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

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Abstract

Policies on greenhouse gas emissions have been shown to generate benefits in reducing local pollutants such as SO_2 and NO_x, but spillover benefits in the reverse direction have not been well studied. This paper estimates one such spillover by examining the impact of New Source Review lawsuits for violating SO_2 and NO_x standards on the CO_2 emissions of US power plants. We model the ambiguity of NSR regulation by using a discrete-time duration model to estimate and predict the likelihood of being named in a lawsuit as a continuous treatment variable. We find that a one percent increase in the NSR lawsuit probability (0.2 standard deviations) reduces CO2 emissions by 0.5 percent, an effect comparable to a $10/ton carbon tax. Further decomposition analysis suggests that most of these carbon co-benefits arise from the shutdown of coal-fired-only power plants in response to the NSR regulations.

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

JEL codes: L94, K32, Q58, H23

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1 Introduction

The notion of efficient policy design requires regulators to compare marginal costs from enacting the associated intervention with *all* potential economic benefits - direct effects as well as indirect and unintended effects. The indirect effects can go the opposite direction and dominate the intended objective of the policy (e.g., Almond et al., 2009), or enhance the existing policy objective and argue for a more stringent or stronger policy (e.g., Freedman et al., 2018). Such regulatory leakage and spillover problems on overlapping policies persist in many areas in the public policy debates. This problem is especially important if objectives from two different policies are similar and can be achieved using similar means of intervention.

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) using different sets of instruments, even though combustion of the fossil fuel is the main cause for both types of pollutants. The US Environmental Protection Agency (EPA) started to regulate SO_2 and NO_x in 1970 under the Clean Air Act (CAA) from the power sector and other sectors, while greenhouse gas emissions from the power sector have not been regulated despite its importance for global warming and climate change until recently regionally.[1] Compliance to these policies could strengthen the effectiveness of each other if these policies create spillover, for instance, regulating SO_2 may decrease CO_2 emissions if power plants switch to a cleaner fuel with a lower carbon content. These policies can also counteract the effectiveness of each other, for example, regulating SO_2 emissions in the power and manufacturing sector could increase CO_2 emissions if plants install more energy-intensive emission control equipment.

The impact of climate policies on SO_2, NO_x, and their health effects, has been studied extensively.[2] However, the spillover of local pollutant policies on greenhouse emissions is rarely studied, and the current literature has found mixed effects.[3] Holland (2012) found that meeting the Clean Air Act (CAA) standards has no effect on CO_2 emissions from California power plants plausibly because California power plants are mostly gas-fired, and Raff and Walter (2019) found meeting CAA standards on SO_2 reduce CO_2 for coal-fired plants by inducing usage of low-sulfur coal. Brunel and Johnson (2017) found that CAA attainment status has no

[1]TThe power sector is a major source of pollution emissions. It accounted for 74 and 34 percent of total SO_2 (7.7 million tons) and CO_2 (6.8 trillion tons) emissions, respectively, in the United States in 2010 (EPA, 2012a, 2016). We focus on coal- and gas-fired power plants, the total of which account for 98, 99, and 99 percent of SO_2, NO_x, and CO_2 emissions from the power sector respectively. Regional regulation on 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.

[3]There are several papers that investigate the magnitude of carbon co-benefits in the electricity market. For example, 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 when studying the changes in marginal damages of air pollution from electricity generation from 2010 to 2017.

effect on CO_2 in the manufacturing sector likely because the manufacturing sector does not have effective margins to reduce carbon intensity or the substitution and spillover channels counteract with each other. This paper studies how regulation of local pollutants affects CO_2 emissions from the US power plants.

Empirical studies on these policies rely on quasi-experimental methods such as difference-in-differences (e.g., Bushnell and Wolfram, 2012; Brunel and Johnson, 2017; Raff and Walter, 2019). However, it is not always clear which group is treated and the perceived stringency of the policy could vary from one year to the other. For instance, the interpretation and enforcement of the law can change from one administration to the next one, and the budget and time constraint to regulate can make it ambiguous which firm will be targeted.[4] In these cases, using the appealed treated group might cause researchers to draw an incorrect policy implication. To address the ambiguity of treatment that is common in many economic policies, this paper proposes a continuous difference-in-differences strategy by using the discrete-time duration model to account for the perceived *treatment (threat)* of the regulation. We estimate a time-varying threat for different firms based on settlement data from environmental lawsuits and estimate how the continuous threat of regulation affect emissions. This estimation strategy can be applied to many other economic policies when treatment is ambiguous, such as anti-trust and anti-competition laws, non-violent civil violations, and corporate compliance investigations.

In this paper, we focus on the New Source Review (NSR) and how NSR lawsuits probabilities affect *both* local pollutants (SO_2, NO_x) *and* CO_2 emissions from power plants in the United States. The NSR was included as part of the 1977 Amendments to the Clean Air Act with the goal of reducing SO_2 and NO_x emissions from the power sector. It regulates not only the construction of new power-generating facilities but also existing facilities to adopt emission control technologies. Although the NSR was instituted in 1977, reform did not take place until 1999 when the US Department of Justice (DOJ), representing the EPA, brought lawsuits to the Supreme Court against 83 power-generating units at 24 power plants.[5] The basis of the lawsuits depends on whether a plant has undergone a change that constitutes unlawful action. To motivate our empirical strategy, we explain the controversy around what constitutes unlawful action, how the stringency of the policy changes over time, and how it varies across plants in different regions in Section 2.1. This ambiguity implies that the EPA has a certain control and freedom on which plant to target, and that we only observe plants involved in the lawsuits but not plants vulnerable to the threat. This challenge leads us to estimate the

[4]Nancy Rose showed in her talk "Reinvigorating Competition Policy: How Can IO Scholars Contribute?" at ASSA 2019 that the number of second requests on public challenges fluctuate and decreased over time and cases on smaller transactions have declined since it is costly to use agency resource to collect evidence and agencies operate on a tight time clock. Even with the FTC guideline, it is not always clear to the firms which case will be investigated.

[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.

probability of being named in an NSR lawsuit, which quantifies the continuous treatment of "getting caught" for each power plant, hereafter the *NSR lawsuit probability*.

Our discrete-time duration model, built on a cross-sectional probit model of NSR lawsuits in Keohane et al. (2009), allows us to predict the lawsuit probability and form a continuous treatment variable that is plausibly exogenous for our analyses on current emissions and plant operations. This dynamic approach is important because we need to allow NSR lawsuit probabilities to vary across plants and over time, and to correlate flexibly over time within a plant as well. However, one can argue that this measure could potentially be biased as factors affecting these probabilities may be correlated with plant operation margins – which leads us to identify the effect of lawsuit probabilities via its functional form assumption in the first stage. To circumvent this problem, we use historical emissions and energy production as in Keohane et al. (2009), then include other cross-sectional variations such as the judicial district where a plant is located. The use of historical data is motivated by the legal arguments within the cases against power plants, where historical violations in 1980s and early 1990s were often cited as the reason they were sued, despite their first legal notice was served much later. 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).

Using predicted NSR lawsuit probabilities from the duration model, we proceed to estimate how these threats affect both regulated and unregulated emissions from US power plants between 1995 and 2015. The effect of NSR lawsuits on CO_2 emissions is ambiguous. Installing and increasing the usage of SO_2 and NO_x control technologies may increase power plants' electricity consumption and CO_2 emissions. Also, building new (usually more efficient and less CO_2 intensive) boilers may become less appealing since doing so may trigger a long and undesirable review process to acquire new source permits (Bushnell and Wolfram, 2012; Evans et al., 2008; Heutel, 2011; List et al., 2004). This type of distortion may limit the potential for CO_2 reduction and even increase CO_2 emissions. Moreover, NSR may reduce CO_2 if plants reallocate production from older units to newer units via intensive margins, the latter of which is likely to be fuel-efficient (as measured by operating heat rate).[6]

We found that NSR lawsuit probability has a significant and sizable effect on SO_2, NO_x, and CO_2 emissions. To separate the scale effect on emissions, we control and instrument for gross electricity generation. Our effects are robust to the inclusion of plant and year fixed effects and other overlapping policies such as the NO_x National Budget Trading Program (NBP), the Clean Air Interstate Rule (CAIR), and the Regional Greenhouse Gas Initiative (RGGI). We find that a one percent increase in the NSR lawsuit probability (about a 0.2 standard deviation) decreases SO_2 by 0.6 percent, NO_x by 1.2 percent, and CO_2 by 0.5 percent. This change is equivalent to

[6] 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. Therefore, the NSR may induce a fuel switch from coal to natural gas since gas produces less SO_2 and NO_x.

yearly reductions in SO_2 emissions by 43.7 thousand metric tons, NO_x by 29.1 thousand metric tons, and CO_2 by almost 10 million metric tons in 2007 – all of which are sizable compared with national emission inventories (EPA, 2016). Evaluating emissions at a 42 dollar-per-metric-ton social cost of CO_2 (SCC), the climate co-benefits would be 415 million US dollars (in 2007 real dollar terms).[7] The magnitude of CO_2 co-benefits implies that it is important to account for climate spillover into the total benefit of regulating pollution emissions from the power sector. Our results also suggest that NSR has been effective in terms of reducing carbon emissions. Specifically, the magnitude of co-benefits from a one percent lawsuit risk is equivalent to the benefit of a \$10/ton carbon tax, using results from Linn et al. (2014).

It is necessary to understand how energy policies can achieve carbon reduction from the power sector efficiently, and whether our findings of climate co-benefits can be generalized to other environmental policies for the power sector. To answer these questions, we decompose the counterfactual CO_2 co-benefits by plants with and without gas-fired generators. We find that each group of both contributes roughly half of the estimated co-benefits. Moreover, we find the intensive and the extensive channels work differently for the two groups of plants. Within co-benefits from coal-fired-only plants, three quarters come from the extensive margin. Specifically, 14.1 percent of co-benefits is from the operating coal-fired-only plants and 44.5 percent is from shutting them down. In contrast, the co-benefits from plants with gas-fired generating capacity is mostly due to the intensive margin. Specifically, we found that operating plants with gas-fired units contributes 29.7 percent of co-benefits, while the extensive margin contributes only 11.7 percent of co-benefits.

To investigate the factors that drive the intensive channels, we further examine how NSR lawsuits induce plants to improve both abatement technologies and thermal efficiency, holding the scale of production and other factors constant. Specifically, higher NSR probabilities have led to significantly lower SOx, NO_x, and CO_2 emission rate (lb/mmBtu), hereafter the *technology channel*. However, a higher NSR lawsuit probability only affects a unit's thermal efficiency (heat rate, mmBtu/mWh) by a small magnitude and the estimate is insignificant, hereafter the *efficiency channel*. This result implies that most of the reduction in SOx, NO_x, and CO_2 emissions from operating plants are the results of improving the abatement technology, rather than power generation efficiency.

This paper contributes to the following strands of literature. First, this study contributes to the literature on regulatory spillover and overlapping policies as discussed initially. In addition, studying the sources of spillover offers important insights for more effective carbon policy design: we quantify various channels that contribute effectively to CO_2 reduction, especially

[7] We assume 3 percent discount rate for the SCC. More assumptions can be found in the EPA 2017 archive https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html

the extensive margin of the fuel switch.[8] Our results provide a reassuring implication that at the current equilibrium, there would not be a leakage from regulating SO_2 and NO_x that leads to an increase in unregulated CO_2 and other greenhouse gases from strengthening the regulation of SO_2 and NO_x production in the power sector.

Second, this paper also contributes to the body of knowledge surrounding on 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 channel in new units, and the induced reduction channel in investments in new technologies in existing units, which is a typical type of distortion from VDR (List et al., 2004; Heutel, 2011; Bushnell and Wolfram, 2012). But past studies have not agreed to the sign and magnitude of environmental impacts (Evans et al., 2008; Keohane et al., 2009; Bushnell and Wolfram, 2012).[9]

Lastly, this paper is also related to the literature on enforcement and compliance (see Helland, 1998; Earnhart, 2004; Gray and Shimshack, 2011), partly because the degree of enforcement is difficult to measure when there is no clear threshold of violation and policies are uncertain. In this paper, we focus on estimating the perceived stringency by estimating the probability of being named in a lawsuit. Doing so allows us to measure the effective intensity of enforcement.

The rest of the paper is organized as follows. Section 2 gives a background on the New Source Review 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, and Section 4 presents results on both stages of our estimation results. Afterward, we present decomposition results in Section 5 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 a within-plant fuel switch. Section 7 presents our conclusion.

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;

[8]Previous work has suggested a fuel switch can induce CO_2 reduction, e.g., (Linn et al., 2014). Broadly speaking, our work is related to the design and impact of the Clean Power Plan and related federal policies on greenhouse gas mitigation (Bushnell et al., 2017; Abito et al., 2018).

[9]The literature has stopped investigating in 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. (We provide the background and changes of NSR from 1977 to 2015 in Section 2.1).

the EPA only mandates buildings constructed after 1978 to make a real state 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 increase with scientific development over the time; and the 1970 Clean Air Act (CAA) only imposes mandates for existing emission sources. The distortion that arises from these differential treatments can create a regulation wedge, or a "leakage", across different units. In the case of the power sector, the 1970 CAA would encourage firms to delay the introduction of new units, extend the lifetime of existing units that are exempt from the CAA regulations, undermine the effectiveness of the regulation, and potentially raise the net cost of the regulation.

The New Source Review (NSR) was created as part of the 1977 Clean Air Act Amendments, to regulate the modification of existing power generating units that were not subject to regulation under the 1970 CAA, and to expedite the process of replacing older and less efficient units with new units. A utility company that plans to undergo a modification to an existing unit in a given plant has an option to voluntarily apply for the New Source "Permit to Construct" which requires the plant to undergo an extensive review process. The proposed utility must provide simulated 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.[10] Although NAAQS is 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 or triggering a lengthy review process, which is also costly to the firm, the utility company can choose to delay modifications, or fail to inform the EPA of their modifications. Doing so may trigger a lawsuit alleging a utility company has violated the Clean Air Act by failing to inform the EPA of the modification or deliberately delaying new modifications to a unit that needs to be improved. In the latter case, the lawsuit usually quotes emission records from previous decades. Later in our estimation, we utilize historical variation of power plant operational characteristics to predict the NSR lawsuit risks. The likelihood of facing an NSR lawsuit, in turn, significantly affects emissions and plant operations.

The ambiguous nature of the lawsuits motivates us to estimate the probability of a lawsuit. First, the power industry was not aware of the NSR threat until November 1999, when the U.S. Department of Justice (DOJ), as an enforcement agent of the EPA, sued 8 utility companies alleging 24 power plants and 83 units violated the NSR.[11] We interpret this as an exogenous increase in NSR lawsuit probability from 1999 onwards.

[10] The utility must adopt to EPA-approved engineering models to project future emission levels. The common models used are AERMOD and CALPUFF.

[11] The utility companies sued in November 1999 were American Electric Power (AEP), Cinergy, Dynergy, FirstEnergy, Southern, TECO Energy, and Tennessean Valley Authority.

Second, it is unclear as to which plants the EPA will target. In those first set of lawsuits, the DOJ alleged major, life-extending modifications had been made to these 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), leaving the EPA with significant discretion as to which plants to target for litigation. For example, the EPA has the flexibility to decide what kind of change is large enough to affect the regional level NAAQS, which means there may be different enforcement levels between plants in CAA attainment vs. non-attainment counties. As another example, the interpretation of the law depends on judges at different federal courts which would affect the expected outcome of the lawsuits. Table 1 shows that emissions from district 5 are comparable to district 3, 4, and 10 but district 5 has had zero lawsuits. This variation in the leniency across regions would, in turn, affect how the EPA targets plants across jurisdictions.

Third, the ambiguous nature of enforcement has changed over time because the NSR program has experienced several periods of rule changes.[12] 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 a rule change of the NSR called the Equipment Replacement Provision (ERP). Starting in December 2002, ERP exempted any routine modification change that requires 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 to install BACT in existing units. Consistent with this rule change, Figure 1 shows that the average number of NSR lawsuits decreased by 2004. After four years, in March 2006, the D.C. Circuit Court vacated the ERP. Consistent with the removal of ERP, in Figure 1 we start to see an increasing pattern of NSR lawsuits after 2006. Since then, the Bush EPA proposed a revision of the NSR that would permit authorities to combine and aggregate emissions from plants modifications when projects across different plants but under the same utility companies were related, known as the "aggregation policy". This rule would effectively reduce the stringency of the NSR, and the final rule was issued in Jan 2009, within the first week of the Obama administration. The new Obama EPA 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 variation in NSR enforcement since 1999, we estimate a time-varying probability of being named in an NSR lawsuit for each plant using a discrete-time duration model, which we then use to estimate the reduced-form relation of lawsuit probability on emissions and plant operations.

The basis of our main hypothesis is that we think firms believe that NSR lawsuits are a credible threat in our sample period and would respond to avoid an allegation. First, the EPA has won existing allegations. Second, the negative consequences of the lawsuit must be so extreme that they would provide plants with an incentive to respond before any threat becomes salient.

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

Most settlements require utility companies to retire, retrofit, or install BACT for specific power-generating units in the plants with alleged modifications. Utilities are required to install BACT in plants allegedly in violation within a proposed short window or face immediate retirement, as well as up to $27,500 per-day in civil penalties. The potential penalty and forced retirement provide good incentives for utility companies to reduce emissions, especially for plants that face a higher risk of a lawsuit. In this paper, we propose and estimate a reduced-form relationship on how NSR lawsuit likelihood affects emissions and plant operation margins.

2.2 Data

To perform extensive ex-post analysis on how the NSR affects emissions and plant operations, we collected data for 1,350 coal- and gas-fired plants from about 800 utility companies between 1995 and 2015. We collected monitoring data that reported SO_2, NO_x, and CO_2 emissions using the Continuous Emission Monitoring System (CEMS) database from the EPA. We also collected power plant operation data including gross load and net power generation, heat input, fuel use, and other plant characteristics using the Form-767, 906 and 923 from the U.S. Energy Information Administration (EIA).

To further examine the extensive margin that drives the emission reduction, we collected nameplate and operating capacities of electricity generating units, 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 data from CEMS and heat input from the EIA Form-767 and Form-923, and thermal efficiency (operating heat rate, defined as heat input needed per unit of power generation) using heat input and power generation. In Table 2, we show that there is a significant amount of variation in the key variables of interest, including emission level, emission rate, heat rate, and likelihood of being named in an NSR lawsuit.

To examine how NSR lawsuit probabilities affect emissions and plant operations, we extracted information from all 31 NSR lawsuit consent decrees covering 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 from the EPA Coal-fired Power Plant Enforcement web page.[13]

It is important to use the most relevant date that defines when a lawsuit becomes a salient threat, because we not only need to estimate the dynamic survival likelihoods consistently but also quantify the date to which the firm will respond by using avert actions to reduce the

[13] EPA Power Enforcement Page 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 got a legal notification when the enforcement data was entered in 2000. See our explanation in the next paragraph and our Appendix Table A.1 for detail.

risk.[14] We link the above lawsuits with detailed lawsuit enforcement data using the Integrated Compliance Information System - Federal Enforcement and Compliance (ICIS - FE&C) data set from the EPA Enforcement and Compliance History Online (EPA ECHO) database. The ICIS-FE&C data set allows us to track all the milestones of the lawsuits and provide detailed enforcement characteristics. An important milestone includes the date the lawsuit was filed in federal court. Prior to the court date, first we observe the date DOJ was referred to proceed allegation as well as the date the enforcement data was entered into the database, and after that we observe the date(s) the complaint is/are filed in the court, as well as the settlement date.[15] We chose to use the date when the data was entered into the enforcement database as the baseline measure to estimate the probability of being sued, because plants will get a notice from the court on this date and would begin to prepare for the lawsuit.[16]

In Appendix Table A.1, we report all NSR lawsuits from 1999 to 2015. On average, cases have settled within about six years.[17] Later for robustness we use other dates to define our lawsuit timing. In addition, no utilities have had multiple lawsuits in our sample. For all lawsuit cases, the DOJ won.

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, historical net generation and heat input data were collected 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 district information to predict NSR lawsuit probabilities. Figure 2 shows the map of federal circuit districts in the U.S., and Table 1 shows the total number of lawsuits by federal judicial circuit district.

[14]This is not an important issue for previous studies since they aim to estimate or construct a cross-sectional NSR risk. For example, Keohane et al. (2009) estimate cross-sectional probit risk 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.

[15]Usually the date of ”enforcement data entered” is recorded right after (a day or a few days) the date when a case is referred to the DOJ. In the next few weeks, we observe the date ”complained filed to court”. In the next few months (and in very few case years if a lawsuit is 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 assumes the lawsuit date is somewhere from the ”DOJ date” to the ”consent decree date”. Lastly, months (in very few case years) after the consent decree date, we observe a date when ”the final order is lodged”.

[16]Ideally we would like to use the DOJ referring date but the data is missing for public regulated plants. Usually, the enforcement data entry date is a few days later than the DOJ date; and the court date is a few month later.

[17]From 1999 to 2015, 37 settled utility companies were required to pay 188 million dollars civil penalty (with an average of 5 million dollars), 34 settled plants were required to spend or pay in total 26 billion dollars for compliance action (with an average of 722 million dollars), and 4 companies to spend or pay in total 26 million in supplementary projects (with an average at 6.5 million dollars). The numbers are from the lawsuit settlements. The compliance action cost includes the sum of the dollar values of injunctive relief and the physical or nonphysical costs of returning to compliance. Injunctive relief represents the actions a regulated entity is ordered to undertake to achieve and maintain compliance, such as installing a new pollution control device to reduce air pollution, or preventing emissions of a pollutant 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.

Finally, we collected information of other overlapping federal or regional environmental and energy policies that might affect power plant operations. Specifically, we collected states and years that would be affected by the Clean Air Interstate Rule (CAIR) which regulates SO_2 and NO_x after 2009, 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. We also collect county-level attainment status of the National Ambient Air Quality Standards (NAAQS) over our sample period. Table 2 displays the summary statistics of key variables used in our analyses.

3 Empirical Strategy

3.1 Estimate NSR Enforcement Likelihoods

To assess the impact of New Source Review lawsuits on plant emissions and operations, we need to identify the plants that are affected by the NSR from other plants, i.e., correct treatment and control groups. Otherwise, a naive comparison between plants involved in an NSR lawsuit and other plants will reveal uninformative effects of the NSR. For instance, Duke Energy had an NSR lawsuit in 2000. This case can be correlated with other reasons that Duke Energy is a heavy emitter in 2000, e.g., that Duke Energy has been a heavy emitter in the past. For another instance, in 2003 Santee Cooper was named in an NSR lawsuit. It is likely that Santee Cooper had a risk of being named in the lawsuit as early as 2000. Therefore, computing changes in emissions from Duke Energy from 1999 to 2000, and examining how this number is compared to how Santee Cooper changes from 1999 to 2000 will misrepresent the effect of an NSR lawsuit.

To make the comparison, previous studies have either adopted engineering assumptions or formed time-invariant control and treatment groups. Ex-ante studies such as EPA Regulatory Impact Analyses (RIAs) have simulated emission trajectories by assuming important parameters like the percentage of plants that might have complied with the 1999 NSR rule before the ERP rule change (e.g., EPA, 2012b, 2015) using the Integrated Planning Model (IPM).[18] NRC (2006) improve on the IPM model by allowing plants to adjust their extensive and intensive margins and use a broader range of assumed parameters, but they still assumed that specific sets of selective plants would undergo retrofit, retire, or repower under the NSR. However, doing so makes the assessment sensitive to the chosen economic assumptions and parameters.

[18] EPA RIAs use the Integrated Planning Model (IPM) by ICF Consulting to simulate the impact of the NSR. "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" (from NRC (2006) Chapter 6).

Previous ex-post studies have 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 status (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 from 1999 to 2002 and after the ERP rule change in 2003. Keohane et al. (2009) use historical emissions and power generation from the 1980s to estimate a cross-sectional likelihood of an NSR lawsuit, and then study how the estimated lawsuit risk affects emissions from 1996 to 2000.

However, to examine the effect of the NSR on changes from 1995 to 2015, we need to allow the likelihood of an NSR lawsuit to vary over time. First, the NSR has experienced several rule changes since 1999 so that the perceived stringency has changed over time. Also, the probability of being named in a lawsuit for a given plant can be correlated and persistent over time. To account for those factors, we deploy a discrete-time duration model to flexibly estimate the likelihood of NSR lawsuits using historical emissions, power generation, capacity, emission control technologies, and lawsuit leniency across 11 federal circuit courts.

Specifically, we begin by motivating a discrete-time survival model $S\left(t|Z_i\right) = S_0(t)\exp\left\{Z_i\delta\right\}$, where $S\left(t|Z_i\right)$ 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:

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

where the hazard rate $\rho_{it} \equiv \Pr\left(lawsuit_{it} = 1\right)$ describes the conditional probability that plant i will be involved in a lawsuit in year t given that i survived in year $t-1$. We explain the covariate Z_i next. The hazard rate of each year t is picked up by year fixed effects ϕ_t. The clock in our c-log-log model increments by year. To allow for correlation within plants, we cluster our standard error at the plant level.

Because we estimate hazard using a discrete-time duration model, the parameters in the vector δ are identified using the cross-sectional variation across plants. Specifically, the covariate Z_i includes the first and second moments in historical emissions and power generation prior to 1999 (from 1985 to 1994, which may trigger a specific allegation of violations in an NSR lawsuit), log generating capacity in 1997, scrubber installation status in 1997, and fixed effects of 11 federal judicial districts. First, we use historical emissions and power generation to identify plants that are more likely to be subject to a lawsuit. Plants named in NSR lawsuits were mostly sued for recent modifications, however, the violations cited in most consent decree dated back to the 1980s and early 1990s.[19] Keohane et al. (2009) similarly use historical emission information to predict the threat of a lawsuit in 1999 and 2000. For robustness, we changed this historical period to predict NSR lawsuit probabilities and we found similar results.

Second, since all consent decrees cite violations in SO_2 and many of them cite enforcement measures to install SO_2 technologies (such as scrubbers), plants without scrubbers are more vulnerable to NSR lawsuits (Reitze, 2001; Jaber, 2004). We therefore include pre-1999 NSR reform scrubber installation to predict NSR lawsuit hazard, as in Bushnell and Wolfram (2012). Moreover, it is possible that the DOJ is more likely to focus on relatively higher-profile cases and larger plants have higher odds of being named in a lawsuit, we therefore include the log of pre-1999 NSR reform capacity in the covariate Z_i to control for the size of a plant.

Lastly, we find 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. Table 1 shows the number of lawsuits by federal circuit districts (All NSR lawsuits are settled in federal circuit court). There have been no lawsuit cases in the 5th Circuit (for LA, MS, and TX) although the emissions from the 5th district are comparable across districts 3, 4, and 6; and 35 lawsuits in the 6th Circuit (for KY, MI, OH, and TN). In order to allow and infer that plants in certain regions are less likely to be targeted (such as the 5th district) and plants in some regions are more likely to be targeted (such as the 6th district), we include fixed effects of the federal circuits to allow pro-business districts to have a different effect on the lawsuit hazard.

We chose the c-log-log model instead of alternative discrete-time duration models such as the proportion 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 variation of the predicted likelihood of a lawsuit is significantly dependent on the historical emission levels. Since our estimation strategy is based on year fixed effects, the variation in both levels of enforcement and interpretation of the NSR, as well as other macro demand and supply shocks over time affect how base year hazard varies over time. These factors affect how NSR likelihood $\hat{\rho}_{it}$ varies from one year to the next given a plant.

3.2 Estimating Effects of NSR Lawsuits

We estimate how NSR lawsuit risk affects plant emissions and operations using predicted probability $\hat{\rho}_{it}$ from Section 3.1. For the log of total emissions (SO_2, NO_x or CO_2) from power

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

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. Because NSR likelihoods are generated regressors, we correct the estimated standard errors by bootstrapping both the complementary log-log model and our main estimation equation above. Our study has both coal-fired plants and gas-fired plants which differs from previous studies on NSR.

Our goal is to identify the effect of NSR probabilities on overall 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*. The vector X_{it} further controls for the natural gas price in a state and by year to control for fuel-switch incentives, in addition to plant and year fixed effects α_i, α_t. In order to separate the effect of averting behavior due to a lawsuit risk from complying behavior due to a lawsuit settlement terms (or expected terms from the allegation), we remove the post-lawsuit years for the plants that have had a lawsuit in our sample.[20]

The key parameter of interest, β_1, presents the marginal effect on percentage changes to emissions if NSR lawsuit probabilities increase by one percent holding output constant. The first stage results allow us to understand the NSR effect on emissions via adjusting output. The second stage explains the effect of NSR on emissions independent of the scale effect. If NSR lawsuits could directly cause actions that would reduce emissions given constant output, we would expect β_1 to be negative. It is also possible, that for certain pollutant emissions, most emission reductions are the result of reduced power generation. In this case, we would expect the first-stage coefficients of $\hat{\rho}$ on $\ln Q_{it}$ to be negative. If the scale effect is the only channel, we also expect β_1 to be small or even insignificant from zero. Because higher demand for electricity can lead to a greater need for power generation and therefore more emissions, we expect β_2 to be positive.

It is possible that plants that have experienced emission reductions and plants that have not experienced emission reductions have different unobserved characteristics which are correlated with the NSR probabilities. For example, plants located farther away from metropolitan areas may be subject to a lower enforcement risk. To control for the potential omitted variable bias, we include plant-level fixed effects, which also implicitly accounts for potential "peer effects" for plants within the same state. In addition, we control for year fixed effect to account for year-to-year national variation in emission levels, and year-to-year national changes in the NSR probabilities. Moreover, estimating Equation (2) at the plant level allows us to account for

[20] In the complementary log-log model, we use observed lawsuits to predict the lawsuit probability not only for other plants but also for any given plant over time. This requires us to include post-lawsuit years for a plant that has had a lawsuit when estimating Equation (1). Those years are not included when estimating Equation (2). For robustness we include those years and control for the post-lawsuit effect and find results robust to the baseline.

potential substitution within a plant across various electricity generators.[21] Since the c-log-log model allows for correlation of hazard across years within a plant, including plant fixed effects and year fixed effects will not tease out variation in the NSR probabilities. Lastly, one might worry that retirement status of the most polluting units would affect both the lawsuit threat and the emissions. However, as we described in the background session and our first stage model on estimating NSR lawsuit probabilities, the risk of lawsuit usually come from historical emissions at the utility level. In addition, in cases that the court rules to certain plants to be closed, many of the plants of the alleged utility company have already closed before the agency filed the lawsuits against the company.

Furthermore, other policies and regulations that aim to reduce emissions from the power sector can affect the SO_2, NO_x, and CO_2 emissions. Therefore, we include a dummy variable that equals to one if a state in a year was regulated under the National NO_x Budget Program, and a dummy variable for the Regional Greenhouse Gas Initiate (RGGI), and another for the Clean Air Interstate Rule (CAIR).

The log of power generation may be endogenous for multiple reasons. Plants may adjust output when they reduce emissions, and there are some technologies (such as scrubbers), which we omitted, but can affect both power generation and emission levels. We adopt a demand shifter, state-year level cooling degree days (CDD), as our instrumental variable to predict the log output. In Section 6 we show our first and second stages are robust to using alternative instruments.

To further understand economic factors that drive our main results, we also estimate Equation (2) on other dependent variables such as emission rates, heat rates, a dummy representing if they have shut down, and examine how results vary across plants with and without gas capacity. We report these results in Section 4.

4 Estimation Results

4.1 Estimates of NSR Lawsuit Likelihoods

In this section, we present estimates of NSR lawsuit likelihoods using the complementary-log-log model described in Section 3.1. In Appendix Table A.2, we report the estimated parameter $\hat{\delta}$ in column 1 and the corresponding marginal effect 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 characteristics are good predictors for hazard. The Wald Chi-squared for the joint-significance test of plant-varying variables excluding year effects is 97. In particular, we

[21] We estimate at two alternative levels: 1) at the utility level to account for substitution pattern within a utility company across plants and find similar results; and 2) at the electricity generating unit (EGU) level to directly estimate the effect across EGUs and find similar results, but emissions are noisier at the EGU level.

found the first and second moments of historical power generation, as well as plant capacity are strong predictors of NSR lawsuit hazard.

Our estimates suggest that plants with a history of producing more outputs are more likely to be named in a lawsuit. For example, column 2 of Table A.2 implies that an increase in historical utility-level power generation of 50 million megawatt hours (about the average of historical generation and one standard deviation of historical generation) would increase the likelihood of being named in the NSR lawsuit by 5.5 percent. Also, we found the coefficient of historical standard deviation to be negative and significant which implies that consistently heavy power generators are more likely to be named in a lawsuit.

Furthermore, our estimates in Table A.2 suggest that plants located in federal judicial districts 4 (DC, MD, NC, SC, VA, WV), 6 (KY, MI, OH, and TN) and 7 (IL, IN, and WI) are more likely to be named in a lawsuit, when compared with other regions that are less pollution-intensive (for example, districts 1 and 2) or with a more pro-business judicial circuit courts (for example, district 5). The average predicted NSR likelihoods across all state is 2.1 percent, and the median is 0.7 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 unconditional probability of having a lawsuit $\hat{\rho}$. In Figure 3 Panel A, we show the average predicted likelihood of having a lawsuit across all plants for each year. The average probability gradually increases over time from 1999. The average NSR lawsuit likelihoods experienced a drop in 2007. This is consistent with the fact that we observe few new lawsuits filed from 2005 and 2007 in Figure 1.

Moreover, we show how our estimation allows us to construct better treatment and control groups than using observed lawsuits for our analysis. In Panel B of Figure 3, the light-colored points show the predicted lawsuit risk if a plant has had a lawsuit in our sample period, and the black points show the lawsuit risk for a plant that never has a lawsuit. In Panel C, we repeat the same exercise and see if lawsuit risks vary if the utility that owns a plant has had a lawsuit in our sample. First, comparing two groups cross-sectionally, we found plants that have never had lawsuits are still subject to a significant positive risk despite that risk is small. It is therefore important to have a probability model and allow the treatment to be continuous across plants in a year. Second, we found that the risk increases over time for both groups and the wedge between these two groups also increases. This evidence suggests that it is important to estimate a dynamic model to account for the correlation in unobserved hazard over time within a plant which is not represented in previous studies (e.g., Bushnell and Wolfram, 2012; Keohane et al., 2009). This exercise also puts the marginal effects of a one-standard-deviation increase in historical power generation. That increase (5.5 percent) is roughly equivalent to the difference in the lawsuit risks between larger and smaller plants in 2015.

4.2 Effect of NSR Lawsuits on Local Pollution and CO_2 Emissions

Using the NSR lawsuit likelihood predicted from Section 4.1, we estimate how NSR risks affect local pollution and CO2 emissions from 1995 to 2015. Since the lawsuit probability is a generated variable, we correct this variable by bootstrapping both the duration Equation (1) and the main IV Equation (2).

In Table 3 Panel A columns 1–3, we report the estimation of Equation (2) on the log of SO_2, NO_x, and CO_2 emissions, treating power generation (log of gross load of power generation) as an exogenous variable. To control for unobservables that can be correlated with the NSR lawsuit probabilities, we control for plant and year fixed effects. Plant fixed effects capture unobserved plant-level characteristics that are time-invariant and affect compliance costs (e.g., geographic factors). Year fixed effects pick up macro factors that affect time variation in NSR lawsuit probabilities and emissions such as changes in the presidential administration and changes in NSR rules (see Section 2.1).

The OLS results in Table 3 Panel A columns 1–3 suggest that NSR lawsuits have a sizable impact on emission reduction, holding other factors constant. Also, we find a modest scale effect, e.g., bigger plants that have a higher demand for electricity generation are more likely to emit significantly more tonnes of SO_2, NO_x, and CO_2.

A remaining concern is that utility companies can adjust the output across their plants to be more efficient which affects the emission levels. This endogeneity problem not only threatens the identification of $\hat{\beta}_2$, but also the key parameter of interest, $\hat{\beta}_1$. The coefficient of NSR lawsuit likelihoods and the power generation output can be simultaneously identified. To address this problem, we use only the exogenous part of power generation, which is affected by the electricity demand, i.e., using a demand shifter. We adopt the number of cooling degree days (CDD) as our instrumental variable, which captures variation in power generation that is affected by the demand shocks.[22] Therefore, our IV is unlikely to be correlated with unobservables from the supply side.

We report our first-stage result of power generation in Appendix Table A.3 column 1. Our first stage is strong, and it passes the weak instrument test. The F-stat for the (joint) significance of our IV is 34.4.[23] Our first stage implies that if the number of cooling degree days increases by 100, the gross load of power generation would increase by 6 percent holding other factors constant.[24] As for the included variables, a greater NSR lawsuit probability will reduce power generation, albeit not statistically significantly in the case of grossload. A 5-percent increase in the NSR lawsuit probability (about one standard deviation) would decrease the gross load of

[22] A greater number of cooling degree days would increase the demand for electricity in the summer months.

[23] The Cragg-Donald F-stat is 13.7, and the Kleibergen-Paap F-stat is 7.0. For robustness we tested the joint significance of IVs when we have more than one IV.

[24] 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 find the main results are robust (not reported).

power generation by about 4.5 percent holding other factors constant. Since gross load includes the electricity intake, we repeat our exercise using net generation in column 2 and find similar results. Our first stage is also robust to alternative demand shifter IVs.

We present our baseline IV results in Panel A of Table 3 from column 4 to 6. Our baseline estimates have signs similar to the OLS results in columns 1 – 3. Comparing the IV results to the OLS results, we find the OLS results bias the estimate upward for SO_2 and slightly upward for NO_x.[25] This implies that we will overestimate the effect of the NSR lawsuit risk on emissions, if we fail to account for the fact that a utility company can allocate power generation from a higher risk plant to a lower risk plant. Since the NSR lawsuit in general target SO_2 and NO_x, we do not see much change in CO_2 coefficient.

First, our baseline IV results suggest a substantial *scale effect* of power generation on emissions. The second-stage coefficient for log output is positive, significant at the one percent level, and fairly large. A one percent increase in the gross load of power generation increases SO_2, NO_x, and CO_2 emissions by 1.0 to 1.2 percent.

Second, we found overlapping regulations and economic conditions affect emissions. In particular, we find that regulation under CAIR will reduce SO_2 and CO_2 emissions, while being regulated under RGGI lead to reduction in SO_2 emissions. Our estimate for the NBP is negative but not significant, which is likely because NBP affect intensive margins and extensive margins differently and the overall effect is not precise when we mix the two channels together.[26] In addition, we find that lower natural gas prices lead to a decrease in emissions (as well as emission rates in later specifications).

Third, we found that NSR lawsuit probabilities have *a direct effect on emission reductions* independent of the indirect effect via reducing power generation, holding other factors constant. The coefficients are negative for all emissions. The magnitude of our baseline suggests that a one percent increase in NSR lawsuit probability (about 0.2 of the standard deviation) would decrease SO_2, NO_x, and CO_2 by 0.6, 1.2, and 0.5 percent respectively.

Our estimates are significant for NO_x and CO_2 and insignificant for SO_2. Despite a lack of precision for SO_2, we explain in Section 4.3 that all our estimates for SO_2 are consistently negative throughout the paper, and are consistently significant for the intensive margin. The large standard error for SO_2 can be driven by noise in the extensive margin and noise for plants without natural gas capacity. We also show in our robustness analysis that our point estimate is consistently negative across alternative specifications.

Our findings regarding the effect of NSR lawsuit probability on local pollution emissions show that local pollutant emissions are reduced as lawsuit probability increases. This result is consistent with results reported in Keohane et al. (2009), but is in contrast with results reported

[25]Due to lack of variation, our OLS coefficients are not significantly different from our IV results.

[26]For example, in Table 3 Panel B we find NBP has a significant effect in reducing SO_2 emissions.

in both Bushnell and Wolfram (2012) and Evans et al. (2008). The latter two studies both found a null effect with regards to SO_2 and NO_x emission rates. The difference between our results and previous null results may be that Bushnell and Wolfram (2012) focuses on the short window right after NSR reform in 1998, and could also be that we include natural gas plants while previous studies only include coal-fired plants so that we capture the fuel-switch margin. As for Evans et al. (2008), there is a methodological difference in defining both the treatment and counterfactual. Evans et al. (2008) uses an bottom-up economic-engineering model and assume ex-ante which plants shall be affected, while this study defines a continuous treatment that is predicted from a duration model.

Our findings on CO_2 emissions suggest that there are sizable climate co-benefits from regulating local pollutant from the power sector via the New Source Review. We later quantify the economic value of our results in Section 5.

There are other environmental policies that affect the power generation sector, such as the NBP and CAA. Whether our climate co-benefit results can be generalized to these policies depends on how each policy affects plant operations. If other policies also affect channels that the NSR triggers, then it would be important to account for climate co-benefits for those cases. Therefore, it is important to study which channel effectively drive the carbon co-benefits to inform more efficient designs of future climate policies. To answer these questions, we next examine how NSR probabilities affect important margins for plant operations.

4.3 How Have NSR Lawsuits Affected Plant Operations?

In this section, we examine how NSR lawsuits affect various margins of plant operations. We first examine intensive margins such as changes in emission rates and thermal efficiency. Then we study the extensive margin, i.e., the decision to operate. In Section 5 we use these estimates to conduct a decomposition analysis.

Overall effects on choices in the production function. We begin by examining the essential choices in the production function. Total emissions depend on the scale of production (electricity generation), the emission intensity (emission rate), and the thermal efficiency (heat rate, the amount of heat needed to generate one unit of power). In Section 4.2 we document a substantial scale effect as shown in our first-stage regression, suggesting that NSR lawsuits can affect emissions by incentivizing utility companies to reduce power generation.

We proceed to examine how NSR lawsuits affect emission and operating heat rates. Panel A of Table 4 reports estimates from Equation (1) taking emission and heat rates as dependent variables. Column 1–3 suggest that the effect of lawsuit probability on emission rates are negative, and statistically and economically significant. This result is consistent with the findings in Table 3. A one percent increase in the lawsuit probability reduces the emission rates of SO_2, NO_x, and CO_2 by 1.3, 1.9, and 1.2 percent respectively. In contrast with Bushnell and Wolfram (2012), which found no effect on SO_2 and NO_x emission rates, our findings suggest that NSR lawsuits have effectively incentivized power plants to adopt technologies to reduce emissions. For robustness, in Section 6, we provide direct evidence on scrubber adoption, NO_x control equipment adoptions, and fuel switch induced by NSR lawsuits.

In contrast with emission rates, Table 4 Panel A column 4 shows that NSR lawsuits do not affect heat rate, i.e., a positive effect in improving thermal efficiency. Moreover, the point estimate in Panel B is small, implying there are limited potential *within-plant* improvements. Nevertheless, we find strong evidence that power plants have adopted a less carbon-intensive approach of power generation and some weak evidence of improvements in thermal efficiency. These results can be the result of a fuel-switch, plant retirement, or improvement in turbine technologies, all of which we document next.

Effects on intensive and extensive margins. Next, we study how NSR lawsuits affect plant extensive and intensive margins. As for extensive margins, we focus on analyzing how NSR lawsuits affect a utility company's decision to shut down a plant. We are interested not only in estimating the marginal effect but also producing consistent operating probabilities to use in our decomposition analysis in Section 5. Therefore, we estimate a logit regression. To estimate the likelihood of operating versus shutting down, we need to isolate the decision within the intensive margin, i.e., the amount of electricity to generate. Therefore, our estimation includes the same set of variables equivalent to the reduced-form version of Equation (2), i.e., we include our demand shifter (CDD) and exclude gross load of power generation.[27]

Table 5 column 1 reports the coefficients from the logit model and column 3 reports the marginal effects. Our results imply that higher NSR lawsuit probabilities have an effect on shutdown. A one percent increase in the NSR lawsuit risk increases the likelihood to shut down by 1.1 percent. As for our demand shifter, we found that a plant facing a higher demand shock is more likely to operate, consistent with our intuition. To show that NSR lawsuit risks do affect the extensive margins, we repeat our analysis using a linear probability model (LPM) in column 2 and 4 and find a negative and significant effect. We chose the logit model to be our baseline specification for the extensive margin because we need to predict the shutdown probability for our decomposition exercise in Section 5, and the LPM will predict operating probability lower than 0 percent and higher than 100 percent.

As for the intensive margin, we repeat our analysis reported in Panel A in Tables 3 – 4 restricting on the sub-sample of operating plants and report our results in Panel B. We found similar signs and a slightly higher magnitude for our estimates. In addition, our parameter of interest is much more precisely estimated than in Panel A. This implies that the lack of precision in the

[27]Because year fixed effects take out too much variation for us to identify the parameter for lawsuit probability, we use a quadratic time trend instead when we estimate the Logit model. We keep the plant fixed effects the same as in Equation (2).

result in Panel A, especially for SO_2, may come from the mix of data generating processes between the extensive and intensive margins.

In summary, we find that NSR lawsuits affect utility companies via both the extensive and intensive margins. To quantify how much each channel contributes to emission reductions, we conduct a decomposition exercise in Section 5.

Plants with or without the capacity to fuel-switch. Last, we investigate how NSR lawsuits affect plants with and without the gas-fired generating capacity. Fuel-switch has been the key driver of reducing carbon emissions in power generation, since natural gas is half as intensive in carbon as coal on average.[28]

We start by examining how overall emission reductions, presented in Panel A of Table 3, differ depending on whether or not a plant has gas capacity. In Panel A of Table 6 columns 1 to 3, we estimate Equation (2) with NSR lawsuit probability interacted with a dummy variable that equals one if the plant has gas-fired capacity. Results in column 3 suggest that while NSR lawsuits reduce CO_2 emissions, having gas-fired generating power compensates for this effect. In other words, the NSR lawsuits mostly affect power plants with only coal-fired generating capacity. This result is also consistent with Holland (2012) that finds null results for California plants which are mostly gas-fired. We find similar results for NO_x, in that most emission reduction comes from coal-fired-only plants. As for SO_2, we find most emission reductions are from plants with gas-fired capacity.

To understand what drives the results in Panel A columns 1–3, we study how NSR lawsuit likelihood affects emission technology (measured by emission rate) and thermal efficiency (measured by heat rate) differently between these two sets of plants. We report our results in Panel A of Table 6 columns 4–7. The estimate of $\hat{\beta}_1$ suggests that improvements in emission and heat rates occur primarily in coal-fired-only power plants that do not have any gas-fired generating capacity. In contrast with our baseline in Table 3, we do find a negative and significant effect on heat rate. The result can come from both intensive and extensive margins for the coal-fired-only plants, which we explain later in Panel B. As for plants with gas-fired units, the estimate of the interaction term is positive (but insignificant) for the CO_2 emission rate and positive and significant for the heat rate. These results imply that a higher NSR lawsuit risk induces plants to shift production to the plants with gas capacity, which are relatively more efficient than the coal-fired units, but much more inefficient than the previously operating gas-fired units.

To further quantify the type of fuel switch that drives the results in Panel A of Table 6, we proceed to study how NSR lawsuit probabilities affect extensive and intensive margins for

[28] According to the carbon dioxide emissions coefficients published by the EIA: https://www.eia.gov/environment/emissions/co2_vol_mass.php

plants with and without gas-fired capacity separately, i.e., the fuel-switch across plants vs. the fuel-switch within operating plants.

To study the cross-plant extensive margin, we repeat our previous logit estimation in Panel A by interacting NSR lawsuit probabilities with a gas-capacity dummy. Panel B of Table 5 columns 3 and 4 show the estimation results and provide evidence of cross-plant fuel-switch. Facing a higher NSR lawsuit risk, coal-only-fired plants are more likely to be shut down and plants that can switch to gas-fired units are more likely to continue to operate. A one percent increase in NSR lawsuit risk will increase the probability of a plant without gas capacity to shut down by 0.12 percent and increase the probability of a plant with gas capacity to shut down by 0.04 percent.

To study the fuel switch within operating plants, we repeat our estimation in Panel A of Table 6 with a gas capacity dummy and report the results in Panel B. Our results are qualitatively similar. In contrast with results in Panel A, we found the effect for heat rate is close to zero and insignificant. The difference between Panel A and B implies that most heat rate improvements that we see for coal-fired-only plants come from the shutdown of coal-fired plants with low thermal efficiency (high heat rate). We investigate the relative importance of each margin in the decomposition presented next.

5 Implications

To understand both the overall contribution to emission reduction from coal- and gas-fired plants and the contribution across various plant operation margins, we decompose emission reduction using our estimation results from the above section.

We begin by considering a one percent increase in the probability of being named in a lawsuit in the year of 2007. We think this is a relatively mild change – from 2007 to 2010, the average predicted probability of being named in a lawsuit increased in total by 6 percent, and a one percent increase translates to about 0.2 of the standard deviation. As the scale is relatively small, our counterfactual and decomposition simulation results imply marginal changes.

Panel A in Table 7 describes the total counterfactual changes in SO_2, NO_x, and CO_2 emissions in 2007 following the increase in the NSR lawsuit risk. We produce the counterfactual using baseline IV estimates in Table 3 columns 4 to 6. As we expect, there is a sizable drop in SO_2 and NO_x emissions, amounting to 44 and 29 thousand metric tons, respectively as these are the regulated emissions targeted by the New Source Review. Importantly, there is also a drop in CO_2 emissions of 0.63 percent, amounting to 10 million metric tons. We interpret this finding as evidence that the New Source Review leads to carbon co-benefits.[29]

[29] We also produce the counterfactual for emission rates and operating heat rate, and it is available upon request.

The magnitude of the co-benefits from NSR lawsuits is sizable in comparison to other indirect instruments that reduce CO_2 emissions studied in the literature. Linn et al. (2014) studied the effect of coal prices on operating heat rates and utilization rates. Using their most conservative estimate with generating-unit fixed effects, they found that a \$10 carbon tax will lead to a 0.6 percent decrease in carbon dioxide emission rates, a number that is close to our effect from a one percent increase in the NSR lawsuit likelihood. In addition, if we evaluate the social cost of carbon (SCC) at 42 dollar-per-metric-ton CO_2, the co-benefits from this exercise would result in a social benefits increase of 415 million US dollars. Knittel et al. (2015) found that a one percent increase in coal price also leads to a 0.6 percent decrease in total CO_2 emissions. A more direct approach to reducing carbon dioxide is through renewable portfolio standards (RPSs) which require 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 2.62 percent – our results are approximately equivalent to one-fifth of their prediction.

After establishing evidence that the NSR leads to a sizable reduction in regulated pollution and unregulated emissions, we aim to understand *how* the risk of NSR lawsuits leads to emission reductions. This is important in determining if the co-benefits that we find can be generalized to other environmental and economic policies, as well as informing the design of new climate policies.

Emission reduction by plants with or without gas capacity. First, we divide our plants into two groups: a group that has no gas-fired generating capacity (group 'c') and a group that has some gas-fired generating capacity (group 'g'). This allows us to understand if the carbon dioxide emissions are coming from a shift from plants without gas capacity to plants with gas capacity. On the other hand, plants with only coal-fired units may be adversely affected by the enforcement, relative to plants with gas-fired units, as they could not easily shift production towards cleaner units in the short run.

We denote the two groups with the indicator variables d_c and d_g respectively, and denote a plant using i and year using t. Changes in emissions, Δz_t, at time t can be expressed as

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

In Table 7 Panel B, we show the decomposition results for these two groups of plants based on estimates from Panel A of Table 6. We use the point estimate of the interaction terms for plants with gas-fired units.[30] Panel B.3 shows that the estimated carbon co-benefits occur through both coal-fired-only power plants (5.7 million metric ton CO_2 reductions), and power plants with gas-fired capacity (CO_2 by 5.3 million metric ton CO_2 reductions). As we will see in the

[30] We do not assume those insignificant estimates are zero since we find consistent point estimates in robust version of Table 6 even though they are not significant.

next decomposition exercise, this is the result of more power plants without gas-fired units being switched off.

The effects on regulated emissions occur in both sets of power plants as well. As for SO_2, Table 7 Panel B.1 shows that the reduction in magnitude is greater for power plants with gas-fired units, contributing 85 percent of total emission changes. NO_x, in contrast, would experience most changes from coal-fired-only plants, which contribute 58.2 percent of total emission changes as shown in Panel B.2.

Emission reduction by intensive and extensive margins. We further analyze the extent of the intensive and extensive margins, in which plants (re-)start or shut down, in explaining emission reductions. We suppress the superscript for coal (c) and natural gas (g) for simplicity. Let η_{it} be a dummy variable which equals one if plant i decides to operate in year t. The expected changes in emissions can be decomposed as.

$$\mathbf{E}(\Delta z_t) = \sum_i \left(\underbrace{\Delta\eta_{it} \cdot (\mathbf{E}z_{it}|\eta_{it} = 1)}_{\text{extensive}} + \underbrace{(\mathbf{E}\eta_{it}) \cdot \Delta z_{it}}_{\text{intensive}} \right)$$

The first term describes the emission changes via the extensive margin, and the second term describes the emission changes for the operating plants, i.e., via the intensive margin. To approximate the *expected* emissions, we use the logit estimates in Table 5 columns 1 and 2 to predict operating probabilities $\hat{\eta}_{it}$. We use Panel B of Table 3 to predict conditional emissions for operating plants $(\hat{z}_{it}|\eta_{it} = 1)$. The above equation reduces to:

$$\widehat{\Delta z_t} = \sum_i \left(\underbrace{\Delta\eta_{it} \cdot (\hat{z}_{it}|\eta_{it} = 1)}_{\text{extensive}} + \underbrace{\hat{\eta}_{it} \cdot \Delta z_{it}}_{\text{intensive}} \right) \tag{4}$$

Table 8 shows the decomposition results. We produce this analysis using estimates from the logit estimates in Table 5 columns 3 and 4 as well as Panel B of Table 6. In this decomposition exercise, we normalize the total effect to match the corresponding numbers to Table 7 Panel B for convenience. Our results remain similar if the normalization is removed.

As shown in Table 8, both the extensive (i.e., shut down of plants) and intensive margins explain sizable shares of the co-benefits. Taking SO_2 for instance, 52% of the reduction is from the extensive margin and 48% of the reduction is from the operating plants. For CO_2, the extensive margin and the intensive margin each explains roughly half of the reduction, with the shutdown of plants contributing 56% of the co-benefits and emission reduction from operating plants contributing 44% of the co-benefits.

Despite the importance of both margins, we found how extensive and intensive margins affect regulated emissions and CO_2 co-benefits vary by plants depending on the presence of gas-fired units. In Table 8, we further separate plants into those with and without gas-fired generating capacity. As for plants without gas capacity, following an increase in NSR lawsuit probability of one percent, shutting down these plants contributes to 44.5 percent of the co-benefits, while operating coal-fired plants contribute to only 14.1 percent of the co-benefits. As for plants with gas capacity, most of the effect comes from the intensive margin: the operating plants with gas-fired units would account for 29.7 percent of the co-benefits, while the extensive margin accounts for 11.7 percent of the total co-benefits. Our results imply most co-benefits result from the shutdown of coal-fired plants without gas capacity and the continuous improvements of those operating plants with gas capacity.

In addition to the unintended co-benefits, we found similar results for the regulated pollutants. We found a sizable reduction in SO_2 and NO_x from both intensive and extensive margins for the coal-fired-only plants, and mostly intensive margin for the gas-fired plants. Our results suggest increasing regulations via NSR lawsuits trigger plants to adjust cross-plant margins and within-plant margins, both of which play an important role for co-benefits and regulated pollutants from the coal-fired-only plants, and the within-plant margin is also sizable from the operating gas-fired plants.

6 Additional Results and Robustness

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

Direct evidence of technology adoption and fuel switch. One interpretation of our baseline result is that plants facing a higher NSR lawsuit risk would adjust *within-plant* margins to reduce emissions. In Table A.4, we found direct evidence of adoption of SO_2 and NO_x abatement technologies such as adoption and use of scrubbers. In contrast, we do not find strong evidence of *within-plant* changes in gas share, suggesting the fuel-switch channel is mostly *between-plant*.

Robustness to macroeconomic conditions. Macroeconomic changes might affect both NSR policies and emission outcomes. We ran our analyses excluding recession years (2008 - 2010) to account for any effects of the recession on investment decisions made by plants in Appendix Table A.5 row 1, and we found consistency between the results.

Include settled plants. Our baseline excludes plants after lawsuits are settled. Doing so allows us to interpret the coefficient as avert action in emission reductions and does not allow us to access how NSR affects emissions from a plant after its settlement. Therefore, our counterfactual emissions tend to be a lower bound. In Appendix Table A.5 row 2 we include plants after a settlement is reached. In order to maintain a consistent interpretation, we include a dummy variable that equals one if a plant is settled in order to remove the effect on emissions that results from the legal obligation described in the settlement. We found our results are consistent with the baseline.

Alternative definition of lawsuit dates. In the baseline, we used the first date recorded in the lawsuit milestone database, i.e., "the date a case is referred to the DOJ", to determine the last year a plant was "survived" in the duration model. As explained in Section 2.2, there are different important milestones in the lawsuit dates, and using different dates has different implications in how long a plant survived. In Appendix Figure A.1 we plot the number of lawsuits using alternative definitions. This shows variation across different lawsuit date definitions. We re-estimated our baseline and reported the results in the Appendix Table A.5 rows 3.a to 3.e. We found our results are consistent across definitions although our estimates are smaller and some point estimates taper off 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. Moreover, using a much later date does not allow us to identify the effect of averting behavior from the effect of complying with the terms of a settlement.

Robustness for the extensive margin estimation. Lastly, since extensive margins can be correlated with decisions of other regional plants, we add an average lawsuit probability from other plants of the same independent system operation (ISO) in the same year to the baseline extensive model. In Appendix Table A.6, we found consistent signs compared to the baseline. The coefficient becomes larger partly due to how this ISO level control is correlated with our key variable of interest.

7 Conclusion

Investigating overlapping policies and understanding the effects of unintended consequences from a policy are important to improve policy making and welfare. If these indirect (net) 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 was surfaced on the benefits and costs of mitigating sulfur dioxide emissions, the Bush administration proposed the Clear Skies Act (CSA), that eventually led to the Clean Air Interstate Rule (CAIR) and a tightening of cap on SO_2 emissions (Schmalensee and Stavins, 2013).

In this paper, we investigate how NSR lawsuits that target SO_2 and NO_x affect unregulated CO_2 emissions and operation margins for coal- and gas-fired power plants in the US. The New Source Review, as part of the 1977 Amendment of the Clean Air Act, regulates plant modifications to mitigate agency's differential treatments favoring old facilities under the 1970 CAA in how they produce pollution emissions, mostly SO_2 and NO_x but can affect greenhouse gas emissions via changing plant operation margins. Because of the ambiguity 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 proposed a discrete-time duration model to measure a time-varying regulatory threat, and we found high-profile plants with large historical emissions and power generation are more likely to be subject to NSR lawsuits. Also, all else equal plants in the Rust Belt have a higher NSR lawsuit probability than plants in other areas or with a more pro-business federal circuit court.

Using our estimates of NSR probabilities, we examine how the NSR 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 also unintendedly 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 one 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 New Source Review 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 inputs such as NSR (on SO_2 and NO_x) and a cap-and-trade program on CO_2 because of the spillover effect.

We further examine and decompose how different margins that plants can adjust in response to NSR lawsuit probabilities affect emission reductions. We found that CO_2 reductions come from both sets of plants with and without gas-fired capacity, but the extensive margin explains an important share of the co-benefits for plants without gas-fired units, while effects on operating plants (i.e. the intensive margin) are more relevant for plants with gas-fired units. Therefore, other environmental policies that can induce a sizable fuel-switch are likely to gain climate co-benefits as well, and 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.

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.

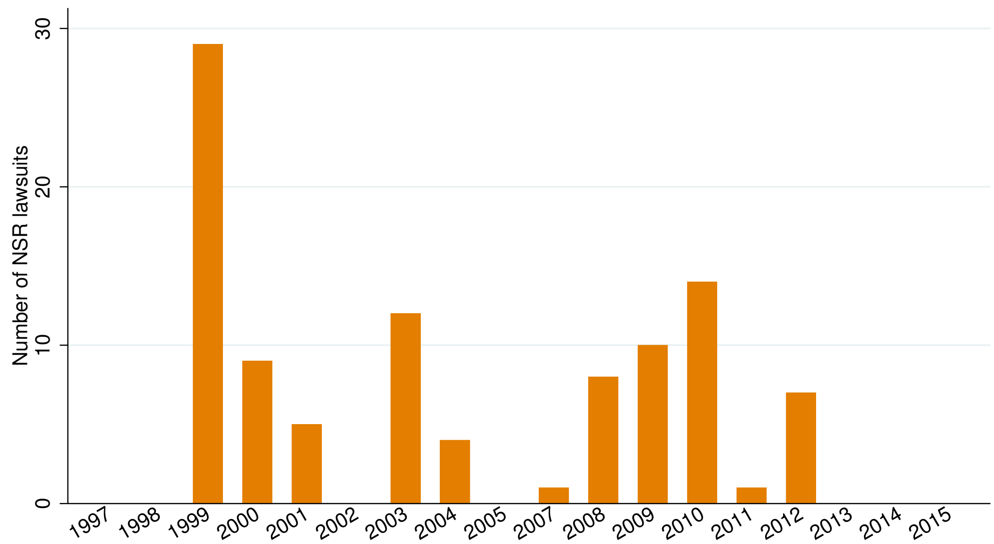
Sekar, S. and B. Sohngen (2014). The effects of renewable portfolio standards on carbon intensity in the United States. Resources for the Future Discussion Paper 14-10.

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 environmnetal regualation. Working Paper Series, Harvard John F. Kennedy School of Government.

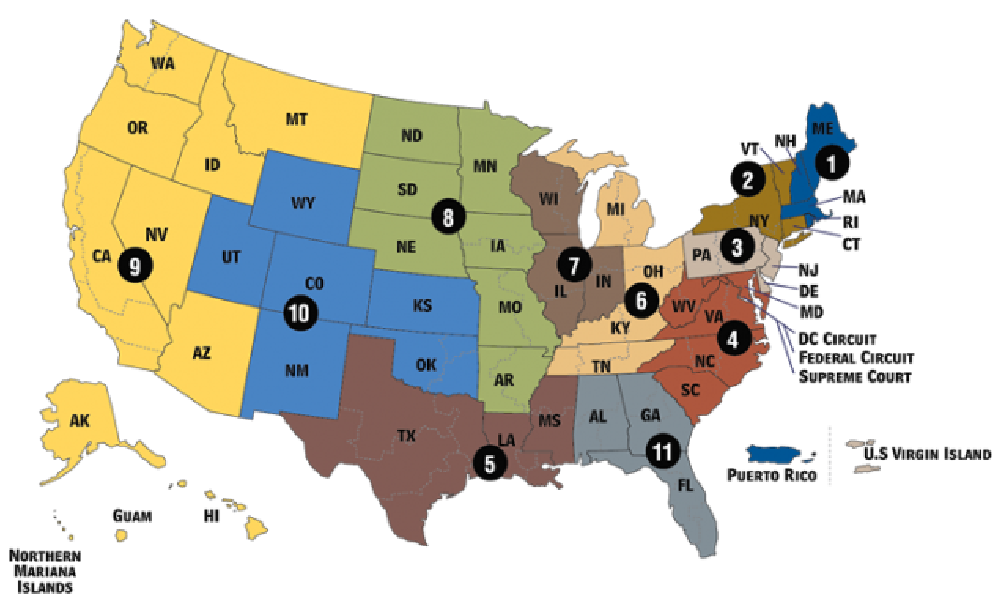
Figures

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.

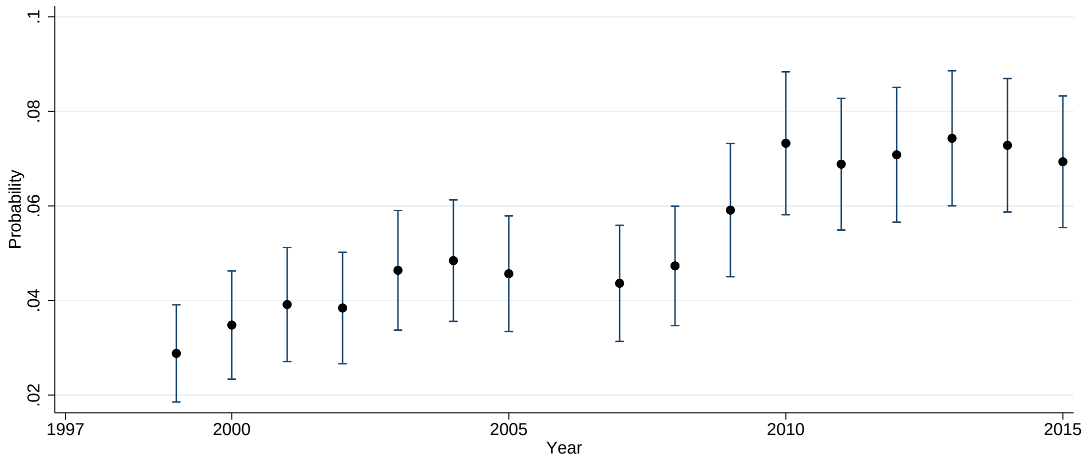
Figure 2: **US federal judicial districts**



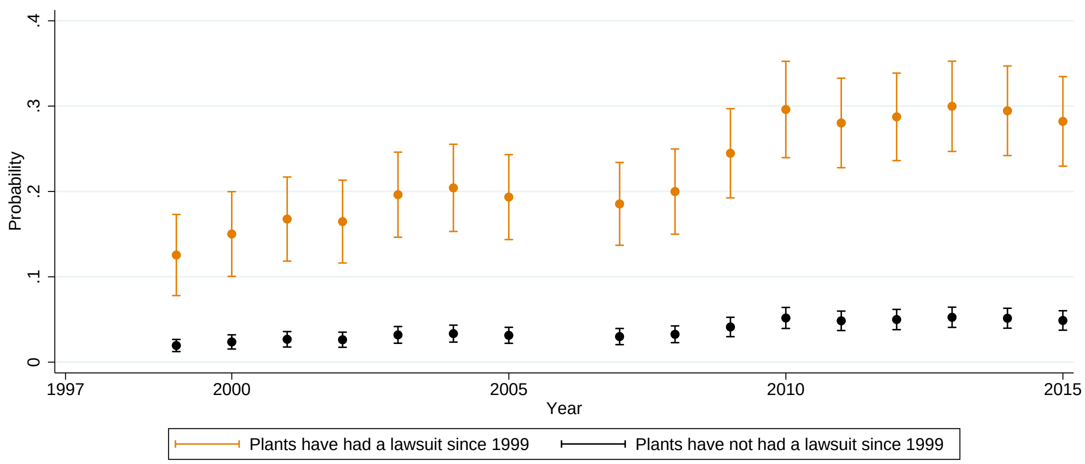
Source : US Court https://www.uscourts.gov/sites/default/files/u.s._federal_courts_circuit_map_1.pdf

Figure 3: **Predicted probability of lawsuit, 1999 – 2015**

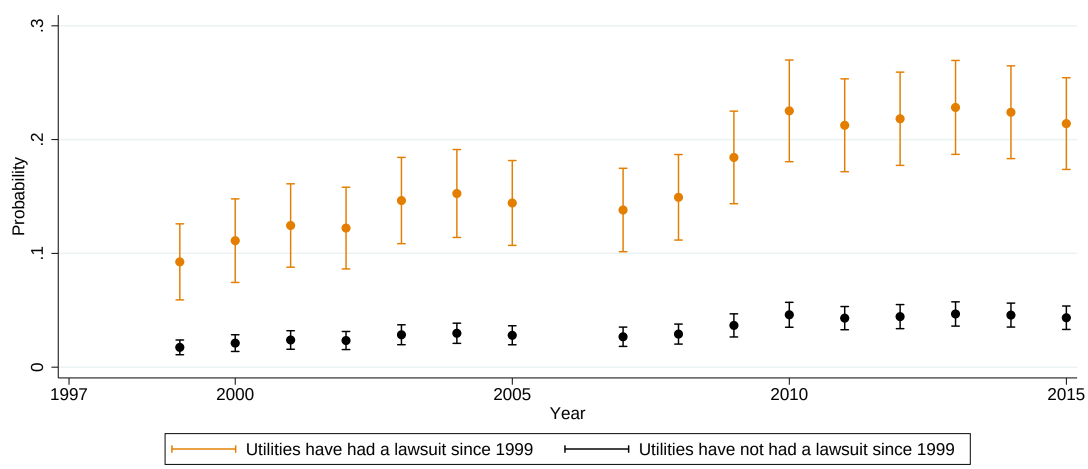
Panel A. Average predicted probability by year



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



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



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

Tables

Table 1: **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 2: **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		21,421

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

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)	-0.011**	-0.013***	-0.004**	-0.006	-0.012***	-0.005**
	(0.004)	(0.003)	(0.002)	(0.006)	(0.003)	(0.003)
Log output (grossload)	0.716***	0.874***	1.371***	1.174***	1.042***	1.250***
	(0.019)	(0.012)	(0.017)	(0.140)	(0.080)	(0.091)
Policy: NBP	0.021	0.033	-0.040	-0.029	0.030	-0.039
	(0.059)	(0.026)	(0.031)	(0.075)	(0.032)	(0.034)
Policy: CAIR	-0.317***	-0.108**	-0.104**	-0.224*	-0.073	-0.129**
	(0.089)	(0.051)	(0.047)	(0.126)	(0.056)	(0.057)
Policy: RGGI	-0.587***	-0.060	0.058	-0.453**	-0.009	0.021
	(0.164)	(0.076)	(0.085)	(0.204)	(0.094)	(0.107)
Log natural gas price	0.352**	0.122	0.069	0.380**	0.137	0.059
	(0.142)	(0.079)	(0.089)	(0.173)	(0.087)	(0.106)
Estimator	OLS	OLS	OLS	IV	IV	IV
Plant FE, Year FE	Y	Y	Y	Y	Y	Y
Number of observations	21,421	21,421	21,421	21,421	21,421	21,421
R-square	0.97	0.98	0.99	0.95	0.98	0.99

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)	-0.004	-0.011***	-0.004***	-0.007	-0.012***	-0.005***
	(0.004)	(0.003)	(0.001)	(0.005)	(0.003)	(0.002)
Log output (grossload)	0.947***	0.842***	0.956***	1.365***	1.082***	1.185***
	(0.028)	(0.015)	(0.005)	(0.113)	(0.088)	(0.082)
Policy: NBP	-0.051	-0.005	-0.026*	-0.109**	-0.039	-0.058**
	(0.048)	(0.028)	(0.014)	(0.055)	(0.032)	(0.024)
Policy: CAIR	-0.367***	-0.101**	-0.033	-0.420***	-0.131**	-0.061*
	(0.093)	(0.048)	(0.023)	(0.097)	(0.056)	(0.034)
Policy: RGGI	-0.326**	0.001	-0.043*	-0.166	0.092	0.044
	(0.162)	(0.080)	(0.023)	(0.169)	(0.088)	(0.043)
Log natural gas price	0.291**	0.126*	0.033	0.317**	0.142*	0.048
	(0.145)	(0.075)	(0.060)	(0.148)	(0.078)	(0.061)
Estimator	OLS	OLS	OLS	IV	IV	IV
Plant FE, Year FE	Y	Y	Y	Y	Y	Y
Number of observations	17,769	17,769	17,769	17,769	17,769	17,769
R-square	0.97	0.98	0.99	0.96	0.95	0.95

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 estimates use 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. 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**

Panel A: Overall effects for all plants

Dep. var: log of	(1) SO_2 rate	(2) NO_x rate	(3) CO_2 rate	(4) Heat rate
Prob (NSR lawsuit)	-0.013**	-0.019***	-0.012*	-0.008
	(0.005)	(0.005)	(0.007)	(0.005)
Log output (grossload)	0.393***	0.218*	0.429*	0.170
	(0.102)	(0.132)	(0.222)	(0.139)
Log natural gas price	0.321**	0.141	0.060	0.004
	(0.154)	(0.156)	(0.242)	(0.173)
Plant FE, Year FE	Y	Y	Y	Y
Number of observations	21,421	21,421	21,421	21,375
R-square	0.94	0.90	0.91	0.89

Panel B: Intensive margin for operating plants

Dep. var: log of	(1) SO_2 rate	(2) NO_x rate	(3) CO_2 rate	(4) Heat rate
Prob (NSR lawsuit)	-0.005	-0.011***	-0.005***	-0.001*
	(0.004)	(0.003)	(0.002)	(0.000)
Log output (grossload)	0.344***	0.081	0.189**	-0.015
	(0.100)	(0.085)	(0.076)	(0.015)
Log natural gas price	0.285**	0.143*	0.046	0.003
	(0.134)	(0.073)	(0.057)	(0.013)
Plant FE, Year FE	Y	Y	Y	Y
Number of observations	17,769	17,769	17,769	17,769
R-square	0.93	0.83	0.28	0.74

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. We bootstrap the duration Equation (1) together with the main Equation (2) to correct for the generated variable – NSR lawsuit probability. The Panel A estimates use the full sample. The Panel B estimates were restricted to operating plants. All columns estimate Equation (2) in which we instrument log gross load power generation using cooling degree days (CDD). All estimations include a historical scrubber dummy interacted with a linear and a quadratic time trend, and controls on overlapping policies (NBP, CAIR and RGGI).

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

Dep var: 1 = Operate Marginal effects	(1) Logit	(2) LPM	(3) Logit	(4) LPM
Prob (NSR lawsuit)	-0.011*	-0.004***	-0.012*	-0.004***
	(0.006)	(0.001)	(0.007)	(0.001)
Prob (NSR lawsuit) $\times$ Gas			0.008	0.000
			(0.012)	(0.002)
IV (CDD)	-0.248***	-0.123***	-0.247***	-0.123***
	(0.034)	(0.008)	(0.032)	(0.008)
Log natural gas price	0.162***	0.036***	0.162***	0.036***
	(0.033)	(0.009)	(0.031)	(0.009)
Plant FE	Y	Y	Y	Y
Linear, quadratic time trend	Y	Y	Y	Y
Number of observations	14,113	21,167	14,113	21,167
Chi(2)	2,880	–	3,437	–
Chi(2)	–	0.72	–	0.72

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. We bootstrap the duration Equation (1) together with the main Equation (2) to correct for the generated variable – NSR lawsuit probability. All point estimates are marginal effects. All estimations include a historical scrubber dummy interacted with a linear and a quadratic time trend, and controls on overlapping policies (NBP, CAIR and RGGI). In column 1 and 3, we estimate a logit regression controlling for factors similar to the first stage of Equation (2). Column 1 reports the coefficients and column 2 reports the marginal effect. In columns 2 and 4 we estimate a linear probability model.

Table 6: **Effect of NSR lawsuits on plants with or without the gas capacity**

Panel A: Overall effects for all plants

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)	-0.003	-0.011***	-0.005*	-0.011**	-0.019***	-0.013*	-0.008
	(0.005)	(0.003)	(0.003)	(0.005)	(0.006)	(0.007)	(0.005)
Prob (lawsuit) × gas	-0.037**	-0.007	-0.002	-0.030*	0.002	0.007	0.006
	(0.019)	(0.010)	(0.006)	(0.016)	(0.013)	(0.013)	(0.010)
Log output	1.186***	1.044***	1.251***	0.403***	0.217	0.426**	0.168
	(0.156)	(0.091)	(0.088)	(0.106)	(0.137)	(0.190)	(0.156)
Log natural gas price	0.385**	0.138	0.059	0.325**	0.140	0.059	0.003
	(0.178)	(0.090)	(0.097)	(0.146)	(0.174)	(0.250)	(0.174)
Plant FE, Year FE	Y	Y	Y	Y	Y	Y	Y
Num. of observations	21,421	21,421	21,421	21,421	21,421	21,421	21,375
R-squared	0.95	0.98	0.99	0.94	0.90	0.91	0.89

Panel B: Intensive margin for operating plants

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)	-0.005	-0.012***	-0.005***	-0.003	-0.011***	-0.004***	-0.001*
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.000)
Prob (lawsuit) × gas	-0.028*	-0.003	-0.005	-0.026*	-0.002	-0.004	-0.001
	(0.015)	(0.008)	(0.005)	(0.014)	(0.008)	(0.004)	(0.001)
Log output	1.377***	1.083***	1.187***	0.355***	0.082	0.191***	-0.014
	(0.106)	(0.086)	(0.077)	(0.105)	(0.081)	(0.072)	(0.015)
Log natural gas price	0.322**	0.142*	0.049	0.289**	0.144**	0.047	0.003
	(0.146)	(0.077)	(0.062)	(0.125)	(0.072)	(0.059)	(0.013)
Plant FE, Year FE	Y	Y	Y	Y	Y	Y	Y
Num. of observations	17,769	17,769	17,769	17,769	17,769	17,769	17,769
R-squared	0.96	0.95	0.95	0.93	0.83	0.28	0.74

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. We bootstrap the duration Equation (1) together with the main Equation (2) to correct for the generated variable – NSR lawsuit probability. All estimations include a historical scrubber dummy interacted with a linear and a quadratic time trend, and controls on overlapping policies (NBP, CAIR and RGGI). The Panel A estimates use the full sample. The Panel B estimates were restricted to operating plants. We repeat our 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: **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	6,855	-43.75	-0.52 %
NO_x (thousand metric tons)	2,403	2,374	-29.08	-1.21 %
CO_2 (million metric tons)	1,912	1,902	-9.87	-0.63 %
Number of plants				1,146

Panel B: Effects by gas-fired generation capacity

Total emissions	Predicted	Simulated	Difference	Percentage change	Number of plants
Panel B.1 – SO_2 (thousand metric tons)					
Plants without gas capacity	4,873	4,859	-14.32	-0.29 %	259
(percentage change)			(14.6 %)		
Plants with gas capacity	2,028	1,944	-83.79	-4.13 %	887
(percentage change)			(85.4 %)		
Total	6,901	6,832	-98.11	-1.42 %	1,146
Panel B.2 – NO_x (thousand metric tons)					
Plants without gas capacity	1,662	1,643	-19.08	-1.15 %	259
(percentage change)			(58.2 %)		
Plants with gas capacity	741	727	-13.72	-1.85 %	887
(percentage change)			(41.8 %)		
Total	2,403	2,370	-32.79	-1.36 %	1,146
Panel B.3 – CO_2 (million metric tons)					
Plants without gas capacity	1,144	1,138	-5.71	-0.50 %	259
(percentage change)			(51.8 %)		
Plants with gas capacity	768	763	-5.31	-0.69 %	887
(percentage change)			(48.2 %)		
Total	1,912	1,901	-11.02	-0.58 %	1,146

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 simulate our results based on Table 6. All numbers are averages weighted by the plant-level gross load.

Table 8: **Counterfactual emission reductions from plants with and without gas capacity, by intensive and extensive margins**

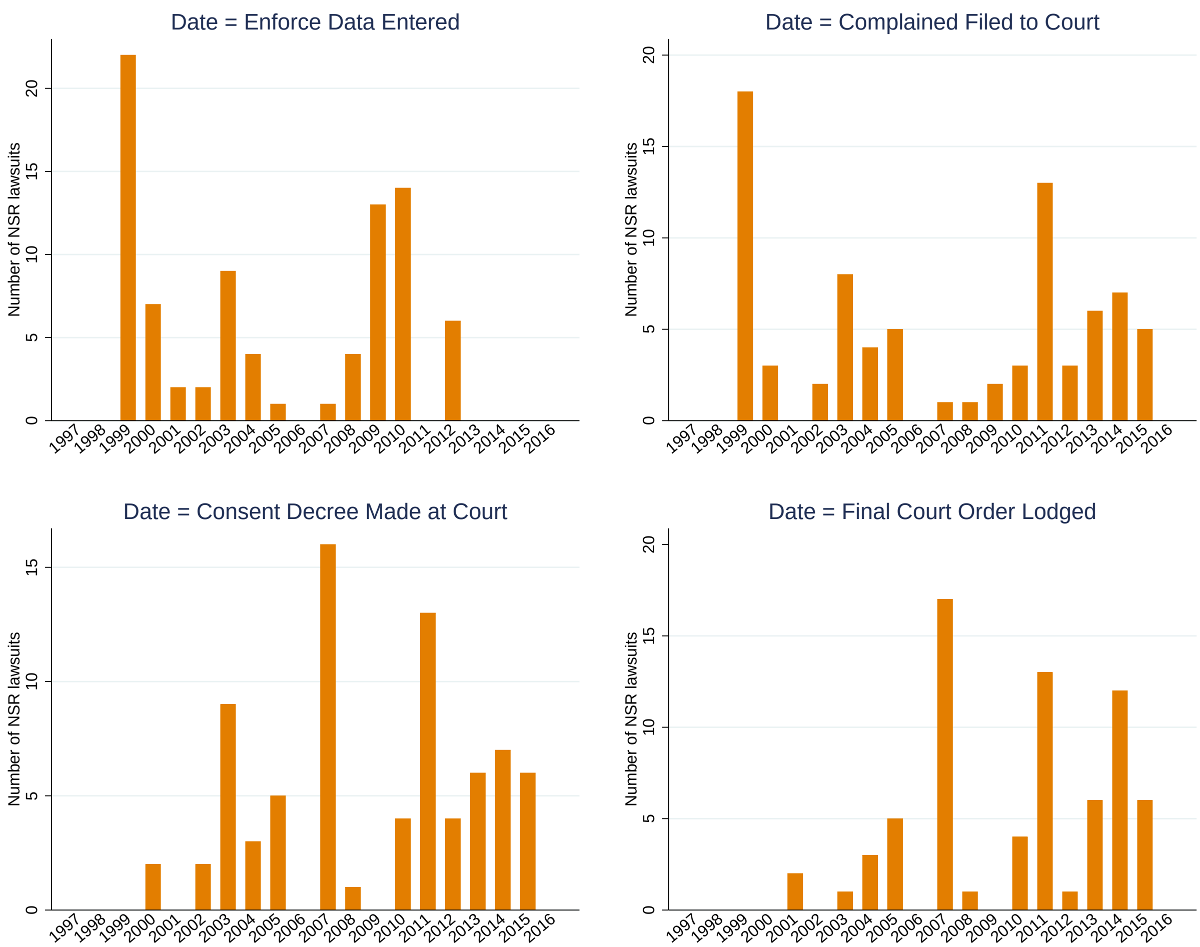
	(1)	(2)	(3)	(4)	(5)	(6)
Change in emissions:	Intensive margins		Extensive margins		Overall effects	
		(percentage changes)		(percentage changes)		(percentage changes)
Panel A. SO_2 (thousand metric tons)						
Plants without gas capacity	-3.15	-0.06 %	-42.38	-0.85 %	-45.52	-0.91 %
(percentage changes)	(3.21 %)		(43.2 %)		(46.4 %)	
Plants with gas capacity	-44.00	-2.09 %	-8.59	-0.41 %	-52.59	-2.50 %
(percentage changes)	(44.8 %)		(8.76 %)		(53.6 %)	
Overall effects	-47.14		-50.97		-98.11	
(percentage changes)	(48.0 %)		(52.0 %)			
Panel B. NO_x (thousand metric tons)						
Plants without gas capacity	-9.58	-0.57 %	-12.19	-0.72 %	-21.77	-1.29 %
(percentage changes)	(29.2 %)		(37.2 %)		(66.4 %)	
Plants with gas capacity	-7.15	-0.94 %	-3.87	-0.51 %	-11.02	-1.45 %
(percentage changes)	(21.8 %)		(11.8 %)		(33.6 %)	
Overall effects	-16.73		-16.06		-32.79	
(percentage changes)	(51.0 %)		(49.0 %)			
Panel C. CO_2 (million metric tons)						
Plants without gas capacity	-1.55	-0.13 %	-4.90	-0.42 %	-6.45	-0.55 %
(percentage changes)	(14.1 %)		(44.5 %)		(58.5 %)	
Plants with gas capacity	-3.27	-0.42 %	-1.29	-0.17 %	-4.57	-0.59 %
(percentage changes)	(29.7 %)		(11.7 %)		(41.5 %)	
Overall effects	-4.83		-6.20		-11.02	
(percentage changes)	(43.8 %)		(56.2 %)			

Notes: We simulated counterfactual emissions in 2007 if likelihood of NSR lawsuits increases by one percent. We decompose the counterfactual emissions from Panel A of Table 7 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 and normalized by the group-specific effects reported in Table 7, Panel A.

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) ('000)	0.605***	0.379***
	(0.125)	(0.130)
Prob (NSR lawsuit)	-0.008	-0.015***
	(0.008)	(0.006)
Plant FE, Year FE	Y	Y
Number of observations	21,422	15,616
R-squared	0.87	0.53
F-stat (of exclusive var)	34.4	-

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). 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 instruments include a historical scrubber dummy interacted with a linear and a quadratic time trend, as well as controls on overlapping policies (NBP, CAIR, and RGGI). Column 1 report the first stage of our baseline estimation. Column 2 use net generation instead.

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**	0.007***	0.022**	0.036**	0.003
	(0.001)	(0.002)	(0.010)	(0.016)	(0.345)
Log output	0.023*	0.077***	0.326*	0.378	-1.603
	(0.014)	(0.028)	(0.180)	(0.274)	(71.615)
Log natural gas price	0.004	-0.087**	-0.352	-0.405	-0.037
	(0.023)	(0.036)	(0.221)	(0.342)	(1.503)
Plant FE, Year FE	Y	Y	Y	Y	Y
Num. of observations	21,421	21,421	15,701	15,701	11,400
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. We bootstrap the duration Equation (1) together with the main Equation (2) to correct for the generated variable – NSR lawsuit probability. All columns estimate Equation (2). Flue-gas desulfurization (FGD), known as scrubber, is an abatement technology to remove SO_2. Other controls include a historical scrubber dummy interacted with a linear and a quadratic time trend, as well as controls on overlapping policies (NBP, CAIR, and RGGI).

Table A.5: **Effect of NSR lawsuits on emissions: Additional robustness**

Panel A: Re-estimate coefficients of Prob (NSR lawsuit) for all plants

Dep. var: log of	SO_2	NO_x	CO_2	SO_2 rate	NO_x rate	CO_2 rate
1. Exclude recession	-0.006	-0.011***	-0.005*	-0.013**	-0.017***	-0.012
	(0.006)	(0.003)	(0.003)	(0.006)	(0.006)	(0.008)
2. Include post-lawsuit	-0.006	-0.013***	-0.004*	-0.012***	-0.019***	-0.010*
	(0.005)	(0.003)	(0.002)	(0.004)	(0.005)	(0.006)
3. Alternative lawsuit date						
3.a Enforcement data entered	-0.006	-0.012***	-0.005**	-0.013**	-0.018***	-0.012
	(0.005)	(0.003)	(0.002)	(0.005)	(0.005)	(0.007)
3.b Refer to DOJ (baseline)	-0.006	-0.012***	-0.005**	-0.013**	-0.019***	-0.012*
	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)	(0.007)
3.c Complained filed	-0.006	-0.011***	-0.003	-0.011**	-0.016***	-0.008
	(0.005)	(0.003)	(0.002)	(0.005)	(0.005)	(0.006)
3.d Consent decree	-0.008**	-0.009***	-0.001	-0.008**	-0.010***	-0.001
	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)	(0.005)
3.e Final order lodged	-0.006**	-0.007***	-0.001	-0.004	-0.006**	0.000
	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)

Panel B: Intensive margin for operating plants

Dep. var: log of	SO_2	NO_x	CO_2	SO_2 rate	NO_x rate	CO_2 rate
1. Exclude recession	-0.007	-0.011***	-0.006***	-0.005	-0.010***	-0.005***
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)
2. Include post-lawsuit	-0.007*	-0.014***	-0.005***	-0.005	-0.013***	-0.004***
	(0.004)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
3. Alternative lawsuit date						
3.a Enforcement data entered	-0.007	-0.012***	-0.005***	-0.005	-0.011***	-0.004***
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)
3.b Refer to DOJ (baseline)	-0.007	-0.012***	-0.005***	-0.005	-0.011***	-0.005***
	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
3.c Complained filed	-0.005	-0.011***	-0.005***	-0.004	-0.010***	-0.004***
	(0.005)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
3.d Consent decree	-0.003	-0.008***	-0.002*	-0.002	-0.008***	-0.002*
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
3.e Final order lodged	-0.001	-0.006***	-0.001*	-0.001	-0.006***	-0.001**
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. Panel A shows the overall results and Panel B shows the results for operating plants. We only report the coefficient of lawsuit probability, and the model is equivalent to the model reported in Tables 3 and 4. Coefficients on other variables are omitted for brevity and are available upon request. In row 1, we exclude observations from 2008 to 2010. In row 2, we include years after the lawsuit date and add a post-lawsuit dummy variable. In rows 3, we use alternative lawsuit dates.

Table A.6: **Effect of NSR lawsuits on extensive margins, Control for ISO**

Dep var: 1 = Operate	(1) Coefficients	(2) Marginal Effects	(3) Coefficients	(4) Marginal Effects
Prob (NSR lawsuit)	-0.065*	-0.009*	-0.074*	-0.011*
	(0.037)	(0.005)	(0.045)	(0.006)
Prob (NSR lawsuit) $\times$ Gas			0.067	0.009
			(0.077)	(0.011)
IV (CDD)	-1.587***	-0.228***	-1.589***	-0.227***
	(0.249)	(0.041)	(0.269)	(0.043)
Log natural gas price	1.057***	0.152***	1.061***	0.151***
	(0.270)	(0.033)	(0.272)	(0.033)
Prob (lawsuit) ISO Year	-0.349***	-0.050***	-0.350***	-0.050***
	(0.093)	(0.014)	(0.098)	(0.015)
Plant FE	Y	Y	Y	Y
Linear, quadratic year trend	Y	Y	Y	Y
Number of observations	14,113	14,113	14,113	14,113
Chi(2)	2,921	–	2,932	–

Notes: Bootstrapped standard error clustered at plant level in parenthesis. *, **, and *** indicate statistical significance at 10, 5 and 1 percent levels respectively. We bootstrap the duration Equation (1) together with the main Equation (2) to correct for the generated variable – NSR lawsuit probability. All estimations include a historical scrubber dummy interacted with a linear and a quadratic time trend, as well as controls on overlapping policies (NBP, CAIR, and RGGI). We estimate a logit regression controling for factors similar to the first stage of Equation (2). Columns 1 and 3 report the coefficients while columns 2 and 4 report the marginal effects.