Carbon Emissions and Shareholder Value: Causal Evidence from the U.S. Power Utilities*

Mayank Kumar†
Amiyatosh Purnanandam‡

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Abstract

We establish a causal link between carbon emissions and shareholder value using the passage of the Regional Greenhouse Gas Initiative (RGGI) that imposed a cap-and-trade policy for carbon emission on electric utilities in several Northeastern and Mid-Atlantic states. The regulation was successful in significantly bringing down the level of CO_2 emission from plants located in the RGGI states compared to unaffected plants. The affected plant's revenue and profitability decreased after the RGGI as they transitioned to cleaner technology. Publicly traded power utility companies in the affected states experienced a drop in their profitability as well. Yet, they had a higher market-to-book ratio after the implementation of the initiative. Increase in value came from an increase in the expected future cash flows of the treated firms and increasing demand of these stocks by institutional funds focused on environmental goals. Our results show that short-term focus on profitability may be a significant impediment to carbon transition.

Keywords: cap-and-trade, carbon emission, pollution, stakeholder value, capitalism
JEL Classification: G21, G28

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†Ross School of Business, University of Michigan; email: mayankkr@umich.edu.
‡Ross School of Business, University of Michigan; email: amiyatos@umich.edu

1 Introduction

How does environmentally friendly policies such as transition to cleaner technology affect shareholder value? The nature and extent of trade-off between shareholder value and stakeholder outcomes has been at the center of policy and academic debates for decades (Friedman, 1970), with a renewed interest in the topic in recent years (Hart and Zingales, 2017; Edmans, 2021; Bebchuk and Tallarita, 2020; Edmans and Kacperczyk, 2022). Specifically, the issue of carbon-transition and its impact on shareholders has taken the center stage of several policy initiatives and academic debates on climate finance. Yet, it has been difficult to establish a causal link between transition to cleaner technology and shareholder value.

There are two primary reasons for this gap in the literature. First, environmental policies of a firm are likely to be correlated with other attributes of the firm that can independently affect shareholder value. For example, unobserved managerial preferences, technological differences, or a firm's investment opportunity set can affect both its investments in pollution control strategies and shareholder value at the same time. The second challenge relates to the measurement of environmental policies of the firm and their impact on pollution. For example, researchers often use ESG scores from outside rating agencies to measure a firm's environmental policies, making them prone to subjective assessment, error, and disagreement (Berg, Koelbel, and Rigobon, 2019). Further, in the absence of a standardized reporting system of externalities across firms, environmental outcomes such as pollution are measured indirectly and often with noise and subjectivity For example, a commonly used measure of carbon emission is based on the Greenhouse Gas (GHG) protocol that provides a set of guidelines to capture the extent of pollution emitted by corporation. These are indirect measures of pollution, the reporting is voluntary, and there are no enforcement mechanisms, all of which leads to a possibility of greenwashing (e.g., see Grewal, Richardson, and Wang (2022)).

We overcome these challenges in this paper by focusing on the U.S. power utilities, a sector that contributes to more than 25% of the country's total carbon emission, and by exploiting a regulation that provides an exogenous variation in the pollution control policies of power utilities located in some of the Northeastern and Mid-Atlantic states of the country.[1] The Regional Greenhouse Gas Initiative (RGGI) is a mandatory, market-based, regional program to reduce CO2 emissions from the power sector in the U.S. It is a cap-and-trade policy where the participating Northeastern and Mid-Atlantic states set a regional cap on carbon emissions from utilities in their states. The initiative provides a meaningful variation in the adoption of clean technology across the RGGI-affected and non-affected states, a variation that is independent of managerial preferences, technological changes, and hidden investment opportunity set of the individual power plants. The governors of the RGGI states signed an MoU for this initiative in 2005 and the cap-and-trade program went into effect in 2008. We compare the environmental and shareholder outcomes across the affected and non-affected states before and after the adoption of the law, paying careful attention to the transition period between 2005-2008 in our empirical analysis.

Our empirical setting is attractive from the measurement viewpoint as well: all the power utilities in the U.S. are required to report their carbon emissions in a consistent manner at a very granular plant level. Specifically, our measure of pollution comes from a Continuous Emissions Monitoring System (CEMS) that all power utilities in the U.S. with more than 25MW generating capacity are required to install at every fossil fuel power plant. The CEMS measures particulate matter concentration or emission rate using pollutant analyzers and reports it continuously. We also obtain information on the level of electricity generation, revenue, and profits at the plant level, which allows us to directly link carbon emission with profitability outcomes. Finally, a subset of these utilities are publicly traded, which allows us to trace the effect of carbon transition on shareholder value.

The adoption of RGGI provides us with an exogenous measure of transition to green

[1] See the data from the Environmental Protection Agency on CO2 emission by sector here: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

technology for three main reasons. First, the initiative required regional cooperation across neighboring states, making it less susceptible to endogeneity concerns that arise due to concomitant changes in other policies at the same time that are typically enacted either at the state level or at the national level. Related, the passage was possible due to the concerted efforts of the bureaucrats in these sates as argued by several leading policy scholars and observers (for example, see Rabe (2010)). Second, utilities in the RGGI states objected to the initiative when it was being actively debated by the lawmakers. Therefore, the policy is less likely to be affected by biases that come from lobbying efforts of the affected party. Finally, the passage of the law required the support of lawmakers from all the states in the region. Since democratic and republican voters and politicians often have considerable disagreement over environmental issues, and even within each party politicians differ on their commitment to green transition, the passage of the RGGI initiative was possible due to convergence in the viewpoint of lawmakers at a given point in time. In fact, whether to join the RGGI was often an important part of the election campaign of both the democratic and republican gubernatorial candidates in these states. New Jersey provides a visible example of the political differences that affected a state's decision to join the initiative: New Jersey initially joined the RGGI under a democratic governor and later withdrew from it in 2011 after the election of Governor Chris Christie, a republican candidate, in 2010. Therefore, the passage of the initiative was primarily driven by political considerations.[2] The unique aspect of geographical clustering, bureaucratic cooperation, and political alignment that were needed for the passage of the RGGI makes it unlikely that the post-RGGI adoption of green technology was driven by any other systematic differences in omitted variables such as managerial ability, preferences, other state-specific laws, non-climate related technological differences, relative pice of coal versus other fuels, or hidden investment opportunity set of utilities in the RGGI states.

Our first set of results compare carbon emissions from fossil-fuel plants located in the

[2] Huber (2013) provides a detailed analysis of various factors, including business and political opposition, behind the passage of this law.

treated states, i.e., the RGGI affected states, with those in all other states, i.e., the control states, in the country in a difference-in-differences setting. Carbon emissions from the treated and control plants show a parallel trend till 2005. But the emissions from the treated plants started to decline immediately after the signing of the MoU in 2005. Between 2005 and 2008, the treated plants reduced their carbon emission by 21% compared to the control plants. After 2008, i.e., after the implementation of the cap-and-trade policy, the reduction was an even larger 50%. These are economically large effects and show that the initiative had the intended effect of controlling pollution in these states.

In addition to comparing the treated states with all other states in the country, we also conduct two tests in which we compare them with power plants only in the states that voted for democrats in the presidential election of 2008 (Democrat states) and with power plants in the states with deregulated electricity market (Deregulated states).[3] These sets of counterfactual states allow us to alleviate concerns that our results are due to coordinated differences in political ideologies, policies or market structure across states. Our results remains similar. Therefore, the reduction in emission is driven by the passage of the initiative, rather than any other changes at the same time in the market for power or other climate related policies that coincide with the political affiliation of the ruling party. We now analyze the implications of the adoption of cleaner technology on shareholder outcomes and the trade-off between stakeholders and shareholders, the key part of our paper.

In terms of real operating decisions, we show that the affected plants significantly cut their electricity generation in the post-RGGI period. More specifically, they reduced their electricity generation from fossil fuel by around 52% compared to control plants. However, the reduction in emission was not driven entirely by the decisions to produce less power from fossil fuels. Even after controlling for the level of electricity generation, the treated plants

[3]Electricity markets in 17 states were deregulated in late 1990s and early 2000s that allowed consumers to select electricity provider of their choice and increased competition in electricity generation market. All RGGI states except Vermont were deregulated between 1996-2000. Details on deregulation can be found here: https://www.electricchoice.com/map-deregulated-energy-markets/

reduced their carbon emission by almost 15%, i.e., carbon emission came down on a per unit of generation basis as well. There are two main mechanisms behind this. First, the power plants specifically reduced generation from the dirtiest fossil fuel: coal. We find that the coal consumption of the treated power plants declined by 70% post-RGGI. On the other hand, there was no significant decline in the consumption of natural gas, which is a relatively cleaner fossil fuel. Second, the affected plants began to use better quality of coal. Carbon emissions vary significantly depending on the type of coal used for power generation. For example, it varies by the mix of carbon, hydrogen, oxygen and sulfur contained in the coal (Hong and Slatick, 1994). Cleaner coals are more expensive. We show that after the RGGI shock, the treated plants started to use more expensive coal, consistent with the view that they adopted cleaner coal in their production decision.

As a result of these decisions, the affected plants experienced a sharp drop in their revenue and profits. Using our difference-in-difference methodology, we show that the fossil-fuel plants had almost 46%-51% reduction in their revenue in the post-RGGI period. Profits, defined as revenue minus fuel costs, decreased by an even higher amount. For an average power plant, profits decreased by around 70% in the post-RGGI period. Our unique setting allows us to estimate the elasticity of carbon emission to revenue and gross profits at a very granular level using an instrumental variable setting. Using RGGI as an instrument for carbon emission in a two-stage regression framework, we estimate the elasticity of plant revenue to carbon emission at 0.87-0.92, depending on the model specification. For an average power plant, the elasticity of gross profits is estimated at 0.84-0.92. These results show that shareholders experience a significant decline in profits when they move towards cleaner technology, and that reduction in CO_2 emissions comes at a cost to the bottom line, at least in the short-term.

We now ask what impact does reducing CO_2 emissions have on the shareholder value. To address this question, in the next part of the paper we analyze these outcomes at the company level. Power plants can be owned by publicly traded companies, private equity, or other investors. We analyze the effect of RGGI shock on profits and shareholder value for the publicly traded power utilities in the affected states as compared to publicly traded utilities in other states, using the same difference-in-difference design that we used for the plant level analysis. At the company level, we do not find any evidence of a decline in annual revenue. The affected utilities transitioned from coal based power generation to cleaner technology to protect their revenue and power supply to customers. However, their profitability decreased considerably: compared to all other utilities in the country, their return on assets (ROA) decreased by around 2.6% in the transition period, i.e., between 2005 and 2008, and over 2.3% thereafter. The decrease in ROA represents almost 70-80% of one standard deviation of the ROA in our sample. Therefore, the transition to clean technology resulted in significant short term losses for the affected firm.

Did the shareholders lose as firms transitioned to cleaner technology that resulted in short-term losses? We next analyze the evolution of shareholder value, measured as the market-to-book value of equity and the market-to-book value of assets, of the utilities in the affected states before and after the passage of the initiative. In the interim period of 2005-08, there is some evidence of a decrease in shareholder value, but the results are economically small and statistically weak. The estimates vary depending on model specification, the measure of market-to-book ratio used, and the set of control firms employed for the counterfactual analysis. However, in the post-2008 period, we find a consistent pattern of an increase in value across model specifications and valuation measure used for the analysis: the treated utilities have 22-36% higher market-to-book ratio of equity, and 4-6% higher market-to-book ratio of assets in the post-2008 period compared to the control states. Therefore, despite a drop in profitability, shareholders gained in the long run as they switched to cleaner technology.

What are the sources of value creation for the treated utilities? Green firms can obtain higher value if their future expected cash flow is higher or if their expected return is lower. As Pástor, Stambaugh, and Taylor (2021) show a green firm can have a lower expected return if investors have a preference for green stocks or if greener assets provide a better hedge against climate risk. Second, the treated firms can have higher value through the cash flow channel. For example, if customers prefer to buy clean energy or if suppliers care about clean firms, then the treated firms may have higher cash flows than the control firms in terms of market's expectation.

We analyze the expected cash flow channel using analysts' long-term growth forecast of the treated and control firms. Using the same difference-in-difference methodology as before, we show that the analysts expected about 2-3% higher long-term growth rate in the earnings of the treated firm after the shock. We also control for analyst fixed effects in these regression models; therefore, our estimates come from changes in forecast of cash flows that are independent of a particular analyst's time-invariant forecasting skills or attitude towards climate risk. It captures changes in cash flow expectation of market participants as the firm transitions to a cleaner technology. Combined with our earlier results that show a decline in realized profitability of the treated firms, these findings uncover the trade-off between short-term and long-term cash flow impact of carbon transition.

In addition to the cash flow channel, a large emerging literature documents that institutional preference for green stocks can result in an upward shift in the demand curve of these stocks. Indeed, institutional investors have become increasingly concerned about climate risk of their portfolio companies and they also exert influence on ESG related outcomes (Krueger, Sautner, and Starks, 2020; Chen, Dong, and Lin, 2020). Stroebel and Wurgler (2021) document that practitioners, academic and policymakers alike recognize the increasing importance of climate risk. Gantchev, Giannetti, and Li (2022) show the effect of institutional shareholder pressure on environmental policies of firms. Further, Baker, Bergstresser, Serafeim, and Wurgler (2022) show that green municipal bonds are often issued at a premium and are more closely held, consistent with the view that some institutional investors exhibit a preference for non-pecuniary benefits from holding such assets. The realized returns on green stocks may go up due to the demand pressure generated by institutional flow into these stocks. At the same time, the expected return can decrease, which lowers the discount rate for the firms' cash flows (Pástor et al., 2021; van der Beck, 2021). Both of these channels can, in turn, result in higher market-to-book ratio of the treated firms. For example, van der Beck (2021) shows that flow of funds into sustainable mutual funds can substantially increase the value of green stocks.

Motivated by these studies, we investigate the flow of ESG-focussed mutual funds into the treated stocks after the RGGI shock to shed light on the institutional preference channel. A key advantage of our work, compared to the earlier literature, is that we are able to tease out the causal effect of institutional fund flow on valuations. We first show that the ESG-funds increased their shareholdings in the affected companies by a significant amount after the RGGI shock. Their shareholding, measured as a percentage of the total outstanding shares of the company, increased by 26% in the affected utilities after the shock. Similarly, as a percentage of their own assets, ESG funds held about 7% more shares in the affected utilities after the shock.

In our final test, we directly relate the valuation premium of treated stocks with the entry of ESG-funds in the market. Since the RGGI shock occurred in the mid-2000, our experimental setting provides a unique setting to assess the effect of ESG-funds on the value of green stocks. During this period, the ESG-focussed funds had just begun their entry into the financial markets, providing us with a rich time-series variation in the number of such funds over time. We show that over time, as the number of ESG-funds increased, the market-to-book ratio of treated stocks increased considerably. Thus a part of valuation increase, despite the decline in profits, can be attributed to the preference of institutional investors for greener firms.

Our paper contributes to a growing literature on climate finance and the effect of pollution on outcomes such as asset prices and shareholder wealth. Krüger (2015) use an event study methodology to show that shareholders react strongly negatively to negative news regarding a company's corporate social responsibility (CSR) policies. Bolton and Kacperczyk (2021) study the link between carbon emissions and stock returns. Acharya, Johnson, Sundaresan, and Tomunen (2022) study the effect of heat exposure on municipal bond yields. Chava (2014) document a significant link between ESG policies and cost of capital. Jiang, Li, and Qian (2019) study the effect of a firm's exposure to rising sea level on its cost of bank loans. Sastry (2022) shows the effect of flood risk and government insurance on lender behavior in the mortgage market. Giglio, Kelly, and Stroebel (2021) provide a comprehensive review of the growing literature on climate finance. Gillan, Koch, and Starks (2021) review the literature on ESG policies and firm risk and value.

Although our empirical design is slightly different, namely a difference-in-differences design with carefully selected control groups, the first part of our paper that pollution decreased as a result of the RGGI has been documented earlier in the energy economic literature (Murray and Maniloff, 2015).[4] This literature has mainly focused on the effect of the RGGI on carbon emissions and collection and deployment of revenue from the auction of carbon caps by the state governments (Hibbard, Tierney, Darling, and Cullinan, 2018). Our key contribution comes from the analysis of shareholder-emission tradeoff. To the best of our knowledge, our paper is the first one to use this exogenous shock to analyze the implication of green technology on firm profitability and shareholder value.

2 RGGI Details

The Regional Greenhouse Gas Initiative (RGGI) is the first mandatory, market-based, regional program to reduce CO2 emissions from the power sector. As a regional 'cap-and-trade' program, states jointly decide on a regional cap on total CO_2 emissions from the power plants for a three-year control period. Each state then originates CO_2 allowances proportional to its share of the regional cap. Power plants with a capacity of 25MW or higher in these states are required to buy 1 allowance for every short tons of CO_2 they emit during this control

[4]The RGGI organization has also documented this effect. Details about the RGGI and their studies can be found on their website: https://www.rggi.org/program-overview-and-design/elements

period. The cap on allowance is set to decrease after every control period, reducing overall CO_2 emissions from the power plants.[5]

While RGGI is not the first cap-and-trade program aimed at reducing emissions, it is different from other similar programs in its distribution of allowances. Unlike other programs that gives out the allowances for free and then allow them to trade in the secondary market, RGGI auctions the CO_2 allowances every quarter. In doing so, it generates revenue for the states and adds actual costs to the power producers. In their comments to the first draft of the RGGI model rule, most of the power utilities companies and energy groups opposed this auction and wanted the allowances to be distributed for free.[6]

Figure 1 presents a brief timeline of the history of RGGI milestones. RGGI was formed as a result of discussions of several Northeastern and Mid-Atlantic states to reduce CO_2 emissions from the power sector. In December 2005, 7 of these states- Connecticut, Delaware, Maine, New Hampshire, New Jersey, New York, and Vermont- entered into a Memorandum of Understanding (MoU) to develop a regional cap-and-trade program to curb emissions from the power sector in these states. In 2006, these states issued a set of proposed regulations in the form of a Model Rule that formed the basis for each state's individual legislation and allowance trading program. In 2007, Massachusetts, Maryland, and Rhode Island, which had participated in the early discussions, signed the MoU. The first CO_2 allowance auction happened in September 2008, and the first compliance period began on January 1, 2009. In 2012, New Jersey became the first (and only) state to withdraw from RGGI after the appointment of the republican governor Chris Christie. Therefore, we exclude New Jersey from our analysis.[7] In 2015, President Obama announced the Clean Power Plan, the first-ever, federal carbon pollution standard for all fossil-fueled power plant aiming to reduce carbon emissions by 32% in the next 15 years. We limit our sample period to the end of 2014 to ensure

[5]The regional cap decreased from 188 million allowances in 2009 to around 84 million in 2014, corresponding to an annual reduction of roughly 15%.

[6]Stakeholder comments and the RGGI program can be found here: https://www.rggi.org/program-overview-and-design/design-archive/original-stakeholder-comments

[7]Our results are robust to the inclusion of New Jersey in the sample.

that our results are not contaminated by the differential effect of this federal announcement on RGGI versus non-RGGI plants.

In sum, the RGGI induced transition to cleaner technology was independent of several other correlated factors that can simultaneously affect pollution outcomes and financial performance of a company. For example, Azar, Duro, Kadach, and Ormazabal (2021) document the role of institutional investors in controlling pollution. Gantchev et al. (2022) document the importance of investor activism on a firm's environmental policies. Therefore, the presence or absence of institutional investors can affect the pollution strategy, as well as the firm performance. Our empirical setting is free from such biases.

3 Data and Descriptive Statistics

Plant level data: Our plant level data covers all the fossil fuel based plants in the country. We use three main sources of data to collect environmental and operational information for power plants and their owners: the US Environmental Protection Agency (EPA), the US Energy Information Administration (EIA), and the Federal Energy Regulatory Commission (FERC). The CO_2 emissions data comes from EPA's Clean Air Markets Division (CAMD). CAMD continuously monitors the level of CO2, NOx, So2, and mercury emissions from all fossil fuel-fired electric generating units (EGUs) over 25MW in nameplate capacity in the U.S.

The measurement of accurate and granular data on carbon emissions is a key advantage of our empirical setting. Prior studies have to often rely on carbon emission estimates from other industries. Most of the non-utility firms today report their emissions based on the standards developed by the Greenhouse Gas (GHG) Protocol Initiative, a multi-stakeholder partnership of businesses, NGOs, and governments. The GHG Protocol standard provides a step-by-step guide for companies to quantify and report their emissions in three categories or scopes based on the sources of the emissions. However, reporting of the emissions is voluntary, and there are no enforcement mechanisms, such as audits, for the reporting. The lack of standards and enforcement mechanisms exacerbate 'greenwashing' and incentivize firms to underreport or selectively report their emissions (Grewal et al., 2022). Our setting allows us to overcome the issues of greenwashing. All fossil-fueled power plants in the US with a capacity of 25MW or higher are required to have the Continuous Emissions Monitoring System (CEMS), an equipment system that measures particulate matter concentration or emission rate using pollutant analyzers and reports it continuously.[8] We use the CO_2 emissions reported by the CEMS for our analysis. This overcomes the issues of managers self-reporting the numbers and using different metrics for their measurements.

Plant-level information on fuel consumption, and net electricity generation is obtained from the EIA Form 923. We aggregate fuel receipts that power plants report in the Form 923 to calculate total fuel costs. While information on electricity generation, carbon emissions, and fuel consumption are available on power plant level, data on revenue (in dollars) and sales (in megawatt hours) are only available at the utility-level. Electric utilities that are investor owned and own one or more power plants are required to report their sales and revenue data monthly to the EIA in the EIA-861M, also called the Monthly Electric Power Industry Report. We use this owner-level data to calculate electricity rate ($/MWh) for each power plant in a quarter. Using net generation and fuel costs on power plant level, we are able to calculate total revenue and gross profit, i.e. total revenue minus total fuel cost. We exclude power plants that have no gross generation of electricity in a quarter, and we winsorize all the variables at 2.5% on both the tails. Our results, however, are not affected by winsorization.

Panel A of Table 1 reports the summary statistics of the power plant-level data in our sample. The sample covers all fossil fuel based power plants in the country, including coal and gas-based plants. The unit of observation is plant-quarter. On average, there are 850 power

[8] For more on CEMS, see here: https://www.epa.gov/emc/emc-continuous-emission-monitoring-systems

plants each quarter in our sample. An average power plant generates 639 GWH of electricity in a quarter and emits 592,000 short tons of CO_2. It generate an average revenue of $53 million. While more than half of the power plants do not use coal as their primary source of fuel, those that do are larger and therefore produce more electricity from coal. A median power plant generates no electricity from coal but a 75th percentile plant consumes over 5,000 billion BTUs of coal and generates 469GWH of electricity from coal. In contrast, a median power plants generates 7.3 GWH of electricity from natural gas while a 75th percentile plant generates only 137.4GWH from natural gas.

Company level data: Our power plant level data is comprehensive. For the market value analysis, however, we are restricted to the set of publicly traded firms that own these power plants. We use Compustat and CRSP to get profitability and market valuation measures for publicly traded utilities. We start with all publicly traded, electric utilities companies that are engaged in the generation, transmission, and/or distribution of electric energy for sale (SIC: 4911, 4931) and exclude firms that do not generate or purchase power from fossil-fueled power plants. Following the power-plant level analysis, we restrict our sample to 2000-2014 and exclude New Jersey from the sample. We obtain profitability measure from the Financial Ratio Suite by the Wharton Research Data Service (WRDS). WRDS uses Compustat and CRSP to provide time series of profitability ratios per company. We use the return on earnings assets (ROEA) as our main measure of profitability. ROEA is calculated as the operating income after depreciation as a fraction of average total earnings assets (TEA) based on most recent two periods, where TEA is defined as the sum of property, plant and equipment and current assets. We specifically focus on the earning assets of the company to measure profitability because it tells us about how profitable the assets of the firm that are used to generate income, as against assets such as intangibles and deferred revenue. We use market-to-book ratio of equity and assets as our measures of valuation. Market-to-book of equity is simply the market value of equity divided by the book value of equity. Market value of assets is calculated as the book value of assets minus the book value of equity plus the market value of equity. Market-to-book ratio of assets is then the market value of assets divided by the book value of assets.

Panel B of Table 1 presents the summary statistics of the profitability and valuation measures of electric utility companies in our sample. An average electric utility company in our sample has a total revenue of around \$1.3 billion and the return on earning assets of 7.9%. The average market-to-book ratio of equity is 1.6 and market-to-book ratio of assets is 1.2.

Earnings forecast data: We obtain analysts' long-term EPS growth forecasts for publicly traded utilities from the Institutional Brokers' Estimate System (IBES). We use the Detail file from the IBES database that provides analyst-by-analyst historical earnings estimates. Our sample consists of around 3600 firm-analyst-quarter observations. A median firm in our sample is covered by 2 analysts each quarter. The median (average) long-term growth forecast in our sample is 5% (5.6%).

ESG ownership data: For ESG ownership analysis, we use CRSP mutual funds holdings database. To identify mutual funds that are ESG-oriented, we screen funds that have ESG-related words in their names.[9] We restrict our sample to funds that were first offered before December 31, 2012 to ensure that we have their holdings information for at least two years before the end of our sample in 2014.

Figure 5 shows the total number of ESG-mutual funds in our sample. There were fewer ESG funds in the early 2000s and the number grew significantly from around 2007. There are on average 10-15 ESG funds each year in our sample before 2007. This number increases to around 40 in the year 2008 and around 60 in the 2010. As the number of fund-firm pairs in our transition period was small, we cannot detect the statistical effect of RGGI on ESG fund holdings in the transition period of 2005-2008. So, for ESG fund-related analysis, we focus on post-2008 as our only treatment period.

[9]Similar to Berg, Heeb, and Kolbel (2022), we select funds that have any of the following words in their names: 'ESG', 'SRI', 'Clean', 'Environment', 'Social', 'Sustain', 'Impact', 'Responsible', 'Climate', 'Green', 'Impact'.

4 Results

We conduct our analysis both at the plant level and at the firm level. The plant level analysis allows us to precisely detect the relation between pollution control strategies and outcomes such as the level of electricity generated at the plant, cost of fuel used and the revenue and profits from the plant. Since we observe the level of CO_2 emission for each plant in our sample, our analysis directly ties emissions to these outcomes. In the second set of results, we focus on aggregate firm level outcomes that allows us to tease out the impact of carbon emissions on shareholder value.

For the plant level analysis, we use the following difference-in-difference research design using quarterly data for all fossil-fuel power plants in the sample:

$$y_{i,t} = Plant_i + yq_t + \beta_1 \times \mathbb{1}(2005\text{-}2008)_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t} \quad (1)$$

$y_{i,t}$ is the outcome variable such as the level of carbon emission or revenue generated by a plant. The model includes plant fixed effects to soak away time invariant differences in the technology used by the plant and other unobserved differences in the level of emissions each plant produces. The year-quarter fixed effects (yq_t) allows us to separate the effect of macroeconomic factors such as the relative cost of coals with varying degree of emission or the demand of electricity in the economy. $Treated_i$ equals one for plants located in a RGGI-state, zero otherwise. We interact the treatment variable to two indicator variables that capture the effect of the RGGI on outcomes. First, we interact it with $\mathbb{1}(2005\text{-}2008)_t$ to tease out the effect of changes in plant behavior soon after the RGGI states signed an MoU in 2005. The second variable $Post2008_t$ captures the differential effect of the enactment of the initiative on the affected plants after the passage of the act. Therefore, our model allows us to estimate the changes in the affected plant's behavior during the interim period, i.e., from the announcement to the enactment of the cap-and-trade policy, as well as during the post-enactment period. Firms can change their behavior while the legislative progress was under way. Our empirical specification captures this effect. More importantly, the inclusion of the interim period indicator variable in the model allows us to capture the market's expectation of the effect of RGGI on firm value when we conduct the valuation analysis later in the paper.

All plants located in the RGGI states are considered as the treated plants. We use three sets of control plants: (a) plants in all other states in the country, (b) plants located only in the states that voted Democrats in the presidential election of 2008 (Democrat states), and (c) plants located only in states with deregulated electricity market (Deregulated states). The first set of control plants has the advantage of larger data and it is free from any assumptions on our part in terms of comparability of the plants across the two sets of states. In our analyses, we ensure that the outcome variables, such as carbon emission, show a parallel trend between the treated and control group. The other two sets of control plants allow us to rule out any concerns that plants behaved differently over this time period because of the political leanings of the lawmakers in the state or the market based forces the firms faced. As we show below, our key results remain the same, no matter which set of control plants we use.

4.1 RGGI and carbon emissions

We begin our analysis by detecting whether the treated and control plants showed a parallel trend before the RGGI or not by estimating the following regression model:

$$Log(CO2)_{i,t} = Plant_i + QuarterYear_t + \sum_{\tau}(year = \tau) \times \beta_{\tau} \times Treated_i + \epsilon_{i,t} \qquad (2)$$

The model uses the set of all plants in the non-RGGI states anywhere in the country as the control plants. The dependent variable is the log of carbon emission measured in short tons per plant per quarter. We use 2005 as the base year and therefore the coefficients on the interaction term measures changes in emission relative to the year when the states signed the MoU. We present the coefficient estimates, and the 95% confidence interval in Figure 2. The figure shows that the two groups followed a parallel trend before the shock. There is no difference in carbon emissions across the treated and control plants in any of the years between 2000 and 2005. After 2005, however, there is a remarkable decrease in emissions from the affected plant.

Table 2 presents results of the regression model in equation 1. Column (1) shows that the affected plants cut their emissions by 40% in the post-2005 period in a difference-in-difference setting, which is both statistically and economically significant. Column (2) separates the effect between the interim period (2005-08) and the post-2008 period: the affected plants cut their emission by 20.5% in the interim period as they began adjusting to the RGGI regulations, and by 49.6% in the post-2008 period.

Carbon emissions at the plant level can come down from two broad operation decisions: (a) on extensive margin, cutting the level of generation from fossil fuel based plants while shifting towards renewable energy, and (b) on intensive margin, using environment-friendly operating decisions such as switching to cleaner and better quality of fossil-fuel.[10] Different types of fossil fuel emit different amounts of CO_2 per unit of energy produced. Natural gas, for example, is a cleaner fossil fuel and emits around 50% less CO_2 than coal. Even within the categories of coal, the extent of emission per unit of generation varies considerably depending on the chemical composition of coal. CO_2 emission across the type of coal varies in the following order from most polluting to least: anthracite, lignite, sub-bituminous, and bituminous (Hong and Slatick, 1994). Depending on the type of coal a plant uses, therefore, the level of pollution differs for the same level of electricity generation.

Is the decrease in emissions solely due to the lower level of generation or is it also due to

[10]For example, Consolidated Edison's Annual Report in 2010 states "CECONY has participated for several years in voluntary initiatives with the EPA to reduce its methane and sulfur hexafluoride emissions. The Utilities reduce methane emissions from the operation of their gas distribution systems through pipe maintenance and replacement programs, by operating system components at lower pressure, and by introducing new technologies."

the use of natural gas and cleaner coal? Column (3) answers this question by controlling for the level of power generation by the plant. Even after controlling for the level of electricity generation, we show that the emissions decreased by a significant 14-15% in the interim and post-2008 period. Therefore, the decrease in emissions came from both the extensive margin and intensive margin. Columns (4) and (5) repeat the analysis with just the democratic states and deregulated states the control plants. Our results remain similar.

4.2 RGGI and real decisions

Table 3 presents the regression analysis of model 1 with three operating decisions as the outcome variable: (a) the level of electricity generated by the plant measured as the log of MWh, (b) the amount of coal used measured in the log of MmBTU, and (c) the amount of gas used measured in the log of MmBTU. The latter two regressions are estimated on coal-based and gas-based plants separately.

Column (1) of the Table shows that the affected plants decreased their net generation by almost 23% in the interim period and 53% in the post-2008 period. This is an economically large reduction in the generation of fossil-fuel based energy. The magnitude of the reduction in the level of electricity generation closely matches the reduction in pollution level described in the previous section. Note that our sample covers fossil-fuel based plants only. At the firm level, the aggregate generation depends on the extent of switch towards renewable sources of energy a firm makes. Our firm level analysis, presented later in the paper, uncovers these effects.

Columns (2) and (3) focuses on reduction in the use of coal and gas, the two main sources of fossil fuels that the power plants use. Most of the reduction occurred in the coal-based plants. In the post-2008 period, the consumption of coal decreased by a significant 70% in the treated plants. The corresponding decrease in the use of gas is a much lower, and statistically insignificant, 13%. This shows that while the act reduced the generation of electricity from fossil-fueled power plants, much of this reduction came from burning the dirtier fossil fuel, coal.

4.3 RGGI and financial outcomes

We begin the analysis of financial outcomes with the effect of RGGI on plant revenue. Figure 3 presents the yearly coefficient estimates and the 95% confidence interval of the following regression model:

$$Log(revenue)_{i,t} = Plant_i + QuarterYear_t + \sum_{\tau}(year = \tau) \times \beta_\tau \times Treated_i + \epsilon_{i,t} \quad (3)$$

The estimation results provide us with an estimate of the difference in the revenue of treated and control plants every year from 2000 to 2014. We use 2005 as the base year. As shown in the figure, the revenue generated by the two groups is indistinguishable in the pre-2005 period, confirming that the two groups showed parallel trend before the RGGI initiative. Afterwards, the affected plants experienced a large decrease in revenue.

Table 4 presents the regression result of equation 1. Since our measure of revenue is estimated based on plant level generation and the rate (i.e., $ per unit of power) at the utility level, we winsorize the revenue at 2.5% in both tails for this analysis to ensure that our findings are not driven by outliers. Our results are not sensitive to these choices.

As shown in the Table, the affected plants' revenue dropped by almost 48% in the post-2008 period compared to all other fossil fuel plants in the country. Compared to plants located only in democratic (deregulated) states, the drop is 46% (51%). Overall, these numbers are consistent with the results documented in the earlier section that shows a large drop in carbon emission accompanied by a large drop in electricity generation.

Such a large decrease in revenue and generation naturally leads to lower consumption of coal as documented above in Table 3. From a profitability perspective, however, we also need to estimate the effect of RGGI on fuel cost used by the plant for a unit of power generation. If firms switch to cleaner sources of coal then it is likely to incur higher cost per unit of generation. We use coal rate, calculated as the total cost of coal per unit of heat input of the coal, to estimate our baseline regression model with a difference-in-difference method. Table 5 presents the result. As shown in Column (1), the treated plants pay 38 cents more in the transition period, and 70 cents more 2008 for each unit of fuel as compared to all other plants in the country. As the average coal rate in our sample is $1.92, this increase in the rate is also economically significant. Columns (2) and (3) shows that the rate difference is around 68 cents and 80 cents compared to plants located in democratic states and deregulated states. Columns (4)-(6) show that the natural gas rate did not have a significant change around this time period for the treated states.

Overall, these findings show that the affected plants had lower revenue and higher fuel costs in the post-RGGI period. Their gross profits, defined as revenue minus fuel cost, should come down as a result of lower revenue and higher per unit cost. Table 6 presents the regression result with gross profit as the dependent variable. Gross profit is calculated as the total revenue from electricity sales from the power plant minus total fuel cost of the power plant in that quarter. Similar to revenue numbers, we winsorize the gross profits at 2.5% on both the tails. As over 5% of the observations have negative profits in our sample, we add the absolute minimum value of the gross profit in our sample to each observation before taking the log.[11] The average plant in our sample experienced a decrease in gross profits of around 19% in the interim period, and 70% post-2008. Comparing with the coefficient estimates in Table 4 that estimates the effect of RGGI on revenue, the coefficient estimates on gross profits are larger in magnitude. This captures the fact that shareholders face lower revenue with increasing costs as the firm switched to cleaner production. Columns (2), (4) and (6) of the Table presents the same analysis after controlling for the level of electricity generation by the plant. The gross profits drops by almost 36% for the full sample, even after

[11]The minimum value of the profits is around 7% of the average gross profits. So, the interpretation of our estimates needs to account for that. Our results are robust to other specifications.

controlling for the level of generation.

4.4 Causal estimate of emission on financial outcomes

Our setting allows us to estimate the causal effect of a unit of carbon emission of plant revenue and profit using a two stage instrumental variable regression framework. We use the passage of the RGGI as an instrument in the first stage regression to get the predicted values of carbon emission. The second stage regression uses the predicted values of emission as the explanatory variable and the revenue or profits as the dependent variable.

Panel A of Table 7 presents the regression results for revenue as the dependent variable. For comparison purposes, Column (1) provides the OLS estimate for a regression of plant revenue on carbon emission. Since both the emissions and financial performance measures are based on the log transformed values, our regression coefficients provide us with the elasticity of financial performance to carbon emission. The OLS regression model provides us with an elasticity estimate of 0.95: a one percent increase in emissions increases revenue by 0.95. The corresponding IV estimate is 0.87 for the full sample, and around 0.92 when we restrict the control plants to democratic or deregulated states only. These estimates are similar to the OLS estimate. In sum, the power plant's revenue is highly sensitive to the level of emissions.

Panel B provides the elasticity for gross profits. The OLS estimate is 0.32: for a power plant with average profits, a 1% higher emission corresponds to 0.36% higher profits. However, the IV estimate for the corresponding full sample is a much higher at 0.79, which corresponds to an elasticity of 0.85 for an average power plant. The OLS estimates are likely to be downward bias, due to at least one unobserved factor. A higher ability manager can lower carbon emissions by performing better maintenance or by making better operational decisions. Such managers can also produce more from the same plant. Thus the hidden managerial ability correlates negatively with carbon emission and positively with the output. As a result, the OLS coefficient is likely to be biased downward.

A clear pattern emerges from the analysis. After the RGGI, the treated plants cut their coal-based power generation. As a result, the pollution came down. At the same time, the shareholders lost in terms of revenue and profits. However, the loss of revenue and profits from the fossil fuel plants need not come at the expense of shareholder value. Firms can switch to alternative sources of power, they can become more efficient, and the market may itself value their profits at a higher price than the other firms that have not yet made the switch. To assess the effect of emission control on shareholder value, we next focus on firm level analysis where we can also observe the market value of the firm's equity.

4.5 Firm level outcomes

Table 9 reports the effects of RGGI on firm revenue. Specifically, the table shows the estimates from the following equation:

$$log(revenue)_{i,t} = Firm_i + yq_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t} \quad (4)$$

where $Treated_i$ is a dummy that equals 1 if the publicly traded utility is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The regression model is similar to the plant level regressions except that we now use the revenue for the entire firm, that includes revenue from renewable sources of energy.

As shown in Table 9 , at the firm level, there is no discernible change in revenue. The affected firms continued to serve their customers in the post-RGGI period. The key difference occurred in the type of power used. Instead of coal fired plants, the treated firms increasingly relied on renewable sources of power such as hydroelectricity. In addition to a switch in their own plants, the affected utilities also began to import hydroelectric power from Canada [12].

[12]Northeastern states significantly increased their hydroelctric imports from Hydro-Quebec, Canada. More on this can be found here: https://www.eia.gov/todayinenergy/detail.php?id=17671

To directly assess the extent of switching to renewable sources of energy, we obtain data on renewable energy generation by the investor-owned utilities from EIA Form-923, and calculate the fraction of total electricity generated from renewable sources at the state-quarter level. We estimate the following regression model to assess whether utilities in the treated state increased electricity generation from renewable sources:

$$Renewable_{j,t} = State_j + QtrYear_t + \beta_1 \times \mathbb{1}(2005\text{-}2008)_t \times Treated_j + \beta_2 \times Post2008_t \times Treated_j + \epsilon_{j,t} \quad (5)$$

The dependent variable measures the fraction of total electricity generated by renewable sources in the state j in quarter t by the investor-owned utilities. $Treated_j$ equals one for the RGGI state and zero otherwise. Table 8 presents the regression results. As shown in Column (1) of the Table, after the enactment of the RGGI, the treated states increased the fraction of renewable energy by a significant 8.15%. The estimates are even larger when we compare the treated states with only the other democratic states (11.15%) or deregulated states (15.66%). Figure 6 shows that the two groups of states followed a parallel trend before the enactment; it was only after 2008 that the treated states started to increase their renewable generation. Overall, these findings show that in the post-RGGI period, the affected states switched to renewable sources of energy that allowed them to protect their revenue despite a significant decline in power generation from fossil fuel plants.

While the firms are able to protect their revenue, it is not clear that their profits also stay the same. As the switch happens towards cleaner power, they are more likely to use expensive coal or incur a higher cost to produce and procure cleaner energy from other sources. They are also likely to incur higher costs in plant maintenance and other operational expenses to produce clean energy. We investigate the impact of clean energy transition on firm profitability measures using the same regression model as in equation 4. For profitability measure, we use the return on earning assets (ROEA) as our dependent variable. This ratio is calculated as the operating income after depreciation as a fraction of average total earnings assets (TEA) based on most recent two periods, where TEA is defined as the sum of property, plant and equipment and current assets. We find that the ROEA declined by 2.6% in the interim period and 2.27% post-2008. This number is both statistically significant and economically large in magnitude as the average firm has a return on earning assets of 7.9%. Results are similar for the other two specifications that use democratic and deregulated states as control firms.

Overall, the shareholders of power companies in the affected states experienced a decline in profits. We now analyze the changes in two measures of shareholder value - the market-to-book ratio of equity and market-to-book ratio of assets - to tease out the valuation effects. Subfigures (a) and (b) of Figure 4 show that the market-to-book ratio of equity and asset values followed a parallel trend before 2005. However, distinct from all our results so far, the treated firms perform better on this measure after the shock. Table 11 presents the results using the same regression model as in equation 4. We focus our discussion on market-to-book ratio of assets. As shown in Column (4) of Panel A, in the post-2008 period, the treated firms have 5.76% higher market-to-book ratio compared to the control firms that uses the full sample. The corresponding estimates are 3.17% and 4.74%, respectively if we use the sample of democratic states or deregulated states only. During the interim period, the treated firms have lower valuation ratios, but the statistical significance and economic magnitude is sensitive to model specification. For example, the market-to-book ratio for the treated firms is 2.52% lower when we use firms in the deregulated states as the control firms. The estimate is significant at 1%. However, the corresponding estimate is a statistically insignificant -2.44% for the entire sample. Overall, we conclude that the treated firms experienced some decline in market value in the interim period as the firms and market's expectations adjusted to the new regulation. In the long run, however, there is consistent pattern of value increase for the treated firms. Thus, despite a drop in profitability and a stable revenue, shareholders of the treated firms were better off in the post-2008 period.

4.6 Sources of value creation

As a firm cuts its carbon emissions, its value can improve either due to an increase in cash flows or due to a decrease in its expected return. As we showed earlier, in the short run, i.e., soon after the implementation of RGGI, the treated firms experienced a decline in their profitability. As these firms adjusted to renewable energy, their current profitability came down. However, if these firms are expected to earn higher cash flows in future, then their market value may still be higher. If power purchasers, for example, show a preference for clean sources of power, then utilities with higher proportion of renewable energy are like to have higher future cash flows. Additionally, if some institutional investors show a preference for green stocks, then the resulting fund flow into the treated stocks can increase their valuation (van der Beck, 2021). Our empirical setting provides an attractive setting to tease out these channels in a causal manner by comparing the treated and control firm's outcomes on these dimensions before and after the RGGI shock.

4.7 Analysts expectation of future cash flows

To assess the effect of carbon transition on market's expectation of future cash flows, we rely on analysts' long term earnings growth forecast. We obtain analyst-firm-quarter level data on the long-term growth rate for all stocks in the sample to estimate the following regression model:

$$g_{i,a,t} = Firm_i + Analyst_a + yq_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t} \tag{6}$$

The regression model is similar to the earlier specification, augmented with the addition of the analyst fixed effects. Therefore, we are able to tease out changes in the expected cash flows of the treated firms compared to the control firms over the transition period, holding fixed the analysts' skill and time-invariant preferences. Results are provided in Table 12.

Column (1) of the Table shows that the treated firms had 2.236% higher growth forecast in the post-2008 period, which is both economically and statistically significant. In economic terms, the estimates represent 40% of the average value of the long-term growth forecast in our sample. There was no difference in earnings forecast across the two sets of firms during 2005-08 period. These results suggest that the market's expectations about future cash flows of the treated firms changed only after the regulation was fully implemented.

Column (2) controls for the current earnings per share of the firm, and therefore it allows us to assess future expectations accounting for the decline in recent profitability. For example, it allows us to rule out the mechanical mean-reversion effects in earning dynamics. Our estimate remain similar. Columns (3) and (4) repeat the analysis for the democratic and deregulated states alone, and find a similar result.

4.8 Investor preference for green companies

Several studies show that some institutional investors prefer green firms, i.e., firms with clean technology (Baker et al., 2022). Krueger et al. (2020) show that institutional investors have started to increasingly care about their portfolio companies' climate risk exposure. During our sample period, which covers a very early period of ESG investing and climate related investing decisions, there was a large increase in the number of mutual funds with a focus towards environment and sustainability performance (see Figure 5). Motivated by these findings, we now study whether such funds increased their shareholding in the treated firms as compared to the control firms. As the number of ESG fund-firm pairs before 2007 was too small to detect statistical effects, we limit this analysis to post-2008 as our only treatment period.

We proceed in two steps: first we study the holdings of ESG funds into the treated stocks and then we relate the entry of ESG-funds to the valuation premium for the treated stocks. For the analysis of ESG-holdings, we use two measures of dependent variable. In the first one, the dependent variable is the percentage of a company's shares held by the ESG funds every quarter. Since our sample covers all the utilities, this analysis allows us to focus on whether the ESG funds increased their holding in cleaner utilities as compared to utilities in other parts of the country. The second measure uses the ESG's holding in a firm as a percentage of its total holding as the dependent variable. Therefore, it measures whether the ESG fund increased its holding in the affected utilities on an overall basis in its portfolio. Both models include firm and fund fixed effects, which allows us to capture the effect of the treatment shock independent of fund-specific factors such as managerial style and past performance.

Table 13 presents the results. Column (2) shows that after 2008, the ESG funds increased their shareholding by 0.27% of the total shares outstanding of the treated firms. As a percentage of their own holdings, the ESG funds increased their exposure by 6.91% in the post-2008 period. These results paint a clear picture. ESG funds moved their portfolio towards cleaner power companies, consistent with the idea of investor preference for such stocks. Such a significant inflow of funds into the treated firms can increase their valuation consistent with the structural model of (van der Beck, 2021).

In the final analysis, we directly investigate the effect of the entry of ESG-funds into the financial market on the valuation premium of the treated stocks. Our empirical setting is especially suitable for such a study because this was an early period of ESG-related investing. Several new funds entered the market with specific focus on green stocks. Therefore, we are able to exploit the time-series variation in the number of ESG funds in the market to study its impact on the valuation of treated and control firms. We estimate the following model:

$$mtb_{i,t} = Firm_i + QtrYear_t + \beta \times Treated_i \times Log(no.\ of\ ESG\ funds)_T + \epsilon_{i,t} \qquad (7)$$

Table 14 presents the results: Columns (1)-(3) use the market-to-book ratio of equity as the measure of valuation, whereas Columns (4)-(6) use the market-to-book ratio of firm. Across all six specifications, we find that the utilities in the RGGI states experienced an increase in valuation as the number of ESG funds increased in the market. These results are consistent with the view that part of green premium enjoyed by the treated stocks came from the flow of funds from investors with a preference for cleaner stocks.

5 Conclusions

Using a regulatory intervention that limited the ability of power plants located in 10 Northeastern and Mid-Atlantic states to emit carbon, we tease out the causal effect of carbon emission on financial performance. Profits drop as a result of the switch to cleaner technology. However, shareholders benefit in the long run by obtaining higher market valuation. Part of this higher valuation comes from the increased expectation of future cash flows of cleaner utilities and the growth of ESG-related mutual funds that held more electric utilities from the treated states. Our results highlight the trade-off between short-term and long-term profits as a result of carbon transition. Further, we show that markets can play an important role along with regulations in reducing emissions, and shareholder value need not be at odds with societal welfare. Despite a decline in short-term profitability, the cleaner utilities ended up with better valuation due to the entry of institutional investors with green preference. Thus, corporate policies that encourage increased focus on short term profits may be a significant reason behind a firm's reluctance to transition to cleaner technology.

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Figure 1: Effect of RGGI on CO_2 emissions

Figure 1 presents a brief timeline of some major milestones in the implementation of the Regional Greenhouse Gas Initiative (RGGI).

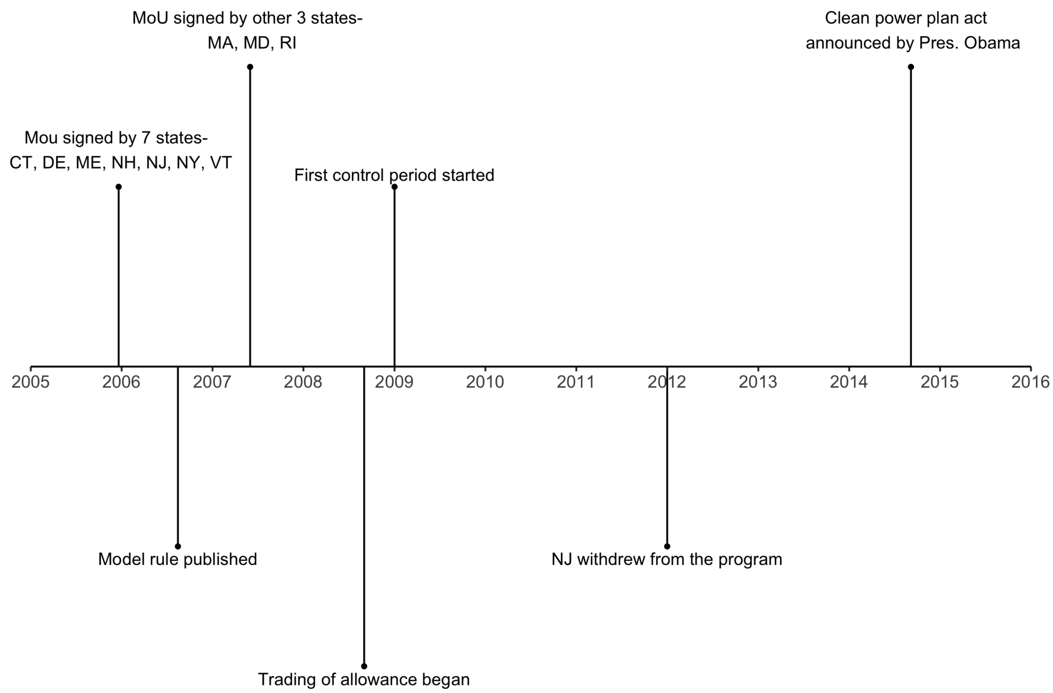


Figure 2: Effect of RGGI on CO_2 emissions

Figure 2 reports the dynamic differences-in-differences estimates of the effect of RGGI on reducing CO_2 emissions in the treated states. Specifically, the figure shows the point estimates and the 95% confidence intervals of β_τ from the following equation:

$$Log(CO2)_{i,t} = Plant_i + QuarterYear_t + \sum_\tau (year = \tau) \times \beta_\tau \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the power plant is located in the RGGI-state, and 0 otherwise. Solid gray vertical line is when the MoU for RGGI was signed; dashed blue vertical line represents the start of the cap-and-trade program. Standard errors are clustered at the state level.

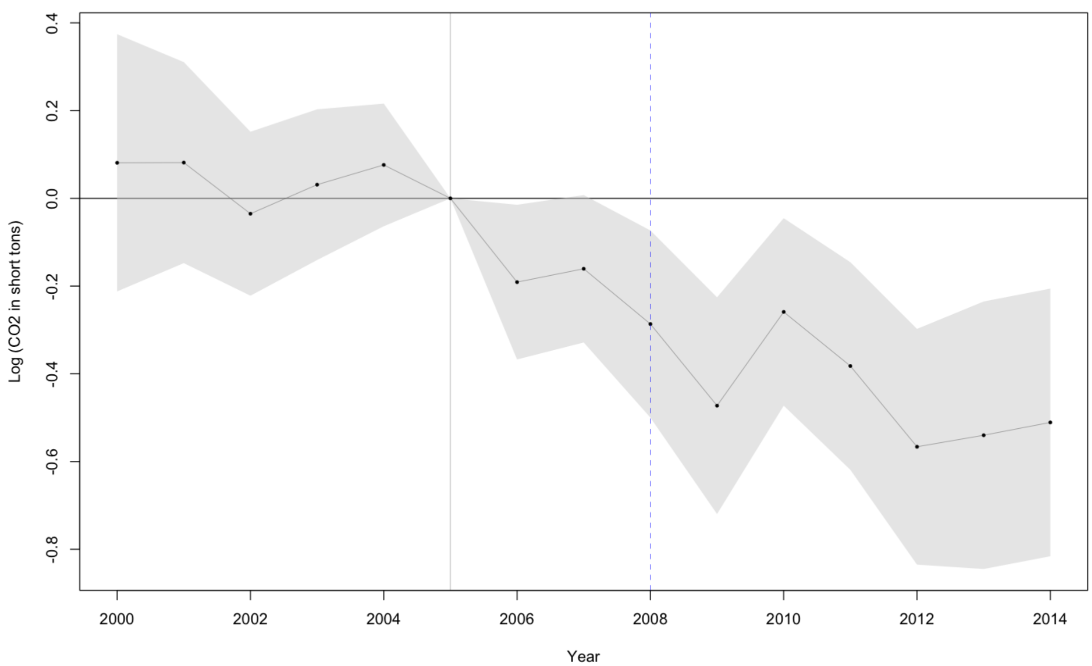


Figure 3: Effect of RGGI on power plant revenue

Figure 3 reports the dynamic differences-in-differences estimates of the effect of RGGI on revenue and profits in the treated states. Specifically, the figure shows the point estimates and the 95% confidence intervals of β_τ from the following equation:

$$y_{i,t} = Plant_i + QuarterYear_t + \sum_\tau (year = \tau) \times \beta_\tau \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. Solid gray vertical line is when the MoU for RGGI was signed; dashed blue vertical line represents the start of the cap-and-trade program. Standard errors are clustered at the state level.

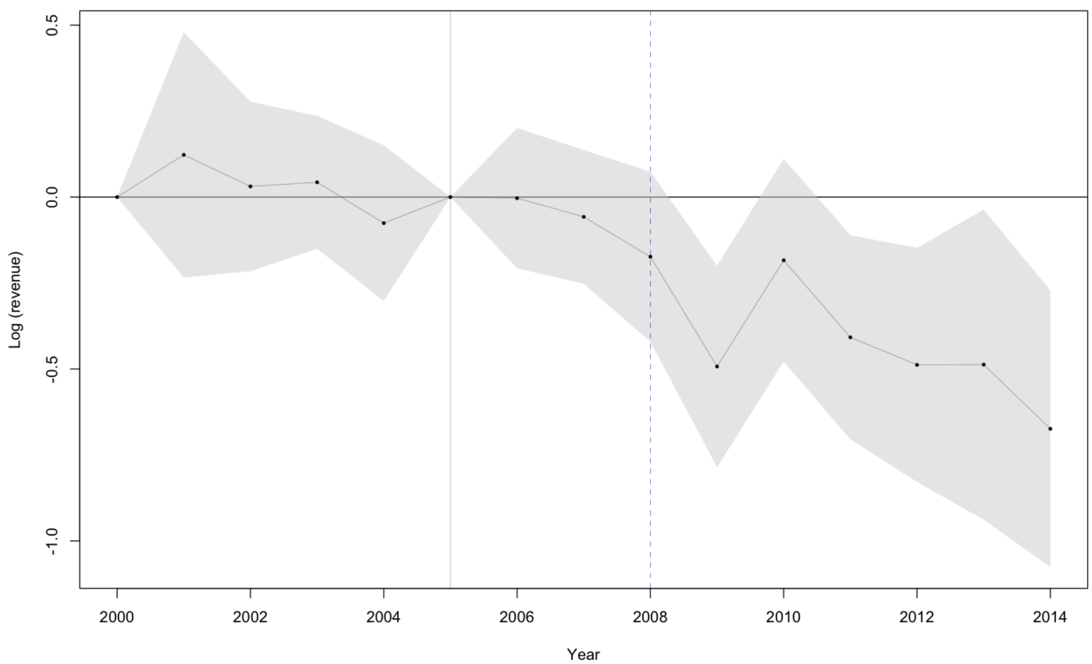


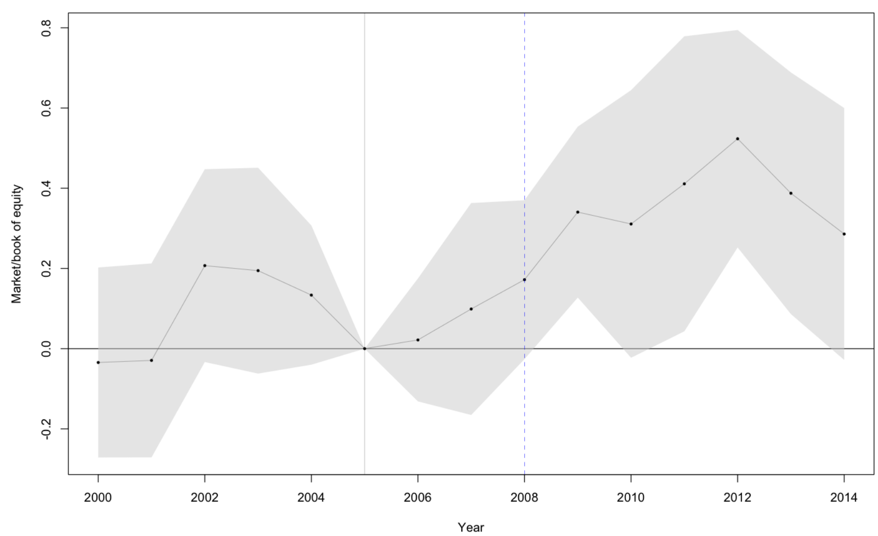
Figure 4: Effect of RGGI on Market valuation

Figure 4 reports the dynamic differences-in-differences estimates of the effect of RGGI on market valuations in the treated states. Specifically, the figure shows the point estimates and the 95% confidence intervals of β_τ from the following equation:

$$Market/Book_{i,t} = Firm_i + QuarterYear_t + \sum_{\tau} (year = \tau) \times \beta_\tau \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the Firm is located in the RGGI-state, and 0 otherwise. Solid gray line is when the MoU for RGGI was signed; dashed blue line represents the start of the cap-and-trade program. Standard errors are clustered at the firm level.

(a) Market / book of equity



(b) Market / book of assets

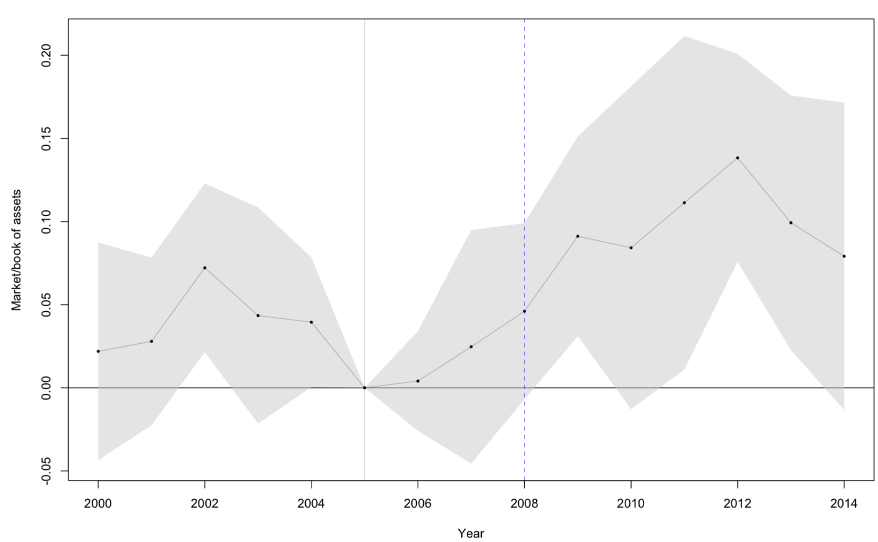


Figure 5: Number of ESG funds over year

Figure 5 shows the increase in the number of ESG-funds in our sample in each year. There are, on average, 15 ESG funds each year until 2006. This number increases to an average of 50 funds each year from 2007-2014.

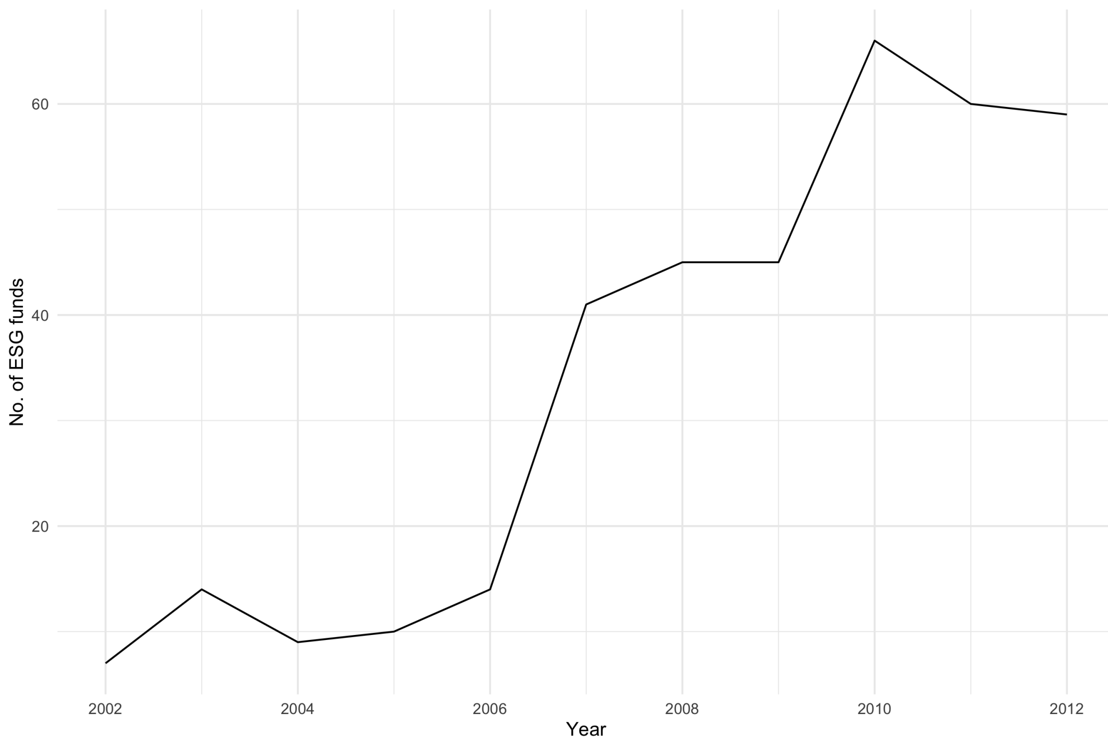


Figure 6: Effect of RGGI on state's renewable energy generation

Figure 6 reports the dynamic differences-in-differences estimates of the effect of RGGI on market valuations in the treated states. Specifically, the figure shows the point estimates and the 95% confidence intervals of β_τ from the following equation:

$$Renewable_{j,t} = State_j + QtrYear_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_j + \beta_2 \times Post2008_t \times Treated_j + \epsilon_{i,t}$$

where $Treated_j$ is a dummy that equals 1 if the state falls under RGGI, and 0 otherwise. The dependent variable, $Renewable_{j,t}$, is the fraction of total electricity generated by renewable sources in the state j in quarter t by the investor-owned utilities. Solid gray line is when the MoU for RGGI was signed; dashed blue line represents the start of the cap-and-trade program. Standard errors are clustered at the firm level.

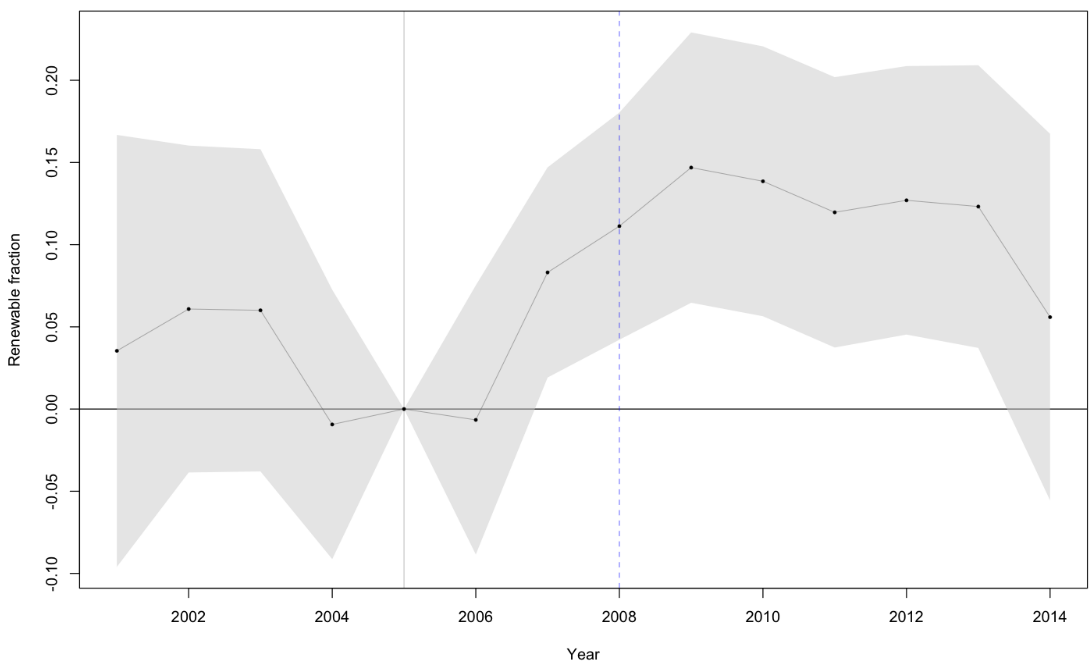


Table 1: Summary Statistics

Table 1 reports the descriptive statistics of the variables used in this paper. Panel A presents characteristics at the power plant level. CO_2 emissions data come from the U.S. Environmental Protection Agency (EPA). Power plant level operational data are from the U.S. Energy Information Administration (EIA). Panel B presents summary statistics of the profitability and valuation ratios used in the paper at the firm level. This data comes from Compustat/CRSP database provided by the Wharton Research Data Services (WRDS).

Panel A: Plant characteristics

Variable	N	Mean	SD	P25	Median	P75
Co2 (1000 short tons)	46344	592.1	909.3	14.4	183.1	739.8
Fuel used (billion BTUs)	43775	6252.1	8777.8	255.0	2504.1	8321.6
Coal used (billion BTUs)	43775	4607.4	8815.8	0.0	0.0	5019.1
Natuaral gas used (billion BTUs)	43775	1391.5	2600.6	0.0	88.3	1384.3
Net generation (GWH)	43775	639.1	886.5	21.5	247.1	883.6
Net generation- coal (GWH)	43775	446.1	866.9	0.0	0.0	468.5
Net generation- natural gas (GWH)	43775	165.5	328.4	0.0	7.3	137.4
Revenue (in million dollars)	36628	52.7	72.5	1.8	19.7	73.3
Gross profit (in million dollars)	17100	49.5	61.7	3.1	25.3	72.6

Panel B: Company valuations and profitability measures

Variable	N	Mean	SD	P25	Median	P75
Total revenue (million dollars)	3580	1417.51	1454.53	302.95	856.00	2291.19
Market value of equity (billion dollars)	3577	6.57	8.20	1.28	3.30	8.77
Book value of equity (billion dollars)	3590	4.04	4.68	0.88	2.31	5.80
Earning assets (billion dollars)	3455	11.89	12.67	2.60	7.46	17.13
Return on earning assets (%)	3514	7.89	3.21	6.50	7.70	9.30
Market / book of equity	3575	1.59	0.59	1.25	1.50	1.81
Market / book of assets	3575	1.15	0.14	1.06	1.13	1.22

Table 2: Effect of RGGI on CO_2 emissions

Table 2 reports the differences-in-differences estimates of the effect of RGGI on reducing CO_2 emissions in the treated states. Specifically, the table shows the estimates from the following equation:

$$log(CO2)_{i,t} = Plant_i + QtrYear_t + \beta \times Treated_i \times Post_t + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. In column 1, $Post_t = 1$ if $year > 2005$ and 0 otherwise. In columns (2) and (3), the variable $Post_t$ is divided into two time dummies: Yr(2005-2008) that takes 1 if year is between 2005 and 2008 and $Post$2008 that takes 1 if $year > 2008$. The dependent variable is log of CO_2 emissions (in short tons).

Columns (1)-(3) show results from the full sample. Column (3) also includes log of net generation of electricity (in MWh) as a control. Column (4) presents results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Column (5) is subsample of plants in the states with deregulated electricity markets. Standard errors are clustered at the state level; t-stats are shown in parentheses.

	Log (CO2 in short tons)				
		Full Sample		Democrat	Deregulated
	(1)	(2)	(3)	(4)	(5)
Post 2005*Treated	-0.4030***				
	(-4.115)				
Yr(2005-2008)*Treated		-0.2050**	-0.1469***	-0.2218**	-0.1844
		(-2.630)	(-3.157)	(-2.303)	(-1.493)
Post 2008*Treated		-0.4961***	-0.1548**	-0.4828***	-0.4886***
		(-4.205)	(-2.655)	(-3.756)	(-3.519)
Log (net gen, MWh)			0.7572***		
			(40.42)		
Plant ID FEs	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓
Observations	44,148	44,148	41,732	27,414	21,345
R^2	0.85	0.85	0.96	0.86	0.85

Clustered (State) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Effect of RGGI on real decisions

Table 3 reports the effects of RGGI on real decisions firms made. The table shows the estimates from the following equation:

$$y_{i,t} = Plant_i + QtrYear_t + \beta_1 \times \mathbb{1}(2005\text{-}2008)_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variables are log of net generation (in MWh) in column (1), log of coal consumed (in MmBtu) in column (2), and log of total natural gas consumed (in MmBtu) in column (3).

Standard errors are clustered at the state level; t-stats are shown in parentheses.

	Log (net gen, MWh) (1)	Log (coal used, MmBtu) (2)	Log (gas used, MmBtu) (3)
Yr(2005-2008)*Treated	-0.2275***	-0.0400	-0.1663*
	(-3.655)	(-0.6691)	(-1.873)
Post 2008*Treated	-0.5258***	-0.6943***	-0.1347
	(-4.749)	(-4.425)	(-0.8528)
Plant ID FEs	✓	✓	✓
Quarter-year FEs	✓	✓	✓
Observations	43,775	16,222	32,360
R^2	0.83	0.85	0.78

Clustered (State) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Effect of RGGI on plant revenue

Table 4 reports the differences-in-differences estimates of the effect of RGGI on the power plant revenue in the treated states. Specifically, the table shows the estimates from the following equation:

$$y_{i,t} = Plant_i + QtrYear_t + \beta_1 \times \mathbb{1}(2005\text{-}2008)_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variable is the log of total revenue from electricity sales.

Column (1) shows results from the full sample. Column (2) presents results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Column (3) is the subsample of plants in the states with deregulated electricity markets. Standard errors are clustered at the state level; t-stats are shown in parentheses.

	Log (revenue)		
	Full Sample	Democrat	Deregulated
	(1)	(2)	(3)
Yr(2005-2008)*Treated	-0.0824	-0.0613	-0.0531
	(-0.9445)	(-0.5539)	(-0.3223)
Post 2008*Treated	-0.4754***	-0.4633***	-0.5133**
	(-3.163)	(-2.803)	(-2.563)
Plant ID FEs	✓	✓	✓
Quarter-year FEs	✓	✓	✓
Observations	36,628	24,708	16,441
R^2	0.83	0.83	0.83

Clustered (State) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Effect of RGGI on fuel rate

Table 5 reports the effect of RGGI on coal and gas rates that power plants paid for the fuel. Specifically, the table shows the estimates from the following equation:

$$Fuel\ rate_{i,t} = Plant_i + QtrYear_t + \beta_1 \times \mathbb{1}(2005\text{-}2008)_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variables are coal rate (in $/MmBtu) in Columns (1)-(3) and gas rate (in $/MmBtu) in Columns (4)-(6).

Columns (1) and (4) show results from the full sample. Columns (2) and (5) present results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Columns (3) and (6) is the subsample of plants in the states with deregulated electricity markets. Standard errors are clustered at the state level; t-stats are shown in parentheses.

	(Coal rate (dollars/MmBtu))			(Gas rate (dollars/MmBtu))		
	Full Sample	Democrat	Deregulated	Full Sample	Democrat	Deregulated
	(1)	(2)	(3)	(4)	(5)	(6)
Yr(2005-2008)*Treated	0.3880***	0.3736***	0.3925***	0.5939	0.6255	2.895
	(5.838)	(4.297)	(4.316)	(1.256)	(0.6938)	(1.409)
Post 2008*Treated	0.7016***	0.6849***	0.8031***	-1.016	-0.8145	-3.490
	(6.609)	(5.047)	(4.902)	(-0.8696)	(-0.4908)	(-0.8158)
Plant ID FEs	✓	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓	✓
Observations	10,665	5,537	2,232	11,412	5,818	2,414
R^2	0.82	0.81	0.82	0.05	0.06	0.07

Clustered (State) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Effect of RGGI on plant profits

Table 6 reports the effect of RGGI on the power plant profits in the treated states. Specifically, the table shows the estimates from the following equation:

$$y_{i,t} = Plant_i + QtrYear_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variable is $log(gross\ profit + c)$, where $gross\ profit$ is total revenue from electricity sales - total fuel cost, and c is the absolute minimum value of profits, a constant we add to keep plants with negative profits in the analysis.

Columns (1) and (2) show results from the full sample. Column (3) and (4) present results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Columns (5) and (6) are the subsample of plants in the states with deregulated electricity markets. Columns (2), (4), and (6) include log of net generation (in MWh) as a control variable. Standard errors are clustered at the state level; t-stats are shown in parentheses.

	Log(profits)					
	Full Sample		Democrat		Deregulated	
	(1)	(2)	(3)	(4)	(5)	(6)
Yr(2005-2008)*Treated	-0.1759***	-0.0563	-0.1998***	-0.0573	-0.1414	0.0035
	(-3.532)	(-0.9382)	(-3.547)	(-0.8054)	(-1.619)	(0.0367)
Post 2008*Treated	-0.6451***	-0.3398**	-0.6208***	-0.2698*	-0.7158***	-0.3729**
	(-4.633)	(-2.390)	(-4.340)	(-1.829)	(-4.030)	(-2.269)
Log (net gen, MWh)		0.2774***		0.3134***		0.3051***
		(12.19)		(9.161)		(9.808)
Plant ID FEs	✓	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓	✓
Observations	16,672	16,672	8,879	8,879	3,654	3,654
R^2	0.86	0.88	0.85	0.89	0.84	0.87

Clustered (State) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Causal effect of CO_2 emissions on revenue and profits

Table 7 reports the impact of CO_2 emissions on plant's revenue and gross profit. The dependent variable is $log(revenue)$ in Panel A and $log(gross\ profit + c)$ in Panel B. In each panel, column (1) shows the estimate from the OLS regression. Columns (2), (3), and (4) show the instrumental variables estimates of the following $2nd$ stage:

$$y_{it} = \alpha_i + \gamma_t + \beta_{IV} log(\hat{CO2}_{it}) + \epsilon_{it}$$

where $log(\hat{CO2}_{it})$ is estimated using the following first-stage:

$$log(\hat{CO2}_{i,t}) = Plant_i + QtrYear_t + \hat{\beta}_1 \times \mathbb{1}(\text{2005-2008}) \times Treated_i + \hat{\beta}_2 \times Post2008_t \times Treated_i$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$.

Columns (1) and (2) in both the panels show results from the full sample. Column (3) is the subsample of plants in states that voted Democrats in the presidential election of 2008. Column (4) is the subsample of plants in the states with deregulated electricity markets. Standard errors are clustered at the state level; t-stats are shown in parentheses.

Panel A: Revenue

	Log (revenue)			
	Full Sample		Democrat	Deregulated
	OLS	Instrumental Variables		
	(1)	(2)	(3)	(4)
Log (CO2 in short tons)	0.9510***	0.8720***	0.9200***	0.9182***
	(43.62)	(5.576)	(5.518)	(5.289)
Plant ID FEs	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Observations	34,815	34,815	23,115	15,171
R^2	0.95	0.95	0.94	0.94

Clustered (State) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Profits

	Log(profits)			
	Full Sample		Democrat	Deregulated
	OLS	Instrumental Variables		
	(1)	(2)	(3)	(4)
Log (CO2 in short tons)	0.3248***	0.7937***	0.7719***	0.8489***
	(13.94)	(3.452)	(3.254)	(3.517)
Plant ID FEs	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Observations	16,382	16,382	8,663	3,600
R^2	0.88	0.82	0.84	0.79

Clustered (State) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Effect of RGGI on state's renewable generation

Table 8 reports the effects of RGGI on renewable generation in treated states. Specifically, the table shows the estimates from the following equation:

$$Renewable_{j,t} = State_j + QtrYear_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_j + \beta_2 \times Post2008_t \times Treated_j + \epsilon_{i,t}$$

where $Treated_j$ is a dummy that equals 1 if the state falls under RGGI, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variable, $Renewable_{j,t}$, is the fraction of total electricity generated by renewable sources in the state j in quarter t by the investor-owned utilities.

Columns (1) shows results from the full sample. Column (2) presents results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Column (3) is the subsample of plants in the states with deregulated electricity markets. Standard errors are clustered at the firm level; t-stats are shown in parentheses.

	Renewable fraction		
	Full Sample	Democrat	Deregulated
	(1)	(2)	(3)
Yr(2005-2008)*Treated	0.0076	0.0106	0.0328
	(0.3013)	(0.3987)	(0.9659)
Post 2008*Treated	0.0815***	0.1115***	0.1566***
	(3.157)	(4.127)	(4.580)
State FEs	✓	✓	✓
Quarter-year FEs	✓	✓	✓
Observations	2,624	1,556	940
R^2	0.86	0.82	0.73

Heteroskedasticity-robust co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Effect of RGGI on firm revenue

Table 9 reports the effects of RGGI on firm-level revenue. Specifically, the table shows the estimates from the following equation:

$$y_{i,t} = Firm_i + QtrYear_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variable is the log of total revenue of the firm.

Columns (1) and (2) show results from the full sample. Column (3) presents results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Column (4) is the subsample of plants in the states with deregulated electricity markets. Columns (2)-(4) also include log of total assets as a control for the size of the firm. Standard errors are clustered at the firm level; t-stats are shown in parentheses.

	Log (revenue)			
	Full Sample		Democrat	Deregulated
	(1)	(2)	(3)	(4)
Yr(2005-2008)*Treated	0.0493	0.0438	0.0229	0.0451
	(0.4541)	(0.5362)	(0.2692)	(0.4934)
Post 2008*Treated	0.0668	-0.0084	-0.0325	-0.0999
	(0.6805)	(-0.0903)	(-0.3565)	(-0.8978)
Log (assets)		0.7810***	0.7341***	0.9309***
		(10.09)	(9.735)	(9.314)
Firm ID FEs	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Observations	3,580	3,578	2,449	1,619
R^2	0.95	0.96	0.98	0.97

Clustered (Firm ID) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Effect of RGGI on firm profitability

Table 10 reports the effects of RGGI on firm's return on assets. Specifically, the table shows the estimates from the following equation:

$$y_{i,t} = Firm_i + QtrYear_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variable is return on earnings assets (ROEA) in %, calculated as the operating income after depreciation as a fraction of average total earnings assets (TEA) based on most recent two periods, where TEA is defined as the sum of property, plant and equipment and current assets.

Columns (1) and (2) show results from the full sample. Columns (3) presents results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Column (5) is the subsample of plants in the states with deregulated electricity markets. Columns (2), (3), and (4) also include log of total assets as a control for the size of the firm. Standard errors are clustered at the firm level; t-stats are shown in parentheses.

	Return on earning assets (in %)			
	Full Sample		Democrat	Deregulated
	(1)	(2)	(3)	(4)
Yr(2005-2008)*Treated	-2.636***	-2.646***	-2.398***	-3.290***
	(-3.323)	(-3.251)	(-2.911)	(-3.248)
Post 2008*Treated	-2.269***	-2.176***	-1.972**	-2.568**
	(-2.956)	(-2.797)	(-2.353)	(-2.423)
Log (assets)		-1.256	-0.8861	-0.2178
		(-1.648)	(-0.9772)	(-0.2513)
Firm ID FEs	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Observations	3,514	3,512	2,380	1,622
R^2	0.48	0.49	0.52	0.53

Clustered (Firm ID) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Effect of RGGI on firm valuation measures

Table 11 reports the effects of RGGI on firm valuation measures. Specifically, the table shows the estimates from the following equation:

$$y_{i,t} = Firm_i + QtrYear_t + \beta_1 \times \mathbb{1}(\text{2005-2008}) \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variables are market to book of equity in columns (1) and (2) of Panel A, and (1) and (3) of Panel B, and market to book of assets in (3) and (4) of Panel A and (2) and (4) of Panel B.

Panel A shows results from the full sample. Panel B presents results from the states that voted Democrats in the presidential election of 2008 and the states with deregulated electricity markets. Standard errors are clustered at the firm level; t-stats are shown in parentheses.

Panel A: Full Sample

	Market/book of equity		Market/book of assets	
	(1)	(2)	(3)	(4)
Yr(2005-2008)*Treated	-0.0337	-0.0378	-0.0232	-0.0244
	(-0.3105)	(-0.3454)	(-0.9228)	(-0.9758)
Post 2008*Treated	0.2267**	0.2593***	0.0485*	0.0576**
	(2.246)	(2.832)	(1.689)	(2.186)
Log (assets)		-0.4165***		-0.1166***
		(-3.207)		(-3.420)
Firm ID FEs	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Observations	3,575	3,575	3,575	3,575
R^2	0.61	0.63	0.61	0.64

One-way (Firm ID) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Matched Samples

	Deregulated only		Democrats only	
	M/B of equity	M/B of assets	M/B of equity	M/B of assets
	(1)	(2)	(3)	(4)
Yr(2005-2008)*Treated	-0.2874***	-0.1028***	-0.0222	-0.0252***
	(-3.485)	(-6.786)	(-0.4353)	(-2.868)
Post 2008*Treated	0.3024***	0.0317**	0.2458***	0.0474***
	(4.404)	(2.341)	(6.228)	(5.690)
Log (assets)	-0.4785***	-0.0963***	-0.2900***	-0.0904***
	(-6.426)	(-5.008)	(-5.741)	(-6.341)
Firm ID FEs	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Observations	1,624	1,624	2,442	2,442
R^2	0.66	0.66	0.65	0.68

One-way (Firm ID) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Effect of RGGI on firm earnings growth forecasts

Table 12 reports the effects of RGGI on analysts' long term growth forecasts of earnings. Specifically, the table shows the estimates from the following equation:

$$y_{i,t} = Firm_i + Analyst_a + QtrYear_t + \beta_1 \times \mathbb{1}(\text{2005-2008})_t \times Treated_i + \beta_2 \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $\mathbb{1}$(2005-2008) takes 1 if year is between 2005 and 2008. $Post2008$ takes 1 if $year > 2008$. The dependent variable is the long term growth forecasts by analysts.

Columns (1) and (2) show results from the full sample. Columns (3) presents results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Column (5) is the subsample of plants in the states with deregulated electricity markets. Columns (2), (3), and (4) also include log of total assets as a control for the size of the firm. Standard errors are clustered at the firm level; t-stats are shown in parentheses.

	LTG forecast			
	Full Sample		Democrat	Deregulated
	(1)	(2)	(3)	(4)
Yr(2005-2008)*Treated	0.4265	0.4028	0.1739	-0.2531
	(0.2812)	(0.2785)	(0.1116)	(-0.1609)
Post 2008*Treated	2.236**	2.171**	2.067**	3.049**
	(2.459)	(2.374)	(2.065)	(2.758)
EPS		0.1932*	0.2823***	0.2431**
		(1.940)	(3.170)	(2.591)
CUSIP ID FEs	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Observations	3,638	3,630	2,598	2,126
R^2	0.40	0.40	0.42	0.46

Clustered (CUSIP ID) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: Effect of RGGI on ESG fund holdings

Table 13 reports the effects of RGGI on ESG-mutual funds' holdings of the electric utilities in a differences-in-differences setting. Specifically, the table shows the estimates from the following equation:

$$y_{i,j,t} = Firm_i + ESG\ Fund_j + QtrYear_t + \beta \times Post2008_t \times Treated_i + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the firm is located in the RGGI-state, and 0 otherwise. $Post2008$ takes 1 if $year > 2008$ and 0 otherwise.

The dependent variable in column (1) is log of total market value of $Firm_i$ that is owned by ESG fund. The dependent variable in (2) is % ownership of the firm by ESG mutual funds. In column (3), the dependent variables is the % of total net assets of $ESG\ Fund_j$ invested in $Firm_i$. Standard errors are clustered at the firm level; t-stats are shown in parentheses.

	Log (value of shares) (1)	% ownership of firm (2)	% of fund total net assets (3)
Post 2008*Treated	0.5403***	0.2685**	0.0691**
	(3.489)	(2.041)	(2.264)
Firm ID FEs	✓	✓	✓
Fund ID FEs	✓	✓	✓
Quarter-year FEs	✓	✓	✓
Observations	8,339	8,337	8,340
R^2	0.85	0.70	0.81

One-way (Firm ID) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 14: Effect of number of ESG-funds on treated firm's Valuations

Table 14 reports the effects of the number of ESG funds on market valuations. Specifically, the table shows the estimates from the following equation:

$$y_{i,t} = Firm_i + QtrYear_t + \beta \times Treated_i \times Log(no.\ of\ ESG\ funds)_T + \epsilon_{i,t}$$

where $Treated_i$ is a dummy that equals 1 if the plant is located in the RGGI-state, and 0 otherwise. $Log(no.\ of\ ESG\ funds)_T$ is the log of total number of ESG-funds holding electric utilities companies in the year T. The dependent variables are Market to book of equity in Columns (1)-(3), and market to book of assets in Columns (4)-(6).

Columns (1) and (4) show results from the full sample. Columns (2) and (5) present results from matched subsamples of power plants in states that voted Democrats in the presidential election of 2008. Columns (3) and (6) are the subsample of plants in the states with deregulated electricity markets.

The sample is restricted to the year 2005 and after to isolate the differential effects of ESG-investments on the treated states' valuations. Standard errors are clustered at the firm level; t-stats are shown in parentheses.

	Market/book of equity			Market/book of assets		
	Full	Democrat	Deregulated	Full	Democrat	Deregulated
	(1)	(2)	(3)	(4)	(5)	(6)
RGGI states × Log (no. of ESG funds)	0.2007**	0.1930**	0.2782**	0.0547**	0.0504*	0.0561*
	(2.357)	(2.099)	(2.345)	(2.190)	(1.901)	(1.755)
Firm ID FEs	✓	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓	✓
Observations	2,238	1,497	982	2,238	1,497	982
R^2	0.73	0.68	0.74	0.70	0.69	0.69

Clustered (Firm ID) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*