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Regulatory Spillover and Climate Co-benefits: Evidence from New Source Review Lawsuits *

H. Ron Chan[†]
University of Manchester

Yichen Christy Zhou[‡]
Clemson University

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Abstract

Though policies on greenhouse gas emissions have been shown to generate benefits in reducing local pollutants such as SO₂ and NO_x, spillover benefits in the reverse direction have not been well studied. This paper estimates one such spillover by examining how SO₂ and NO_x regulations of the New Source Review affect CO₂ emissions of US power plants. We address the ambiguity surrounding the stringency of enforcement of the regulations by using a discrete-time duration model that allows us to predict the likelihood of being named in a lawsuit, and to use this likelihood as a continuous treatment variable. We find that a 1 percent increase in the probability of being sued reduces CO₂ emissions by 0.3 percent, an effect comparable to a carbon tax of \$10 per ton. Further decomposition analysis suggests that most of these carbon co-benefits arise from the shutdown of both coal-fired-only power plants and certain power-generating units.

Keywords: New Source Review, environmental lawsuits, pollution emissions, climate policies, fuel switches

JEL codes: L94, K32, Q58, H23

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[†]Corresponding Author. Department of Economics, University of Manchester, Arthur Lewis Building-2.007, Manchester, M13 9PL, United Kingdom. Contact: ron.chan@manchester.ac.uk

[‡]John E. Walker Department of Economics, 320M Wilbur O. and Ann Powers Hall, 225 Walter T. Cox Blvd., Clemson, SC, 29634, USA. Contact: yichen2@clemson.edu

1 Introduction

Efficient policy design requires that regulators compare marginal costs from enacting an associated intervention with *all* its potential economic benefits; they include direct, and indirect or unintended effects. Indirect or unintended effects can often go the opposite direction of the intended effects and to such a degree that they eclipse the objectives of the policy (e.g., [Almond et al., 2009](#)). Alternatively, indirect or unintended effects can enhance the sought-after objectives (e.g., [Freedman et al., 2018](#)), and they might argue for even stringent policy measures. Such regulatory leakage and spillover problems from overlapping policies persist in many areas in the public policy debates.

Our paper focuses on spillovers in environmental policies across multiple pollutants. Fossil fuel generators produce local pollutants, such as sulfur dioxide (SO₂), nitrogen oxides (NO_x), and global pollutants such as carbon dioxide (CO₂), but regulators often design separate policy instruments to target these pollutants. For example, in the 1970s, the US Environmental Protection Agency (EPA) began using provisions of the Clean Air Act (CAA) to regulate SO₂ and NO_x emissions from electricity generation and other sectors; regional regulations on CO₂ only began recently since 2009 in the New England area under the Regional Greenhouse Gas Initiative (RGGI). These policies could either strengthen or weaken the effectiveness of one another – depending on the spillovers on other types of pollutants and ways in which the regulated companies choose to comply. For example, regulating SO₂ emissions may decrease CO₂ emissions if power plants choose to comply by switching to a cleaner fuel with a lower carbon content; by contrast, regulating SO₂ emissions in the energy and manufacturing sectors could have a detrimental effect by increasing CO₂ emissions if plants respond by installing more energy-intensive emission control equipment.

The impacts of climate policies on SO₂ and NO_x emissions and on human health, have been well studied.¹ However, only a few studies examine the spillover effects that go the other way around – how do regulations of local pollutants affect global greenhouse gas emissions? The answers from a few previous studies that have addressed this question are mixed. For example, [Holland \(2012\)](#) found that meeting the CAA standards *had no effect* on CO₂ emissions in California power plants, plausibly because most plants are gas-fired, while [Raff and Walter \(2019\)](#) found that by inducing usage of low-sulfur coal, meeting CAA standards on SO₂ emissions *reduced* CO₂ emissions for coal-fired plants. [Brunel and Johnson \(2017\)](#) found that CAA attainment status *had no effect* on CO₂ emissions in the manufacturing sector, likely

¹This list includes but is not limited to [Burtraw et al. \(2003\)](#), [Groosman et al. \(2011\)](#), [Muller \(2012\)](#), and [Parry et al. \(2015\)](#). Other works have studied cross-media substitution from air pollution regulation to water pollution ([Gibson, 2018](#)) and from renewable energy subsidies to local pollutants ([Novan, 2017](#)). A theoretical work by [Böhringer and Rosendahl \(2010\)](#) shows that renewable quotas together with carbon trading can promote investment in dirty technology compared to carbon trading alone.

because of a lack of effective margins to reduce carbon intensity, or because the substitution and spillover channels counteract each other.²

Our paper studies how regulation on SO₂ and NO_x emissions affects CO₂ emissions from US power plants. We use a continuous difference-in-differences strategy that relies on a discrete-time duration model to account for the perceived treatment (threat) of regulation. We estimate a time-varying threat for different plants based on settlement data from environmental lawsuits, and estimate how the continuous threat of regulation affects emissions. This estimation strategy addresses the ambiguity of treatment that surfaces in many previous empirical studies, which relied on quasi-experimental methods such as difference-in-differences approaches (e.g., [Bushnell and Wolfram, 2012](#); [Brunel and Johnson, 2017](#); [Raff and Walter, 2019](#)). Under such approaches, it is not always clear on how to define treatment, and exposure to the treatment may vary across plants. Also, the perceived stringency of the policy can vary over time. For example, the interpretation and enforcement of a law can change from one administration to the next; the budget and time constraints to regulate can make the degree to which firms are targeted ambiguous – possibly leading researchers to draw incorrect policy conclusions from responses of an ill-defined or wrong “treatment group”.³

In this paper, we study the New Source Review (NSR) program, a provision of the Clean Air Act that requires new and existing power-generating facilities to adopt emission control technologies to reduce SO₂ and NO_x emissions. We examine how the likelihood of lawsuits for violating NSR regulations affects *both* emissions of local pollutants (SO₂, NO_x) *and* CO₂ emissions from power plants in the US. Although the NSR was instituted in 1977, reforms did not take place until 1999 when the US Department of Justice (DOJ), representing the EPA, brought the first set of lawsuits to the US Supreme Court against 83 power-generating units at 24 power plants. Since then, this manner of enforcement has continued, leading to settlements involving 275 units from 85 plants between 1999 and 2015. The EPA has thus far won all NSR lawsuits that proceed to court – a record that has led power plants to attempt to reach the most favorable settlements possible. The basis of an NSR lawsuit depends on whether a plant has undergone a change that constitutes an unlawful action. Our empirical strategy thus takes into account the context surrounding the decision to bring a lawsuit – controversy around what constitutes an unlawful action, how the stringency of the policy changes over time, and how it varies across plants in different regions. Such ambiguities present a research challenge, which motivates us to find a way to observe not just the plants involved in a lawsuit but plants that

²Though their research questions are not to study carbon co-benefits per se, several other papers have also investigated the magnitude of carbon co-benefits in the electricity-generation sector. [Cullen and Mansur \(2017\)](#) and [Fell and Kaffine \(2018\)](#) studied the effect of fuel prices and wind generation of carbon dioxide emissions. [Holland et al. \(2018a\)](#) accounted for carbon benefits in marginal damages of air pollution from electricity generation.

³“Reinvigorating Competition Policy: How Can IO Scholars Contribute?” – a 2019 presentation by Nancy Rose to a policy panel of the Allied Social Science Association – showed that the number of second requests on public challenges had decreased over time, and that cases on smaller transactions had declined; the reasons cited were the costs of using agency resource to collect evidence, and the tight time frames used by agencies. Even with the Federal Trade Commission guidelines, it is not always clear to the firms which case will be investigated.

are vulnerable to the threat of a lawsuit. We address this issue by estimating the probability of being named in an NSR lawsuit, which quantifies the continuous treatment of “being caught” for violations at each power plant; hereafter, we refer to this as the *NSR lawsuit probability*.

We build our discrete-time duration model on the cross-sectional probit model of NSR lawsuits used in [Keohane et al. \(2009\)](#). Our model allows us to predict the lawsuit probability and form a continuous treatment variable that is plausibly exogenous for our analyses on emissions and plant operations. This dynamic approach is important because we need to allow the NSR lawsuit probabilities to vary across plants and over time, and to correlate over time within a plant. To predict these probabilities, we use historical emissions and energy production information as in [Keohane et al. \(2009\)](#), other cross-sectional variation (such as the judicial circuit court in which a plant is located) and year fixed effects. The use of historical data is motivated by the legal arguments documented in lawsuit decrees against power plants: historical violations in 1980s and early 1990s were often cited as the reason why they were sued, even when the first legal notices were not served until much later.⁴

Using the predicted NSR lawsuit probability, we proceed to estimate how the lawsuit threat affects both regulated and unregulated emissions from US power plants between 1995 and 2015. The effect of a higher lawsuit risk on CO₂ emissions can be ambiguous. Installing and increasing the usage of SO₂ and NO_x control technologies may increase a plant’s electricity consumption, and therefore increase CO₂ emissions. Building new (usually more efficient and less CO₂ intensive) boilers may not be appealing because doing so may trigger a long and undesirable review process to acquire New Source Review permits ([Bushnell and Wolfram, 2012](#); [Evans et al., 2008](#); [Heutel, 2011](#); [List et al., 2004](#)). These types of distortions may limit the potential for CO₂ emissions reduction, or may even increase CO₂ emissions. Alternatively, a higher lawsuit risk may reduce CO₂ emissions if a plant reallocates power generation from an older unit to a newer, more efficient unit (with a lower operating heat rate); or from a coal-fired unit to a gas-fired unit.

We find that a higher NSR lawsuit probability leads to a sizable and significant reduction on all SO₂, NO_x, and CO₂ emissions. We control and instrument for gross electricity generation to separate the scale effect on emissions, and we include plant and year fixed effects in our regressions. We find that a 1 percent increase in the NSR lawsuit probability (an increase of about 0.2 of a standard deviation) decreases SO₂ emissions by 0.9 percent, NO_x emissions by 0.9 percent, and CO₂ emissions by 0.4 percent. These changes are equivalent to yearly reductions in SO₂ emissions by 68 thousand metric tons, NO_x emissions by 34 thousand metric tons, and CO₂ emissions by 6.9 million metric tons in 2007 – all of which are sizable compared with national emission inventories ([EPA, 2016](#)). Evaluating at a \$42 per-metric-ton social cost of CO₂, the climate co-benefits would be \$290 million (in 2007 dollars), the size of which is comparable to

⁴The use of historical data is also in line with the empirical literature in economic growth which uses initial capital stock as the proxy for the effect of capital (e.g., [Blundell et al., 1992](#)).

the benefit of a \$10/ton carbon tax, using results from [Linn et al. \(2014\)](#).⁵ The magnitude of CO₂ co-benefits implies that it is important to account for climate spillover in computing total economic benefits of regulating pollution emissions from the energy sector. Our results also suggest that the NSR has been effective in reducing carbon emissions. Our results are robust to inclusion of other overlapping policies.

To investigate the factors that drive the emissions reductions, we further examine how a higher lawsuit probability induces plants to improve abatement technologies (the technology channel) and thermal efficiency (the efficiency channel). We find that a higher NSR lawsuit probability has led to significantly lower SO₂, NO_x, CO₂ emission rates, and higher thermal efficiency (lower heat rate). However, for plants that stay open we find no improvement in heat rate. Our results suggest emissions reductions are coming from both improvements in the abatement technology and the shutdown of inefficient plants.

We decompose the counterfactual emissions reductions by plants with and without the natural gas capacity, along the intensive and the extensive margins. While both margins are important across all SO₂, NO_x, and CO₂ emissions, the extensive margins contributes 61 percent of the CO₂ co-benefits. Within the extensive margins, the majority of the reduction of the CO₂ is due to the closure of coal-fired-only power plants. Closing or retiring these plants also accounts for the majority of SO₂ and NO_x emissions reductions.

Since a plant may have multiple electricity generating units (EGUs), intensive improvements within a plant can be driven by improvements within a single EGU, or by a reallocation of resources across multiple units achieved by shutting down some units. We repeat our estimation and counterfactual exercises at the EGU level to distinguish between these two margins. We find that a 1 percent increase in the NSR lawsuit probability leads to a 1.2 percent reduction in SO₂ emissions and a 0.8 percent reduction in NO_x emissions for operating EGUs; these results are similar to those at the plant level. However, a similar regression shows that the effect for CO₂ emissions drops to 0.1 percent. These results suggest that the carbon co-benefits found at the plant level would mostly come from reallocation across EGUs. Also, we find that a higher NSR lawsuit risk reduces the probability of operating a coal-fired EGU, but increases this probability for gas-fired EGUs. Along those lines, we decompose our previous plant-level intensive margins (our counterfactual emissions reductions for plants that stay open) at the EGU level. We find that more than 95 percent of the CO₂ co-benefits within an active plant are due to EGUs shutting down.

This paper contributes to the following strands of literature: First, this study contributes to the literature on regulatory spillover and overlapping policies as discussed above. Also, studying the sources of spillover offers important insights for a more effective carbon policy design; we

⁵We assume a 3 percent discount rate for the social cost of carbon. More assumptions can be found in the EPA 2017 archive https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html

quantify various channels that contribute effectively to CO₂ emissions reduction, especially the extensive margin of the fuel switches at both plant and EGU levels.⁶ Our results also provide reassurance to policy makers that at the current equilibrium, a leakage to CO₂ emissions will be unlikely from regulating SO₂ and NO_x – or from strengthening existing regulations.

Also, this paper adds to the knowledge regarding how the NSR created vintage-differentiated regulations distortion, and how this distortion affects SO₂ and NO_x emissions. Past studies have found evidence of the delayed investment in new units, and investment reduction of new technologies in existing units (List et al., 2004; Heutel, 2011; Bushnell and Wolfram, 2012). Past studies have reached different conclusions about the sign and magnitude of environmental impacts (Evans et al., 2008; Keohane et al., 2009; Bushnell and Wolfram, 2012). Using a longer panel and a different estimation strategy, we provide evidence of effective emissions reductions of regulated pollutants, and we examine the channels that drive the emission reductions.

Lastly, this paper is also related to the literature on enforcement and compliance (see Helland, 1998; Earnhart, 2004; Gray and Shimshack, 2011) in that we examine a case in which the degree of enforcement is difficult to measure; policies are uncertain; and no clear threshold of violation exists. We estimate the perceived stringency of enforcement by estimating the probability of being named in a lawsuit, and we use this to examine the effectiveness of enforcement.

The rest of the paper is organized as follows: Section 2 gives a background on the NSR program, and briefly describes our data sources. Section 3 presents our two-step approach in estimating the probability of being litigated, and how that probability affects emissions and plant operation. Section 4 presents the estimation results. Section 5 presents the decomposition exercises used to quantify plant-level and EGU-level intensive and extensive margins that explain our carbon co-benefits results. Section 6 presents additional evidence on emission control technology adoptions and within-plant fuel switches. Section 7 concludes.

2 Data and Background of the NSR

2.1 The New Source Review Program

Many regulations and mandates in the United States impose different standards between new and existing units. For example, the Corporate Average Fuel Economy (CAFE) standard only targets new vehicles; building codes only regulate the energy efficiency of new buildings; the EPA only mandates buildings constructed after 1978 for a disclosure or safety certification for lead paint; the U.S. Food and Drug Administration (FDA) only reviews applications of new drugs without repeated review of previously approved drugs, even though the standard of approval may tighten over the time; and the 1970 Clean Air Act (CAA) only imposes mandates

⁶Previous work has suggested fuel switches can induce CO₂ emissions reductions, e.g., (Linn et al., 2014). Broadly speaking, our work is related to design of policies on greenhouse gas mitigation (Bushnell et al., 2017; Abito et al., 2018).

for new emission sources. The distortion that arises from these differential treatments creates a regulation wedge that may lead to leakages and spillovers. In the case of the electricity generation sector, the provisions of the 1970 CAA could encourage firms to delay introduction of new units, extend the lifetime of existing units, undermine the effectiveness of the regulation, and potentially raise the net cost of the regulation.

To address these issues the New Source Review (NSR) was created as part of the 1977 Clean Air Act Amendments. It was designed to regulate the modification of existing power generating units that were not subject to regulation under the original act, and to expedite the process of replacing older and less efficient units. Under the NSR, a utility company that plans to undergo a modification to an existing unit in a given plant has an option to voluntarily apply for a “Permit to Construct”, which requires the plant to undergo an extensive review process. This process must provide evidence that the modified unit will meet the requirement of the National Ambient Air Quality Standards (NAAQS) in the county where the unit is located. Although NAAQS are very specific at the county level, there is no specific rule regulating the emission rate at the end of each pipe. Therefore, the review process usually requires applying plants to install the Best Available Control Technology (BACT). To avoid installing costly BACT, and to avoid triggering a lengthy review process, which is also costly to the firm, the utility company can choose to delay modifications, or choose not to inform the EPA of their modifications. However, either of these actions may trigger a lawsuit alleging a utility company has violated the Clean Air Act provisions. In the wake of these lawsuits, the resulting consent decrees generally quote emission records from previous decades, suggesting the risk of facing a lawsuit is correlated with historical plant operations. Therefore, we utilize historical variation to predict the risk of facing an NSR lawsuit as our treatment.

However, the nature of NSR lawsuits remains somewhat ambiguous. As a result, rather than defining treatment and control groups, we empirically estimate a plant-specific probability of involving in a lawsuit, explicitly for three reasons. First, in a given year, it is unclear as to which plants the EPA will target. In those first set of lawsuits, the DOJ alleged that major, life-extending modifications had been made to old units, without the proper permitting process under the NSR. However, the definition of “major” modifications has been open to interpretation, and has changed over time (to discuss below), giving the EPA significant discretion over which plants it will target. For example, the EPA can decide if a plant’s major modification can affect the regional level of NAAQS, and if it falls under non-attainment. The interpretation of the law also depends on judges at different federal courts, which would affect the expected outcome of the lawsuits. In turn, this variation in the leniency may affect how the EPA targets plants across jurisdictions. Table 2 shows that, while emissions are similar from four circuits (the third, fourth, fifth and tenth circuits) of the US Courts of Appeals, the number of lawsuits that surface in these districts differs. For example, no lawsuits were filed in the Fifth Circuit, while eight lawsuits were filed in the Tenth Circuit over the same period of time.

Second, in addition to cross-sectional ambiguity, the enforcement also varies over time. The NSR program has been through several rule changes. The electricity-generation industry was not aware of the NSR threat until November 1999, when the US Department of Justice (DOJ), as an enforcement agent of the EPA, sued 8 utility companies alleging that 24 power plants and 83 units violated the NSR.⁷ Correspondingly, Figure 1 shows a spike in the number of NSR lawsuits in 1999 during the Clinton Administration. During the first term of the Bush Administration, the EPA went through with an NSR rule change, known as the Equipment Replacement Provision (ERP). Starting in December 2002, the ERP exempted any routine modification changes that require less than 20 percent of the capital cost of a given plant in one year. The high threshold effectively removed the risk that companies would be required to retrofit or install BACT in existing units. Consistent with this rule change, Figure 1 shows that the average number of NSR lawsuits decreased around 2004. After four years, in March 2006, the D.C. Circuit Court vacated the ERP. Consistent with the removal of ERP, we see an increasing trend of NSR lawsuits after 2006 in Figure 1. Subsequently, the Bush EPA proposed a revision of the NSR to permit authorities to combine and aggregate emissions from plant modifications when projects involved different plants of a utility company. Known as the “aggregation policy”, this rule would have effectively reduced the stringency of the NSR. The final rule was issued in January 2009, within the first week of the Obama administration, which delayed the effective date of the aggregation policy to March 2010. Consistent with the rule change, Figure 1 shows that the average number of NSR lawsuits declined after 2010.

Lastly, using the *existence* of a lawsuit to define treatment would neglect the effect of the *potential* of facing a lawsuit – on both emissions and plant operations. For example, the NSR brought lawsuits against Duke Energy in 2000, and against Santee Cooper in 2003. Using the *presence* of a lawsuit as the criterion for treatment would thus define Duke Energy as treated and Santee Cooper as a control (untreated plant) beginning in 2000 and continuing until 2003. Comparing emission changes between these two plants over that period may underestimate the treatment effect, since a potential lawsuit may have altered the incentives and operations for Duke Energy prior to 2000, and for Santee Cooper before 2003.

Thus, our main hypothesis assumes that firms believe that NSR lawsuits are a credible threat in our sample period (1995-2015), and that they would respond optimally to avoid an allegation. This hypothesis is further supported by the historical record. First, the EPA has won all allegations it has brought thus far – a history that underscores that such threats are credible. Second, the negative consequences a lawsuit can be so extreme that they provide plants an incentive to respond before any threat becomes salient (i.e., before the threat becomes an actual allegation). Most settlements require utility companies to retire, retrofit, or install BACT for specific power-generating units involved within a proposed short window, or to face civil

⁷The utility companies sued in November 1999 were American Electric Power (AEP), Cinergy, Dynergy, FirstEnergy, Southern, TECO Energy, and Tennessee Valley Authority. We interpret this as an exogenous increase in the NSR lawsuit probability from 1999 onwards.

penalties of up to \$27,500 per day for delays. The potential penalties and forced changes can thus be very costly to utility companies with high-risk plants.⁸

2.2 Data

We put together a dataset for 1,357 coal- and gas-fired plants and their 5,648 electricity generating units (EGUs) from 836 utility companies between 1995 and 2015 for our analysis. We collected monitoring data on SO₂, NO_x, and CO₂ emissions from the EPA Continuous Emission Monitoring System (CEMS) database. We collected power plant operation data including gross load and net power generation, heat input, fuel use, and other plant characteristics using Forms-767, 906 and 923 from the U.S. Energy Information Administration (EIA). We conduct our main analysis at the plant-year level since the data are noisier at the EGU level. We later explore within-plant operations at the EGU level.

In addition to emissions, we computed emission rates (tonnes of emissions per unit of heat input) using emissions data and heat input, as well as thermal efficiency (operating heat rate, defined as heat input needed per unit of power generation) using heat input and power generation. To examine the extensive margin, we collected nameplate and operating capacities of EGUs, and their retirement status from the EIA Form-860. Table 1 shows that there is a good amount of variation in the key variables of interest, including emissions, emission rates, operating heat rates, and the share of plants under an NSR lawsuit in a year.

We extracted NSR lawsuit consent decrees from EPA Coal-fired Power Plant Enforcement web page.⁹ There are 31 lawsuits involving 85 power plants and 275 power generating units, starting from the first cases in November 1999 to the last case of Duke Energy in 2015.

It is important to carefully define the date when a lawsuit became a salient allegation.¹⁰ We gathered detailed lawsuit enforcement milestones and settlement characteristics using the Integrated Compliance Information System - Federal Enforcement and Compliance (ICIS-FE&C) data set from the EPA Enforcement and Compliance History Online (ECHO) database.

⁸From 1999 to 2015, 37 settled utility companies were required to pay \$188 million civil penalties; the average was \$5 million. The settlement required the 34 targeted plants to spend or pay \$26 billion for compliance action; the average payment was \$722 million. Four companies were required to spend or pay \$26 million in total for supplementary projects; the average was \$6.5 million. The compliance action cost includes the sum of the dollar values of injunctive relief and the physical or nonphysical costs of returning to compliance. Injunctive relief represents the actions a regulated entity is ordered to undertake to achieve and maintain compliance, such as installing a new pollution control device to reduce air pollution, or preventing emissions of a pollutant. The supplementary cost applies to the types of environmentally beneficial projects which a defendant/respondent agrees to undertake in a settlement of an enforcement action, but which the defendant/respondent is not otherwise legally required to perform. Data are from the lawsuit decrees described in Section 2.2.

⁹Link: <https://www.epa.gov/enforcement/coal-fired-power-plant-enforcement>. Readers will notice there are no lawsuits in 2015 in Figure 1 since Duke Energy first received a legal notification when the enforcement data were entered in 2000. See our explanation in the next paragraph and Appendix Table A.1 for detail.

¹⁰This is not an important issue for previous studies since they estimate or construct cross-sectional NSR risk. For example, Keohane et al. (2009) estimate cross-sectional probit risks in 1999 and 2000. Bushnell and Wolfram (2012) assume the NSR risk starts in 1998 and ends in 2002 for all coal-fired plants without scrubbers.

We observe the date when the case was referred to the DOJ to proceed litigation; the date the enforcement data were entered into the database; and, after that, the date the complaint was filed in the court. We then observe the court date when a consent decree is made, and the date when final order is lodged.¹¹ We use the “enforcement data entered date” as the baseline measure to estimate the probability of being sued: this date is right after the first milestone, the “referred to DOJ date,” and plants receive a notice from the court on this date, and could begin to prepare for the lawsuit at that time.¹² Later for robustness we use other dates to define our lawsuit timing. Also, no utilities have had multiple NSR lawsuits filed against them in our sample.

To predict NSR lawsuit probabilities, we collected historical emissions and power generation data prior to the first wave of NSR reform in 1999. Although the CEMS dataset does not track emissions prior to 1995, we can observe historical net generation and heat input data from 1980 to 1995 in EIA Form-767. Similar to [Keohane et al. \(2009\)](#), we imputed historical SO₂ emissions using information on power generation, fuel quality, and fuel use. We also collected federal judicial circuit court information. [Figure 2](#) shows the map of U.S. federal circuit districts. [Table 2](#) shows how the number of lawsuits varies by federal judicial circuit court.

Lastly, we obtained information of overlapping federal or regional environmental and energy policies that might affect power plant operations. We collected states and years that were affected by the Clean Air Interstate Rule (CAIR) which has regulated SO₂ and NO_x emissions since 2010; the NO_x Budget Trading Program (NBP) which was in place from 2003 to 2008; and the Regional Greenhouse Gas Initiative (RGGI) which has regulated CO₂ emissions since 2009 in some states in the New England region. Also, we collected county-level attainment status of the National Ambient Air Quality Standards (NAAQS) over our sample period.

In addition to the above dummy variables that vary at the state-year and county-year level, we added to our dataset the plant-year level emission allowances for SO₂ and NO_x allocated to each plant under the Acid Rain Program (ARP) and NBP from the EPA Air Markets Program Data (AMPD) Compliance Allowance data set. We observe allocation at plant-year level but most variation is at the plant level. To complement the allowance data, we further gathered annual allowance price for SO₂ emissions.

¹¹After the “referred to DOJ” date, we observe the “enforcement data entered” date recorded within a day or at most a few days later. Over the next few weeks, we then observe the date “complained filed to court.” Then, within a few months (or, in very few case, within a period that extends to years if a lawsuit has been pushed back), we observe the date when a “consent decree is made at the court.” As a reference, [Keohane et al. \(2009\)](#) use 1999, which implicitly defines the lawsuit date from the “DOJ date” to the “consent decree date”. Then, months (or, in very few cases, years) after the “consent decree” date, we observe a date when “the final order is lodged.”

¹²Ideally we would like to use the “referred to DOJ date” but the data are missing for a few public regulated plants. The “enforcement data entered date” is in average a few days later than the “referred to DOJ date” and our estimation is at yearly level. This choice does not affect our analysis.

3 Empirical Strategy

3.1 Estimate NSR Enforcement Likelihoods

In this section, we describe the discrete-time duration model that we use to estimate the likelihoods of experiencing an NSR lawsuit.

Previous studies on the (treatment) effect of the NSR have either adopted engineering models for ex ante analysis or formed time-invariant control and treatment groups for ex-post assessment. Ex-ante studies such as EPA Regulatory Impact Analyses (RIAs) have simulated emission trajectories by assuming important parameters such as the percentage of plants that might have complied with the NSR rule using the Integrated Planning Model (IPM) (see EPA, 2012b, 2015).¹³ NRC (2006) improves on the IPM model by allowing plants to adjust their extensive and intensive margins (at either the plant or EGU levels) and by using a broader range of assumed parameters; nevertheless, the NRC still specified which sets of selective plants would undergo retrofit, retire, or repower under the NSR. These models, powerful in making various simulations, are sensitive to economic parameters and make implicit assumptions on intention-to-treat (ITT).

Previous ex post studies either assumed time-invariant control and treatment groups or estimated time-invariant risks of litigation using cross-sectional methods. Bushnell and Wolfram (2012) use the historical installation of SO₂ emission control devices (i.e., whether a plant had a scrubber before 1999) to separate plants into a control group that is relatively safe from the NSR litigation and a treatment group that is vulnerable to the NSR. They then examine how plant operations and emission rates vary across groups before and after the ERP rule change in 2003. Keohane et al. (2009) estimate a cross-sectional probit likelihood of an NSR lawsuit, and then study how the estimated lawsuit risk affects emissions from 1996 to 2000.

We begin by considering a discrete-time duration model $S(t|Z_i) = S_0(t) \exp\{Z_i\delta\}$, where $S(t|Z_i)$ is the rate of plant i surviving to year t without being involved in a lawsuit, and Z_i includes covariates to predict survival probability. By rewriting the survival function into a complementary hazard function and applying a log-log transformation to the baseline hazard, we transform the dynamic duration model into the complementary log-log hazard (C-log-log) model. The discrete-time hazard rate for plant i in year t is given by:

$$\rho_{it} = 1 - \exp\{-\exp\{Z_i\delta + \phi_t\}\} \tag{1}$$

¹³To simulate the impact of the NSR, the EPA uses a regulatory model developed by ICF Consulting. As NRC (2006), Chapter 6, states, “IPM is a deterministic model of the electricity sector that uses linear programming techniques to find a lowest-cost approach to determine how electricity generators might meet projected demand and the amounts and types of generating-capacity investment and retirement sufficient to meet peak demand and regional reserve requirements.”

where $\rho_{it} \equiv \Pr(\text{lawsuit}_{it} = 1)$ is the conditional probability that plant i is involved in a lawsuit in year t given that i survived in $t - 1$. The year fixed effects ϕ_t capture temporal changes of the stringency and the interpretation of the NSR, macroeconomic shocks, and other unobservables that vary over time. To allow for correlation within plants, we cluster our standard errors at the plant level.

Z_i includes the first and second moments in historical emissions and power generation prior to 1999 (from 1985 to 1994), log generating capacity in 1997, scrubber installation status in 1995, and dummy variables that represent 11 federal circuit courts. First, we include in Z_i first and second moments of historical emissions and power generations. They can be useful predictors since violations cited in most consent decrees dated back to the 1980s and early 1990s even though plants named in NSR lawsuits were mostly sued for recent modifications.¹⁴ [Keohane et al. \(2009\)](#) similarly use historical emissions to predict the lawsuit risk in 1999 and 2000.

Also, we include in Z_i historical scrubber installation. All consent decrees cite violations in SO₂ emissions and most mandate alleged entities to install SO₂ BACT such as scrubbers. Thus plants without scrubbers are more likely to be sued ([Bushnell and Wolfram, 2012](#); [Reitze, 2001](#); [Jaber, 2004](#)). Moreover, DOJ may tend to target relatively higher-profile cases against larger plants. We therefore include in Z_i the log of generation capacity by 1995 to control for the size of a plant.

Third, we include in Z_i dummy variables of the federal circuits to capture the variation in leniency and other unobservables varying by federal circuit districts. As we discussed in Section 2.1, plants named in NSR lawsuits are not proportionately drawn from the distribution of all plants but instead cluster around the Rust Belt, and are rarely seen around the pro-business federal circuit courts. For instance, Table 2 shows that there have been no lawsuit case in the Fifth Circuit (for LA, MS, and TX) and 35 lawsuits in the Seventh Circuit (for IL, IN, and WI) – even though the emission levels in these two districts are comparable.

We choose the c-log-log model instead of alternative discrete-time duration models such as the proportional hazard model. The former allows us to predict not only the conditional hazard rate but also the base year hazard rate, which enables us to predict the unconditional probability of a lawsuit $\hat{\rho}_{it}$. This is important for our analysis since we need to use the unconditional lawsuit probability to estimate the effects of a higher lawsuit risk on emissions.

Before we discuss how we use the estimated $\hat{\rho}_{it}$ in the next stage of our analysis, it is important to discuss how the parameters in equation (1) are identified with our model. δ 's are identified using cross-sectional variations across plants, and we allow a shift term ϕ_t to capture the increase of hazard rate over time by comparing changes in risks (e.g., policy changes). These

¹⁴For instance, *Ohio Edison* was sued in 2003 on the basis of modifications made at the Sammis Plant between 1984 and 1998 ([Jaber, 2004](#)).

two estimated effects form the estimated policy risk $\hat{\rho}_{it}$ non-linearly from the functional form assumption in equation (1). Later in Section 6 part D, we investigate alternative ways that generate more plant-year variation by controlling for plant-time-varying controls; we also explore other specifications such as logit and probit models to relax the functional form assumption – we find robust results.

3.2 Estimating Effects of NSR Lawsuits

We proceed to estimate how the NSR lawsuit risk affects plant emissions and operations. For the log of total emissions (SO₂, NO_x, or CO₂) from power plant i in year t , we estimate:

$$\ln emiss_{it} = \beta_1 \hat{\rho}_{it} + \beta_2 \ln Q_{it} + \gamma X_{it} + \alpha_i + \alpha_t + u_{it} \quad (2)$$

where $\hat{\rho}_{it}$ is the predicted probability of facing an NSR lawsuit for plant i in year t , ranging from 0 to 100.¹⁵ Because $\hat{\rho}_{it}$ is a generated variable, we correct the estimated standard errors by bootstrapping both the complementary log-log model (1) and our main estimation equation (2). In contrast to past studies on the NSR that focus on coal-fired plants (Keohane et al., 2009; Bushnell and Wolfram, 2012; Raff and Walter, 2019), our sample includes both coal- and gas-fired plants.

Our goal is to identify the effect of a higher NSR probability on emissions, captured by β_1 . We control for the log of gross load power generation, $\ln Q_{it}$, so that β_1 is conditional on the emissions reductions from reducing power generation, i.e., *the scale effect*. Plant fixed effects α_i capture time-invariant unobservables at the plant level correlated with compliance costs and production such as geographic region and the type of turbine. Year fixed effects α_t capture temporal changes in macroeconomic conditions shared across plants. X_{it} also includes a dummy variable that represents whether a utility company has a scrubber installed in 1995 interacted with a linear year trend. We include historical scrubber status in both equations (1) and (2) because having a scrubber can be correlated with both lawsuit probability and emissions independent of lawsuit probability.¹⁶

To separate the effect of averting behavior from a higher NSR lawsuit risk from the effect of complying to a lawsuit settlement, we remove the post-lawsuit years for the plants that have had a lawsuit when we estimate equation (2) after we estimate equation (1). Later in Section 4.4 we add post-lawsuit years back, and estimate both (i) the effect of facing a lawsuit threat $\hat{\rho}_{it}$ before the threat becomes salient (i.e., when a plant learns that it will be named in a lawsuit) to avoid an undesirable outcome, and (ii) the effect of facing an actual allegation when a plant reduces emissions to comply with the terms in the consent decree.

¹⁵We scale up $\hat{\rho}_{it}$ by 100 in our bootstrap for simpler interpretation.

¹⁶The duration model implicitly allows the historical scrubber status to both generate cross-sectional variation in $\hat{\rho}_{it}$, and to allow the variation to persist at different rate across plants. Therefore, in equation (2) we need to interact this dummy with the year trend to capture variation at plant-year level.

We next consider and correct for potential endogeneity of power generation. Plants can adjust output to reduce emissions. Also, unobserved technologies can be correlated with both power generation and emissions. We adopt a demand shifter, the number of cooling degree days (CDD) of a state in a year, as our instrumental variable (IV) for log power generation. Therefore, we use only the exogenous part of power generation driven by the demand shock to predict emissions.

As we have included the NSR lawsuit risk in the first stage of the IV regression where we instrument power generation with demand shifters, we allow the NSR lawsuit risk to affect emissions in two ways. In addition to the *direct* effect of lawsuit risk on emissions that we aim to capture in our paper, the first stage of the IV regression also allows for any *indirect* effect of lawsuit risk on emissions via changes in outputs. For example, the plant may reduce their electricity production to reduce emissions, in response to a rising lawsuit risk.

We expect β_1 to be negative for SO_2 and NO_x emissions if a higher lawsuit risk motivates power plants to take actions to reduce regulated emissions conditional on output adjustment. If β_1 is also negative for CO_2 , it implies that a higher lawsuit risk induces climate co-benefits. We expect β_2 to be positive since higher demand for electricity would lead to more emissions, all else being equal. If the scale effect is the driver for emission reductions, we expect β_1 to be small or even insignificant from zero after controlling for $\ln Q_{it}$, similar to the findings in [Holland \(2012\)](#).

4 Estimation Results

4.1 Estimates of NSR Lawsuit Likelihoods

In this section, we present estimates of the complementary-log-log equation (1). In Appendix Table A.2, we report the estimated parameter $\hat{\delta}$ in column 1 and the corresponding marginal effects in column 2. Our hazard model fits the data well with an overall Wald Chi-squared equal to 337. We found that historical plant emissions, operations, and plant characteristics are good predictors for the NSR lawsuit probability. The Wald Chi-squared for the joint-significance test of plant-specific variables excluding year effects is 97.

We find that the coefficient for the average of historical gross generation is positive and significant, while the coefficient for the standard deviation of the historical gross generation is negative and significant. In contrast, the coefficients for the first and second moments of emissions are not statistically significant. Despite that we find the first moment of historical emission has a consistently positive sign in alternative specifications, we do not find historical emissions have a sizable or significant coefficient when specifying alternative sets of historical moments. These results suggest that plants with higher but consistent outputs are more likely to be named in a lawsuit. Similar results are also found for larger plants, measured by their

nameplate capacity. These results coincide with the anecdotes that regulating agencies tend to target high-profile cases.

Consistent with suggestive evidence in Table 2, Table A.2 suggests that plants located in the Fourth Circuit (DC, MD, NC, SC, VA, WV), 6 (KY, MI, OH, and TN) and the Seventh Circuit (IL, IN, and WI) are more likely to be named in a lawsuit, when compared with other circuits that are less pollution-intensive (for example, the First and the Second Circuits) or with a more pro-business judicial circuits (for example, the Fifth Circuit). The average predicted lawsuit risk $\hat{\rho}_{it}$ across all states is 2.1 percent, while Tennessee, West Virginia, Kentucky, Indiana, and Ohio have an NSR risk of 11.5, 10.4, 10.2, 8.8, and 7.6 percent respectively.

Using our estimates, we generate the predicted probability of being involved in a lawsuit. In Figure 3 Panel A, we show that $\hat{\rho}_{it}$ gradually increases over time with a slight a drop in 2007. The overall trend is consistent with the number of lawsuits filed during our sample period in Figure 1.

Our duration estimates allow us to construct better treatment and control groups than using observed lawsuits. In Panel B of Figure 3, the light-colored dots show the predicted lawsuit risk if a plant had a lawsuit in our sample period, and the black dots show the lawsuit risk for a plant that never had a lawsuit. First, comparing two groups cross-sectionally, plants that have never had lawsuits are still subject to a significant positive risk, even though that risk is small – suggesting the importance of constructing a continuous treatment. Second, the risk increases over time for both groups, and the wedge between these two groups diverges. This evidence suggests the importance of accounting for correlation in hazard across plants over time. This exercise also puts the marginal effects of a one-standard-deviation increase in historical power generation in context. That increase (5.5 percent) is roughly equivalent to one-half of the wedge in the lawsuit risks between plants that have had a lawsuit and plants that have not had a lawsuit up to 2005. In Panel C, we repeat the same exercise, comparing the utilities that own a plant that has had a lawsuit with other utility companies whose plants have not faced a lawsuit. We find similar evidence.

4.2 Effect of a Higher NSR Lawsuit Risk on Local Pollution and CO₂ Emissions

In this section, we show how a higher NSR lawsuit risk $\hat{\rho}_{it}$ affects local pollution and CO₂ emissions. In Table 3 Panel A columns 1–3, we report the OLS estimation of equation (2) on the log of SO₂, NO_x, and CO₂ emissions, treating power generation (log of gross load) as an exogenous variable. The results suggest that a higher NSR lawsuit risk is correlated with emission reduction, holding other factors constant. Also, we find evidence of the scale effect, that plants that produce more power are likely to generate more emissions.

Next, we proceed to our IV estimation of equation (2). We report our first-stage in Appendix Table A.3 column 1. Our first stage is strong, and it passes the weak instrument test.¹⁷ Our first stage implies that if the number of cooling degree days increases by 10, the gross load of power generation would increase by 0.6 percent holding other factors constant. As for the included variable, a greater NSR lawsuit probability will reduce power generation, albeit statistically insignificantly. Since using emission abatement technology requires electricity, it can be relevant to use net generation which excludes the electricity consumption from gross load generation. We repeat our exercise using net generation in column 2 and we find similar results. Our first stage is also robust to alternative demand shifters as IVs (unreported).

We present our baseline IV estimates in Table 3 Panel A columns 4–6. Our IV results have the same sign as the OLS results in columns 1–3, and we find that the OLS results bias the estimates slightly upward for SO₂ and NO_x emissions.

We find a *direct effect of the lawsuit risk* on emission reductions, independent of the scale effect. The coefficients are negative and statistically significant for all emissions. A 1 percent increase in the NSR lawsuit probability (about 0.2 of a standard deviation) would decrease SO₂, NO_x, and CO₂ emissions by 0.9 percent, 0.9 percent, and 0.4 percent respectively. Also, our baseline provides evidence of an *indirect scale effect* of power generation on emissions. The second-stage coefficient for log output is positive and significant. A 1 percent increase in the gross load of power generation increases SO₂, NO_x, and CO₂ emissions by 1 to 1.2 percent. Combining these numbers with our first-stage coefficient, a 1 percent increase in the lawsuit probability could lead to 0.7–0.8 percent (imprecise) emissions reductions via reducing power generation.

Our findings on local emissions (SO₂ and NO_x) are consistent with those of Keohane et al. (2009); they contrast with the findings of Bushnell and Wolfram (2012) and Evans et al. (2008), both of whom found a null effect with regards to SO₂ and NO_x emission rates. The discrepancy between Bushnell and Wolfram (2012) and our results could be that we have a longer time span; they focus on the initial reform and the ERP period. Another reason could be differences in our definitions of control and treatment groups and the resulting differences in findings and interpretations.¹⁸ As for Evans et al. (2008), there is a methodological difference in defining both the treatment and counterfactual. Evans et al. (2008) use a bottom-up economic-engineering model, and they assume ex ante which plants will be affected; by contrast, our study estimates the continuous treatment from data.

¹⁷The F-stat for the significance of our IV is 37. The Cragg-Donald F-stat is 13.7, and the Kleibergen-Paap F-stat is 7.0. For robustness we test the joint significance of IVs when we have more than one IV.

¹⁸The difference is unlikely driven by the fact that we include both coal-fired and gas-fired plants, while they include coal-fired plants only, because we later find reductions in emissions for plants without gas capacity (as shown Table 7 Panel A).

4.3 How Have a Higher Lawsuit Risk Affected Plant Operations?

To understand the driving factors and effective margins that lead to emissions reductions and CO₂ co-benefits, we proceed to investigate how a higher NSR lawsuit risk affects important margins in plant operations.

A. Emission rates and operating heat rate. Emissions z for a plant in a year (subscripts suppressed) can be expressed as $z = e \times \theta \times Y$, where e is the emission rate (i.e., emissions per unit of heat input), θ is the operating heat rate (i.e., heat input per unit of electricity generation), and Y is the level of electricity generation. Conditional on the scale Y , the overall emissions depend on how a plant operates, aka the emission rate and operating heat rate. Therefore, we proceed to examine how lawsuit risk affects e and θ .

We present our baseline specifications on emission rate and operating heat rate in Panel A of Table 4. Columns 1–3 suggest that the effect of a higher lawsuit probability on emission rates is negative and statistically significant. This result is consistent with our findings in Table 3. A 1 percent increase in the lawsuit probability reduces the emission rates of SO₂, NO_x, and CO₂ by 1.7 percent, 1.8 percent, and 1.3 percent respectively. We find similar results for the operating heat rate, shown in column 4. A 1 percent increase in the lawsuit probability reduces the heat rate by 1 percent. This improvement in thermal efficiency can be due to a fuel-switch, plant retirement, or improvement in turbine technologies, all of which we investigate later in Section 6. Overall, we find a higher NSR lawsuit probability has incentivized power plants to adopt technologies to reduce emissions and enhance thermal efficiency.

B. Extensive and intensive margins at the plant level. We can also express and decompose emissions z for a plant in a year as $z = \eta \times E\{z|\eta = 1\}$. The first component, $\eta \equiv Prob(Operate = 1)$, is the extensive margin on how likely a utility company keeps a plant operating (opposed to shut down) as the lawsuit risk gets higher. The second component, $E\{z|\eta = 1\} \equiv E\{z|Operate = 1\}$, indicates the intensive margin.

We first limit our intensive margin analysis at the plant level, which includes all possible means the utility company can take for plants that stay operating. For example, an operating plant may adjust the amount of power generation. As we will discuss later in Section 4.3 part D, a plant may adjust emission rate e or operating heat rate θ of an operating plant via adjusting e and θ of EGUs in this plant; it may also reallocate electricity generation across EGUs or even shut down some EGUs to reduce the plant-level emission rate e and improve operating heat rate θ .

We consider the incentive to temporarily shut down an active plant as an averting action before being named in a potential lawsuit to be different from the incentive to shut down as a compliance of the settlement. Here we focus on estimating the averting action effect. Later, in Section 4.4, we analyze both incentives.

We estimate a logit model. To be consistent with our baseline, in the logit model we include the same set of variables in equation (2) and exclude gross load of power generation. Our explanatory variables include the lawsuit probability, cooling degree days (CDD), linear and quadratic time trends, and plant fixed effects.

Table 5 column 1 reports the marginal effects. A 1 percent increase in the lawsuit risk reduces the likelihood that the plant will continue operating by 0.5 percent (i.e., raises the likelihood that the plant will shut down by 0.5 percent). To show that our result is robust to functional form, we repeat our analysis using a linear probability model (LPM) in column 2, and we find a similar result. We choose the logit model over the LPM because we need to generate the predicted probability to operate $\hat{\eta}$ that ranges from zero to one for decomposition exercises in Section 5.

In the above analysis, we define the extensive margin using the absolute amount of power generation, i.e., we consider a plant is shut down in a year when it generates zero kilowatt-hour of grossload electricity that year. An alternative way to examine the extensive margin is to measure the relative power generation compared to a plant's power generation capacity, i.e., to use the capacity factor. In Table 6, we repeat the above analysis using the capacity factor as a continuous dependent variable and find results consistent with Table 5.¹⁹

For the intensive margin, we restrict our analysis on the sub-sample of plants that generate a non-zero level of electricity in a given year. In Tables 3, the magnitude of point estimates in Panel B (relative to Panel A) suggests that the intensive margin makes a sizable contribution to the overall emission reduction. A 1 percent increase in the NSR lawsuit risk would increase SO₂, NO_x, and CO₂ emissions by 0.8 percent, 1.0, percent and 0.5 percent, respectively, for plants that are in operation.

We conduct a similar exercise for emission rates and heat rate and report our results in Panel B of Table 4. Results for SO₂, NO_x, and CO₂ emission rates are similar to Panel A although the point estimates are much smaller. Also, we find no evidence of heat rate improvement. These results suggest that a higher lawsuit risk encourages utility companies to improve emission intensity for plants that stay open, but does not lead to much in the way of improved thermal efficiency for those plants.

C. Capability to switch fuel. With natural gas being half as carbon intensive as coal on average, fuel switching can be an important channel to reduce carbon emissions in power generation. We proceed to investigate the contribution of fuel switches in CO₂ co-benefits.

In Panel A of Table 7, we repeat our baseline with the NSR lawsuit probability interacted with a dummy variable that equals one if a plant has gas-fired capacity. For CO₂, column 3 suggests that a higher lawsuit risk would reduce CO₂ emissions from plants without gas capacity (i.e.,

¹⁹In addition to using the capacity factor directly as a continuous variable, our results (unreported) are identical if we use the capacity factor to define a dummy variable as the dependent variable.

coal-fired-only plants), and this result is consistent with a CO₂ emission rate reduction (in column 6) and a heat rate reduction (in column 7). In contrast, we find gas-fired plants do not respond to lawsuit probability in their CO₂ emissions, CO₂ emission rate, and heat rate. Our results are consistent with those of [Holland \(2012\)](#), who finds no reduction of CO₂ emissions for California plants that are mostly gas fired. We see a similar pattern for both NO_x emissions and emission rate.

Our results for SO₂ are slightly different to CO₂; we do not obtain precise estimates in column 1 although the point estimate is negative. We find that gas-fired plants reduce more SO₂ emissions and emission rate than coal-fired-only plants but that the estimates are not significant.

We then examine the extensive and intensive margins for plants with and without gas-fired capacity. We report the extensive margins in column 3 of [Table 5](#). Facing a higher NSR lawsuit risk, coal-fired-only plants are more likely to be shut down; by contrast, the plants with gas potential are unaffected. A 1 percent increase in the NSR lawsuit risk will reduce the probability to operate for plants without gas capacity by 0.9 percent (i.e., increase the probability of shutting down the plant by 0.9 percent). For a plant with gas capacity, this same increase in the lawsuit risk will increase the probability that it will close by just 0.2 percent, and the effect is not statistically significant.

We report the intensive margins in Panel B of [Table 7](#). The results are consistent with those in Panel A, although the magnitudes are smaller. Later, in [Section 5](#), we use estimates in [Tables 5](#) and [7](#) to quantify the relative contribution in emissions reductions from extensive and intensive margins for coal-fired-only and gas-fired plants.

D. Operations at the electricity generating unit (EGU) level. Our above discussions have presented outcomes for operating plants (i.e., the intensive margin). However, one question still remains: what actions underlie the changes at the intensive margin at the plant level? In our sample, an average plant operates 2.5 electricity generating units (EGUs), and this gives a plant plenty of opportunities to adjust when facing an exogenous shock. Facing a higher lawsuit risk, a plant could shut down or reduce production in the relatively older, less efficient, more pollution-intensive EGUs, which are likely coal-fired units. A plant could also improve each individual EGU on its emission intensity and thermal efficiency, such as by increasing the usage of scrubbers to lower the SO₂ emission rate. As we show in [Figure 4](#), the intensive margin at the plant level consists of various intensive- and extensive-margin decisions at the EGU level. Therefore, we extend our analysis from the plant-year level to the EGU-year level. To be consistent with our main analysis, we modify the plant fixed effects into EGU fixed effects so our key parameter is identified by variation within an EGU.²⁰

²⁰When we bootstrap our duration model with the main estimation using the EGU-level data, we draw samples of predicted lawsuit risk $\hat{\rho}$ at the plant level. Our results are robust and almost identical if we draw $\hat{\rho}$ at the EGU level. The standard errors are still clustered at the plant level to account for correlation within a plant.

We report the EGU-level intensive estimates in Panel A.1 of Table 8, and extensive estimates in column 1 of Panel B. Our intensive results have a similar magnitude compared to Panel B of Table 3 and Table 4, except that the coefficient on CO₂ is much smaller and only statistically significant at the 10 percent level, and that the coefficient on CO₂ emission rate is statistically insignificant. This result suggests that the CO₂ co-benefits from operating plants are unlikely to have come from improvements from EGUs that stay open (a.k.a. the EGU-level intensive margin); more likely the co-benefits come from re-allocation across EGUs within a plant by shutting down some EGUs (a.k.a. the EGU-level extensive margin).

We next interact the lawsuit risk with a dummy variable that equals one if an EGU uses natural gas as the primary fuel. We report our results in Panel A.2 of Table 8 and column 2 of Panel B. Panel B suggests that facing a higher lawsuit risk, gas-fired units are more likely to operate and coal-fired units are more likely to shut down. As for emissions reductions from EGUs that stay open, Panel A.2 suggests that most improvements come from coal-fired units.

To assess the extensive margin condition on an operating plant, we repeat our logit estimation, and restrict the sample to plants that stay open (as shown in columns 3–4 in Panel B). These estimates suggest that shutting down coal-fired units is an important factor that is consistent with the intensive-margin results previously reported in Panel B of Tables 3, 4, and 7. Later, in Section 5, we use our EGU-level estimates to further decompose our plant-level counterfactuals.

4.4 The Effects of Lawsuit Compliance and Overlapping Policies

In this section, we investigate potential bias arising from other policies and regulatory pressures. We begin by comparing the effect of complying with a realized lawsuit allegation and the effect of facing a higher lawsuit risk. Next, we incorporate the effect of other environmental and climate policies that also target power plants.

A. The effect of a realized allegation. In Sections 4.2 and 4.3 we discussed emissions reductions following an increase in the lawsuit risk. This effect differs from a realized allegation that later leads to a settled lawsuit. We interpret a reaction to increased risk as a strategic preemptive choice made in hopes of reducing the likelihood of being subjected to a lawsuit; such actions are similarly documented and interpreted as “averting regulatory enforcement” by Keohane et al. (2009). By contrast, a realized allegation in a lawsuit can induce various incentives that would either lead to more or fewer emissions. For example, after the litigation starts and before the lawsuit is settled, a plant may reduce emissions in order to reduce the penalty. (It should be noted, however, that the evidence cited usually involves historical emissions, rather than current emissions). Also, a plant may generate fewer emissions if the consent decree mandates the plant to adopt specific emission control technologies. Alternatively, a plant may emit as

much as possible if the plant that is the subject of the lawsuit is likely to be forced to retrofit or retire soon.²¹

To distinguish and compare these two effects, we expand our dataset to include observations after a plant is named in a lawsuit. We repeat our baseline with an additional dummy variable that equals one if a plant has been charged before or by that year; hereafter, we refer to this as the *allegation dummy variable* in the text and “*being charged*” in the tables. Also, we modify our lawsuit risk $\hat{\rho}_{it}$ by interacting it with a dummy variable that equals one if a plant was not yet the subject of a lawsuit. Doing so sets the lawsuit probability zero after a plant was charged, and makes the coefficient of the lawsuit probability comparable to our baseline.²²

We report our results in Table 9 Panel A. The coefficient of the lawsuit risk $\hat{\rho}_{it}$ is robust to the inclusion of an allegation dummy variable. Also, the coefficient of being charged is negative, and in a few cases, statistically significant, suggesting a realized lawsuit charge leads to emissions reductions. The effect of having a realized allegation is similar to the effect of facing a much higher lawsuit risk for the regulated emissions. For example, being charged in a lawsuit will lead to a reduction in NO_x emissions by 44 percent, the effect of which is equivalent of increasing lawsuit risk by roughly 63 percent. In contrast, being charged in a lawsuit leads to a reduction in CO₂ emissions of just 0.1 percent, and the effect is insignificant; this effect is equivalent of increasing lawsuit risk by roughly 0.25 percent. This result is not surprising given that the NSR does not directly target CO₂ emissions.

We next investigate the effect of a realized allegation on plant-level extensive and intensive margins. Appendix Table A.5 Panel B shows that the marginal effect of a higher lawsuit risk on the extensive margin is robust to the inclusion of a realized allegation. Also, the coefficient of having been charged is positive. This result is consistent with the speculation that once a plant knows it will be required to retrofit, retire, or repower by a certain time (usually a grace period of a few years after the settlement), the plant is likely to operate to its full potential in its last few years of lifetime.

We report the plant-level intensive margin results in Panel A of Appendix Table A.5. In summary, our baseline result of the lawsuit risk is robust. Having a realized allegation would reduce emissions for plants that stay open. This effect is in contrast with the extensive margin – i.e., plants are more likely to operate once it is alleged. These two margins work in the opposite

²¹One would argue that it is plausible that a plant may have believed a priori (or with insider information) that it will definitely be charged with violations through a lawsuit; therefore the profit-maximizing decision is to run the high-risk plant at the highest capacity, rather than to reduce emissions, or shut down the plant before such actions are mandated by the legal process. However, even in this case, a plant does not know when it will face charges until the time that it receives formal notification from the regulating agency. Therefore, we interpret the effect from a higher lawsuit risk as distinct from the effect facing an actual lawsuit.

²²Without interacting $\hat{\rho}_{it}$ with “being charged = 0”, the coefficient of $\hat{\rho}_{it}$ will pick up both the effects from a higher lawsuit risk and the effect of being named in a lawsuit because of the expanded time frame for the plants that have had a lawsuit. Our results are similar if we do not interact $\hat{\rho}_{it}$ with the “being charged = 0”.

directions - this result is consistent with some imprecise estimates of the allegation dummy variable in Table 9.

B. Allowances surrender requirement followed by the lawsuit. Among 31 companies whose cases were settled in our sample period, the settlements required 28 of them to surrender all of their SO₂ allowances (linked to the alleged plants and units that were the subject of the lawsuits) under the Acid Rain Program (ARP), and 19 companies to surrender their NO_x allowances allocated by the National Budget Program (NBP).²³ The companies were required to do so within a certain time frame, ranging from 2 to 16 years after the lawsuit had been filed. Therefore, the allowances allocated from the ARP and NBP could affect emissions.

To account for this factor, we include a dummy variable that equals one if the plant is required to surrender its SO₂ allowances within a year. We similarly include a dummy variable for a NO_x allowances surrender requirement. We show that our results are robust in Panel B of Table 9, although some coefficients are not as precise as our baseline due to the additional controls. Some of the effect of being charged that we find in Panel A can be attributed to the surrendering SO₂ allowances.

Larger plants usually have more permits; the allocation of permits varies mostly across plants and not much over time. To account for the heterogeneity, we interact the above surrender dummies with log allocated allowances of SO₂ emissions (from ARP) and NO_x emissions (from NBP) using AMPD data. We report our results in Panel C of Table 9. We find robust results, although our estimates are less precise than our baseline because of the additional controls. Furthermore, one would argue the stock of allowances held by a plant at the end of a year may be a better control since a higher stock of allowances enables a plant to produce more. We choose yearly allocation to avoid the endogeneity issue of the stock of allowances. Nevertheless, results are similar if we repeat Panel C using the stock of allowances held (see Appendix Table A.11 Panel A).

C. Overlapping policies. The above exercise controls for the effect of surrendering allowances through ARP and NBP allocations after plants were charged. However, ARP, NBP, and other environmental and climate policies may affect power plants before the arrival of an allegation. For example, SO₂ emissions are regulated and traded under the ARP, and the plants may adjust various margins which may affect SO₂ and other emissions. Therefore, ARP can be correlated to both emissions and lawsuit risk.

We add to our baseline the log of SO₂ allowances interacted with the log of SO₂ permit price. The permit price is higher early in our sample so that the interaction term allows the allocation to have a stronger effect on emissions earlier in our sample. Our results shown in Panel A of

²³Among all these cases, the consent decrees indicated that these companies can still purchase allowances in the allowance market. The surrender requirement means that companies will not be able to use their allocated allowances or allowances they previously stocked up by the deadline stated in the consent decrees.

Table A.6 are robust.²⁴ The interaction term is positive for SO₂ and NO_x, suggesting that the higher the value of the SO₂ allowances allocated to a plant, the more SO₂ and NO_x emissions.

We continue to rule out the effects from other policies, unlike the ARP for which the national permit price is available. In Panel B of Table A.6, we add to the baseline an indicator variable that equals one if a plant is regulated under the NO_x Budget Trading Program (NBP) in a year, an indicator for the Clean Air Interstate Rule (CAIR), and an indicator for the Regional Greenhouse Gas Initiative (RGGI). Our results are robust with additional policy indicators. Being regulated under NBP, CAIR, or RGGI is correlated with lower level of emissions.

Also, we observe for each plant the county it is located, and whether that county is a CAA non-attained county each year for SO₂, NO_x, PM10, and PM2.5. We therefore control for the CAA non-attainment status for SO₂, NO_x, and PM (both PM10 and PM2.5) of a plant in a given year. Table A.6 Panel C reports the results and we find results similar to our baseline results. Later in Section 6, we further discuss other potential confounding factors by considering the natural gas price, the deregulation of the power sector, potential leakage of emissions within a state across plants, alternative duration models, and other factors.

A higher natural gas price would encourage plants to use more coal and less natural gas, plausibly leading to more emissions. In Appendix Table A.7 Panel A, we control for log of natural gas price at a state in a year and find our results robust. Moreover, the effect of natural gas price may be stronger for plants using more natural gas. Therefore, in Panel B we interact the log of natural gas price with gas share. The lawsuit risk coefficients are similar to our baseline.

5 Implications

To quantify the contribution to emissions reductions from coal- and gas-fired plants across various plant operation margins, we conduct a counterfactual analysis and decompose emissions reductions using our estimates from the previous section. We begin by considering a 1 percent increase in the probability of being named in a lawsuit in 2007. We interpret our counterfactual and decomposition simulations as marginal changes. From 2007 to 2010, for example, the average lawsuit risk increased by 6 percent, and a 1 percent increase in that period translated to about 0.2 of a single standard deviation.

²⁴The specification in Panel A of Table A.6 is very different from the specifications in Panel C of Table 9. Panel C of Table 9 has SO₂ allocation interacted with a surrender dummy that does not equal to one until the deadline to surrender permits a few years after the settlement. Also, this specification includes years after plants were charged. By contrast, Panel A of Table A.6 exclude years after plants were charged in a lawsuit. Nevertheless, results are similar if we use the expanded sample and include the “being charged” dummy variable. Also, results are robust if we use the stock of allowances measured by allowance held by a plant at the end of a year (see Appendix Table A.11 Panel B).

Panel A in Table 10 shows the overall counterfactual changes in SO₂, NO_x, and CO₂ emissions in 2007 following a 1 percent increase in the NSR lawsuit risk. We produce the counterfactual using baseline IV estimates in Table 3 columns 4 to 6. This change would lead to a sizable drop in SO₂ and NO_x emissions, amounting to 68 thousand and 34 thousand metric tons, respectively. CO₂ emissions would drop by 0.3 percent, amounting to close to 7 million metric tons. If we evaluate the social cost of carbon at \$42 per metric ton, this CO₂ co-benefits results in a social benefit of some \$290 million.

The magnitude of the above CO₂ co-benefits is comparable to those that result from other policy instruments. Linn et al. (2014) studied the effect of coal prices on operating heat rates and utilization rates. Using their most conservative estimate with EGU fixed effects, a \$10 carbon tax will lead to a 0.6 percent decrease in CO₂ emissions, the size of which is equivalent to a 2 percent increase in the NSR lawsuit risk. Knittel et al. (2015) found that a 1 percent increase in coal price leads to a 0.6 percent decrease in CO₂ emissions – the effect of which is equivalent a 2 percent increase in the NSR lawsuit risk. Renewable portfolio standards (RPSs) can also affect carbon emissions by requiring an electricity network to purchase a certain percentage of power from renewables. Sekar and Sohngen (2014) show that RPSs implemented in 2007 decrease total CO₂ emissions by 2.6 percent, comparable to the effect of an 8 percent increase in the NSR lawsuit risk.

A. Emissions reductions by plants with or without gas capacity. We decompose the above counterfactual emissions reductions to quantify the relative contribution from various margins that a plant can adjust. First, we distinguish plants that have no gas-fired generating capacity (group ‘c’) from plants that have some gas-fired generating capacity (group ‘g’) using indicators d_c and d_g . Plants with only coal-fired units may be adversely affected by a higher lawsuit risk, relative to plants with gas-fired units, because production may not be able to easily shift from coal toward cleaner fuel sources in the short run. The overall changes in emission Δz_t come from two groups of plants can then be expressed as:

$$\Delta z_t = \sum_i \{d_c \Delta z_{it}^c + d_g \Delta z_{it}^g\} \quad (3)$$

Next, we decompose changes in emissions along intensive and extensive margins *at the plant level*. We illustrate this decomposition in Figure 4. The plant-level intensive margin covers cases where a plant adjusts its overall emission rates while keeping the plant running; a plant can also shut down to lower its emissions, which we refer to as the plant-level extensive margin. As in Section 4.3, we use $\eta \equiv Prob(Operate = 1)$ to denote such an extensive margin. The expected changes in overall emissions can be further expressed as:

$$\mathbf{E}(\Delta z_t^j) = \sum_{i \in j} \left(\Delta \eta_{it} \cdot \underbrace{(\mathbf{E} z_{it} | \eta_{it} = 1)}_{\text{extensive}} + \underbrace{(\mathbf{E} \eta_{it})}_{\text{intensive}} \cdot \Delta z_{it} \right), \quad j \in \{c, g\}$$

To approximate the *expected* probability to operate, $E\eta_{it}$, we predict the operating probability $\hat{\eta}_{it}$ using the logit estimates in Table 5. To approximate the expected emissions for operating plants, $(Ez_{it}|\eta_{it} = 1)$, we generate predicted emissions for operating plants $(\hat{z}_{it}|\eta_{it} = 1)$ using Table 7 Panel B. The above equation reduces to:

$$\widehat{\Delta z}_t^j = \sum_{i \in j} \left(\underbrace{\Delta \eta_{it}}_{\text{extensive}} \cdot (\hat{z}_{it}|\eta_{it} = 1) + \hat{\eta}_{it} \cdot \underbrace{\Delta z_{it}}_{\text{intensive}} \right), \quad j \in \{c, g\} \quad (4)$$

Panel B of Table 10 shows the decomposition results. Both the extensive and intensive margins explain sizable and comparable shares of the reductions in SO₂, NO_x, and CO₂ emissions. In particular for CO₂ co-benefits, the extensive margin explains 61 percent of the reduction, and the intensive margin explains the remaining 39 percent.

Moreover, we find the extensive margin makes a greater contribution from plants in group *c* (i.e., plants without gas capacity), than from those in group *g* (i.e., plants with some gas capacity). For CO₂ co-benefits, the closures of coal-fired-only plants account for 54 percent of the emission reductions. Our results imply that most of our counterfactual carbon co-benefits result from shutting down the coal-fired plants that lack gas-fired capacity. This channel is also sizable for SO₂ and NO_x emissions reductions (37 percent and 61 percent).

The intensive margin also contributes to some emissions reductions. For CO₂ co-benefits, both types of plants similarly account for about 20 percent of emissions reductions. For SO₂ emissions, the intensive margin from plants in group *g* accounts for substantial reductions; for NO_x emissions, the intensive margin from plants in group *c* makes sizable contributions.

B. Decompose the intensive margin: changes at the EGU level. A remaining question is to what measures are responsible for the emissions reductions at the plant-level intensive margin. As illustrated in Figure 4, there are two potential channels. An operating plant can reduce emission rates across all the operating generating units by installing emission control equipment or improving their thermal efficiency (i.e., by making changes along *the EGU-level intensive margin*). Meanwhile, an operating plant can also shut down a subset of generating units with higher emission rates or with less-efficient thermal efficiency (i.e., by making changes along *the EGU-level extensive margin*). As the size of these two EGU-level margins warrant different policy directives and instruments, we decompose the plant-level intensive margin into these two EGU-level margins.

We repeat the decomposition exercise in Equation (4) at the EGU level conditional on plants that will stay open following a hypothetical 1 percent increase in the NSR lawsuit likelihood. We produce the EGU-level counterfactual decomposition based on Panel A.2 and Panel B.2 of Table 8, and we tabulate our counterfactual results in Table 11.

When we decompose the plant-level intensive margin, we find that most of the emissions reductions come from the EGU-level extensive margin. The pattern is the strongest for CO₂. In

particular, shutting down a subset of EGUs within an operating plant accounts for SO₂, NO_x, and CO₂ emissions reductions from those operating plants by 59 percent, 70 percent, and an enormous 97 percent, respectively. This result is intuitive, as there is no effective emissions control equipment for CO₂ at the unit level; such decreases can only be achieved by improving thermal efficiency. Thus, the only viable means to reduce CO₂ emissions is to shut down (inefficient) generating units. Given that 60 percent of CO₂ co-benefits are from plant-level intensive margin, our results imply that 98 percent of co-benefits stem from closing EGUs (including closing a subset of EGUs within a plant and closing all EGUs in a plant that lead to a plant shutdown).

In contrast to the CO₂ results, we do find that measures along the EGU-level intensive margin lead to reduction in SO₂ and NO_x emissions for plants that stay running. This is likely due to the viable emission control technologies for SO₂ and NO_x emissions. Moreover, most of this effect comes from gas-fired units. These simulation results also imply that improvements in SO₂ and NO_x emission rates and operating heat rate that we find earlier in Section 4.3 part A are most likely from (i) an improvement in operating gas-fired EGUs, or (ii) a reallocation of electricity generation across EGUs via (re-)starting and/or shutting down some units.

6 Additional Results and Robustness

In this section, we provide direct evidence of an increase in emission abatement technology adoption and additional robustness to our baseline results.

A. Direct evidence of technology adoption. We previously examined the extensive and intensive margins at the plant and EGU levels that would explain the emissions reductions following a higher NSR lawsuit risk. Here we present more evidence. In Appendix Table A.4 Panel A, we repeat our baseline model on the following outcome variables: the adoption of scrubbers (an SO₂ abatement technology, also referred to as flue-gas desulfurization (FGD) units), the adoption of NO_x abatement technology, the usage of scrubber measured by the log of energy consumption from the FGD, the log of operating cost for using scrubbers, and the gas share (measured by the ratio of natural gas heat input among heat inputs from all types of fuel including coal, natural gas, and other fuel). Columns 1 to 4 provide direct evidence of adopting and using SO₂ and NO_x abatement technologies, consistent with our findings of the emission rates of SO₂ and NO_x and our EGU-level counterfactuals. We do not find strong evidence of changes in gas shares.

In Panel B of Appendix Table A.4, we further expand this analysis to include post-lawsuit years and inclusion of allegation dummy. We find both higher risk and a realized allegation induce usage of scrubber and NO_x control. For example, having a lawsuit will increase the likelihood

to use scrubber by 8.6 percentage points, and this size is comparable to a 28.7 percent increase in lawsuit risk before the plant knows for sure it is being charged.

B. Economic conditions and the organization of the power industry. In this subsection we consider other factors in the macro economy and in the electricity-generation sector that may bias our results. Firstly, because our sample period covers the 2008 recession, we repeat our analyses with 2008 and 2009 indicators interacting with the lawsuit risk to allow for different effects during the recession years should the recession have altered investment decisions and plant operations. Table A.7 Panel C shows that our results are robust. Also, a higher lawsuit risk has null effect on some pollutants during the recession years, consistent with our prior. Our results are also robust if we drop the years 2008 and 2009 from our sample.

Moreover, we address potential concerns that the organization of the power industry and other characteristics of the plants may affect our results. For example, regulated utilities and deregulated utilities may respond to a higher lawsuit risk differently. Also, the engineering design of turbines may affect adjustable margins. Therefore, in Panel D, we repeat our baseline separately with the following additional controls: an indicator for deregulated plants, an indicator for divested plants, and an indicator if a plant has combined heat and power (CHP). We find that our baseline robust to these additional controls.²⁵

C. Potential correlation across plants. In addition to economic conditions, a higher lawsuit risk of a plant can correlate to emissions in other plants in the area closed to the plant. The overall effect is ambiguous. For example, the electricity demand is usually considered as inelastic in the short term. When a plant reduces its emissions via reducing power generation, another plant could increase its share of the supply, which could lead to more emissions. Also, a regulating agency may avoid targeting multiple plants in the same region at the same time. In both cases, a plant may react one of two ways. If other area plants have a higher lawsuit risk, a plant in the same area may respond by choosing to take advantage of a situation by generating more power and higher levels of emissions, or by viewing the risk to others as a credible warning and choosing to reduce emissions.

Therefore in Appendix Table A.8 Panel A, we control for the average lawsuit risk of other plants in the same state in a year. Similarly, we control for the average lawsuit risk of other plants in the same independent system operation (ISO) in Panel B, and in the same judicial circuit court in Panel C. Results are robust throughout these specifications although some estimates become less precise with additional controls. Also, we find that if other plants have a higher lawsuit risk, a plant in the same state, ISO, or judicial district is likely to reduce emissions.

²⁵Most within-plant time-series variation in deregulation occurs before 1999 and there are marginal changes after 2000. For divestiture, most time-series variation happens before 2004. For CHP, we observe most time-series changes before 2003. Results are robust if we interact these indicators with the lawsuit risk and we do not find much heterogeneity when allowing for differential effects.

D. Alternative models to estimate the lawsuit risk. We proceed to examine whether our results are sensitive to how we estimate the lawsuit risk. In our baseline duration model, temporal variation in $\hat{\rho}_{it}$ is mostly generated via year fixed effects although the functional form of the c-log-log model further generates correlation within a plant over time.

We start by estimating richer specifications to generate the time-series variation within a plant. In Appendix Table A.9 Panel A, we allow the year fixed effects to interact with historical capacity in specification A.1; the year fixed effects to interact with historical emissions and historical output in specification A.2; and the juridical district fixed effects to interact with the year fixed effects in specification A.4. Also, we test in specification A.3 by interacting historical emissions and historical output with the concurrent SO₂ allowances price to capture the fact that a large emitter may have a different lawsuit risk when the SO₂ price is high (earlier in our sample) versus when it is low (later in our sample). All these specifications are robust to the baseline.

In Section 6 Part C, we consider the possibility that emissions might be correlated across plants. Yet the lawsuit risk can be correlated across plants as well. Therefore in Panel B of Table A.9, we control for the number of plants sued in the same judicial court, state, or ISO in our c-log-log duration model. Our IV results are similar using alternative $\hat{\rho}_{it}$ although the coefficient of SO₂ becomes less precise. Also, we check how sensitive our results are with respect to cross-sectional variation in historical moments. We repeat our model against alternative sets of in historical moments, and we find robust results.

Lastly, some of the variation in $\hat{\rho}_{it}$ is generated by the functional form of the c-log-log model. Therefore, we relax our functional form assumption, and specify alternative probability models including the linear probability model (LPM), logit, and probit with the same right-hand-side variables as our c-log-log model. Panel C shows that the logit and probit models generate similar a magnitude of the point estimate and slightly larger standard errors. The LPM generates consistent signs and larger point estimates for most outcome variables. Since LPM may generate a lawsuit risk below zero and greater than 100 percent, it is sufficient to see that the signs are consistent with our baseline except for the case of SO₂, which is not precisely estimated.

E. Alternative definition of lawsuit dates. In the baseline, we use “the enforcement data entered date” (usually a few days after the date a case is referred to the DOJ), to determine the last year a plant “survived” in the duration model. As explained in Section 2.2, there are five different important milestones in the lawsuit dates, with different implications in how long a plant survived. In Appendix Figure A.1 we plot the number of lawsuits using alternative definitions and show variation across different lawsuit date definitions. We repeat the baseline using alternative date definition in the Appendix Table A.10. Our results are consistent across definitions although some estimates become smaller when we use a later lawsuit date. These

results suggest the importance of using an earlier date that is relevant for a plant’s decision-making process. The results imply which dates create more salient incentive.

7 Conclusion

Investigating overlapping policies and understanding the effects of unintended consequences from a policy are fundamental in improving policy making and welfare. If these (net) indirect effects are positive, the regulator could consider a more stringent regulation as there are previously unaccounted economic benefits. For example, in 2002, after new evidence surfaced on the benefits and costs of mitigating sulfur dioxide emissions, the Bush administration proposed the Clear Skies Act (CSA), which eventually led to the Clean Air Interstate Rule (CAIR) and a tightening of the cap on SO₂ emissions (Schmalensee and Stavins, 2013).

In this paper, we investigate how the threat of lawsuits that targeted SO₂ and NO_x emissions through the New Source Review (NSR) program of the US Environmental Protection Agency affected unregulated CO₂ emissions and operation margins for coal- and gas-fired power plants. Though this policy targets SO₂ and NO_x emissions, the NSR can affect greenhouse gas emissions by changing how a power plant operates. Because of the ambiguous nature of the policy, it is not immediately obvious on how one should use a standard difference-in-differences model to evaluate the policy. We use a discrete-time duration model to measure a time-varying regulatory threat as a continuous treatment variable. All else being equal, we find that plants with large levels of historical emissions and power generation are more likely to be subject to NSR lawsuits, plants in the Rust Belt, or those within a more “pro-business” federal court circuits.

Using the predicted NSR lawsuit probability, we examine how a higher lawsuit risk affects power plant emissions and operations using a panel data set from 1995 to 2015. We find a higher probability of NSR lawsuits not only reduces SO₂ and NO_x emissions, but it happens to reduce CO₂ emissions by a sizable magnitude, even though CO₂ emissions are not regulated by the NSR. We found that the CO₂ emissions reductions from a 1 percent increase in lawsuit risk are comparable to the effect of a \$10/ton carbon tax. This magnitude of carbon reduction suggests that future benefit analyses of the NSR should account for climate co-benefits from greenhouse gas emission reductions. It also suggests the importance of accounting for the interaction of policies that regulate the same industry on different outputs – such as the interaction between the NSR regulation of SO₂ and NO_x emissions, and a cap-and-trade program on CO₂ emissions – because of the spillover effects.

In our decomposition exercise, we found that CO₂ reductions come from plants with and without gas-fired capacity, with the majority of the reductions coming from closure of coal-fired-only plants. The extensive margins explain most of the carbon co-benefits, with 61 percent explained by plants shutting down. The intensive margins, through improvements in emission

rates and thermal efficiency, explain the remaining 39 percent of the reductions. The intensive margins at the plant level are mostly driven by shutting down electricity generating units within an operating plants – likely because the intensive margins at the unit level lead to reductions in SO₂ and NO_x emissions only, whereas shutting down generating units leads to CO₂ emissions reductions as well. Our results imply that other environmental policies that can induce a sizable fuel-switch are likely to gain climate co-benefits as well. Thus, it is important to account for the co-benefits in future analyses of these policies.

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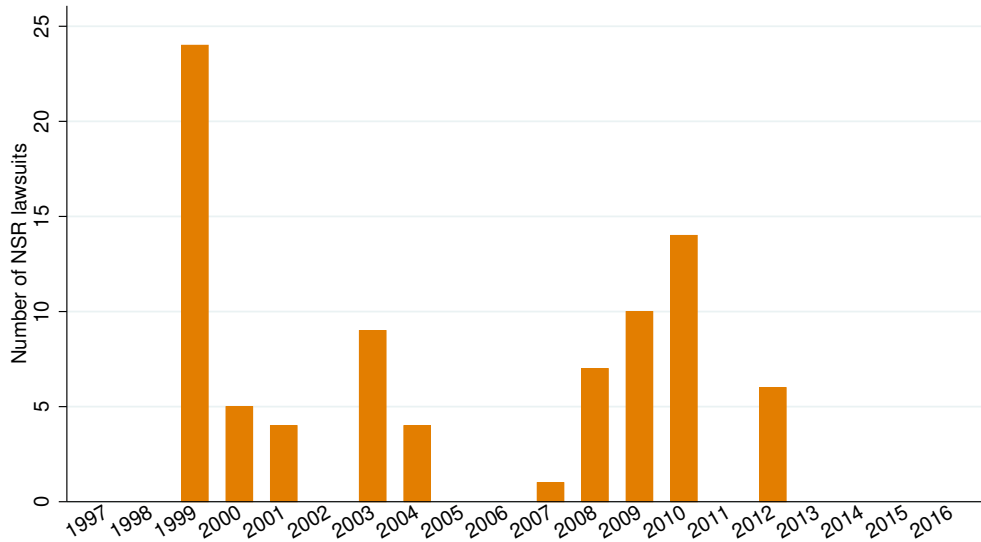
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Figures

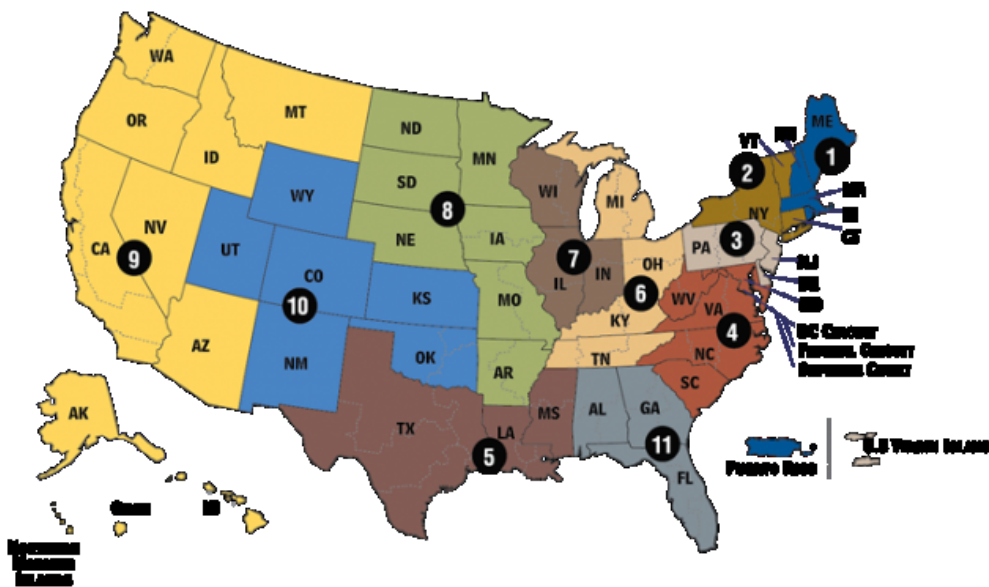
Figure 1: Number of plants involved in an NSR lawsuit, 1997 – 2015



Source: EPA Power Enforcement Web Page and Integrated Compliance Information System - Federal Enforcement and Compliance (ICIS - FE&C) dataset.

Notes: In this figure we use the date referring to DOJ. We plot the figure using alternative dates in A.1.

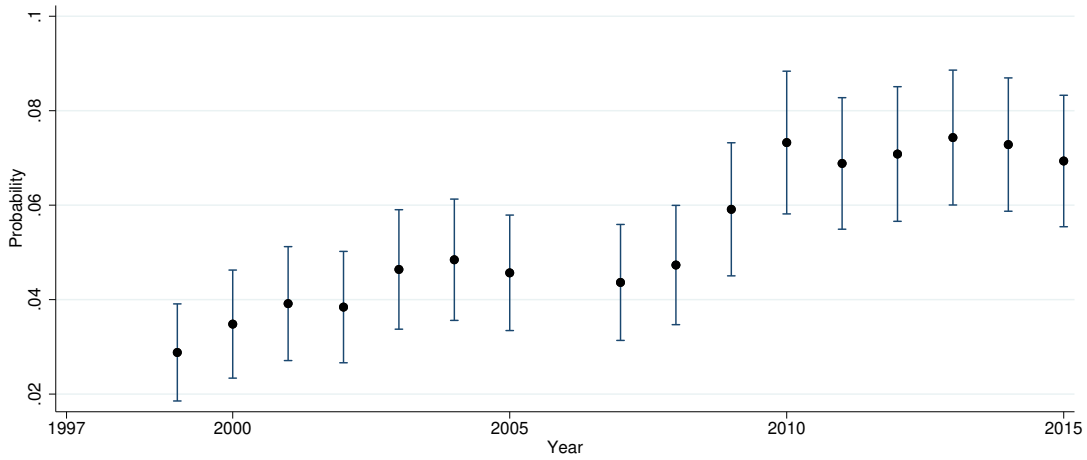
Figure 2: US federal judicial circuit courts



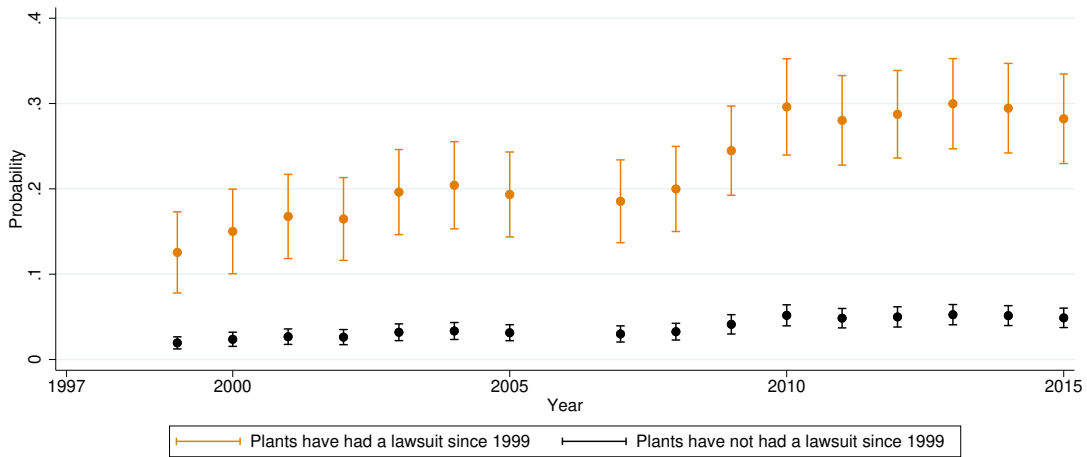
Source : US Court https://www.uscourts.gov/sites/default/files/u.s._federal_courts_circuit_map_1.pdf

Figure 3: Predicted probability of lawsuit, 1999 – 2015

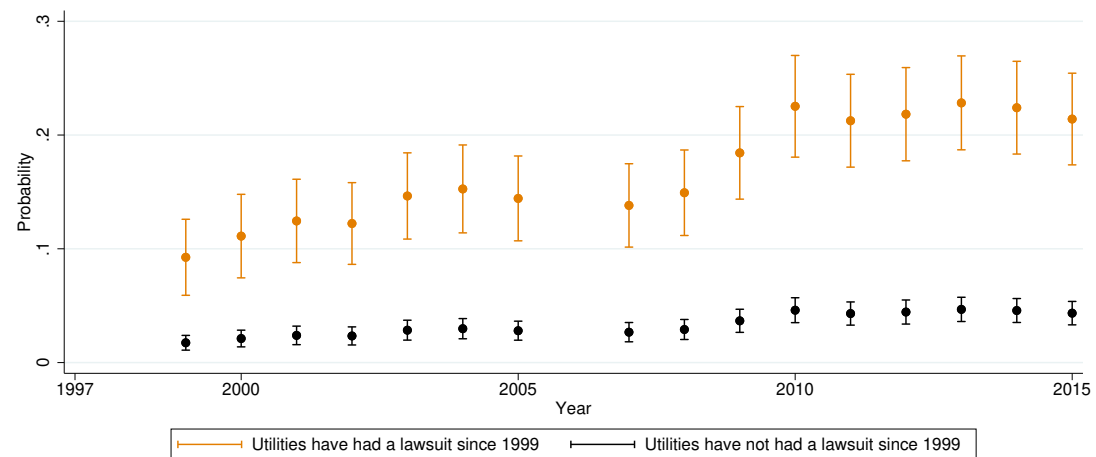
Panel A. Average predicted probability by year



Panel B. If a plant has had a lawsuit since 1999



Panel C. If the utility of a plant has had a lawsuit since 1999



Notes: This figure draws the 95-percent confidence interval of the average predicted probability of facing an NSR lawsuit for each year, based on Equation (1) and estimation results in Appendix Table A.2.

Figure 4: **Illustrating the Decomposition Simulations**

Plant-level extensive margin

Plant-level intensive margin

Overall effect

Tables

Table 1: **Summary statistics of emissions and plant operations, 1999–2015**

	Mean	Std. Dev.
NSR lawsuit (1 - if a plant is in an NSR lawsuit in a year)	0.042	0.203
SO ₂ emissions (Kilo US short tons)	7.0	19.4
NO _x emissions (Kilo US short tons)	3.0	7.4
CO ₂ emissions (Mn. US short tons)	1.9	3.5
SO ₂ emissions rate (lb/mmBtu)	0.39	0.80
NO _x emissions rate (lb/mmBtu)	0.18	0.24
CO ₂ emissions rate (lb/mmBtu)	135.9	448.7
Heat rate (Giga Btu per kWh)	0.11	0.02
Gross load output (Mega Watt Hours, MWh)	2.18	3.56
Number of observations		21,184

Note: A unit of observation is a plant in a year.

Table 2: **Number of NSR lawsuits and total emissions by U.S. judicial district**

US Federal Judicial District Number:	Number of Plants with NSR Lawsuit	Total emissions 1999–2015		
		SO ₂ (million metric tons)	NO _x (million metric tons)	CO ₂ (billion metric tons)
Circuit 1: MA, ME, NH, RI, Puerto Rico	1	1.8	0.5	0.6
Circuit 2: CT, NY, VT	0	3.6	1.1	1.0
Circuit 3: DE, NJ, PA, US Virgin Island	2	16.8	4.7	2.8
Circuit 4: DC, MD, NC, SC, VA, WV	8	16.3	6.0	3.7
Circuit 5: LA, MS, TX	0	14.7	7.1	6.2
Circuit 6: KY, MI, OH, TN	35	50.8	19.2	9.8
Circuit 7: IL, IN, WI	24	20.2	7.2	4.6
Circuit 8: AR, IA, MN, MO, ND, NE, SD	10	10.4	5.3	3.4
Circuit 9: AK, AZ, CA, HI, ID, MT, NV, OR, WA, Guam, N. Mariana Islands	1	2.9	4.2	3.3
Circuit 10: CO, KS, NM, OK, WY, UT	1	4.5	4.2	2.7
Circuit 11: AL, FL, GA	2	22.4	8.2	5.8
Total from all circuits	84			

Source: EPA Coal-fired Power Plant Enforcement webpage

Table 3: Effect of NSR lawsuits on emissions

Panel A: Overall effects for all plants						
<i>Dep. var: log of</i>	(1)	(2)	(3)	(4)	(5)	(6)
	SO ₂	NO _x	CO ₂	SO ₂	NO _x	CO ₂
Prob (NSR lawsuit)	-0.012*** (0.004)	-0.010*** (0.003)	-0.003 (0.002)	-0.009** (0.004)	-0.009*** (0.002)	-0.004** (0.002)
Log output (grossload)	0.716*** (0.015)	0.865*** (0.012)	1.356*** (0.019)	1.128*** (0.149)	1.007*** (0.091)	1.212*** (0.085)
Estimator	OLS	OLS	OLS	IV	IV	IV
Plant FE, Year FE	Y	Y	Y	Y	Y	Y
Number of observations	21,184	21,184	21,184	21,184	21,184	21,184
R-square	0.97	0.98	0.99	0.43	0.82	0.89
First-stage F-statistic				37.1	37.1	37.1

Panel B: Intensive margin for operating plants						
<i>Dep. var: log of</i>	(1)	(2)	(3)	(4)	(5)	(6)
	SO ₂	NO _x	CO ₂	SO ₂	NO _x	CO ₂
Prob (NSR lawsuit)	-0.007* (0.004)	-0.009*** (0.003)	-0.003*** (0.001)	-0.008** (0.004)	-0.010*** (0.003)	-0.005*** (0.001)
Log output (grossload)	0.963*** (0.030)	0.841*** (0.016)	0.956*** (0.005)	1.215*** (0.097)	1.035*** (0.083)	1.160*** (0.072)
Estimator	OLS	OLS	OLS	IV	IV	IV
Plant FE, Year FE	Y	Y	Y	Y	Y	Y
Number of observations	16,860	16,860	16,860	16,860	16,860	16,860
R-square	0.97	0.95	0.95	0.34	0.46	0.60
First-stage F-statistic				196.1	196.1	196.1

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. All columns estimate Equation (2). We bootstrap the duration Equation (1) together with the main Equation (2) to correct for the generated variable – NSR lawsuit probability. The Panel A uses the full sample. The Panel B estimates were restricted to operating plants. All estimations include a historical scrubber dummy interacted with a linear and a quadratic time trend. NSR lawsuit probability ranges from 0 to 100. Columns (1) – (3) are estimated using OLS. Columns (4) – (6) report our baseline IV results, in which we instrument log gross load power generation using cooling degree days (CDD).

Table 4: Effect of NSR lawsuits on emission rates and thermal efficiency

<i>Dep. var: log of</i>	(1)	(2)	(3)	(4)
	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
Panel A: Overall effects for all plants				
Prob (NSR lawsuit)	-0.017*** (0.004)	-0.018*** (0.004)	-0.013*** (0.005)	-0.010*** (0.004)
Panel B: Intensive margin for operating plants				
Prob (NSR lawsuit)	-0.008** (0.004)	-0.009*** (0.003)	-0.004*** (0.001)	-0.000 (0.000)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 on emission rates and heat rate and report coefficient on the NSR lawsuit probability.

Table 5: Effect of NSR lawsuits on extensive margins: Operate or shut down

<i>Dep var: 1 = Operate</i>	(1)	(2)	(3)	(4)
Report marginal effects of	Logit	LPM	Logit	LPM
Prob (NSR lawsuit)	-0.005** (0.002)	-0.003*** (0.001)	-0.009** (0.004)	-0.003*** (0.001)
Prob (NSR lawsuit) \times gas plant			0.007* (0.004)	0.002* (0.001)
IV (CDD)	-0.263*** (0.019)	-0.149*** (0.008)	-0.262*** (0.021)	-0.149*** (0.008)
Plant FE, linear and quadratic time trend	Y	Y	Y	Y
Number of observations	17,606	21,184	17,606	21,184
Log-likelihood	-1,822	-	-1,816	-
R-squared	-	0.71	-	0.71

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. In column 1 and 3, we report marginal effects from Logit regressions controlling for factors similar to the first stage of Equation (2). In columns 2 and 4 we report results from a linear probability model. We bootstrap the duration Equation (1) together with the probability model (logit or LPM) to correct for the generated variable – NSR lawsuit probability.

Table 6: Effect of NSR lawsuits on extensive margins: Analysis using capacity factor

Panel A: Redo Extensive margin analysis in Table 5 using capacity factor

<i>Dep var: Capacity factor (from 0 to 1)</i>	(1)	(2)	(3)	(4)
Report marginal effects of	Logit	LPM	Logit	LPM
Prob (NSR lawsuit)	-0.006** (0.002)	-0.001** (0.000)	-0.008*** (0.002)	-0.001*** (0.000)
Prob (NSR lawsuit) \times gas plant			0.006** (0.004)	0.001* (0.001)
Plant FE, linear and quadratic time trend	Y	Y	Y	Y
Number of observations	18,087	21,184	18,087	21,184
Log-likelihood	-2,589	-	-2,584	-
R-squared	-	0.76	-	0.76

Panel B: Redo Panel A and set cap. factor < 0.01 as zero

<i>Dep var: Capacity factor (from 0 to 1)</i>	(1)	(2)	(3)	(4)
Report marginal effects of	Logit	LPM	Logit	LPM
Prob (NSR lawsuit)	-0.004** (0.002)	-0.001** (0.000)	-0.006*** (0.002)	-0.001*** (0.000)
Prob (NSR lawsuit) \times gas plant			0.005** (0.002)	0.001* (0.001)
Plant FE, linear and quadratic time trend	Y	Y	Y	Y
Number of observations	18,210	21,184	18,210	21,184
Log-likelihood	-4,084	-	-4,077	-
R-squared	-	0.76	-	0.76

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. Panel A repeats the results in Table 5 using capacity factor as the dependent variable. Panel B further consider plants with capacity factor less than 0.01 as not operating and define them as zero. Results in both panels are robust if we construct a shutdown dummy using capacity factor (unreported).

Table 7: Effect of NSR lawsuits on plants with or without the gas capacity

<i>Dep. var: log of</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SO ₂	NO _x	CO ₂	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
Panel A: Overall effects for all plants							
Prob (lawsuit)	-0.004	-0.010***	-0.006**	-0.016***	-0.022***	-0.017***	-0.012***
	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.004)
Prob (lawsuit)	-0.012	0.003	0.004	-0.005	0.010**	0.011*	0.007
× gas plant	(0.007)	(0.003)	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)
Panel B: Intensive margin for operating plants							
Prob (lawsuit)	-0.005	-0.012***	-0.005***	-0.005	-0.011***	-0.004***	-0.001*
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.000)
Prob (lawsuit)	-0.009	0.004	0.001	-0.009	0.004	0.001	0.000
× gas plant	(0.006)	(0.003)	(0.002)	(0.006)	(0.003)	(0.001)	(0.000)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 Columns 4–6 and Table 4 with an interaction of NSR lawsuit probability interacted with a dummy that equals 1 for plants with gas-fired generating capacity.

Table 8: Effect of NSR lawsuits on electricity generating units (EGUs)

Panel A: Intensive margins for operating EGUs							
<i>Dep. var: log of</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SO ₂	NO _x	CO ₂	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
A.1 All operating EGUs							
Prob (lawsuit)	-0.012*** (0.004)	-0.008*** (0.002)	-0.001* (0.000)	-0.011*** (0.004)	-0.008*** (0.002)	-0.000 (0.000)	-0.001** (0.000)
Number of observations	37,067	37,067	37,067	37,067	37,067	37,067	37,067
First-stage F-statistic	462.1	462.1	462.1	462.1	462.1	462.1	462.1
A.2 All operating EGUs with or without the gas capacity							
Prob (lawsuit)	-0.012*** (0.004)	-0.012*** (0.002)	-0.001* (0.000)	-0.011*** (0.004)	-0.011*** (0.002)	0.000 (0.000)	-0.001*** (0.000)
Prob (lawsuit) × gas unit	-0.004 (0.008)	0.011*** (0.004)	0.000 (0.004)	-0.005 (0.007)	0.010*** (0.008)	-0.001 (0.011)	0.001* (0.007)
Number of observations	37,067	37,067	37,067	37,067	37,067	37,067	37,067
First-stage F-statistic	468.8	468.8	468.8	468.8	468.8	468.8	468.8
Panel B: Extensive margin: Likelihood for an EGU to operate							
<i>Dep var: 1 = Operate</i>	B.1 All EGUs			B.2 EGUs in operating plants			
	(1)	(2)	(3)	(4)			
Report marginal effects of:	Logit	Logit	Logit	Logit			
Prob (NSR lawsuit)	-0.001*** (0.000)	-0.003*** (0.001)	-0.001 (0.002)	-0.018* (0.010)			
Prob (NSR lawsuit) × gas unit		0.010*** (0.003)		0.058*** (0.019)			
Number of observations	52,967	52,967	32,878	32,878			
Log-likelihood	-23,500	-23,000	-17,900	-17,200			

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table re-estimate our IV estimation from Table 3 to Table 5 at the EGU level with EGU fixed effects instead of plant fixed effects. To be consistent with our main estimation, we still sample generated lawsuit probability at the plant level when bootstrapping the duration equation together with our IV equations. Since we do not observe natural gas capacity at the EGU level as at the plant level (in Table 8), we define the gas dummy in this table as whether an EGU's first or the second primary fuel is natural gas. Panel A reports intensive margins for operating EGUs. In Panel B.1 we report extensive margins for all EGUs, in Panel B.2 we report extensive margins for EGUs in an operating plant.

Table 9: Effect of NSR lawsuit probability and lawsuit allegation

<i>Dep. var: log of</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SO ₂	NO _x	CO ₂	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
Panel A: Included Post-allegation Years and Control for Allegation							
Prob (lawsuit)	-0.007*	-0.007***	-0.004*	-0.014***	-0.015***	-0.011**	-0.008**
× (Being charged = 0)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.003)
Being charged = 1	-0.230	-0.440***	-0.001	-0.244	-0.442***	-0.009	-0.045
	(0.154)	(0.072)	(0.076)	(0.174)	(0.166)	(0.207)	(0.150)
Num. of observations	22,100	22,100	22,100	22,100	22,100	22,100	22,100
First-stage F-stat	36.9	36.9	36.9	36.9	36.9	36.9	36.9
Panel B: Further Control for Emission Allowances Surrender							
Prob (lawsuit)	-0.007*	-0.008***	-0.003*	-0.015***	-0.015***	-0.011**	-0.008**
× (Being charged = 0)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.003)
Being charged = 1	-0.021	-0.281***	-0.068	-0.111	-0.359**	-0.152	-0.142
	(0.143)	(0.072)	(0.073)	(0.153)	(0.147)	(0.188)	(0.136)
Surrender SO ₂ allowances	-0.674***	-0.261**	0.067	-0.582**	-0.167	0.160*	0.107*
	(0.236)	(0.112)	(0.054)	(0.227)	(0.120)	(0.087)	(0.058)
Surrender NO _x allowances	0.251	-0.207	0.154**	0.404	-0.059	0.303**	0.209***
	(0.297)	(0.162)	(0.075)	(0.299)	(0.188)	(0.120)	(0.078)
Num. of observations	22,100	22,100	22,100	22,100	22,100	22,100	22,100
First-stage F-stat	37.1	37.1	37.1	37.1	37.1	37.1	37.1
Panel C: Further Control for ARP and NBP Emission Allocation							
Prob (lawsuit)	-0.008**	-0.008***	-0.003	-0.014***	-0.014***	-0.008*	-0.007*
× (Being charged = 0)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Being charged = 1	-0.024	-0.279***	-0.064	-0.158	-0.400***	-0.192	-0.179
	(0.142)	(0.071)	(0.068)	(0.146)	(0.135)	(0.169)	(0.124)
Surrender SO ₂ allowances	-0.066***	-0.031***	0.005	-0.058***	-0.024**	0.012	0.009*
× log ARP allocation	(0.019)	(0.009)	(0.004)	(0.019)	(0.011)	(0.008)	(0.006)
Surrender NO _x allowances	-0.014	0.012	-0.011**	-0.030	-0.003	-0.027***	-0.018***
× log NBP allocation	(0.018)	(0.010)	(0.005)	(0.019)	(0.012)	(0.009)	(0.006)
Num. of observations	22,100	22,100	22,100	22,100	22,100	22,100	22,100
First-stage F-stat	37.8	37.8	37.8	37.8	37.8	37.8	37.8

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 Columns 4–6 and Table 4 including additional observations after a plant go through a lawsuit. In Panel A, in addition to the continuous lawsuit probability treatment, we add an actual lawsuit treatment measured by whether a plant has a lawsuit settled in or after a year. In Panel B, we further control for whether the lawsuit decree requires a plant to surrender its emission allowances by that year or has been required to surrender in a year before that year. In Panel C, we further interact the surrender dummies with a plant’s allocated allowances each year.

Table 10: Counterfactual emission reductions if the NSR likelihood increases by one percent in 2007

Panel A: Effects of emission reduction for all plants					
Total emissions	Predicted	Simulated	Difference	Percentage Change	
SO ₂ (thousand metric tons)	6,898	6,830	-68.15	-0.85 %	
NO _x (thousand metric tons)	2,403	2,369	-34.15	-1.21 %	
CO ₂ (million metric tons)	1,912	1,905	-6.87	-0.31 %	
Number of plants				1,146	

Panel B: Effects by gas-fired generation capacity						
	(1)	(2)	(3)	(4)	(5)	(6)
Change in emissions:	Intensive margins		Extensive margins		Overall effects	
	(percentage changes)		(percentage changes)		(percentage changes)	
SO ₂ (thousand metric tons)						
Plants without gas capacity	4.71	(0.08 %)	-39.77	(-0.67 %)	-17.53	(-0.59 %)
Plants with gas capacity	-25.35	(-1.17 %)	-4.65	(-0.22 %)	-30.00	(-1.39 %)
Overall effects	-20.64		-44.42		-65.06	
NO _x (thousand metric tons)						
Plants without gas capacity	-14.05	(-0.70 %)	-12.56	(-0.63 %)	-26.62	(-1.33 %)
Plants with gas capacity	-5.45	(-0.67 %)	-2.17	(-0.27 %)	-7.62	(-0.93 %)
Overall effects	-19.51		-14.73		-34.24	
CO ₂ (million metric tons)						
Plants without gas capacity	-1.38	(-0.10 %)	-3.48	(-0.25 %)	-4.86	(-0.35 %)
Plants with gas capacity	-1.14	(-0.14 %)	-0.46	(-0.06 %)	-1.60	(-0.20 %)
Overall effects	-2.52		-3.94		-6.46	

Notes: We simulated counterfactual emissions in 2007 if likelihood of NSR lawsuits increases by one percent. In Panel A, we simulate counterfactuals based on estimates of the coefficient of NSR lawsuit probability on emissions in Table 3. In Panel B, we decompose the counterfactual emissions from Panel A on operate probability and emissions. We further separate the effects by presence of gas-fired generating capacity. Our decomposition is based on results reported in Table 7. The overall effects and the percentage changes are calculated based on emissions reductions for each of the two groups of plants with or without gas capacity. All numbers are averages weighted by the plant-level gross load.

Table 11: Decomposing the plant-level intensive margins – plant FE

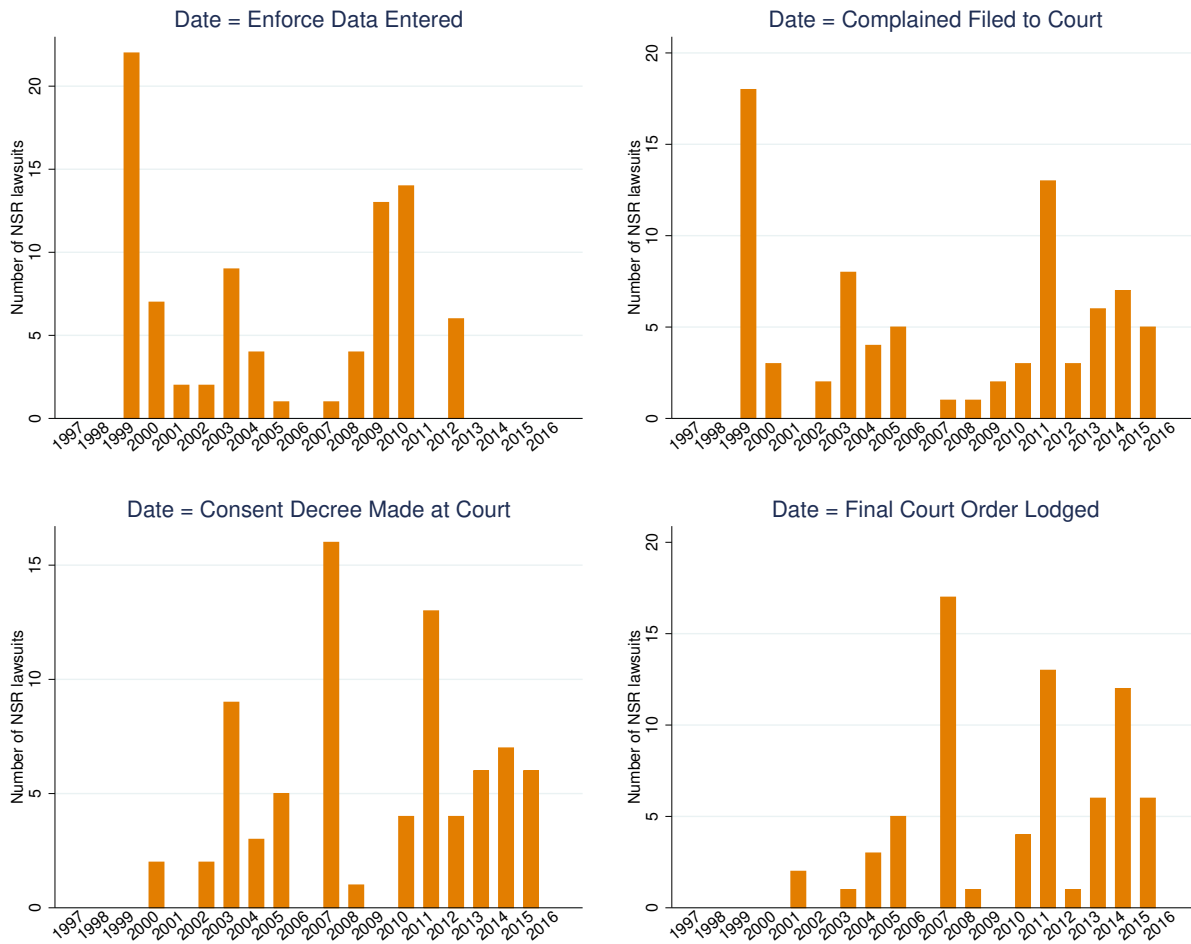
	(1)	(2)	(3)	(4)	(5)	(6)
Change in emissions:	EGU-level Intensive margins (percentage changes)		EGU-level Extensive margins (percentage changes)		Total effects (percentage changes)	
Panel A. SO ₂ (thousand metric tons)						
EGUs without gas capacity	1.76	(0.03 %)	-6.57	(-0.12 %)	-4.81	(-0.09 %)
EGUs with gas capacity	-10.16	(-0.89 %)	-5.49	(-0.48 %)	-15.66	(-1.38 %)
Total effects	-8.40		-12.06		-20.46	
Panel B. NO _x (thousand metric tons)						
EGUs without gas capacity	-1.06	(-0.06 %)	-6.73	(-0.38 %)	-7.79	(-0.44 %)
EGUs with gas capacity	-4.87	(-0.93 %)	-6.84	(-1.31 %)	-11.71	(-2.24 %)
Total effects	-5.93		-13.58		-19.51	
Panel C. CO ₂ (million metric tons)						
EGUs without gas capacity	0.02	(0.00 %)	-1.28	(-0.11 %)	-1.27	(-0.11 %)
EGUs with gas capacity	-0.10	(-0.02 %)	-1.16	(-0.22 %)	-1.26	(-0.23 %)
Total effects	-0.08		-2.44		-2.52	

Notes: We simulated counterfactual emissions in 2007 if likelihood of NSR lawsuits increases by one percent. We decompose the intensive margins and normalized by the respective group-specific effects reported from Panel B of Table 10 on operate probability and emissions, and further separate the effects by presence of gas-fired generating capacity. Our decomposition is largely based on the results reported in Table 8 by restricting the sample to operating plants, and such regression results are available upon request. The total effects and the percentage changes are calculated based on emissions reductions for each of the groups of EGUs with or without gas capacity within operating plants. All numbers are averages weighted by the EGU-level gross load.

Online Appendix

A. Additional Figures and Tables

Figure A.1: Number of plants involved in an NSR lawsuit by alternative definitions of lawsuit dates, 1997 – 2015



Source: EPA Power Enforcement Web Page and Integrated Compliance Information System - Federal Enforcement and Compliance (ICIS - FE&C) dataset

Table A.1: Companies and plants sued for violating NSR

Utility Companies	Date Enforcement Data Enter	Date Settlement	Power Plants Sued for Violating NSR
Amer. Electric Power	Oct 01, 1999	Oct 9, 2007	John Amos, Big Sandy, Cardinal, Clinch River, Conesville, Gen Gavin, Glen Lyn, Kammer, Kanawha River, Mitchell, Mountaineer, Muskingum River, Rockspport, Phil Sporn, Picway, Tanners Creek
Illinois Power Company	Oct 21, 1999	Mar 7, 2005	Baldwin, Havana, Henneepin, Vermilio, Woodriver
Southern Indiana Gas & Electricity	Oct 21, 1999	Jun 6, 2003	Cully
Tampa Electric Company	Oct 28, 1999	Sep 10, 2001	Gannon, Big Bend
Alabama Power Company	Oct 28, 1999	Aug 24, 2015	James Miller
Ohio Edison Company	Nov 9, 1999	Mar 18, 2005	Burger, Eastlake, Sammis, Mansfield
Virginia Electric & Power	Apr 3, 2000	Sep 20, 2016	Chesapeake, Chesterfield, Clover, Mount Storm
Duke Energy	Jul 14, 2000	Sep 10, 2015	Allen, Buck, Cliffside, Dan River, Riverbend
PSEG	Oct 25, 2001	Nov 30, 2006	Bergen, Hudson Mercer, Kearny
Minnkota Power Corp	Mar 13, 2002	Apr 25, 2006	Milton Young
Alcoa Inc.	Feb 15, 2002	Feb 17, 2007	Alcoa Allowance
NV Energy	Oc 20, 2002	Apr 2, 2009	Clark
Wisconsin Electric Power	Apr 17, 2003	Apr 1, 2016	Port Washington, Pleasant Prairie, Presque Isle, South Oak Creek, Valley
East Kentucky Power	May 28, 2003	Jul 2, 2007	Spurlock, Dale, Copper
Santee Cooper	Sep 23, 2003	Mar 16, 2004	Cross, Grainger, Jefferies, Winyah
Westar Energy	Sep 30, 2004	Jan 25, 2010	Jefferey
Northern Indiana Pub Ser	Oct 12, 2004	Jan 13, 2011	Bailly, Mitchell, Michigan City, Schahfer
Louisiana Generating	Mar 30, 2005	Dec 20, 2012	Big Cajun
Kentucky Utilities Comp	May 1, 2006	Feb 3, 2009	Brown
Salt River Project	Oct 6, 2007	Aug 12, 2008	Coronado
Consumers Energy Comp	Oct 8, 2008	Sep 16, 2014	Campbell, Cobb, Karn, Weadock, Whiting
Minnesota Power & Light	Jan 26, 2009	Jul 16, 2014	Boswell, Laskin, Taconite Harbor
Dominion Energy	Sep 29, 2009	Apr 1, 2013	Brayton Point, Kincaid, State Line
Amer Municipal Power	Oct 1, 2009	May 18, 2010	Gorsuch
Hoosier Energy	Oct 1, 2009	Jul 23, 2010	Mrom, Ratts
Wisconsin Power & Light	Oct 2, 2009	Apr 22, 2013	Columbia, Edgewater, Nelson Dewey
Wisconsin Public Service	Oct 2, 2009	Apr 22, 2013	Pulliam, Weston
Tennessee Valley Authority	May 5, 2010	Apr 11, 2011	Allen, Bull Run, Colbert, Cumberland, Gallantin, Sevier, Johnsonville, Kingston, Paradise, Shawnee, Widows Creek
Dairyland Power Co-op	Oct 12, 2010	Mar 10, 2014	Alma, Madgett, Genoa
Four Corners Steam	May 16, 2011	Jun 24, 2015	Four Corners Steam
Interstate Power & Light	Jul 9, 2012	Jul 15, 2015	Burlington, Dubuque, Lansing, Kapp, Ottumwa, Prairie Creek, Sutherland, Six Street

Source: EPA Power Enforcement Webpage

Table A.2: Duration estimation for NSR lawsuits

<i>Dependent variable: NSR Lawsuit = 1</i>	(1) Coefficients	(2) Marginal Effects
Historical emission average	-0.032 (0.080)	-0.002 (0.006)
Historical emission st. dev.	0.033 (0.078)	0.002 (0.005)
Historical output average (10 ⁶ mega watt hours)	0.031*** (0.008)	0.002*** (0.001)
Historical output st. dev.	-0.334*** (0.064)	-0.023*** (0.004)
1 = Presence of scrubber before 1995	-0.146 (0.260)	-0.010 (0.018)
Plant capacity in 1997	0.480*** (0.145)	0.034*** (0.010)
US federal judicial district: Circuit 1	0.020 (1.142)	
US federal judicial district: Circuit 3	0.649 (0.829)	
US federal judicial district: Circuit 4	1.954*** (0.699)	
US federal judicial district: Circuit 5	-2.061* (1.223)	
US federal judicial district: Circuit 6	2.572*** (0.673)	
US federal judicial district: Circuit 7	2.467*** (0.678)	
US federal judicial district: Circuit 8	0.428 (0.798)	
US federal judicial district: Circuit 9	-0.232 (0.875)	
Year FE	Y	Y
Number of observations	11500	11500
Chi(2)	337.20	

Notes: Standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table reports results of Equation (1). Column 1 reports the coefficients and column 2 reports the marginal effect. US judicial district circuits 2, 10 and 11 were omitted.

Table A.3: First stage results for power generation

<i>Dep var: log of</i>	(1) Gross load	(2) Net generation
Number of cooling degree days (CDD) (in 1k)	0.591*** (0.111)	0.396*** (0.126)
Prob (NSR lawsuit)	-0.007 (0.008)	-0.011** (0.004)
Number of observations	22,100	16,225
R-squared	0.87	0.52
F-stat (of exclusive var)	37.1	-

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table reports the first-stage estimates of Equation (2) in Table 3 and 4. We bootstrap the duration Equation (1) together with the main Equation (2) to correct for the generated variable – NSR lawsuit probability. We use the number of cooling degree days as the excluded variable. Other included variables include a historical scrubber dummy interacted with a linear and a quadratic time trend. Column 1 report baseline first-stage results. Column 2 uses net generation to measure power generation instead of gross load.

Table A.4: Effect of NSR lawsuits on scrubbers, NO_x controls, and gas share

Panel A. Repeat baseline estimation on other outcomes					
<i>Dep. var:</i>	(1) Scrubber	(2) NO _x control	(3) log FGD energy consumption	(4) log FGD operating cost	(5) Gas share of heat input
Prob (lawsuit)	0.002** (0.001)	0.005*** (0.001)	0.056** (0.022)	0.053*** (0.019)	0.000 (0.000)
Log output	0.023 (0.015)	0.077*** (0.028)	1.011 (0.852)	0.819 (0.707)	0.005 (0.015)
Num. of observations	21,184	21,184	15,455	15,455	11,161
R-square	0.61	0.61	0.47	0.47	0.38
Panel B. Include post-allegation years and control for lawsuit allegation					
<i>Dep. var:</i>	(1) Scrubber	(2) NO _x control	(3) log FGD energy consumption	(4) log FGD operating cost	(5) Gas share of heat input
Prob (lawsuit)	0.003*** (0.001)	0.005*** (0.001)	0.060** (0.021)	0.055*** (0.018)	0.000 (0.000)
× (Being charged = 0)					
Being charged = 1	0.086*** (0.029)	0.179*** (0.090)	0.270 (0.585)	0.665 (0.562)	-0.007 (0.015)
Log output	0.013 (0.014)	0.091*** (0.029)	0.719 (0.869)	0.439 (0.489)	0.007 (0.014)
Num. of observations	22,100	22,100	16,371	16,371	12,065
R-square	0.59	0.59	0.45	0.45	0.37

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively.

Table A.5: Include post-allegation years and control for lawsuit allegation: Intensive and Extensive Margins

Panel A: Intensive margins for plants that stay operating							
<i>Dep. var: log of</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SO ₂	NO _x	CO ₂	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
Prob (lawsuit)	-0.008**	-0.008***	-0.004***	-0.008**	-0.008***	-0.004***	-0.000*
× (Being charged = 0)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.000)
Being charged = 1	-0.300**	-0.518***	-0.098*	-0.293**	-0.495***	-0.085	-0.011
	(0.146)	(0.080)	(0.058)	(0.143)	(0.074)	(0.053)	(0.010)
Number of observations	17,769	17,769	17,769	17,769	17,769	17,769	17,769
First-stage F-statistic	198.0	198.0	198.0	198.0	198.0	198.0	198.0

Panel B: Extensive margin: Likelihood for a plant to operate		
<i>Dep var: 1 = Operate</i>	(1)	(2)
Report marginal effects of:	Logit	LPM
Prob (NSR lawsuit) × (Being charged = 0)	-0.005***	-0.003***
	(0.002)	(0.000)
Being charged = 1	0.117**	0.016
	(0.060)	(0.018)
Number of observations	18,413	22,100
Log-likelihood	-1,843	
R-squared		0.71

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table re-estimate our IV estimation from Table 9. Panel A restricts the sample on plants that stays operating. Panel B re-estimate column 1 and 2 of Table 5 with post-lawsuit years and an additional control on having a allegation.

Table A.6: Controlling for overlapping policies

<i>Dep. var: log of</i>	SO ₂	NO _x	CO ₂
A. Controlling for ARP SO ₂ allowances and permit prices			
Prob (lawsuit)	-0.007*	-0.009***	-0.004*
	(0.004)	(0.002)	(0.002)
Log SO ₂ allowances × log SO ₂ permit price	0.003***	0.001	-0.000
	(0.001)	(0.001)	(0.001)
B. Controlling for NBP, CAIR, and RGGI regulated dummies			
Prob (lawsuit)	-0.008*	-0.009***	-0.003
	(0.004)	(0.002)	(0.002)
Regulated under NBP	0.033	0.033	-0.036
	(0.063)	(0.031)	(0.036)
Regulated under CAIR	-0.217*	-0.071	-0.111*
	(0.124)	(0.058)	(0.065)
Regulated under RGGI	-0.443**	-0.031	-0.002
	(0.205)	(0.090)	(0.113)
C. Controlling for CAAA non-attainment status			
Prob (lawsuit)	-0.008**	-0.010***	-0.004**
	(0.004)	(0.002)	(0.002)
SO ₂ non-attainment = 1	0.204	0.113	0.015
	(0.184)	(0.134)	(0.171)
NO _x non-attainment = 1	-0.693**	0.403**	0.166
	(0.309)	(0.173)	(0.138)
PM non-attainment = 1	0.013	0.026	-0.015
	(0.050)	(0.024)	(0.019)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 with additional controls. In Panel A we include SO₂ allocation and permit price. In Panel B we control for dummies that equal to one if a firm locates in a state in a year that is regulated by NBP, CAIR, and RGGI. In Panel C we control for CAAA attainment status for various pollutants.

Table A.7: **Controlling for economic conditions**

<i>Dep. var: log of</i>	SO ₂	NO _x	CO ₂
A. Controlling for the natural gas price			
Prob (lawsuit)	-0.009** (0.004)	-0.010*** (0.002)	-0.005*** (0.002)
Log natural gas price	0.298* (0.163)	0.164* (0.087)	0.107 (0.082)
B. Controlling for the natural gas price and the share of natural gas capacity			
Prob (lawsuit)	-0.009** (0.004)	-0.012*** (0.003)	-0.004** (0.002)
Log natural gas price	-0.221 (0.207)	-0.018 (0.178)	-0.393** (0.153)
Gas share	-5.181*** (0.567)	-1.939*** (0.437)	-1.643*** (0.255)
Log natural gas price × gas share	0.616*** (0.189)	0.497** (0.234)	0.772*** (0.213)
C. Controlling for the recession			
Prob (lawsuit)	-0.009** (0.004)	-0.009*** (0.002)	-0.004** (0.002)
Prob (lawsuit) × Year 2008	0.008*** (0.003)	0.002 (0.001)	-0.001 (0.001)
Prob (lawsuit) × Year 2009	0.007** (0.003)	-0.008*** (0.002)	-0.000 (0.001)
D. Controlling for other factors			
<i>Estimates of Prob (lawsuit) with additional controls:</i>			
1. Deregulation == 1	-0.008** (0.004)	-0.009*** (0.002)	-0.004** (0.002)
2. Divestiture == 1	-0.010** (0.004)	-0.010*** (0.002)	-0.003* (0.002)
3. Combined heat and power (CHP) == 1	-0.009** (0.004)	-0.009*** (0.002)	-0.004** (0.002)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 with additional controls. In Panel A we include log natural gas price. In Panel B we further interact natural gas price with the gas share of a plant. In Panel C we interact lawsuit probability with the recession year dummies.

Table A.8: **Controlling for Lawsuit Probability from Other Plants**

<i>Dep. var: log of</i>	SO ₂	NO _x	CO ₂	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
A. Lawsuit Probability from Other Plants in the Same State							
Prob (lawsuit)	-0.008** (0.004)	-0.009*** (0.002)	-0.004** (0.002)	-0.017*** (0.004)	-0.018*** (0.004)	-0.013*** (0.005)	-0.010*** (0.004)
Average Prob (lawsuit) from other plants	-0.009** (0.004)	-0.009*** (0.002)	-0.004** (0.002)	-0.017*** (0.004)	-0.018*** (0.004)	-0.013*** (0.005)	-0.010*** (0.004)
B. Lawsuit Probability from Other Plants in the Same Electricity ISO							
Prob (lawsuit)	-0.009** (0.005)	-0.010*** (0.003)	-0.003 (0.002)	-0.017*** (0.005)	-0.017*** (0.004)	-0.010** (0.005)	-0.008** (0.004)
Average Prob (lawsuit) from other plants	-0.009*** (0.003)	-0.008*** (0.002)	-0.001 (0.002)	-0.012*** (0.004)	-0.011*** (0.003)	-0.004 (0.004)	-0.003 (0.003)
C. B. Lawsuit Probability from Other Plants in the Same Federal Judicial District							
Prob (lawsuit)	-0.009** (0.005)	-0.010*** (0.003)	-0.003 (0.002)	-0.017*** (0.005)	-0.017*** (0.004)	-0.010** (0.005)	-0.008** (0.004)
Average Prob (lawsuit) from other plants	-0.009*** (0.003)	-0.008*** (0.002)	-0.001 (0.002)	-0.012*** (0.004)	-0.011*** (0.003)	-0.004 (0.004)	-0.003 (0.003)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 with alternative lawsuit dates.

Table A.9: **Alternative duration estimation**

<i>Dep. var: log of</i>	SO ₂	NO _x	CO ₂	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
Estimates of <i>Prob (Lawsuit)</i> :							
A. Additional time-varying controls in the c-log-log duration model							
1. Historical capacity	-0.008*	-0.008***	-0.004**	-0.015***	-0.016***	-0.012***	-0.008**
× year FE	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.003)
2. Hist. emission, output	-0.007*	-0.008***	-0.003**	-0.013***	-0.014***	-0.009**	-0.007**
× year FE	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
3. Hist. emission, output	-0.010**	-0.010***	-0.004*	-0.019***	-0.018***	-0.013***	-0.009***
× log SO ₂ price	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.003)
4. Judicial district FE	-0.002	-0.007***	-0.004**	-0.010**	-0.014***	-0.011***	-0.008***
× year FE	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
B. Controls for NSR lawsuits of other plants sued in the same							
1. Federal judicial district	-0.006	-0.007**	-0.004**	-0.011***	-0.012***	-0.009*	-0.006
	(0.006)	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
2. State	-0.008	-0.010***	-0.007***	-0.015***	-0.017***	-0.014**	-0.009*
	(0.006)	(0.003)	(0.002)	(0.005)	(0.004)	(0.005)	(0.005)
3. Electricity ISO	-0.006	-0.007**	-0.004**	-0.011***	-0.012***	-0.009*	-0.006
	(0.006)	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
C. Alternative duration model							
1. Linear probability model	0.002	-0.010***	-0.013***	-0.018***	-0.030***	-0.033***	-0.021***
	(0.005)	(0.003)	(0.003)	(0.005)	(0.006)	(0.008)	(0.006)
2. Logit	-0.010	-0.009**	-0.006	-0.021***	-0.020***	-0.017*	-0.012*
	(0.007)	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.007)
3. Probit	-0.010	-0.009**	-0.007	-0.024***	-0.023***	-0.021*	-0.014*
	(0.007)	(0.004)	(0.005)	(0.007)	(0.008)	(0.012)	(0.008)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 with alternative lawsuit dates.

Table A.10: Alternative lawsuit date definition

<i>Dep. var: log of</i>	SO ₂	NO _x	CO ₂	SO ₂ rate	NO _x rate	CO ₂ rate	Heat rate
1. Refer to DOJ	-0.008** (0.004)	-0.009*** (0.002)	-0.004** (0.002)	-0.017*** (0.004)	-0.018*** (0.004)	-0.013*** (0.005)	-0.010*** (0.004)
2. Enforcement data entered (baseline)	-0.009** (0.004)	-0.009*** (0.002)	-0.004** (0.002)	-0.017*** (0.004)	-0.018*** (0.004)	-0.013*** (0.005)	-0.010*** (0.004)
3. Complained filed	-0.009** (0.005)	-0.010*** (0.003)	-0.003 (0.002)	-0.017*** (0.005)	-0.017*** (0.004)	-0.010** (0.005)	-0.008** (0.004)
4. Consent decree	-0.009*** (0.003)	-0.008*** (0.002)	-0.001 (0.002)	-0.012*** (0.004)	-0.011*** (0.003)	-0.004 (0.004)	-0.003 (0.003)
5. Final order lodged	-0.007*** (0.002)	-0.006*** (0.002)	-0.001 (0.001)	-0.008** (0.003)	-0.007*** (0.003)	-0.002 (0.003)	-0.001 (0.002)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. This table repeats our IV estimation in Table 3 with alternative lawsuit dates.

Table A.11: Effect of the stock of emission allowances

Panel A: Repeat Panel C of Table 9 using stock of allowances (instead of allowance allocation)

<i>Dep. var: log of</i>	(1) SO ₂	(2) NO _x	(3) CO ₂	(4) SO ₂ rate	(5) NO _x rate	(6) CO ₂ rate	(7) Heat rate
Prob (lawsuit)	-0.010** (0.004)	-0.009** (0.002)	-0.001 (0.002)	-0.013*** (0.004)	-0.011*** (0.004)	-0.004 (0.005)	-0.007 (0.004)
× (Being charged = 0)							
Being charged = 1	-0.115 (0.153)	-0.305*** (0.074)	-0.023 (0.068)	-0.137 (0.139)	-0.312** (0.127)	-0.036 (0.165)	-0.067 (0.123)
Surrender SO ₂ allowances	-0.053*** (0.017)	-0.027*** (0.008)	0.008* (0.005)	-0.039** (0.018)	-0.013 (0.011)	0.022** (0.010)	0.016** (0.007)
× log ARP allocation held							
Surrender NO _x allowances	-0.010 (0.019)	0.012 (0.010)	-0.011** (0.005)	-0.024 (0.020)	-0.002 (0.012)	-0.025** (0.011)	-0.017** (0.007)
× log NBP allocation held							
Num. of observations	22,100	22,100	22,100	22,100	22,100	22,100	22,100
First-stage F-stat	43.3	43.3	43.3	43.3	43.3	43.3	43.3

Panel B: Repeat Panel A of Table A.6 using stock of allowances (instead of allowance allocation)

<i>Dep. var: log of</i>	SO ₂	NO _x	CO ₂
Prob (lawsuit)	-0.011* (0.004)	-0.010*** (0.002)	-0.002 (0.002)
Log SO ₂ allowances held × log SO ₂ permit price	0.000 (0.002)	-0.000 (0.001)	-0.002* (0.001)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively.