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 SO_2 and NO_x, spillover benefits in the reverse direction have not been well studied. This paper estimates one such spillover by examining how SO_2 and NO_x regulations of the New Source Review affect CO_2 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 CO_2 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

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*Department of Economics, University of Manchester, Arthur Lewis Building-3.078, Manchester, M13 9PL, United Kingdom. Contact: ron.chan@manchester.ac.uk

†John E. Walker Department of Economics, Clemson University, Sirrine Hall #223, Clemson, SC 29634, USA. Contact: yichen2@clemson.edu

1 Introduction

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

Environmental policies typically regulate local pollutants, such as sulfur dioxide (SO_2) and nitrogen oxides (NO_x), and global pollutants such as carbon dioxide (CO_2). Regulators often employ different sets of instruments on different pollutants, even though fossil fuel combustion is the main cause for both local and global pollutant types. For example, in the 1970s, the US Environmental Protection Agency (EPA) began using provisions of the Clean Air Act to regulate SO_2 and NO_x emissions from electricity generation and other sectors; however, it does not regulate greenhouse gas emissions from the electricity generation sector. Despite both the importance of greenhouse gases as a source of global warming, and the contributions of the electricity generation sector to greenhouse gas emissions, regulation of these emissions and this sector only began relatively recently, from regional efforts begun in 2009.[1] Different emissions policies at regional and national levels could either strengthen or weaken the effectiveness of one another – depending on the spillovers on other types of pollutants, which may be determined by the ways in which the regulated companies choose to comply. For example, regulating SO_2 may decrease CO_2 emissions if power plants decide to comply by switching to a cleaner fuel with a lower carbon content; by contrast, regulating SO_2 emissions in the energy and manufacturing sectors could have a detrimental effect by increasing CO_2 emissions if plants respond by installing more energy-intensive emission control equipment.

The impacts of climate policies on SO_2 and NO_x emissions and on human health, have been well studied.[2] However, few studies examine the spillover effects that go the other way around. How do regulations of local pollutants affect global greenhouse emissions? The answers

[1]The electricity generation sector is a major source of pollution emissions. In 2010, it accounted for 74 percent of total SO_2 (7.7 million tons) emissions and 34 percent of CO_2 (6.8 trillion tons) emissions in the United States(EPA, 2012a, 2016). We focus on coal- and gas-fired power plants, the total of which account for 98 percent of SO_2 emissions, 99 percent of NO_x emissions, and 99 percent CO_2 emissions from the electricity generation sectors. Regional regulation of CO_2 started in 2009 in the New England area under the Regional Greenhouse Gas Initiative (RGGI).

[2]This 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.

from the few previous studies that have addressed this question are mixed.[3] For example, Holland (2012) found that meeting the Clean Air Act (CAA) standards *had no effect* on CO_2 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 SO_2 *reduced* CO_2 emissions for coal-fired plants. Brunel and Johnson (2017) found that CAA attainment status *has no effect* on CO_2 in the manufacturing sector, likely because of a lack of effective margins to reduce carbon intensity, or because the substitution and spillover channels counteract each other.

Our paper studies how regulation of emissions of the local pollutants SO_2 and NO_x affects emissions of CO_2 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, which is important to address the ambiguity that arises because of different levels of enforcement in various regions of the country, and because of changes in the stringency of enforcement practices with changing political administrations. 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 which plant is treated, and the exposure to the treatment may vary across plants. Moreover, the perceived stringency of the policy can also 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".[4]

In this paper, we address these issues by focusing on the New Source Review (NSR), a provision of the Clean Air Act that requires new and existing power-generating facilities to adopt emission control technologies to adopt emission control technologies to reduce SO_2 and NO_x emissions; we examine how the likelihood of lawsuits for lawsuits for violating NSR regulations affects *both* emissions of local pollutants (SO_2, NO_x) *and* CO_2 emissions from power plants in the US. Although the NSR was instituted in 1977, reforms did not take place until

[3]Though their research questions are not to study carbon co-benefits per se, several 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 from 2010 to 2017.

[4]"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.

1999 when the US Department of Justice (DOJ), representing the EPA, brought the first lawsuits to the US Supreme Court against 83 power- generating units at 24 power plants.[5] 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 are vulnerable to the threat of a lawsuit. This is a crucial distinction. 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 variations, 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.[6]

Using the predicted NSR lawsuit probabilities, we proceed to estimate how the lawsuit threat affected both regulated and unregulated emissions from US power plants between 1995 and 2015. The effect of the lawsuit risk on unregulated CO_2 emissions can be ambiguous. Installing and increasing the usage of SO_2 and NO_x control technologies may increase a plant's electricity consumption, and therefore increase CO_2 emissions. Building new (usually more efficient and less CO_2 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

[5]This enforcement action has continued and brought settlements against a total of 275 units from 85 plants between 1999 and 2015. The EPA has won all NSR lawsuits, and power plants can make an effort to obtain the best favorable settlement.

[6]The 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).

potential for CO_2 emissions reduction, and may even increase CO_2 emissions. Alternatively, a higher lawsuit risk may reduce CO_2 emissions if plants reallocate power generation from older units to newer, more efficient units that are likely to be more fuel-efficient (with a lower operating heat rate); or if they shift electricity production from coal-fired units to gas-fired units that have both a lower CO_2 emission rate and a lower operating heat rate.[7]

We find that NSR lawsuit probability has a significant and sizable effect on SO_2, NO_x, and CO_2 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 estimation. A 1 percent increase in the NSR lawsuit probability (an increase of about 0.2 of a standard deviation) decreases SO_2 emissions by 0.9 percent, NO_x emissions by 0.9 percent, and CO_2 emissions by 0.4 percent. This change is equivalent to yearly reductions in SO_2 emissions by 68 thousand metric tons, NO_x emissions by 34 thousand metric tons, and CO_2 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 CO_2, the climate co-benefits would be $290 million (in 2007 dollars).[8] The magnitude of CO_2 co-benefits implies that it is important to account for climate spillover when one calculates the 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. Specifically, the magnitude of co-benefits from a 1 percent lawsuit risk is equivalent to the benefit of a $10/ton carbon tax, using results from Linn et al. (2014). Our results are robust to the inclusion/exclusion of post-lawsuit years of observations, and to obtaining separate effects of a lawsuit threat as well as a settled lawsuit. Our results are robust to inclusion of other overlapping policies.

To investigate the factors that drive the emissions reductions, we further examine whether and how a higher lawsuit probability induces plants to improve both abatement technologies (the technology channel) and thermal efficiency (the efficiency channel). Holding the scale of production and other factors constant, we find that a higher NSR lawsuit probability has led to significantly lower SO_2, NO_x, and CO_2 emission rates (lb/mmBtu), but has had little effect on a unit's thermal efficiency (operating heat rate, mmBtu/mWh). This result implies that emission reductions are mostly coming from improvements in the abatement technology, rather than in generation efficiency - in other words through the technology channel rather than through the efficiency channel.

Moreover, we decompose the counterfactual CO_2 co-benefits by plants with and without gas-fired generating units, along the intensive and the extensive margins. The results show that both while both margins are important across all SO_2, NO_x, and CO_2 emissions, the extensive

[7]In 2010 the average SO_2 emission rate was 0.84 lbs/mmBtu for coal-fired generating units and 0.02 lbs/mmBtu for natural-gas-fired units. The average emission rate of NO_x was 0.27 lb/mmBtu for coal-fired generators and 0.13 lb/mmBtu for gas-fired generators according to EIA https://www.eia.gov/todayinenergy/detail.php?id=37752.

[8]We 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

margins contributes 61 percent of the carbon co-benefits. Within the extensive margins, the majority of the reduction of the CO_2 is due to the closure of coal-fired-only power plants. Closing or retiring these plants also account for the majority of SO_2 and NO_x emissions reductions.

We repeat our estimation and counterfactual exercises at the electricity-generating-unit (EGU) level to study whether the intensive margins at the plant level are driven by improvements within a generating unit, or by a reallocation of resources across units achieved by shutting down some units. We find that a 1 percent increase in NSR lawsuit probability leads to a 1.2 percent reduction in SO_2 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 CO_2 emissions drops to 0.1 percent. These results suggest that the carbon co-benefits found at the plant level would mostly come from shutting down or retiring EGUs. In the extensive margin regressions, we find that NSR lawsuit probability reduces the probability of operating a coal-fired EGU, but increases this probability for gas-fired EGUs. Along those lines, we decompose our simulated intensive margins at the EGU level and find that more than 95 percent of the CO_2 co-benefits within a 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. In addition, studying the sources of spillover offers important insights for a more effective carbon policy design; we quantify various channels that contribute effectively to CO_2 emissions reduction, especially the extensive margin of the fuel switches.[9] Our results also provide reassurance to policy makers that at the current equilibrium, a leakage to CO_2 emissions will be unlikely from regulating SO_2 and NO_x – or from strengthening existing regulations.

Also, this paper adds to the knowledge regarding how the NSR created vintage-differentiated regulations (VDR) distortion, and how this distortion affects SO_2 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).[10] Using a longer panel and a different estimation strategy, we provide evidence of effective emission reductions of regulated pollutants, and we examine the channels that drive the emission reductions.

[9] Previous work has suggested fuel switches can induce CO_2 reduction, e.g., (Linn et al., 2014). Broadly speaking, our work is related to future design of policies on greenhouse gas mitigation (Bushnell et al., 2017; Abito et al., 2018).

[10] The literature has stopped investigating the impact of the NSR since the Equipment Replacement Provision (ERP) of NSR in 2003, which in practice relax the stringency of NSR. However, ERP was revoked in 2007 and NSR has been strengthened and relaxed a few times since then, so an updated study is needed. See background and changes of NSR from 1977 to 2015 in Section 2.1.

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. In this paper, 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 how the NSR affects the probability of being litigated, and how that probability affects plant operation and emissions. Section 4 presents the estimation results. Section 5 presents the decomposition exercises used to quantify margins that explain our carbon co-benefits results. Section 6 presents additional evidence on intensive margins, such as emission control technology adoptions and within-plant fuel switches. Section 7 concludes.

2 Data and Background of 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 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 variations 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 (discussed below), giving the EPA significant discretion over which plants it will target. For example, the EPA has the flexibility to decide which changes are large enough to affect the regional level of NAAQS – which means that plants in CAA attainment and non-attainment counties may face different levels of enforcement. The interpretation of the law also depends on judges at different federal courts, which would affect the expected outcome of the lawsuits. 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. In turn, this variation in the leniency across regions affects how the EPA targets plants across jurisdictions.

Second, in addition to cross-sectional ambiguity, the enforcement also varies over time because the NSR program has experienced several rule changes.[11] 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.[12] 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

[11] More details on the EPA's NSR reform webpage https://www.epa.gov/nsr/nsr-regulatory-actions#nsrreform.

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

the Equipment Replacement Provision (ERP). Starting in December 2002, 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 related utility companies. 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. To incorporate such a variation in NSR enforcement since 1999, we estimate a time-varying lawsuit risk for each plant (see Section 3.1 for details).

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. Also, settlements require plants to install BACT or to retire the unit involved within a proposed short window, or to face civil 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.[13]

[13]From 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.

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 SO_2, NO_x, and CO_2 emissions from the EPA Continuous Emission Monitoring System (CEMS) database.[14] 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.

To examine the extensive margin, we collected nameplate and operating capacities of EGUs, and their retirement status from the EIA Form-860. To study the intensive margin, we computed emission rates (tonnes of emissions per unit of heat input) using emission dataand 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. 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 plant-years that the plant in under an NSR lawsuit.

We extracted NSR lawsuit consent decrees from EPA Coal-fired Power Plant Enforcement web page.[15] 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.[16] 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. 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

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 in the first place. 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.

[14]CEMS exclude small power plants. The effect of NSR lawsuits from those units is likely small.

[15]Link: 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 our Appendix Table A.1 for detail.

[16]This 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.

date when final order is lodged.[17] 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.[18] Later for robustness we use other dates to define our lawsuit timing. In addition, no utilities have had multiple 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 SO_2 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 SO_2 and NO_x 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 CO_2 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 allowance for SO_2 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 SO_2. Our main analysis focuses on the pre-lawsuit period.

[17] After the "referred to DOJ" date, we observe the "enforcement data entered" date recorded right after it (generally 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 "OJ 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."

[18] Ideally 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. So 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 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).[19] NRC (2006) improves on the IPM model by allowing plants to adjust their extensive and intensive margins 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 SO_2 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 NSR litigation and a treatment group that is vulnerable to 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 survival 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 are 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 following complementary log-log hazard (C-log-log) model. The discrete-time hazard rate for plant i in year t is given by:

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

where $\rho_{it} \equiv \Pr(lawsuit_{it} = 1)$ 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 changes of the

[19] To 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.”

stringency of the NSR and the interpretation of NSR, macro demand and supply 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 1995, scrubber installation status in 1995, and dummy variables that represent 11 federal circuit courts.[20] First, we include in Z_i historical emissions and power generation variables because the violations cited in most consent decree dated back to the 1980s and early 1990s although plants named in NSR lawsuits were mostly sued for recent modifications.[21] Keohane et al. (2009) similarly use historical emission information to predict the threat of a lawsuit in 1999 and 2000.

Also, we include in Z_i historical scrubber installation. All consent decrees cite violations in SO_2 and most mandate alleged entity to install SO_2 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 focus on relatively higher-profile cases and 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. While all NSR lawsuits are settled in federal circuit courts, 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 Sixth Circuit (for KY, MI, OH, and TN) – 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 the NSR in Section 3.2.

Because δ is identified using cross-sectional variation, the cross-sectional variation in $\hat{\rho}_{it}$ depends on the historical characteristics and other cross-sectional characteristics. The temporal variation in $\hat{\rho}_{it}$ within a plant is generated from year fixed effect and depends on the choice of the functional form. Later in Section 4.1, we investigate alternative specifications that generate more plant-year variation by interacting Z_i with year fixed effects or other time-varying variables such as the SO_2 allowance price. We also explore other probabilistic models such as logit and probit models to relax the functional form assumption. We find robust results.

[20] For robustness, we changed the definition of historical period and we found similar results.

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

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 (SO_2, NO_x, or CO_2) from power plant i in year t, we estimate:

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

where $\hat{\rho}_{it}$ is the predicted probability of facing an NSR lawsuit for plant i in year t, ranging from 0 to 100.[22] 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 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 emission reduction 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.[23]

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 in our sample.[24] Later in Section 4.4 we add post-lawsuit years back, and estimate the effects of two types of treatments separately: (1) 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), and (2) the effect of facing an actual allegation, which lead to emission reduction because of compliance.

We next consider and correct for potential endogeneity of power generation. Plants can adjust output to reduce emissions. Also, unobserved technologies can be correlated to 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. In Section 6 we show our robust results using alternative IV(s).

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

[23]The 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. We need to interact this dummy with the year trend in (2) to capture variation at plant-year level as well.

[24]We include post-lawsuit years in equation (1) since the c-log-log model needs to use observed lawsuits to predict lawsuit probability. Those years are excluded in our baseline equation (2).

We expect β_1 to be negative for SO_2 and NO_x 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 chance of facing regulatory action (in the form of being involved to a lawsuit) induce plants to lower CO_2 emissions; in other words, the policy induces climate co-benefits. 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 $\ln Q_{it}$ as in Holland (2012). We expect β_2 to be positive since higher demand for electricity would lead to more emissions, conditional on other factors.

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 269. 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.

The coefficient of the first moment of historical emissions is negative and the coefficient of the second moment is positive, suggesting that plants that had occasionally generated extremely high emissions are more likely to be sued than others. Also, the coefficient of the first moment of gross load is positive and the coefficient of the second moment is negative, suggesting plants that consistently produce more power are more likely to be named in a lawsuit than others.

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 involving 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 CO_2 Emissions

In this section, we estimate how a higher NSR lawsuit risk $\hat{\rho}_{it}$ affects local pollution and CO_2 emissions. We correct the standard error of β_1 by bootstrapping both the equations (1) and (2) together.

In Table 3 Panel A columns 1–3, we report the OLS estimation of equation (2) on the log of SO_2, NO_x, and CO_2 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 with a higher demand for electricity generation are likely to generate more emissions.

Next, we present 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.[25] 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. The sign of this estimate is consistent with the possibility that plants may lower emissions by reducing power generation. 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 shifter IVs.

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 SO_2 and NO_x.

[25] The F-stat for the (joint) 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.

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 SO_2, NO_x, and CO_2 emissions by 0.9 percent, 0.9 percernt, 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 SO_2, NO_x, and CO_2 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) emission reduction via reducing power generation.

Our findings on local emissions (SO_2 and NO_x) are consistent with tose 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 SO_2 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.[26] As for Evans et al. (2008), there is a methodological difference in defining both the treatment and counterfactual. Evans et al. (2008) use an bottom-up economic-engineering mode, and they assume ex ante which plants will be affected; by contrast, our study estimates the continuous treatment from data.

4.3 How Have a Higher Lawsuit Risk Affected Plant Operations?

To understand the driving factors and effective margins that lead to emission reductions and CO_2 co-benefits, and to provide insights for future policies on the electricity generation sector, we proceed to investigate how a higher NSR lawsuit risk affects important margins in plant operations.

A. Emission rates and operating heat rate. Conditional on being in operation, 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, θ is the operating heat rate, and Y is the electricity generation. Conditional on scale, the overall emissions depend on emission rate and heat rate. Therefore we proceed to examine these two margins.

We repeat our baseline 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 SO_2, NO_x, and CO_2 by 1.7

[26] The 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 6 Panel A).

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. In addition, we can express and decompose emissions z for a plant in a year as $z = \eta \times \mathbf{E}\{z|\eta = 1\}$. 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, $\mathbf{E}\{z|\eta = 1\} \equiv \mathbf{E}\{z|Operate = 1\}$, indicates the intensive margin on emissions from plants that keeps operating.

The incentive to temporarily shut down an active plant as an averting action before being named in a potential lawsuit differs from the incentive to shut down as a compliance of the settlement. We focus on estimating the averting action effect. Later, in Section 4.4, we explain the difference between the two factors and estimate the effects on emissions from both incentives.

We estimate a logit model, and we include the same set of variables in equation (2) but 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 continueoperating 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 to estimate our baseline extensive margin because we need to generate the predicted probability to operate $\hat{\eta}$ from zero to one for decomposition simulations in Section 5.

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 SO_2, NO_x, and CO_2 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 SO_2, NO_x, and CO_2 emission rate 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 has been an important channel to reduce carbon emissions in power generation.[27] We proceed to investigate the contribution of fuel switches in CO_2 co-benefits.

In Panel A of Table 6, we repeat our baseline with the NSR lawsuit probability interacted with a dummy variable that equals one if the plant has gas-fired capacity. For CO_2, column 3 suggests that a higher lawsuit risk would reduce CO_2 emissions from plants without gas capacity (i.e., coal-fired-only plants), and this result is consistent with a CO_2 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 CO_2 emissions, CO_2 emission rate, and heat rate. Our results are consistent with those of Holland (2012), who finds no reduction of CO_2 emissions for California plants that are mostly gas fired. We see a similar pattern for both NO_x emissions and emission rates.

In contrast, our results or SO_2 are slightly different to CO_2; we do not obtain precise estimates in column 1 although the point estimate is negative. We find that gas-fired plants reduce more SO_2 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 margin 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., will 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 margin results in Panel B of Table 6. 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 6 to quantify the relative contribution in emission 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, across multiple EGUs, on emission intensity and thermal efficiency such as by increasing the usage of

[27] According to the EIA: https://www.eia.gov/environment/emissions/co2_vol_mass.php

scrubbers to lower the SO_2 emission rate. In summary, 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.[28]

We report the intensive estimates in Panel A.1 of Table 7, 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 CO_2 is much smaller and only statistically significant at the 10 percent level, and that the coefficient on CO_2 emission rate is statistically insignificant. This result suggests that the CO_2 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 7 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 emission 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 6. 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 Section 4.3 we discussed emission reductions via various margins 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

[28]When 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.

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.[29]

To 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 became the target of later litigation, and makes the coefficient of the lawsuit probability comparable to our baseline.[30]

We report our results in Table 8 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 CO_2 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 CO_2.

We next investigate the effect of a realized allegation on the 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

[29] One 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.

[30] For plants that have had a lawsuit, our duration model generates the lawsuit probability before and after the plant being charged. When we estimate our baseline, we drop observations after a plant is charged to focus on estimating the effect from a higher lawsuit risk. Without 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".

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 intensive margin in Panel A of Appendix Table A.5. In summary, our baseline result of the lawsuit risk is robust. Also, 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. This two margins work in the opposite directions which is consistent with some imprecise estimates of the allegation dummy variable in Table 8.

B. Allowance 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 SO_2 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).[31] 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 SO_2 allowance within a year. We similarly include a dummy variable for a NO_x allowance surrender requirement. We show that our results are robust in Panel B of Table 8, 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 SO_2 allowance.

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 SO_2 (from ARP) and NO_x (from NBP) using AMPD data. We report our results in Panel C of Table 8. Again, we find robust results, although our estimates are less precise than our baseline because of the additional controls.

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, SO_2 emissions are regulated and traded under the ARP, and the plants may adjust various margins which may affect SO_2 and other emissions. Therefore, ARP can be correlated to both emissions and lawsuit risk.

We add to our baseline the log of SO_2 allowance interacted with the log of SO_2 permit price. The permit price is higher early in our sample so that the interaction term allows the allocation

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

to have a stronger effect on emissions earlier in our sample. Our results shown in Panel A of Table A.6 are robust.[32] The interaction term is positive for SO_2 and NO_x, suggesting that the higher the value of the SO_2 allowance allocated to a plant, the more SO_2 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 SO_2, NO_x, PM10, and PM2.5. We therefore control for the CAA non-attainment status for SO_2, 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.

5 Implications

To quantify the contribution to emission reductions from coal- and gas-fired plants across various plant operation margins, we conduct a counterfactual analysis and decompose emission 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 consider one percent increase as a mild change; 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. Therefore, we interpret our counterfactual and decomposition simulations as marginal changes.

Panel A in Table 9 shows the overall counterfactual changes in SO_2, NO_x, and CO_2 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 SO_2 and NO_x emissions, amounting to 68 thousand and 34 thousand metric tons, respectively. Also, CO_2 emissions would drop by 0.3 percent, amounting to close to 7 million

[32]The specification in Panel A of Table A.6 is very different from the specifications in Panel C of Table 8. Panel C of Table 8 has SO_2 allocation interacted with a surrender dummy that does not equals 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.

metric tons. If we evaluate the social cost of carbon at $42 per metric ton, this CO_2 co-benefits results in a social benefit of some $290 million.

The magnitude of the CO_2 co-benefits from an increase in the lawsuit risk 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 CO_2 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 CO_2 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 CO_2 emissions by 2.6 percent, comparable to the effect of an 8 percent increase in the NSR lawsuit risk.

A. Emission reduction by plants with or without gas capacity. We then decompose the above counterfactuals to quantify the relative contribution by various margins that plants 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 indicator variables 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 changes in emission for each plant i in year t

$$\Delta z_t = \sum_i \left\{ d_c \Delta z_{it}^c + d_g \Delta z_{it}^g \right\} \tag{3}$$

Within each group (c or g), we further decompose the changes in emissions based on intensive and extensive margins, in which plants (re-)start or shut down. As in Section 4.3, we use $\eta \equiv Prob(Operate = 1)$ to denote the extensive margin on how likely a utility company is to keep a plant operating (as opposed to shutting it down). The expected changes in emissions in each group of plants can be decomposed as:

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

For each group, the first term describes the emission changes via the extensive margin, and the second term describes the emission changes for plants that stay open (i.e., via the intensive margin). To approximate the *expected* probability to operate, $\mathbf{E}\eta_{it}$, we predict the operating probability $\hat{\eta}_{it}$ using the logit estimates in Table 5. To approximate the expected emissions for operating plants, $(\mathbf{E} z_{it} | \eta_{it} = 1)$, we generate predicted emissions for operating plants $(\hat{z}_{it} | \eta_{it} = 1)$ using Table 6 Panel B. The above equation reduces to:

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

Panel B of Table 9 shows the decomposition results. Both the extensive and intensive margins explain sizable and comparable shares of the reductions in SO_2, NO_x, and CO_2 emissions. In particular for CO_2 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 form those in group g (i.e., plants with some gas capacity). For CO_2 co-benefits, the closure of coal-fired-only plants account for 54 percent of the emission reductions. Results are similar for SO_2 and NO_x emissions. As for the intensive margin, the effect sizes are similar for both groups of plants. However, we obtain mixed results for SO_2 emissions.

We found that the contribution of the extensive and intensive margins to CO_2 co-benefits varies by the plant group that indicates whether the plant has gas capacity (i.e., whether the plants are in group c or g). For each type of the emissions, we obtain a larger extensive margins effect for plants without gas-fired generation capacity – indicating that following an increase in NSR lawsuit risk, plants without gas-fired units are more likely to shutdown relative to plants with gas-fired units. For the intensive margins, the effect sizes are similar for these two groups of plants (once again, mixed results for SO_2 emissions). Our results imply that most of our estimated carbon co-benefits result from shutting down the coal-fired plants that lack gas-fired capacity.

B. Decompose the intensive margin: changes at the EGU level. A remaining question is to what measures are responsible for the emissions reduction at the plant-level intensive margin. 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 on *the EGU-level intensive margin*). An operating plant can also shut down some generating units with higher emission rates or with a less-efficient operating heat rate (i.e., by making changes on *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 7, and we tabulate our counterfactual results in Table 10.

When we decompose the plant-level intensive margin, we find that most of the estimated effects come from the EGU-level extensive margin. The pattern is the strongest for CO_2. In particular, shutting down EGUs within an operating plant accounts for SO_2, NO_x, and CO_2 emissions reduction 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 operating units; such decreases can only be achieved by improving thermal efficiency. Thus, the only viable means to reduce CO_2 emissions is to shut down (inefficient) generating units. Given that 60 percent of CO_2 co-benefits are from plant-level intensive margin, our results imply that 98 percent of co-benefits stem from closing EGUs (and plants).

Although the EGU-level intensive margins barely contribute to CO_2 co-benefits for plants that stay open, we do find that measures along the EGU-level intensive margin reduce SO_2 and NO_x emissions for those plants. Moreover, most of this effect stems from gas-fired units. These simulation results also imply that improvements in emission rate and operating heat rate that we find from our estimation 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 reduction following a higher NSR lawsuit risk. Here we provide more evidence of adjustments that plants make to reduce emissions. In Appendix Table A.4, we repeat our baseline model on the following outcome variables: the adoption of scrubbers (an SO_2 abatement technology, also referred to as flue-gas desulfurization (FGD) units) of a plant in a year, 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 SO_2 and NO_x abatement technologies, consistent with our findings of the emission rates of SO_2 and NO_x and our EGU-level counterfactuals. We do not find strong evidence of changes in gas shares.

B. Economic conditions and the organization of the power industry. We assessed the effect of overlapping policies in Section 4.4. Here we further consider other factors in the macro economy and in the electricity-generation sector that may bias our results. First, 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.

Moreover, 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. Our results are also robust if we drop the years 2008 and 2009 from our sample. Also, we find that a higher lawsuit risk has null effect on some pollutants during the recession years, consistent with our prior.

Lastly, 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.[33]

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. So if a plant decides to reduce emissions via reducing power generation, another plant could increase its share of the supply, which would 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.

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,

[33] Most within-plan 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.

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 SO_2 allowance price to capture the fact that a large emitter may have a different lawsuit risk when the SO_2 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 SO_2 become less precise.

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-size 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 SO_2, 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.[34]

[34]Results are similar if we expand the sample to include post-allegation years and include the alleged dummy, if we use alternative lawsuit dates to generate $\hat{\rho}_{it}$ and define the alleged dummy.

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 should 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 SO_2 emissions (Schmalensee and Stavins, 2013).

In this paper, we investigate how the threat of lawsuits that targeted SO_2 and NO_x emissions through the New Source Review (NSR) program of the US Environmental Protection Agency affected unregulated CO_2 emissions and operation margins for coal- and gas-fired power plants. Though this policy targets SO_2 and NO_x emissions, they 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. 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 have a higher NSR lawsuit probability than plants in other areas, or those within a more "pro-business" federal court circuits, all else being equal.

Using 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 SO_2 and NO_x emissions, but it happens to reduces CO_2 emissions by a sizable magnitude, even though CO_2 is not regulated by the NSR. We found that the CO_2 emission reduction from a 1 percent increase in lawsuit risk is 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 SO_2 and NO_x emissions, and a cap-and-trade program on CO_2 emissions – because of the spillover effects.

In our decomposition exercise, we found that CO_2 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 margin results are mostly driven by shutting down electricity generating units within an operating plants – likely because the intensive margins that operating units can adjust lead to reductions in SO_2 and NO_x emissions only, whereas shutting down generating units leads to CO_2 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.

References

Abito, J. M., C. R. Knittel, K. Metaxoglou, and A. Trindade (2018). Coordinating separate markets for externalities. Working Paper, University of Pennsylvania.

Almond, D., Y. Chen, M. Greenstone, and H. Li (2009). Winter heating or clean air? unintended impacts of China's Huai River policy. *American Economic Review: Papers & Proceedings 99*(2), 184–190.

Blundell, R., S. Bond, M. Devereux, and F. Schiantarelli (1992). Investment and Tobin's q: Evidence from company panel data. *Journal of Econometrics 51*(1–2), 233–257.

Böhringer, C. and K. E. Rosendahl (2010). Green promotes the dirtiest: On the interaction between black and green quotas in energy markets. *Journal of Regulatory Economics 37*(3), 316–325.

Brunel, C. and E. P. Johnson (2017). Two birds, one stone? Local pollution regulation and greenhouse gas emissions. Working Paper, American University.

Burtraw, D., A. Krupnick, K. Palmer, A. Paul, M. Toman, and C. Bloyd (2003). Ancillary benefits of reduced air pollution in the US from moderate greenhouse gas mitigation policies in the electricity sector. *Journal of Environmental Economics and Management 45*(3), 650–673.

Bushnell, J. B., S. P. Holland, J. E. Hughes, and C. R. Knittel (2017). Strategic policy choice in state-level regulation: The EPA's Clean Power Plan. *American Economic Journal: Economic Policy 9*(2), 57–90.

Bushnell, J. B. and C. D. Wolfram (2012). Enforcement of vintage differentiated regulations: The case of New Source Review. *Journal of Environmental Economics and Management 64*(2), 137–152.

Chan, H. R., H. Fell, I. Lange, and S. Li (2017). Efficiency and environmental impacts of electricity restructuring on coal-fired power plants. *Journal of Environmental Economics and Management 81*, 1–18.

Cullen, J. A. and E. T. Mansur (2017). Inferring carbon abatement costs in electricity markets: A revealed preference approach using the shale revolution. *American Economic Journal: Economic Policy 9*(3), 106–133.

Earnhart, D. (2004). Panel data analysis of regulatory factors shaping environmental performance. *The Review of Economics and Statistics 86*(1), 391–401.

Ellerman, A. D., P. L. Joskow, R. Schmalensee, J.-P. Montero, and E. M. Bailey (2000). *Markets for Clean Air: The U.S. Acid Rain Program*. Cambridge: Cambridge University Press.

EPA (2012a). Inventory of US greenhouse gas emissions and sinks: 1990-2010. Technical Report EPA-430-R-12-001, Office of Transportation and Air Quality, U.S. Environmental Protection Agency.

EPA (2012b). Regulatory impact analysis (RIA) for the final standards of performance for greenhouse gas emissions from new, modified, and reconstructed stationary sources: Electric utility generating units. Technical Report EPA-452-R-12-001, Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency.

EPA (2015). Regulatory impact analysis (RIA) for the final standards of performance for greenhouse gas emissions from new, modified, and reconstructed stationary sources: Electric utility generating units. Technical Report EPA-452-R-15-005, Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency.

EPA (2016). 2014 National emissions inventory (NEI), Technical support document (TSD). Technical report, Office of Transportation and Air Quality, U.S. Environmental Protection Agency.

Evans, D. A., B. F. Hobbs, C. Oren, and P. K. L. (2008). Modeling the effects of changes in new source review on national SO2 and NOx emissions from electricity-generating units. *Environmental Science and Technology 42*(2), 347–353.

Fell, H. and D. T. Kaffine (2018). The fall of coal: Joint impacts of fuel prices and renewables on generation and emissions. *American Economic Journal: Economic Policy 10*(2), 90–116.

Freedman, M., E. Owens, and S. Bohn (2018). Immigration, employment opportunities, and criminal behavior. *American Economic Journal: Economic Policy 10*(2), 117–151.

Gibson, M. (2018). Regulation-induced pollution substitution. Working Paper, Williams College.

Gray, W. B. and J. P. Shimshack (2011). The effectiveness of environmental monitoring and enforcement: A review of the empirical evidence. *Review of Environmental Economics and Policy 5*(1), 3–24.

Groosman, B., N. Z. Muller, and E. O'Neill-Toy (2011). The ancillary benefits from climate policy in the United States. *Environmental and Resource Economics 50*(4), 585–603.

Harrington, W. (1988). Enforcement leverage when penalties are restricted. *Journal of Public Economics 37*, 29–53.

Helland, E. (1998). The enforcement of pollution control laws: Inspections, violations, and self-reporting. *The Review of Economics and Statistics 80*(1), 141–153.

Heutel, G. (2011). Plant vintages, grandfathering, and environmental policy. *Journal of Environmental Economics and Management 61*(1), 36–51.

Holland, S. P. (2012). Spillovers from climate policy to other pollutants. In D. Fullerton and C. Wolfram (Eds.), *The Design and Implementation of U.S. Climate Policy*, pp. 79–90. University of Chicago Press.

Holland, S. P., E. T. Mansur, N. Z. Muller, and A. J. Yates (2018a). Decompositions and policy consequences of an extraordinary decline in air pollution from electricity generation. NBER Working Paper No. 25339.

Holland, S. P., E. T. Mansur, N. Z. Muller, and A. J. Yates (2018b). Decompositions and policy consequences of an extraordinary decline in air pollution from electricity generation. NBER Working Paper No. 25339.

Jaber, M. B. (2004). Utility settlements in New Source Review lawsuits. *Natural Resources & Environment 18*(3), 22–30.

Keohane, N. O., E. T. Mansur, and A. Voynov (2009). Averting regulatory enforcement: Evidence from New Source Review. *Journal of Economics and Management Strategy 18*(1), 75–104.

Knittel, C. R., K. Metaxoglou, and A. Trindade (2015). Natural gas prices and coal displacement: Evidence from electricity markets. NBER Working Paper No. 21627.

Linn, J., E. Mastrangelo, and D. Burtraw (2014). Regulating greenhouse gases from coal power plants under the clean air act. *Journal of the Association of Environmental and Resource Economists 1*(1/2), 97–134.

List, J. A., D. L. Millimet, and W. McHone (2004). The unintended disincentive in the Clean Air Act. *Advances in Economic Analysis and Policy 4*(2), 75–104. Special Edition: The Pollution Haven Hypothesis.

Muller, N. Z. (2012). The design of optimal climate policy with air pollution co-benefits. *Resource and Energy Economics 34*(4), 696–722.

Novan, K. (2017). Overlapping environmental policies and the impact on pollution. *Journal of the Association of Environmental and Resource Economists 4*(1), 153–199.

NRC (2006). *New Source Review for Stationary Sources of Air Pollution*. Washington D.C.: The National Academies Press. Committee on Changes New Source Review Program for Stationary Sources of Air Pollution Members, Board on Environmental Studies and Toxicology, Division on Earth and Life Studies, National Research Council, National Academies of Science.

Parry, I., C. Veung, and D. Heine (2015). How much carbon pricing is in countries' own interests? the critical role of co-benefits. *Climate Change Economics 6*(4), 1550019.

Raff, Z. and J. M. Walter (2019). Regulatory avoidance and spillover: The effects of environmental regulation on emissions at coal-fired power plants.

Reitze, A. W. (2001). *Air Pollution Control Law: Compliance and Enforcement*. Environmental Law Institute.

Schmalensee, R. and R. N. Stavins (2013). The SO_2 Allowance Trading System: The ironic history of a grand policy experiment. *Journal of Economic Perspectives 27*(1), 103–122.

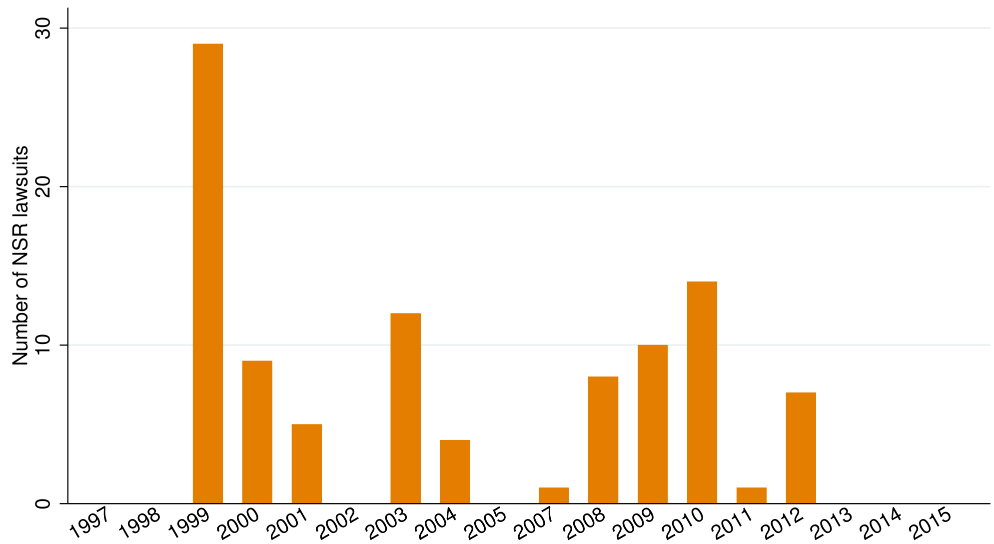
Sekar, S. and B. Sohngen (2014). The effects of renewable portfolio standards on carbon intensity in the United States. Resources for the Future Discussion Paper 14-10.

Srivastava, R. K., W. Jozewicz, and C. Singer (2001). SO_2 scrubbing technologies: A review. *Environmental Progress & Sustainable Energy 20*(4), 219–228.

Stavins, R. N. (2005). Vintage-differentiated environmental regulation. Working Paper Series, Harvard John F. Kennedy School of Government.

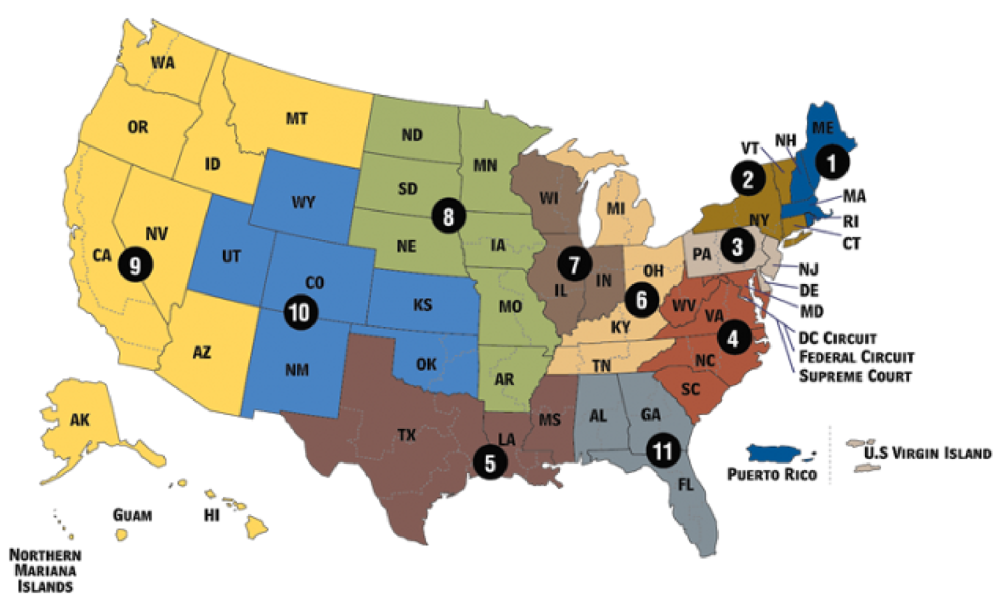
Figures

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



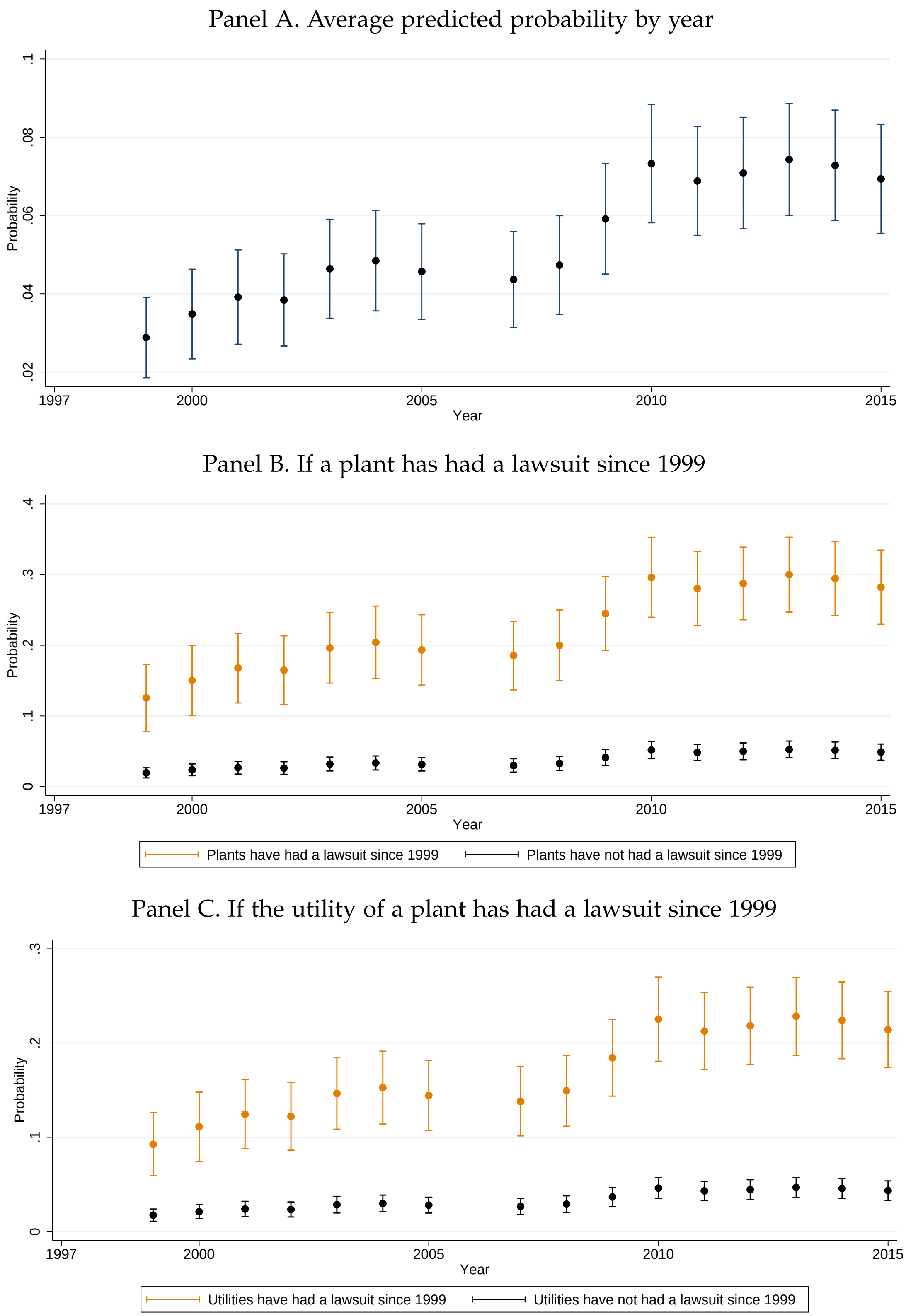
Source: EPA Power Enforcement Web Page and Integrated Compliance Information System - Federal Enforcement and Compliance (ICIS - FE&C) dataset.
Notes: In this figure we use the date referring to DOJ. We plot the figure using alternative dates in A.1.

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**



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.

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

Dep. var: log of	(1) SO_2	(2) NO_x	(3) CO_2	(4) SO_2	(5) NO_x	(6) CO_2
Prob (NSR lawsuit)	-0.012***	-0.010***	-0.003	-0.009**	-0.009***	-0.004**
	(0.004)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)
Log output (grossload)	0.716***	0.865***	1.356***	1.128***	1.007***	1.212***
	(0.015)	(0.012)	(0.019)	(0.149)	(0.091)	(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

Dep. var: log of	(1) SO_2	(2) NO_x	(3) CO_2	(4) SO_2	(5) NO_x	(6) CO_2
Prob (NSR lawsuit)	-0.007*	-0.009***	-0.003***	-0.008**	-0.010***	-0.005***
	(0.004)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
Log output (grossload)	0.963***	0.841***	0.956***	1.215***	1.035***	1.160***
	(0.030)	(0.016)	(0.005)	(0.097)	(0.083)	(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**

Dep. var: log of	(1) SO_2 rate	(2) NO_x rate	(3) CO_2 rate	(4) Heat rate
Panel A: Overall effects for all plants				
Prob (NSR lawsuit)	-0.017***	-0.018***	-0.013***	-0.010***
	(0.004)	(0.004)	(0.005)	(0.004)
Panel B: Intensive margin for operating plants				
Prob (NSR lawsuit)	-0.008**	-0.009***	-0.004***	-0.000
	(0.004)	(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 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**

Dep var: 1 = Operate / Report marginal effects of	(1) Logit	(2) LPM	(3) Logit	(4) LPM
Prob (NSR lawsuit)	-0.005**	-0.003***	-0.009**	-0.003***
	(0.002)	(0.001)	(0.004)	(0.001)
Prob (NSR lawsuit) × gas plant			0.007*	0.002*
			(0.004)	(0.001)
IV (CDD)	-0.263***	-0.149***	-0.262***	-0.149***
	(0.019)	(0.008)	(0.021)	(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 plants with or without the gas capacity**

Dep. var: log of	(1) SO_2	(2) NO_x	(3) CO_2	(4) SO_2 rate	(5) NO_x rate	(6) CO_2 rate	(7) 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 7: **Effect of NSR lawsuits on electricity generating units (EGUs)**

Panel A: Intensive margins for operating EGUs

Dep. var: log of	(1) SO_2	(2) NO_x	(3) CO_2	(4) SO_2 rate	(5) NO_x rate	(6) CO_2 rate	(7) Heat rate
			A.1 All operating EGUs				
Prob (lawsuit)	-0.012***	-0.008***	-0.001*	-0.011***	-0.008***	-0.000	-0.001**
	(0.004)	(0.002)	(0.000)	(0.004)	(0.002)	(0.000)	(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***	-0.012***	-0.001*	-0.011***	-0.011***	0.000	-0.001***
	(0.004)	(0.002)	(0.000)	(0.004)	(0.002)	(0.000)	(0.000)
Prob (lawsuit) × gas unit	-0.004	0.011***	0.000	-0.005	0.010***	-0.001	0.001*
	(0.008)	(0.004)	(0.004)	(0.007)	(0.008)	(0.011)	(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

	B.1 All EGUs		B.2 EGUs in operating plants	
Dep var: 1 = Operate	(1)	(2)	(3)	(4)
Report marginal effects of:	Logit	Logit	Logit	Logit
Prob (NSR lawsuit)	-0.001***	-0.003***	-0.001	-0.018*
	(0.000)	(0.001)	(0.002)	(0.010)
Prob (NSR lawsuit) × gas unit		0.010***		0.058***
		(0.003)		(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 7), 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 8: **Effect of NSR lawsuit probability and lawsuit allegation**

Dep. var: log of	(1) SO_2	(2) NO_x	(3) CO_2	(4) SO_2 rate	(5) NO_x rate	(6) CO_2 rate	(7) 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 Allowance 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 allowance	-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 allowance	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 allowance	-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 allowance	-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 allowance 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 allowance each year.

Table 9: **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 6. 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 10: **Decomposing the plant-level intensive margins – plant FE**

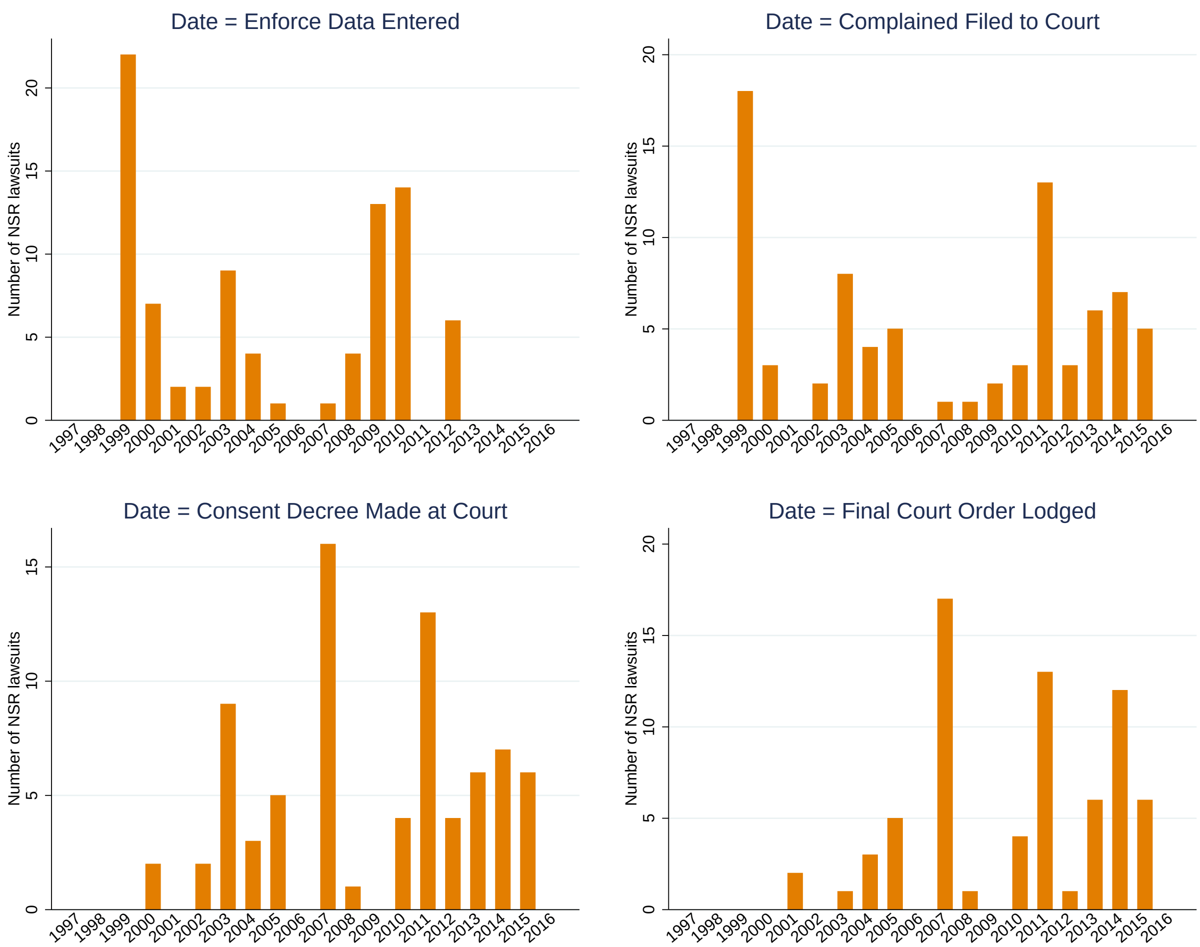
	(1)	(2)	(3)	(4)	(5)	(6)
Change in emissions:	EGU-level Intensive margins		EGU-level Extensive margins		Total effects	
		(percentage changes)		(percentage changes)		(percentage changes)
Panel A. SO_2 (thousand metric tons)						
EGUs without gas capacity	1.76	(0.03 %)	-6.57	(-0.12 %)	-4.81	(-0.09 %)
EGUs 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 9 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 7 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, Rocksport, 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
Wisconsic 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**

Dependent variable: NSR Lawsuit = 1	(1) Coefficients	(2) Marginal Effects
Historical emission average	-0.105***	-0.005***
	(0.029)	(0.001)
Historical emission st. dev.	0.106***	0.005***
	(0.028)	(0.001)
Historical output average (10^6 mega watt hours)	0.022***	0.001***
	(0.004)	(0.000)
Historical output st. dev.	-0.252***	-0.011***
	(0.028)	(0.001)
1 = Presence of scrubber before 1995	0.028	0.001
	(0.087)	(0.004)
Plant capacity in 1997	0.548***	0.025***
	(0.038)	(0.002)
1 = Presence of gas-fired units	-0.806***	-0.036***
	(0.091)	(0.004)
US federal judicial district: Circuit 1	0.707	
	(0.444)	
US federal judicial district: Circuit 3	0.429	
	(0.297)	
US federal judicial district: Circuit 4	1.860***	
	(0.246)	
US federal judicial district: Circuit 5	-1.446***	
	(0.404)	
US federal judicial district: Circuit 6	2.512***	
	(0.232)	
US federal judicial district: Circuit 7	2.461***	
	(0.236)	
US federal judicial district: Circuit 8	0.895***	
	(0.275)	
US federal judicial district: Circuit 9	-0.356	
	(0.403)	
Year FE	Y	Y
Number of observations	14189	14189
Chi(2)	2090.06	

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**

Dep var: log of	(1) Gross load	(2) Net generation
Number of cooling degree days (CDD) (in 1k)	0.591***	0.396***
	(0.111)	(0.126)
Prob (NSR lawsuit)	-0.007	-0.011**
	(0.008)	(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**

Dep. var:	(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**	0.005***	0.056**	0.053***	0.000
	(0.001)	(0.001)	(0.022)	(0.019)	(0.000)
Log output	0.023	0.077***	1.011	0.819	0.005
	(0.015)	(0.028)	(0.852)	(0.707)	(0.015)
Num. of observations	21,184	21,184	15,455	15,455	11,161
R-square	0.87	0.59	0.62	0.71	0.97

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 other outcome variables.

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

Panel A: Intensive margins for plants that stay operating

Dep. var: log of	(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)	-0.008**	-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

Dep var: 1 = Operate Report marginal effects of:	(1) Logit	(2) 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 8. 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**

Dep. var: log of	SO_2	NO_x	CO_2
A. Controlling for ARP SO_2 allowance and permit prices			
Prob (lawsuit)	-0.007*	-0.009***	-0.004*
	(0.004)	(0.002)	(0.002)
Log SO_2 allowance $\times$ 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**

Dep. var: log of	SO_2	NO_x	CO_2
A. Controlling for the natural gas price			
Prob (lawsuit)	-0.009**	-0.010***	-0.005***
	(0.004)	(0.002)	(0.002)
Log natural gas price	0.298*	0.164*	0.107
	(0.163)	(0.087)	(0.082)
B. Controlling for the natural gas price and the share of natural gas capacity			
Prob (lawsuit)	-0.009**	-0.012***	-0.004**
	(0.004)	(0.003)	(0.002)
Log natural gas price	-0.221	-0.018	-0.393**
	(0.207)	(0.178)	(0.153)
Gas share	-5.181***	-1.939***	-1.643***
	(0.567)	(0.437)	(0.255)
Log natural gas price × gas share	0.616***	0.497**	0.772***
	(0.189)	(0.234)	(0.213)
C. Controlling for the recession			
Prob (lawsuit)	-0.009**	-0.009***	-0.004**
	(0.004)	(0.002)	(0.002)
Prob (lawsuit) × Year 2008	0.008***	0.002	-0.001
	(0.003)	(0.001)	(0.001)
Prob (lawsuit) × Year 2009	0.007**	-0.008***	-0.000
	(0.003)	(0.002)	(0.001)
D. Controlling for other factors			
Estimates of Prob (lawsuit) with additional controls:			
1. Deregulation == 1	-0.008**	-0.009***	-0.004**
	(0.004)	(0.002)	(0.002)
2. Divestiture == 1	-0.010**	-0.010***	-0.003*
	(0.004)	(0.002)	(0.002)
3. Combined heat and power (CHP) == 1	-0.009**	-0.009***	-0.004**
	(0.004)	(0.002)	(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**

Dep. var: log of	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**	-0.009***	-0.004**	-0.017***	-0.018***	-0.013***	-0.010***
	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Average Prob (lawsuit)	-0.009**	-0.009***	-0.004**	-0.017***	-0.018***	-0.013***	-0.010***
from other plants	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
B. Lawsuit Probability from Other Plants in the Same Electricity ISO							
Prob (lawsuit)	-0.009**	-0.010***	-0.003	-0.017***	-0.017***	-0.010**	-0.008**
	(0.005)	(0.003)	(0.002)	(0.005)	(0.004)	(0.005)	(0.004)
Average Prob (lawsuit)	-0.009***	-0.008***	-0.001	-0.012***	-0.011***	-0.004	-0.003
from other plants	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
C. B. Lawsuit Probability from Other Plants in the Same Federal Judicial District							
Prob (lawsuit)	-0.009**	-0.010***	-0.003	-0.017***	-0.017***	-0.010**	-0.008**
	(0.005)	(0.003)	(0.002)	(0.005)	(0.004)	(0.005)	(0.004)
Average Prob (lawsuit)	-0.009***	-0.008***	-0.001	-0.012***	-0.011***	-0.004	-0.003
from other plants	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(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**

Dep. var: log of	SO_2	NO_x	CO_2	SO_2 rate	NO_x rate	CO_2 rate	Heat rate
Estimates of *Prob (Lawsuit)*:							
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**

Dep. var: log of	SO_2	NO_x	CO_2	SO_2 rate	NO_x rate	CO_2 rate	Heat rate
1. Refer to DOJ	-0.008**	-0.009***	-0.004**	-0.017***	-0.018***	-0.013***	-0.010***
	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
2. Enforcement data entered	-0.009**	-0.009***	-0.004**	-0.017***	-0.018***	-0.013***	-0.010***
(baseline)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
3. Complained filed	-0.009**	-0.010***	-0.003	-0.017***	-0.017***	-0.010**	-0.008**
	(0.005)	(0.003)	(0.002)	(0.005)	(0.004)	(0.005)	(0.004)
4. Consent decree	-0.009***	-0.008***	-0.001	-0.012***	-0.011***	-0.004	-0.003
	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
5. Final order lodged	-0.007***	-0.006***	-0.001	-0.008**	-0.007***	-0.002	-0.001
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(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.