not awarded for offsets projects if the number of awarded (versus bought) permits would exceed 3.3% of the firm's total permits, ensuring that firms cannot use excessive numbers of offsets projects to avoid emissions reductions.[2] Compliance periods last for three years, at which point state monitoring agencies check to make sure that states have not exceeded their allowances. Interim monitoring also occurs, and requires states to keep allowances equal to 50% of interim year emissions. In order to ensure compliance, the RGGI stipulates that firms who emit over their allowable limit are fined an amount equal to three times what the cost of the permits for the excessed emissions would have been.[3] States are also given the option to impose additional fines and sanctions as they see fit.

In 2009, the states originally set the regional cap at 188 million tons of carbon dioxide. Throughout the first compliance period, however, emissions decreased significantly as a result of unforeseen factors, the most likely one being falling natural gas prices. Though the allowances

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[2] According to the RGGI's "Model Rule," a document meant to provide a blueprint for states when they write their own implementing legislation (https://www.rggi.org/docs/ProgramReview/_FinalProgramReviewMaterials/Model_Rule_FINAL.pdf).

[3] According to the U.S. Environmental Protection Agency's technical support document, "Survey of Existing State Policies and Programs that Reduce Power Sector CO2 Emissions," published June 2, 2014 (http://www2.epa.gov/cleanpowerplantoolbox/survey-existing-state-policies-and-programs-reduce-power-sector-co2-emissions).

continued to sell at prices above the established reserve price,[4] the permit prices had dropped to less than $2 by the end of 2011. The cap was reduced for the second compliance period to 165 million tons of carbon dioxide, though weak demand persisted.[5] In 2012, the states announced their intention to aggressively lower the emissions cap for the next compliance period by roughly 45%, and established a system whereby the cap would decrease even further in subsequent years.[6] Prices quickly jumped, and cleared at $5.41 at the most recent auction (March 11, 2015), over $3 more than the reserve price.

Very little empirical research has looked at the RGGI since its creation in 2009. As stated earlier, New Jersey opted to leave the program midway through 2011, with Governor Chris Christie claiming that the "gimmicky" program merely "[drove] up energy costs for consumers" (Baxter 2011). This occurred despite the fact that by 2014, the remaining RGGI participants had purportedly reduced their CO_2 emissions by roughly 40 percent, and invested over $700 million towards various energy reduction programs (RGGI 2014b). That said, to my knowledge there have been no empirical studies looking specifically at the initiative's effects on energy prices or health outcomes.

d. Energy Prices

Some studies have looked empirically at the interaction between carbon trading programs and energy prices in markets outside of the United States. Fezzi and Bunn (2010) attempted to estimate the effect of an increase in the price of carbon on electricity prices in the United Kingdom and Germany, finding that increases in carbon prices led to a small yet significant

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[4] Detailed data on every RGGI auction can be found on the program's website at http://www.rggi.org/market/co2_auctions/results.

[5] Summary of emissions cap trends taken from the Center for Climate and Energy Solutions' site page on the Regional Greenhouse Gas Initiative, updated December 2013 (http://www.c2es.org/us-states-regions/regional-climate-initiatives/rggi).

[6] Laid out in the updated "Model Rule" (https://www.rggi.org/docs/ProgramReview/_FinalProgramReviewMaterials/Model_Rule_FINAL.pdf).

increase in the price of electricity, both in the short- and long-run. Chevallier (2010) found evidence in Australia over a ten-year period that the mere news of significant developments in the country's carbon trading agenda corresponded with increased volatility in the wholesale electricity market, while government white papers on carbon trading developments led to a decrease in volatility, trends which reflect the continuing degree of uncertainty surrounding the economic effects of carbon trading. It is difficult to overstate the importance of empirical studies on this subject, given the large number of conflicting theoretical studies that have been conducted. Indeed, Nelson, Kelley, and Orton (2012) conducted a comprehensive review of various economic firms' models and projections regarding Australian carbon pricing strategies,[7] and found that the results of these models varied wildly. Even more troubling, they found little to explain why the estimates diverged so starkly.

e. Asthma

Earlier research has elucidated various links between air quality and health. Taylor (2014) found that individuals born near polluting steel plants experienced higher old-age mortality rates than those born in areas with cleaner air, illustrating that the effects of air pollution on health outcomes may only become clear in the long-term. As alluded to earlier, many of the health-related negative consequences of climate change will accrue only in the relatively long-term. Various studies have now shown that increased incidence and severity of asthma, especially in children, may be one of the earliest consequences of anthropogenic climate change, one that we are already beginning to witness. These studies posit that climate change will increase the frequency of weather events that lead to higher concentrations of pollen, mold, and fungi, all of which trigger asthma (Beggs and Bambrick 2005; Amrita 2011). At the very

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[7] The preferred Australian strategy ended up being a carbon tax, enacted in 2012 that lasted little more than two years before being repealed by a successive more conservative administration.

least these studies have shown that increased asthma prevalence has mirrored increases in carbon dioxide emissions over the past half-century.

These effects of carbon emissions on asthma may not be as indirect and long-term as these studies suggest, however. As stated previously, Burtaw et al. (2003) postulated that decreases in CO_2 should bring corresponding decreases in other harmful emissions that are associated with carbon emissions, such as NO_x. The effects of these emissions reductions are typically more profound in the short-term, given that, unlike carbon emissions, they carry with them immediate short-herm health consequences. The U.S. Environmental Protection Agency, for example, states that elevated levels of even short-term nitrogen dioxide (NO_2) can lead to increased bronchial reactivity in persons suffering from asthma, leading to increased emergency care visits (EPA 2012). Studies have backed this statement with empirical analysis. Brender, Maantay, and Chakraborty (2011) conducted a review of studies relating to environmental hazards and adverse health outcomes, finding that a majority of those studies suggested that residential proximity to various polluting agents, including fossil fuel-powered electricity generation centers, led to increased incidents of hospitalization as a result of asthma, possibly having an even stronger effect on asthma hospitalization than heavily trafficked roads.

III. Methodology

To examine the economic and health-related outcomes of interest, I will be using various difference-in-differences (DID) regressions, using data from New Jersey and two other control states, Maryland and Delaware. These states were chosen as ideal controls (over those other states still participating in the RGGI) given their proximity to New Jersey, as well as the fact that all three states are part of the same federally regulated Regional Transmission Organization (PJM Interconnection). The regressions will follow the same basic equation:

$$Y_{st} = \beta_1\ NewJersey\ + \beta_2\ post + \beta_3\ (NewJersey * post) + \beta_4 X + u$$

where Y_{st} is a dependent variable of interest (in this case, electricity prices or asthma outcomes); *NewJersey* is a dummy variable equal to 1 for New Jersey, and 0 for the control states; *post* is a dummy variable equal to 1 for those quarters after the treatment and equal to 0 for all earlier quarters; *NewJersey*post* is an interaction term for New Jersey during the post-treatment period; and *X* represents the various control variables. The specified treatment period varies somewhat across regressions. Those variations will be noted in the appropriate sections. Note that, in my analysis of health-related outcomes, I was unable to compare New Jersey to Delaware as insufficient data existed for the latter state. As a result, the analysis of those outcomes is limited to New Jersey and Maryland.

IV. Economic Outcomes

a. *Data*

The data for my analysis of electricity prices come from several publically available sources. My dependent variable of interest is retail electricity prices for the residential sector in each state. The U.S. Energy Information Administration (EIA) provides this information on a quarterly, state-by-state basis. I also control for the quantity of electricity consumed, which is reported quarterly by the EIA and measures the total retail sales of electricity to the residential sector in millions of kilowatthours. [8] Finally, I attempt to control for the prices of natural gas and coal, also reported by the EIA. Given that the quantity of electricity provided is at least partially determined by the price of electricity, there is a substantial risk that any independent variable that directly measures quantity will be endogenous in a regression on prices. As such, I include two instrumental variables for quantity.

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[8] In my regressions, I list these values in hundreds of millions of kilowatthours, to avoid yielding coefficient results that go out five or six decimal places.

The first instrumental variable I use is a temperature index, which measures the severity of temperature changes. The EIA uses the total number of heating degree days (HDDs) and cooling degree days (CDDs) per month as a means of gauging the effect of temperature on electricity demand. These two statistics measure how cold or hot (respectively) a location is over a specific period of time relative to some base temperature, usually 65 degrees Fahrenheit.[9] Previous studies on electricity prices have found that temperature changes can be used as reliable indicators of exogenous changes in electricity demand (Dergiades and Tsoulfidis 2008; Fezzi and Bunn 2010). Fezzi and Bunn (2010) specifically use HDDs and CDDs to model this relationship. According to that study, at temperatures between 55° F and 60° F, electricity usage for heating or cooling is at a minimum. Thus, heating degree days under 55° F can be used to measure increased electricity usage for heating, and cooling degree days above 60° F can be used to measure increased electricity usage for cooling. Unfortunately, the best state-level data on HDDs and CDDs, provided by the U.S. National Oceanic and Atmospheric Administration (NOAA), uses 65° F as the baseline for both metrics. As a result, I do not use temperature degree days, instead constructing my own temperature index, measuring the degree to which average quarterly temperatures for each state deviate from the 55-60° F range.[10] State-by-state monthly temperature averages were available from NOAA, and were used to compute quarterly averages.

The second instrumental variable I use is per capita income. The U.S. Bureau of Economic Analysis (BEA) provides quarterly information on total personal income on a state-

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[9] From the EIA's website, regarding HDDs: "A measure of how cold a location is over a period of time relative to a base temperature, most commonly specified as 65 degrees Fahrenheit. The measure is computed for each day by subtracting the average of the day's high and low temperatures from the base temperature (65 degrees), with negative values set equal to zero. Each day's heating degree days are summed to create a heating degree day measure for a specified reference period. Heating degree days are used in energy analysis as an indicator of space heating energy requirements or use." Cooling degree days are similar, but are used as indicators of energy requirements associated with cooling buildings and houses on hot days.

[10] I conducted several regressions and found that this measure of temperature, as opposed to a heating/cooling degree day scale with a baseline at 65° F, is significantly correlated with electricity demand.

by-state basis, which, together with population data from the U.S. census, can be used to compute income per capita on a state-by-state, quarterly basis. Population data is only provided on an annual basis, making this computed measure of income per capita somewhat inaccurate. That said, quarterly changes in population over the course of a year are likely to be relatively small, thus these computed measures should not deviate much from actual values. Previous studies have used other variables as proxies for electricity demand, such as the occupied stock of houses for a given year (Dergiades and Tsoulfidis 2008). However, this data is only provided consistently on a yearly or national basis. First stage regressions reveal significance between both of these instruments and the quantity of electricity sold to the residential sector.

To control for the factors that may alter a utility's cost of supplying electricity to a consumer, and thus alter the price that company charges, I look at the prices of two fuel inputs: natural gas and coal. According to the EIA, the main determinants of a power plant's cost of production, relative to other fuel types, are capital costs, fuel costs, operations and maintenance costs, financing costs, and the predicted utilization rate for that particular plant.[11] However, plant-level costs are often proprietary or otherwise not readily available, nor are such costs especially relevant to the state-wide focus of my model, and would also be almost impossible to incorporate in any systematic way. Additionally, the EIA's aforementioned analysis is limited to the creation of *new* power generation operations, and is less useful for measuring the costs of production at preexisting plants.

One of the aforementioned inputs that is important for preexisting plants is the cost of fuel. Indeed, PJM, the organization responsible for providing electricity to Maryland, Delaware, and New Jersey, states that fuel is "the electricity industry's largest single expense," going on to

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[11] Taken from the EIA's "Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2014." The report itself goes into greater detail, but this general information was taken from an April 17, 2014, press release for the report (http://www.eia.gov/forecasts/aeo/electricity_generation.cfm).

mention the predominance of natural gas and coal as their primary fuel inputs.[12] As such, I have attempted to control for variation in natural gas and coal prices. I use the Henry Hub natural gas spot price, a nationally important metric, to track the change in that fuel's cost. Coal spot prices are less monolithic, with various markets existing in the Northeast United States. Unfortunately, the EIA does not report historical coal spot prices, labeling the information proprietary. It is also unclear which of these markets New Jersey, Delaware, and Maryland rely on, as that decision most likely varies over time in response to market factors. The EIA does, however, report the cost of coal shipments to the electric power sector by plant state on a quarterly basis. Given the completeness of this data, I believe this is the best available measurement to track variation in the price of coal for electricity generation.

Table 1 provides summary statistics for these variables. Graph 1 tracks the quarterly retail electricity prices for the three states in question, beginning with the first quarter of 2009 and ending with the third quarter of 2014. The treatment date for this graph is specified as the end of 2011, when New Jersey officially removed itself from the RGGI. Other potential treatment dates will be analyzed in the following section of this paper. Several important preliminary observations can be made based on this raw data. First, as expected, electricity prices are very volatile, and seem to be somewhat cyclical in nature, which would make sense due to the seasonal nature of temperature-induced demand fluctuations. Second, New Jersey appears to experience much higher electricity prices on average relative to Delaware and Maryland. Third, and of particular interest to my research question, New Jersey does not appear to have benefited from lower prices after the treatment, at least relative to Delaware and Maryland, nor does it

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[12] From a PJM fact sheet titled "The Cost of Electricity," released on March 26, 2014 (http://www.pjm.com/~/media/about-pjm/newsroom/fact-sheets/the-cost-of-electricity-fact-sheet.ashx).

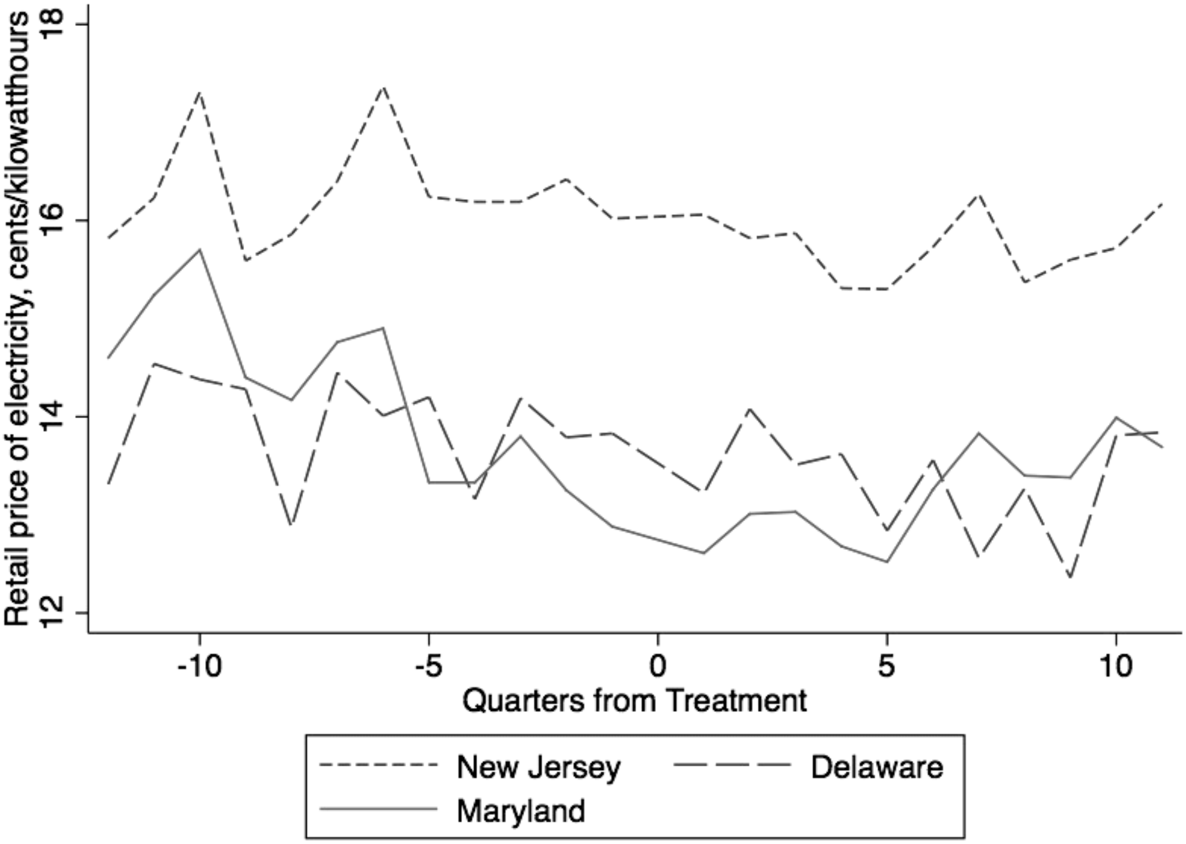
appear to have been suffering from price increases during the pre-treatment period, at least upon first cursory glance.

Table 1. Summary Statistics for Economic Outcomes
The data reports on all quarters from the start of 2009 to the third quarter of 2014.

State	Count	Mean	Standard Deviation	Range
Delaware				
Price	23	13.63826	.6109355	2.18
Quantity	23	11.50687	2.133337	6.083592
Temperature	23	10.78841	5.525301	17.26667
Income	23	43.08609	1.949794	6.489998
Coal	23	91.37435	8.6699	26.12
Maryland				
Price	23	13.7287	.8694005	3.179999
Quantity	23	68.91432	9.789327	29.55532
Temperature	23	10.96812	5.675559	19.1
Income	23	52.16783	2.11021	6.66
Coal	23	84.91609	6.577266	21.06
New Jersey				
Price	23	16.03739	.5278362	2.070001
Quantity	23	72.43987	13.85332	44.40536
Temperature	23	10.85797	6.931157	24.23333
Income	23	53.40261	2.340602	7.289997
Coal	23	99.51217	6.836607	25.95
Total				
Price	69	14.46812	1.306231	5.010001
Quantity	69	50.95369	29.76803	92.94775
Temperature	69	10.8715	5.987215	24.23333
Income	69	49.55217	5.090503	17.18
Coal	69	91.9342	9.467056	37.21
Natural Gas	23	3.976957	.9157036	4.13

Price refers to the retail price of electricity, measured in cents per kilowatthour. Residential quantity is measured in hundreds of millions of kilowatthours. Temperature measures how many degrees (in Fahrenheit) outside the 55-60 degree range the average quarterly temperature was. Income per capita is measured in thousands of dollars. The price of coal shipments to the electric power sector by plant state is measured in dollars per short ton. The Henry Hub natural gas spot price is measured in dollars per million British thermal units (btu), and is a national metric, thus those values are the same for each state, and listed only in the "Total" subsection of the above table. Temperature data was taken from the National Oceanic and Atmospheric Administration. Income data was taken from the Bureau of Economic Analysis. All other data was taken from the Energy Information Agency.

Graph 1. Average Quarterly Retail Price of Residential Electricity (cents per kilowatthour)
The treatment date is defined as the end of December 2011.



b. *Regression Results*

The results of four regressions on retail prices of electricity are displayed at the end of this section, in Table 2. As stated previously, these regressions assume the treatment effect occurs at the end of 2011, and assumes an immediate effect. The first specification is the basic DID regression mentioned earlier, with no controls. Earlier observations about New Jersey's prices being on balance greater are confirmed at the 1% significance level. The three states also experience on balance lower electricity prices after the treatment, which is also significant at the 1% level. Post-treatment prices in New Jersey, however, do not differ significantly from post-treatment prices in the other states. The second specification incorporates a control variable for the quantity of electricity provided, while the third specification also adds variables that attempt to control for natural gas and coal prices. Simply incorporating quarterly natural gas and coal prices poses various endogeneity problems, given that one of the main mechanisms through which the treatment might have exerted downward pressure on retail prices would have been through a relative increase in the price of natural gas and coal, carbon-emitting fuels. I have therefore lagged those prices by one quarter in an attempt to alleviate this issue. The fourth specification instruments for quantity using temperature and per capita income. All of these regressions were estimated with standard errors robust to heteroskedasticity and clustering at the state-level. For each subsequent regression, the statistically significant coefficients retain their original signs.

I then conduct several more sets of regressions, altering the date of the treatment and adopting different assumptions about how long it took for the treatment to take an effect. The results displayed in Table 3 assume that the treatment occurs midway through 2011, closer to the date when Governor Christie first announced his plans to withdraw New Jersey from the RGGI (May 2011). It is plausible that electricity companies began to alter their behavior after the announcement. The aforementioned work done by Chevallier, where Australian prices responded to government consideration of a carbon program, lends evidence to this possibility. Furthermore, it is possible that these alterations in behavior took time. Table 3 thus assumes the treatment took two quarters to take effect, defining the pre-treatment period as up to and including the second quarter of 2011, and the post-treatment period as onward from and including the first quarter of 2012. Observations between these time periods are dropped. Table 4 also uses the announcement as the treatment, but allows four quarters for the treatment to take effect, defining the pre-treatment period as up to and including the second quarter of 2011, and the post-treatment period as onwards from and including the third quarter of 2012. Table 5 returns to the original treatment date (New Jersey's actual withdrawal from the program) but allow two quarters for firms and prices to fully be affected, as was done in Table 3.

For each set of regressions, the final and most exhaustive model, which incorporates fuel input price controls and instruments for quantity, yields results consistent with those of Table 2. New Jersey continues to experience higher prices at the 1% significance level. The post-treatment period, however it is defined, continues to experience lower prices at (at least) the 5% significance level. All other coefficients (with the exception of the constant) remain statistically insignificant, including the primary treatment effect of interest (the interaction between the New Jersey and post-treatment indicators).

Table 2. Regression Results for Electricity Prices
Pre-treatment period ending December 2011, with an effect that is immediate and not delayed
Specification 4 instruments quantity with temperature and income per capita measurements.

	(1)	(2)	(3)	(4)
Variables	Price			
NewJersey	2.246***	2.146***	2.409**	2.637***
	(0.124)	(0.102)	(0.289)	(0.158)
post	-0.781**	-0.780**	-0.745**	-0.752**
	(0.175)	(0.175)	(0.0883)	(0.0883)
NewJerseyPost	0.225	0.227	0.265	0.273
	(0.175)	(0.175)	(0.217)	(0.221)
Quantity		0.00309	0.00115	-0.00391
		(0.00272)	(0.00399)	(0.00233)
NatGas			0.0127	-0.00397
			(0.0856)	(0.0912)
Coal			-0.0192	-0.0253
			(0.0213)	(0.0222)
Constant	14.06***	13.93***	15.64**	16.45**
	(0.124)	(0.116)	(1.634)	(1.798)
Observations	69	69	69	69
R-squared	0.808	0.812	0.824	0.815

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 3. Regression Results for Electricity Prices
Pre-treatment period ending June 2011, with an effect that is delayed by two quarters
Specification 4 instruments quantity with temperature and income per capita measurements.

	(1)	(2)	(3)	(4)
Variables	Price			
NewJersey	2.139***	2.008***	2.214***	2.406***
	(0.215)	(0.139)	(0.200)	(0.0530)
post	-0.905*	-0.903*	-0.842**	-0.839**
	(0.266)	(0.266)	(0.154)	(0.153)
NewJerseyPost	0.332	0.331	0.357	0.368
	(0.266)	(0.266)	(0.307)	(0.312)
Quantity		0.00417	0.00272	-0.00154
		(0.00272)	(0.00368)	(0.00167)
NatGas			0.0172	0.00283
			(0.0844)	(0.0915)
Coal			-0.0149	-0.0204
			(0.0188)	(0.0189)
Constant	14.18***	14.01***	15.27***	15.98***
	(0.215)	(0.153)	(1.441)	(1.525)
Observations	63	63	63	63
R-squared	0.812	0.819	0.826	0.820

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 4. Regression Results for Electricity Prices
Pre-treatment period ending June 2011, with an effect that is delayed by four quarters
Specification 4 instruments quantity with temperature and income per capita measurements.

	(1)	(2)	(3)	(4)
Variables	Price			
NewJersey	2.139***	1.955***	2.245**	2.417***
	(0.215)	(0.109)	(0.240)	(0.0978)
post	-0.895**	-0.897**	-0.843**	-0.845**
	(0.195)	(0.197)	(0.118)	(0.115)
NewJerseyPost	0.279	0.271	0.330	0.347
	(0.195)	(0.197)	(0.233)	(0.230)
Quantity		0.00586	0.00415	0.000257
		(0.00290)	(0.00388)	(0.00145)
NatGas			0.0375	0.0251
			(0.0839)	(0.0904)
Coal			-0.0221	-0.0267
			(0.0174)	(0.0170)
Constant	14.18***	13.94***	15.74***	16.35***
	(0.215)	(0.137)	(1.272)	(1.280)
Observations	57	57	57	57
R-squared	0.802	0.816	0.831	0.825

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 5. Regression Results for Electricity Prices
Pre-treatment period ending December 2011, with an effect that is delayed by two quarters
Specification 4 instruments quantity with temperature and income per capita measurements.

Variables	(1) Price	(2)	(3)	(4)
NewJersey	2.246***	2.099***	2.427**	2.633***
	(0.124)	(0.0936)	(0.327)	(0.201)
post	-0.771**	-0.773**	-0.763***	-0.774***
	(0.104)	(0.105)	(0.0487)	(0.0473)
NewJerseyPost	0.172	0.171	0.244	0.259
	(0.104)	(0.105)	(0.142)	(0.139)
Quantity		0.00452	0.00242	-0.00224
		(0.00286)	(0.00413)	(0.00219)
NatGas			0.0360	0.0212
			(0.0841)	(0.0891)
Coal			-0.0250	-0.0302
			(0.0206)	(0.0211)
Constant	14.06***	13.87***	15.99***	16.70***
	(0.124)	(0.115)	(1.539)	(1.653)
Observations	63	63	63	63
R-squared	0.799	0.807	0.827	0.819

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

c. *Discussion*

The aforementioned results shed doubt on claims that participation in the RGGI was causing an increase in the price of electricity in New Jersey. These results may provide evidence for the counterarguments many environmentalists made against Christie's decision to leave the program, namely that his focus on the carbon capping aspect of the RGGI was too narrow. Funds generated from RGGI carbon permit auctions were, as a function of the program's design, dispersed to the participating states, and intended to be used to limit the negative effects that the carbon caps may have had on prices and employment. New Jersey received over $100 million in carbon allowance proceeds through December 31, 2010, and had already legislated that the majority of these proceeds go towards funding energy efficiency projects and providing financial assistance to low-income households in paying their electric bills.[13] However, the beneficial effects of these remedies on electricity prices should not be overstated in this particular context. The latter investment target would not have had a direct effect on the retail prices that firms charge, and the former investment aim was directed largely at the commercial, industrial, and institutional sectors.

Another possible reason that the above regressions did not yield any significant results stems from limitations in the dataset. Some sources have speculated that the reason electricity prices have declined recently across-the-board for all states lies in the sharp decline of natural gas prices. While I attempted to control for this with lagged prices, these prices were measured in quarters, a longer timeframe than one might expect it to take for electricity prices to respond to changes in the natural gas price. The negative coefficient on coal prices is also somewhat surprising. One would expect that higher coal prices would lead to higher electricity prices, as companies would be forced to charge more to make up for the increased costs of fuel. This peculiarity may be related to the aforementioned endogeneity problem, inherent in any independent variable that measures natural gas and coal prices.

As mentioned earlier, the cap in the initial compliance period (the only period that New Jersey participated in) was set at a much higher level than firms were actually emitting. It is thus possible that firms did not actually alter their behavior to account for the cap during that period. If this were the case, we would not expect to see changes in New Jersey firm behavior, and thus not expect any significant difference between New Jersey's pre- and post-treatment experiences. This is also one possible explanation for the aforementioned lack of results. However, even if this were indeed the case, where firms in RGGI states did not actually change their behavior

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[13] From a press release on the RGGI's website, "Investment of Proceeds from RGGI CO2 Allowances," published February 2011 (http://www.rggi.org/docs/Investment_of_RGGI_Allowance_Proceeds.pdf. Last accessed 2/18/2015).

during the pre-treatment, it could still be argued that, were Governor Christie's claims true, prices in New Jersey would have been relatively lower in the post-treatment period compared to those in Maryland and Delaware, as firms in those states began to adjust their behavior under the promise of aggressive future caps.

V. Health Outcomes

a. *Data*

I use the Behavioral Risk Factor Surveillance System (BRFSS) annual survey data from 2010 through 2012 to measure various asthma-related health outcomes. The BRFSS survey is an annual, cross-sectional survey conducted via telephone by the Centers for Disease Control and Prevention (CDC). BRFSS covers all fifty states and various U.S. territories, and interviews subjects regarding a variety of chronic health conditions (such as diabetes, arthritis, asthma, and others) and various behavioral and demographic factors that may contribute to these conditions (such as smoking, diet, frequency of exercise, alcohol consumption, and others). Data is collected year-round, and the dates of each interview are recorded in the dataset. Of specific use in this project is the related Asthma Call-back Survey (ACBS), a follow-up survey conducted by the CDC on those individuals surveyed by BRFSS who responded that their children have asthma. The ACBS is also conducted year-round, and asks a variety of in-depth questions regarding the intensity of the child's asthma.

Though the ACBS is impressively detailed in its questions, it is lacking in its scope. Not all states conduct the follow-up survey, and those that do sometimes only conduct the survey sporadically, skipping certain years. Maryland and New Jersey conducted the survey in 2010, 2011, and 2012. Delaware did not. The CDC has also not released ACBS data for any years after

2012, limiting data for the post-treatment period. As such, I will only compare asthma rates in Maryland and New Jersey during these truncated pre- and post-treatment periods.

The asthma-related health outcomes of most interest for my research will be whether an ACBS respondent's child experienced any asthma-related symptoms in the 30 days prior to being interviewed and whether the ACBS respondent's child experienced any attacks or episodes of asthma in the 3 months prior to being interviewed. While there are other asthma-related variables included in the ACBS that may be interesting dependent variables to focus on, such as average number of emergency room visits over the past year, these variables' longer time horizons make them of limited use to this project, given that even though they may have been asked and answered in the post-treatment period, they may refer to past time periods that extend into the pre-treatment interval. The ACBS contains many variables that could be used as controls, including but not limited to race, income level, and access to health care.

Tables 6 and 7 provide summary statistics for the actual number of symptoms and episodes reported. A fairly large range characterizes data for each outcome. For example, the incidence of symptoms varies widely, with some children experiencing symptoms on a daily basis, and others being completely symptom-free (for the 30 day period in question). Graphs 2 and 3 provide histograms showing the distributions of the survey responses for each of these variables. Both histograms are extremely right-skewed, illustrating how, while most respondents' children experienced few or zero asthma symptoms and attacks, several experienced a very high frequency. This generates substantial variation in the average number of symptom days or episodes per month that are not necessarily representative of the actual population, given that the number of respondents surveyed each month varies. As such, I will look mainly at whether or not respondents experienced any number of symptoms and attacks during the period in question, as opposed to the actual frequencies of symptoms and attacks. Graphs 4 and 5 reflect this focus, tracking the number of survey children who experienced any asthma-related symptoms in the past 30 days and the number of survey children who experienced an asthma attack or episode in the past 3 months, respectively. Given the aforementioned variation in sample size, the graphs display the proportion of that month's respondents who experienced symptoms or had an attack. A cursory glance at the graphs shows that trends vary widely, and immediate conclusions are harder to draw from these graphs than they were for the electricity price trends. It does appear, however, that New Jersey experiences somewhat less volatility than Maryland, at least with regard to these variables.

Table 6. Summary Statistics for Asthma Symptom Days

Number of symptom days a respondent experienced in the past 30 days				
State	Count	Mean	Standard Deviation	Range
Maryland				
2010-2012	282	2.72695	6.077195	30
2010	96	2.71875	6.011748	30
2011	91	3.032967	6.50205	30
2012	95	2.442105	5.764373	30
New Jersey				
2010-2012	392	3.278061	6.81404	30
2010	145	3.703448	7.267817	30
2011	118	4.042373	7.532714	30
2012	129	2.10075	4.789058	30

Number of respondents experiencing any symptoms in the past 30 days			
State	Count	No	Yes
Maryland			
2010-2012	282	191	91
2010	96	66	30
2011	91	57	34
2012	95	68	27
New Jersey			
2010-2012	392	250	142
2010	145	91	54
2011	118	74	44
2012	129	85	44

All data taken from the Centers for Disease Control and Prevention’s Behavioral Risk Factor Surveillance System (BRFSS) Asthma Call-back Survey.

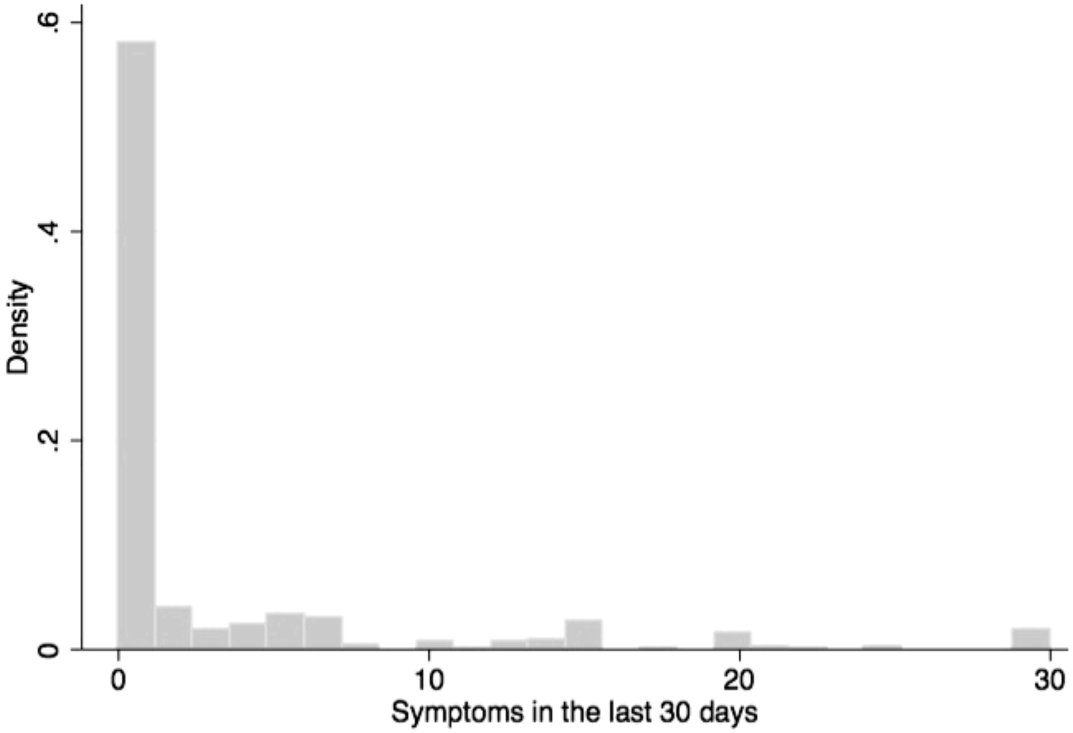
Table 7. Summary Statistics for Asthma Attacks

Number of asthma attacks a respondent experienced in the past 3 months				
State	Count	Mean	Standard Deviation	Range
Maryland				
2010-2012	282	.7269504	1.79954	15
2010	96	.7394833	1.668563	10
2011	91	.9230769	2.400142	15
2012	95	.5263158	1.128378	5
New Jersey				
2010-2012	392	.7270408	2.20427	20
2010	145	.7172414	2.033413	15
2011	118	.8983051	2.599769	20
2012	129	.5813953	1.990986	20

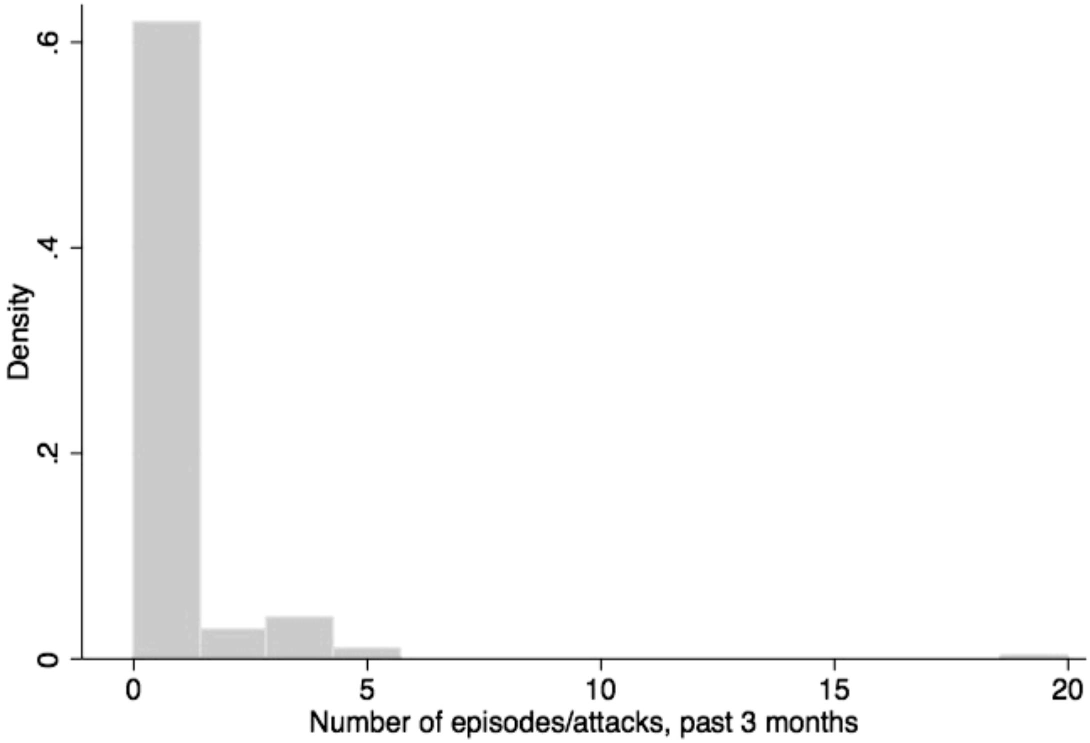
Number of respondents experiencing any asthma attacks in the past 3 months			
State	Count	No	Yes
Maryland			
2010-2012	282	202	80
2010	96	67	29
2011	91	64	27
2012	95	71	24
New Jersey			
2010-2012	392	296	96
2010	145	110	35
2011	118	86	32
2012	129	100	29

All data taken from the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (BRFSS) Asthma Call-back Survey.

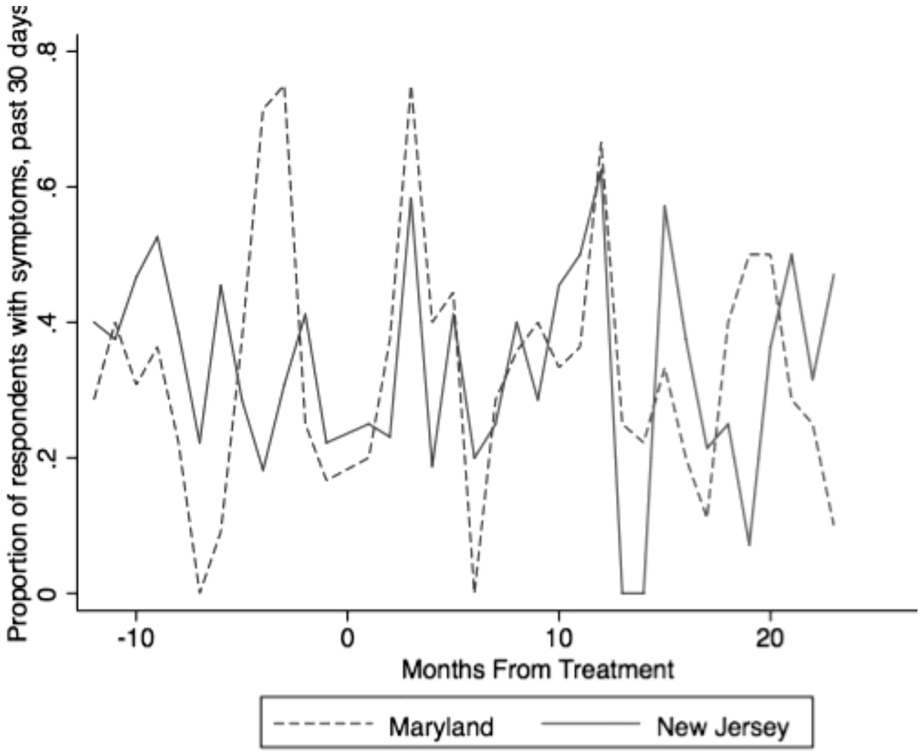
Graph 2. Distribution of Asthma Symptom Days (both states combined)



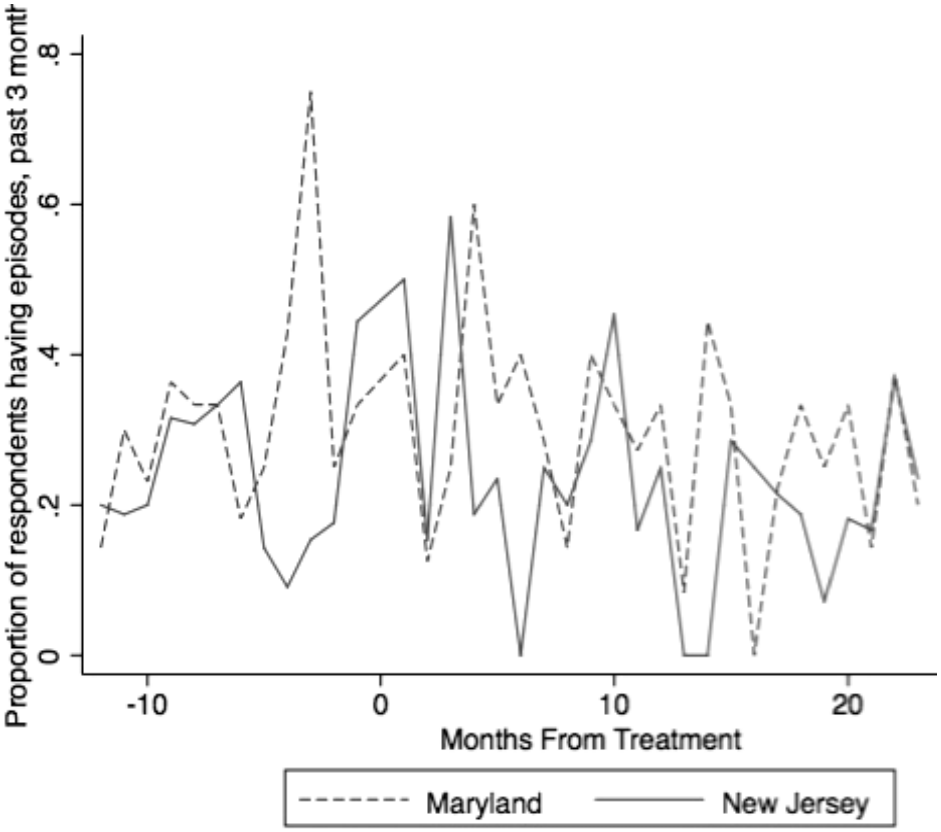
Graph 3. Distribution of Asthma Attacks (both states combined)



Graph 4. Incidence of Any Asthma Symptom Days (past 30 days)



Graph 5. Incidence of Any Asthma Attacks (past 3 months)



b. *Regression Results*

Initial regressions focused on whether or not respondents experienced asthma-related symptoms in the 30 days prior to being surveyed. Four of these regressions are displayed in Table 8. Using BRFSS survey data, I was able to control for the reported race of the child, the responding parent's income level,[14] the responding parent's education level,[15] whether or not the family had health insurance, and whether or not an individual who smoked habitually lived in the house. With regard to treatment timing, the four regressions in the table follow a pattern similar to that used in the electricity regressions: the first model specifies a pre-treatment period ending in December 2011, with an immediate effect; the second model a pre-treatment period ending in June 2011, with the effects delayed by two quarters; the third model a pre-treatment period ending in June 2011, with the effects delayed by a full year; the fourth model a pre-treatment period ending in December 2011 with the effects delayed by two quarters. Responses from the first month of each post-treatment period were excluded, given that reports of symptoms could be referring to periods during the pre-treatment period (or, in those specifications that assume a delayed effect, the period that was dropped to allow for that delay). In all of the regressions, there is no significant difference between the experiences of those in New Jersey, those in the post-treatment period, or those in New Jersey during the post-treatment period. Only income level has a significant coefficient with a negative sign.

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[14] I created six income levels, using the information provided by BRFSS. The first level includes those who earn under $15,000 a year; the second level includes those who earn between $15,000 and $30,000 a year; and so on at intervals of $15,000, with the highest level being those who earned more than $70,000 a year.

[15] The education levels were the same as those used by BRFSS: level one denotes those who never attended school or only kindergarten, level two being those who attended elementary school (defined as going up to eighth grade), level three being those who completed some high school, level four being those who graduated high school (or obtained a GED), level five being those with some college education, and level six being those who graduated from college.

Table 8. Regression Results for Asthma Symptoms

Specification 1 establishes a pre-treatment period ending December 2011, with an immediate effect. Specification 2 establishes a pre-treatment period ending June 2011, with treatment effects delayed by two quarters. Specification 3 establishes a pre-treatment period ending June 2011, with treatment effects delayed by four quarters. Specification 4 establishes a pre-treatment period ending December 2011, with treatment effects delayed by two quarters.

Variables	(1) Any Asthma Symptom in the Past 30 Days	(2)	(3)	(4)
NewJersey	0.0270	0.0195	0.0158	0.0252
	(0.0474)	(0.0549)	(0.0553)	(0.0477)
post	-0.0830	-0.0668	-0.128	-0.136
	(0.0656)	(0.0690)	(0.0993)	(0.0976)
NewJerseyPost	0.0386	0.0444	0.181	0.166
	(0.0845)	(0.0883)	(0.121)	(0.119)
ChildBlack	-0.0101	-0.0402	-0.0345	-0.00155
	(0.0495)	(0.0537)	(0.0609)	(0.0551)
ChildAsian	-0.00588	-0.0369	-0.0750	-0.0316
	(0.0966)	(0.109)	(0.119)	(0.104)
ChildHawaiianPacific	0.134	-0.355	-0.431	0.0941
	(0.338)	(0.475)	(0.478)	(0.340)
ChildIndianNative	0.261	0.363*	0.291	0.186
	(0.184)	(0.197)	(0.215)	(0.198)
IncomeLevel	-0.0315**	-0.0285**	-0.0404***	-0.0409***
	(0.0124)	(0.0136)	(0.0153)	(0.0137)
ParentEduLevel	0.0259	0.0325	0.0550*	0.0421
	(0.0244)	(0.0262)	(0.0292)	(0.0268)
Insurance	0.0969	0.105	0.220*	0.201*
	(0.100)	(0.104)	(0.114)	(0.109)
HomeSmoke	-0.0769	-0.000426	-0.0192	-0.0890
	(0.0806)	(0.0893)	(0.0932)	(0.0835)
Constant	0.339**	0.265*	0.124	0.221
	(0.144)	(0.153)	(0.173)	(0.161)
Observations	618	519	416	515

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

Table 9 displays the results of similar regressions that use whether or not the respondent's child experienced an asthma episode or attack within the previous three months as the dependent variable. I only run two regressions on this dependent variable, given that the latter two treatment manipulation strategies used above, which delay the effect until midway through 2012, would have required dropping all respondents except those who answered in the final three months of 2012, an extremely limited post-treatment period. These regressions yield similar results to those that were conducted on symptom incidence: the only significant coefficients were those relating to income level, which were also negative.

Table 9. Regression Results for Asthma Attacks
Specification 1 establishes a pre-treatment period ending December 2011, with an immediate effect. Specification 2 establishes a pre-treatment period ending June 2011, with treatment effects delayed by two quarters.

Variables	(1) Any Asthma Attack in the Past 3 Months	(2)
NewJersey	-0.0393	-0.0717
	(0.0436)	(0.0508)
post	-0.0723	-0.0898
	(0.0647)	(0.0681)
NewJerseyPost	0.0219	0.0503
	(0.0818)	(0.0857)
ChildBlack	-0.0356	-0.0676
	(0.0460)	(0.0503)
ChildAsian	0.0591	0.115
	(0.0888)	(0.101)
ChildHawaiianPacific	-0.252	-0.272
	(0.311)	(0.440)
ChildIndianNative	-0.0940	-0.0619
	(0.181)	(0.198)
IncomeLevel	-0.0403***	-0.0308**
	(0.0115)	(0.0127)
ParentEduLevel	0.00987	-0.000711
	(0.0227)	(0.0246)
Insurance	0.0879	0.0714
	(0.0937)	(0.0982)
HomeSmoke	-0.0214	0.0595
	(0.0741)	(0.0828)
Constant	0.442***	0.469***
	(0.134)	(0.143)
Observations	596	497

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

c. *Discussion*

The fact that the asthma-related regressions yielded few significant results is not necessarily surprising, given that individual asthma experiences tend to develop and change over a long period of time. Indeed, some of the insignificant coefficients make little intuitive sense, such as the negative sign attributed to the smoking variable. Even with a more comprehensive dataset, there is reason to doubt whether the treatment would have had a significant and measurable effect during such a short time period. It is important to remember that New Jersey was only a part of the program for two years. As such, it is possible that they did not participate long enough to experience the benefits that would have accrued from a sustained decrease in pollution. Future research should continue to monitor New Jersey's progress, looking to see if states such as Maryland see eventual improvements in asthma-related outcomes relative to New Jersey as they continue to participate in the program.

As far as future research is concerned, plant-level data and analysis would likely be particularly useful. As previous studies have mentioned, pollution from power plants has the most pronounced effects on those living in close proximity to the plants. Analysis on data that took this into account, and focused on those living closest to pollution, would be more likely to yield meaningful results. The type of fuel that a particular plant uses to generate electricity is also important, even within the subcategory of fossil fuels. Most of the previous literature has focused on the harmful effects of coal pollution, as this method of generating electricity results in much higher levels of secondary pollutants in addition to carbon dioxide. Switching from a fuel such as natural gas to some form of renewable energy would be more likely to reduce carbon emissions while not necessarily resulting in significant decreases in the air pollutants that cause asthma.

VI. Conclusion

Global warming is increasingly being recognized as one of the direst challenges facing humanity in the twenty-first century. As explained earlier, many of the most fundamental causes of excessive pollution are economic in nature. There is thus little doubt that economic solutions are necessary to address such a problem. Unfortunately, many of these solutions, such as carbon allowances and permits, are steeped in controversy. Many worry about the short-term economic consequences that such changes may bring, especially in the form of widespread increases in consumer prices. This research project has shown that, at least in some cases, these worries may be overblown. Despite proclamations to the contrary, New Jersey did not experience reduced electricity prices after freeing its power plant operators from the carbon program's restrictions. However, this research also suggests, as many advocates for the global warming cause must no doubt concede, that the benefits of decreasing carbon pollution operate on a much longer time horizon than the potential costs. New Jersey did not see any significant increases in certain asthma-related metrics after allowing firms to return to coal and natural gas generation mixes.

These results indicate that policymakers would do well not to overstate the potential immediate health benefits of switching to non-carbon sources of energy. Policymakers should instead continue to press the importance of maintaining a long time-horizon when evaluating climate change solutions, while also rebutting those who would argue that any such solutions necessarily invite negative economic consequences. This issue is particularly important for policymakers in states participating in the RGGI, who may soon be fighting against pressure to leave the program. This research also seems to suggest that, for such rebuttals to have meaning and salience, states pursuing carbon-trading programs would do well to couple such programs with other reforms, such as energy efficiency upgrades, as the RGGI states have sought to do.

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