Spillovers from Climate Policy

Preliminary Draft: Comments Welcome

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Abstract

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1 Introduction

Spillovers from climate policy (also known as ancillary benefits or ancillary costs) have important implications for policy design, modeling, and benefit-cost analysis. Spillovers arise since climate policy could lead, for example, to a reduction in particulate matter (PM) emissions as well as CO_2 emissions. In this case, the ancillary benefits of reduced PM emissions from the policy should be included in a benefit-cost analysis and may well lead the benefit-cost analysis to recommend more stringent climate policies. Unfortunately, spillovers can be either positive or negative since firms change production processes in response to climate policies, and these changes may lead either to an increase or decrease in emissions of other pollutants. After presenting a theoretical description of spillovers from climate policy, this paper tests for and decomposes climate policy spillovers in electric power generation.

Climate policy spillovers have received attention in the estimation of health benefits from reduced air pollution. This extensive literature, which is recently surveyed in Bell *et al.* (2008), varies considerably in its sophistication with regard to air quality modeling and the responses of polluters to climate policy.[1] For example, Cifuentes *et al.* (2001) simply assumes climate policy uniformly reduces pollution across all spatial areas. Other studies use much more sophisticated air quality modeling to estimate the effects of emissions reductions. Bell *et al.* conclude that although the various studies are difficult to compare the results provide "strong evidence" that the short-term ancillary benefits to public health of climate policy are "substantial."

Burtraw *et al.* (2003) focus on the responses to climate policy of electric power generators.[2] Using a sophisticated model of electricity supply, the authors show that a carbon tax would have ancillary health benefits from reduced NO_X emissions of about $8 per metric ton of carbon. Since emissions of SO_2 are capped, they note that there are no ancillary health benefits from SO_2 emissions, but they estimate additional benefits from avoided future investment in emissions control equipment. Groosman *et al.* (2009) estimate similar effects with a sophisticated model of pollutant transport.[3]

[1] See also European Environment Agency (2004).

[2] Ancillary benefits have also been studied in transportation, see Walsh (2008) and Mazzi and Dowlatabadi (2007).

[3] The more conservative estimates in Groosman *et al.* recognize that emissions of SO_2 are capped.

Ancillary benefits from climate policy have also been studied in agriculture and forestry where climate policy could benefit soil quality, wildlife habitat, water quality, and landscape aesthetics.[4] Finally, ancillary benefits have been estimated to be substantial in developing countries where regulation of pollutants may be less stringent.[5]

2 The Theory of Spillovers from Climate Policy

Emissions are generally modeled using one of three equivalent approaches: as an input in the production process, as a joint product which is a "bad", and as abatement from some hypothetical level, e.g., business as usual.[6] The first approach has a number of advantages for modeling spillovers from climate policy since it is readily adaptable to modeling multiple pollutants and allows for a broad range of substitution possibilities. Moreover, it allows a simple way to model climate policies such as a carbon tax or cap and trade as an increase in the price of CO_2 emissions (from a zero price).

In this framework, climate policy spillovers are shifts in input demands in response to an increase in the price of CO_2. Theory shows that input demand may either increase or decrease, depending on whether the input is a substitute or a complement to CO_2. Additionally, theory shows that the effects of climate policy can be decomposed into two effects: an output effect, which generally decreases the demand for all inputs, and a substitution effect, which depends on whether the inputs are net substitutes or net complements for CO_2.[7] Importantly, demand for pollution inputs that are net substitutes can still fall with climate policy if the output effect outweighs the substitution effect.[8]

To illustrate these principles, consider electricity generation which leads to emissions of

[4] See Feng *et al.* (2004), Plantinga and Wu (2003), and Pattanayak *et al.* (2002). Ebakidze and McCarl (2004) point out that ancillary benefits must be skeptically considered with agricultural offsets since offset emissions reductions from other sectors might also have ancillary benefits.

[5] See Dudek *et al.* (2003) for analysis of ancillary benefits in Russia; Dessus and O'Connor (2003) for analysis of Chile; and Joh *et al.* (2001) for analysis of Korea.

[6] Advanced texts in microeconomic theory illustrate the general equivalence of the first two approaches by modeling "netputs" rather than "inputs" and "outputs". The third equivalent approach, modeling pollution abatement, is by far the most common approach. However, it is less useful for modeling spillovers since it requires the definition of a hypothetical emissions level. This definition is unclear when modeling emissions of multiple pollutants.

[7] These effects are equivalent to income and substitution effects from demand theory.

[8] Decomposing responses into output and substitution effects is also useful since output effects may not be effective for reducing emissions if regulations are incomplete or firms have market power. See Holland (2009) for further discussion of output effects with incomplete regulation.

SO_2 and NO_X as well as CO_2. Suppose climate policy caused dual fuel generating units to switch from fuel oil to natural gas. Since natural gas generally has lower sulphur content than fuel oil, SO_2 and CO_2 would be net complements: for a given amount of electricity emissions of SO_2 would be lower in response to climate policy. Since the output effect also serves to to reduce SO_2 emissions, climate policy would have ancillary benefits from SO_2. Now suppose that climate policy caused natural gas-fired generating units to increase their combustion temperature, which reduces CO_2 emissions but increases NO_X emissions. Thus CO_2 and NO_X are net substitutes. Note however, that since the output effect leads to a reduction in NO_X emissions, the overall effect may still be a reduction in NO_X emissions from climate policy if the output effect is stronger than the substitution effect. In other words, climate policy could have ancillary benefits or ancillary costs.

Spillovers are illustrated in Figure 1 for the case of electricity production which has emissions of both CO_2 and NO_X . The first panel of Figure 1 shows the input demand for CO_2. If marginal productivity is decreasing (the usual case) then the input demand (equivalently the value of the marginal product) is downward sloping. The profit maximizing firm would increase use of an input if the value of the marginal product were greater than the marginal cost of the input. Thus at the optimum the value of the marginal product equals the marginal cost of the input. In the unregulated equilibrium, this marginal product would be zero and CO_2 emissions would be $e^0_{CO_2}$. If climate policy increases the price of CO_2 emissions to t_{CO_2}, for example through cap and trade or a carbon tax, then CO_2 emissions would fall to $e^1_{CO_2}$.

Panel B of Figure 1 illustrates the spillovers to NO_X emissions from climate policy. In the absence of climate policy, the NO_X input demand is illustrated by the downward sloping solid line and NO_X emissions are $e^0_{NO_x}$. The response of NO_X emissions to climate policy depends on two factors: *i*) whether NO_X and CO_2 are substitutes or complements and *ii*) regulations on NO_X emissions. In general NO_X and CO_2 can be substitutes or complements. If NO_X and CO_2 are complements, then climate policy leads to an inward shift in the input demand for NO_X , *i.e.,* decreases the demand for NO_X emissions. On the other hand, if NO_X and CO_2 are substitutes, then climate policy increases the demand for NO_X emissions.

Whether or not climate policy changes NO_X emissions depends crucially on the environ-

mental regulation of the NO_X emissions. Two polar cases illustrate the effects: cap and trade in NO_X v. a NO_X tax. If NO_X is subject to an emissions cap (as in RECLAIM or in the NO_X Budget Program), then climate policy does not change NO_X emissions but changes the price of permits in the NO_X market. For example, if NO_X and CO_2 are complements, then climate policy decreases demand for NO_X emissions. Since emissions are capped, NO_X emissions remain at $e^0_{NO_x}$, but the NO_X price falls from $p^0_{NO_x}$ to $p^{2C}_{NO_x}$.[9]

On the other hand, if NO_X emissions are subject to price regulation, then NO_X emissions change in response to climate policy. For example, if NO_X and CO_2 are complements, then climate policy would decrease demand for NO_X emissions and emissions would decrease from $e^0_{NO_x}$ to $e^{1C}_{NO_x}$. Alternatively, if NO_X and CO_2 are substitutes, then climate policy would *increase* NO_X emissions from $e^0_{NO_x}$ to $e^{1S}_{NO_x}$.

Panel C of Figure 1 shows the effect of climate policy in the electricity market. Since climate policy increases the marginal cost of electricity production, the equilibrium price of electricity will rise from p^0_{MWh} to p^1_{MWh} and the equilibrium production will fall from q^0_{MWh} to q^1_{MWh}. This output effect will serve to reduce emissions of both CO_2 and NO_X . Note that the output effect makes it unlikely that NO_X and CO_2 would be gross substitutes since the substitution effect (which would tend to increase NO_X emissions) would need to outweigh the output effect (which would tend to decrease NO_X emissions).[10]

To illustrate the proper valuation of spillovers from climate policy, suppose that electricity production requires three inputs, a market input k with market price w, and two non-market, environmental inputs: CO_2 and NO_X . Assume that the non-market inputs have (implicit) prices (t_{CO2} for CO_2 and t_{NOx} for NO_X) and have environmental damages $\tau_{CO2} * CO2$ and $\tau_{NOx} * NOx$. Further assume that the electricity production function is given by $q = f(k, CO2, NOx)$, consumer surplus is given by $U(q)$, and the electricity market is competitive so the marginal utility

[9]Since NO_X emissions do not change, there are no spillover benefits from climate policy. However, there may be benefits from avoided future investment in NO_X control technologies. See Burtraw *et al.* (2003) for an application to the SO_2 market.

[10]Regulation under the Clean Air Act Amendments (CAAAs) may specify a maximum NO_X emissions rate. In this case, the conditional NO_X input demand is perfectly inelastic over the regulated range. Note furthermore that climate policy cannot increase the conditional NO_X input demand (or the emissions rate regulation would be violated). Since the output effect may still serve to reduce NO_X emissions, NO_X and CO_2 cannot be gross substitutes, *i.e.,* climate policy cannot increase NO_X emissions with emissions rate regulation.

$U'(q)$ equals the market price. The profit maximizing firm use the inputs such that the value of the marginal product equals the input price, *i.e.,* such that $U'(q)f_1 = w$, $U'(q)f_2 = t_{CO2}$, and $U'(q)f_3 = t_{NOx}$ where f_i is the ith marginal product.

The change in social surplus from a marginal change in the carbon tax is then given by:

$$\begin{aligned}
&\frac{d}{dt_{CO2}}[U(q) - wk - \tau_{CO2}CO2 - \tau_{NOx}NOx] \\
&= (U'f_1 - w)\frac{dk}{dt_{CO2}} + (U'f_2 - \tau_{CO2})\frac{dCO2}{dt_{CO2}} + (U'f_3 - \tau_{NOx})\frac{dNOx}{dt_{CO2}} \\
&= (t_{CO2} - \tau_{CO2})\frac{dCO2}{dt_{CO2}} + (t_{NOx} - \tau_{NOx})\frac{dNOx}{dt_{CO2}}. \qquad (1)
\end{aligned}$$

Equation [1] decomposes the change in social surplus from climate policy into a direct effect and a spillover effect. There are several things to note about [1]. First, the direct effect is positive (increases social surplus) if the carbon tax is less than damages. Second, the spillover effect can be either positive or negative. If the NO_X tax is less than damages, the spillover effect is positive if NO_X and CO_2 are complements, *i.e.,* if $\frac{dNOx}{t_{CO2}} < 0$. Conversely, the spillover effect is negative (reduces social surplus) if NO_X and CO_2 are substitutes. Third, the spillover effect is zero if NO_X emissions are currently regulated at damages *i.e.,* if $t_{NOx} = \tau_{NOx}$ or if NO_X emissions are capped, *i.e.,* $\frac{dNOx}{dt_{CO2}} = 0$. This shows that the spillover benefits only arise because of a failure in the NO_X environmental regulations. Finally, note that the optimal carbon tax may not be equal to carbon damages. In fact, the optimal carbon tax should be higher than carbon damages in the case where the spillover effects are positive.

For a larger change in the carbon tax, the change in social surplus is given by:

$$\Delta U - w\Delta k - \tau_{CO2}\Delta CO2 - \tau_{NOx}\Delta NOx. \qquad (2)$$

The first term is the change in consumer surplus from climate policy, and the second term is the change in the market input costs. These two terms, which combined are negative, are generally considered the abatement cost of the climate policy. The third term is the change in carbon damages, which is positive. In a benefit-cost analysis, this third term is the benefit of the policy. The final term is the change in NO_X damages and is the spillover benefit (or cost) of the climate

policy. Note that it is somewhat arbitrary whether this spillover term is labeled an additional benefit of the climate policy or is part of the abatement cost of the policy.[11]

The analysis in this section also contains theoretical predictions which can be used to aid in the identification of empirical models. Although spillover effects can be either positive or negative, the own price effects must be negative. In particular, both the input demand and conditional input demand must be decreasing in the own price and output effects must be negative.[12]

3 Estimation Strategy

The theoretical framework in Section 2 describes how firms respond to climate policy by reducing CO_2 emissions and potentially affecting emissions of other pollutants as well. Unfortunately, we cannot test these effects empirically in industries which are not yet subject to climate policy. Moreover, in industries currently subject to climate policy, it would be difficult to disentangle the effects of climate policy separately from the effects of other environmental regulations.

To overcome these difficulties, I exploit the symmetry of input substitution and estimate the response of CO_2 emissions to the change in the price of NO_X emissions.[13] This has two advantages. First, NO_X emissions have been regulated extensively so it is possible to design an estimation strategy with variation in NO_X regulations. Second, CO_2 was not regulated, so there is no need to disentangle the effects of the NO_X regulation from CO_2 regulation.

To estimate the response of CO_2 emissions to a change in the NO_X prices, I use changes in attainment status under the CAAAs as a proxy for changes in prices of environmental inputs. Under the CAAAs, regions that fail to achieve an ambient air quality standard for a certain pollutant are deemed to be in nonattainment status for that pollutant. Designation as nonattainment status triggers additional regulations, which vary according to each state's implementation plan (SIP), for returning to attainment status.[14] In this study, the change in attainment status for 1-hour ozone is a proxy for a change in the price of emissions of NO_X , which is a primary ozone precursor.

[11] For example, reductions in other input costs could also be considered "spillover benefits".

[12] See Appendix 1 for details.

[13] See Appendix 1 for details on the symmetry of input substitution.

[14] For detailed descriptions of the regulatory effects of nonattainment designation under the CAAAs, see Greenstone (2002).

The estimation strategy uses a fixed effects estimator to estimate the effect of a change in attainment status on the emissions of NO_X and CO_2.[15] The basic estimating equation is:

$$\ln(\text{Emiss}_{it}) = \beta \text{Nonattain}_{it} + \gamma X_{it} + f_i + g_i t + \nu_{jt} + \epsilon_{it} \tag{3}$$

where Emiss_{it} is emissions from generating unit i at time t; Nonattain_{it} is a dummy variable indicating that unit i is in nonattainment status for 1-hour ozone at time t; X_{it} is a vector of controls for other regulations; f_i is a unit-specific fixed effect; $g_i t$ is a unit-specific linear trend; ν_{jt} is a market-year-month fixed effect for market j; and ϵ_{it} is the error term. To correct for possible serial correlation, the error term, ϵ_{it}, is clustered at the generating unit.

The parameter of interest is β, which indicates the response of emissions to a change in attainment status.[16] Since the nonattainment dummy is a proxy for an increase in the price of NO_X emissions, the estimated coefficient captures the own price effect when NO_X emissions are the dependent variable. With CO_2 emissions as the dependent variable, the estimated coefficient captures the spillover. A positive (negative) coefficient indicates that NO_X and CO_2 are gross substitutes (complements).

Most of the potentially confounding variation is controlled for by the fixed effects. The unit-specific fixed effects capture any differences in emissions across units due to fuel-mix, generation technology, generator capacity, installed emissions control equipment, or any other time-invariant characteristics of the generating units. The unit-specific linear trends capture any trends at the unit level, *e.g.,* phasing out of old units. The market-year-month fixed effects are a vector of indicators for each month of each year for each market, *e.g.,* one indicator is for January 1999 for the northern California market (NP15) and another indicator is for January 1999 for the southern market. The market-year-month fixed effects capture all variation over time such as seasonal effects and changes in relative fuel prices, in labor costs, in capital costs, and in regulations affecting all generators as well as differences across the markets. This flexible set of fixed effects captures most of the potentially confounding effects.

The controls, X_{it}, capture changes is other regulations such as changes in attainment status

[15] Results are also presented for SO_2.

[16] The percentage change in emissions from nonattainment designation is given by $e^{\beta} - 1$.

for other pollutants, *e.g.,* carbon monoxide, nitrogen dioxide, and particulate matter, as well as other regulations under the Acid Rain Program.[17]

Given this extensive set of nonparametric controls, model identification is based on variation in the attainment status of generating units over time in the sample. With one change in attainment status, the estimator would be similar to the well-known difference-in-differences estimator.[18] Intuitively, the generating units with unchanged attainment status would serve as controls for the generators with changed attainment status (the treated group).[19] With a one-time change in attainment status, the estimated effect would be biased if there were unobserved differential trends in emissions that were correlated with the change in attainment status. This threat to identification is addressed in two ways. First, the main study analyzes California, which had multiple changes into and out of attainment status over the sample period. These multiple changes diminish the potential for bias from unobserved trends. Second, the model incorporates unit-specific linear trends to control for any unit-specific trends, which would not be captured by the market-year-month fixed effects.

The regulatory changes that accompany nonattainment designation vary and are subject to local discretion. The estimated spillover effect could therefore be biased if regulatory authorities used the additional statutory authority to attempt to reduce emissions of other pollutants. In this case, changes in attainment status would indicate variations in the prices of both NO_X emissions and other pollutants, and the estimated effect would combine the direct and spillover effects. This potential confounding is limited by analyzing spillovers on CO_2 emissions. During the sample period, there was still substantive disagreement over whether CO_2 was a harmful pollutant and CO_2 was neither listed nor regulated by the EPA as a criteria pollutant. This lack of regulatory attention to CO_2 emissions suggests that the nonattainment indicator is not a proxy for an increase in the price of CO_2 emissions and that the spillover effect is properly identified.[20]

[17] When the dependent variable is daily emissions, a flexible function of daily average temperature controls for changes in demand for electricity within the month. The temperature controls are not included when the dependent variable is average monthly emissions since it would be perfectly collinear with the market-year-month effects.

[18] With no variation in attainment status, the nonattainment indicator would be perfectly collinear with the unit fixed effects.

[19] Some of the controls are always in attainment status whereas some are always in nonattainment status.

[20] This argument does not hold for SO_2 emissions.

Identification is supported by the testable predictions from theory. In particular, Appendix 1 shows that the own price effect should be non-positive for factor demands. A negative own price effect, estimated by β in [3] with NO_X emissions as the dependent variable, is consistent with the theoretical predictions and provides evidence that the change in nonattainment status is a proxy for an increased price of NO_X emissions.[21]

Additional testable predictions provide further evidence that the model is properly identified. Specifically, the conditional own price effect should be non-positive. The conditional factor demand, which is the input demand for a given level of output, can be estimated by conditioning on output. In particular, by estimating the equation:

$$\ln(\text{Emiss}_{it}) = \beta^c \text{Nonattain}_{it} + \beta^{MWh} \ln(\text{MWh}_{it}) + \gamma X_{it} + f_i + g_i t + \nu_{jt} + \epsilon_{it} \tag{4}$$

with NO_X emissions as the dependent variable, the coefficient β^c estimates the conditional own price effect if MWh_{it} properly conditions for output. Thus an estimated β^c less than or equal to zero is consistent with the requirement that the conditional own price effect be non-positive.

The output effect should be non-positive for own prices, *i.e.,* $\frac{dNOx^c}{dq}\frac{dq}{dp_{NOx}}$ should be non-positive. This provides another testable implication: the own price effect should be stronger than the conditional own price effect, i.e., $\beta - \beta^c \leq 0$.

I also present results from regressing output on the same set of controls. This allows for a direct test of the output effect.[22]

A similar procedure can be used to separate the spillover effect on CO_2 emissions into output and substitution effects. In particular, by estimating [3] and [4] with CO_2 emissions as the dependent variable, output and substitution effects can be estimated. This does not provide further testable implications of the theory since cross price effects can be either negative or positive. However, separating the spillover effects into output and substitution effects is important for understanding the policy and modeling implications of spillovers.

[21] Theory makes no prediction about the sign of the spillover effect, estimated with CO_2 emissions as the dependent variable.

[22] Specifically, the regression is: $\ln(\text{MWh}_{it}) = \beta' \text{Nonattain}_{it} + \gamma X_{it} + f_i + g_i t + \nu_{jt} + \epsilon_{it}$. This result estimates separately all four derivatives in the Slutsky equation in the appendix. In particular, the identity $\beta = \beta^{MWh}\beta' + \beta^c$ holds since the sample and all conditioning variables are identical.

4 Data

This analysis requires data on emissions, generation, attainment status, and other regulations. Availability of the emissions data limit the sample to the years 1997-2004. Emissions data come from the hourly U.S. EPA continuous emissions monitoring systems (CEMS) for power plants. The data are very accurate, include all fossil-fuel fired generators meeting certain requirements, and have been used in a number of studies.[23] The primary level of analysis is at the generating unit level as defined by the EPA.[24] The hourly data are aggregated to the month for three reasons.[25] First, a number of units report emissions in hours for which they report no output. Aggregation accurately captures emissions and output while incorporating any start-up emissions from generating units. Second, if regulations caused a unit to be run on fewer hours, disaggregated data would not capture this reduction since the estimating equations only analyze proportional changes. Aggregation captures the zero production hours for the proportional estimating equation. Finally, the data is highly serially correlated. Aggregation reduces the problem of serial correlation.

Since California had the most variation in attainment status, the primary analysis focuses on California. Of the twelve counties in California with changes in attainment status, only three counties have relevant power plants: Contra Costa, San Francisco, and San Diego.[26,27] The redesignation months of August 1998 and July 2003 are dropped from the sample for all units.[28] After dropping non-reports and data inconsistencies, the model identification is based on changes in attainment status at 29 of 178 generating units.[29] The data are discussed further in the appendix.

The average year online across the 178 units in the sample is 1982.[30] The fourteen units

[23]For example, see Puller (2007), Holland and Mansur (2008).

[24]A unit may consist of one or more smokestacks, boilers and/or generators.

[25]Results for daily aggregation are also presented as a robustness check.

[26]Appendix Table 1 shows the power plants and number of units in these three counties reporting in the CEMS data before and after a change in attainment status. Six counties had no power plants during the sample. Santa Clara County had no power plants when its designation changed in 1999. The Kern and Solano County redesignations were for partial counties. Kern County had three power plants coming online after 2001 and Solano County had four power plants coming online after 2002, but these plants were not in redesignated areas.

[27]San Diego was declared to be in nonattainment of the new 8-hour ozone standard in 2004. The estimation controls for this redesignation.

[28]The effective dates of the redesignations (Aug. 10, 1998 and July 28, 2003) are from 63 FR 37258-37280 and 68 FR 37976-37978.

[29]Five units report zero emissions and generation throughout the sample. The five reporting units at Hunters Point are aggregated since four units report zero generation but positive emissions.

[30]Appendix Table 1 reports the average year online of the generators at each power plant. Since generators and units are not necessarily the same, the age of each unit cannot be known. The average age (year online) of the

which are always in attainment are somewhat older: average year online is 1978; whereas the 139 units which were never in attainment were somewhat newer: average year online is 1984. The units which switch attainment status also tend to be somewhat older on average. The relevant units in Contra Costa and San Francisco counties, which were designated as not in attainment in 1999, are quite a bit older: average year online is 1961. The units in San Diego, which was designated to be in attainment in 2004, are slightly older than average: average year online is 1978. The unit fixed effects control for these differences in the age of the units.[31]

5 Estimation Results

The main results from estimating equations [3], [4], and the output equation are presented in Table 1. The preferred specification (in Panel A) controls for other regulatory programs, while the specification in Panel B omits these controls. Throughout, the unit fixed effects, unit-specific linear trends, and market-year-month fixed effects are highly significant but are not reported.

Each column in the tables reports the results from one of seven regressions. Column (1) reports the results from estimating equation [3] where $\ln(NO_X)$ is the dependent variable. This equation estimates the NO_X factor demand since it does not control for output. Similarly, columns (3) and (5) capture the factor demands for CO_2 and SO_2. Columns (2), (4), and (6) estimate the conditional factor demands since they control for output, *i.e.,* ln(MWh). Column (7) reports estimates from regressing output on the same set of controls.

The three testable implications, which relate to the own price effects, are shown in columns (1) and (2). In Panel A, the estimated 38% reduction in NO_X emissions from nonattainment designation is significant at the 5% level. When controlling for output, the estimated 20% reduction is significant at the 10% level. Both own-price effects are non-positive. Finally, the estimated own price effect is larger for the factor demand than for the conditional factor demand, *i.e.,* the output effect is negative.[32] Thus, the regression results are consistent with the theoretical predictions.

generators at plant thus is a proxy for the age of the units.

[31]The unit fixed effects cannot control for different trends at different age units. The unit-specific linear trends address this issue. In addition, the sample is split to estimate the model separately for units with different average plant age.

[32]Since the output effect is estimated from two separate regressions, this is not a formal statistical test, but rather a comparison of the point estimates. The 95% confidence interval for each point estimate includes the other estimate,

Moreover these results show that approximately half of the 38% reduction in NO_X emissions can be attributed to substitution effects with the remainder being attributable to output effects.

The pollutant spillover effects are reported in columns (3)-(6). For CO_2, the point estimate indicates that nonattainment designation reduced CO_2 emissions by 22%, suggesting gross complementarity. Controlling for output, the point estimate indicates quite small net substitutability ($\sim$ 2%) with a 95% confidence interval from -0.06 to 0.12. This quite limited net effect suggests that almost all of the (statistically insignificant) reduction in CO_2 emissions can be attributed to output effects.

Similarly, the results for SO_2, columns (5) and (6), also suggest a rather substantial (but statistically insignificant) gross complementarity with NO_X but negligible net effects. As detailed above, SO_2 emissions are quite small for all but a few units in California so the SO_2 results are less reliable. In addition, SO_2 emissions are themselves regulated and thus the estimates can be confounded by an increase in general regulatory stringency.

The point estimates for output (column seven in Panel A) suggest that nonattainment designation reduced output by 27%. Although this point estimate suggests quite a large effect, it is not statistically significant.

The output controls imply emissions elasticities for the three pollutants of 0.8, 0.9, and 0.9 with respect to output. These estimates are statistically significant and statistically less than one implying that the emissions rates (emissions per MWh) are declining in output. However, the limited net effects suggest that the emissions rates do not vary substantially with changes in prices of other environmental inputs, *i.e.,* pollutant spillovers do not change emissions rates.

The controls for other regulations are mostly not significant individually. Only three of 28 estimated coefficients are statistically different from zero. Moreover, the four estimated coefficients are only jointly significant in the regression in column (6). Despite this lack of statistical significance, it is important to control for the potential confounding from other regulations.

The controls for other regulations are omitted for the regression results in Panel B. The estimated coefficients of interest are larger when not controlling for the other regulatory programs

e.g., the 95% confidence interval around -0.473 includes -0.219.

and statistical significance increases. In particular, the pollutant spillovers for CO_2 and SO_2, which were previously insignificant, are now significant as is the change in output. Although these other regulations are only weakly correlated with the 1-hour ozone designation, the regressions cannot disentangle the effects sufficiently to attribute the observed reduction in CO_2 and SO_2 emissions to the change in 1-hour ozone attainment status.

The results are subject to two additional caveats. First, the power of the test is reduced since electric power generators were likely not the marginal polluter targeted by the change in attainment status. In particular, the state implementation plans (SIPs) for reducing NO_X emissions do not focus on electric power generation. Second, the estimates cannot control for local economic conditions which may have been correlated with changes in attainment status.

6 Conclusion

Spillovers from climate policy are important for policy design, modeling and benefit-cost analysis. This paper contributes to the understanding of climate policy spillovers by presenting a model of climate policy spillovers. The models shows that spillovers arise from output effects (which have ancillary benefits) and substitution effects (which may have ancillary benefits or ancillary costs). The ambiguous net effect highlights the importance of polluters' responses to climate policy.

The paper then tests for ancillary benefits from climate policy in electricity power generation using the theory. The estimates are consistent with ancillary benefits from climate policy. However, the effects are not precisely estimated and cannot be separated cleanly from the effects of other environmental regulation.

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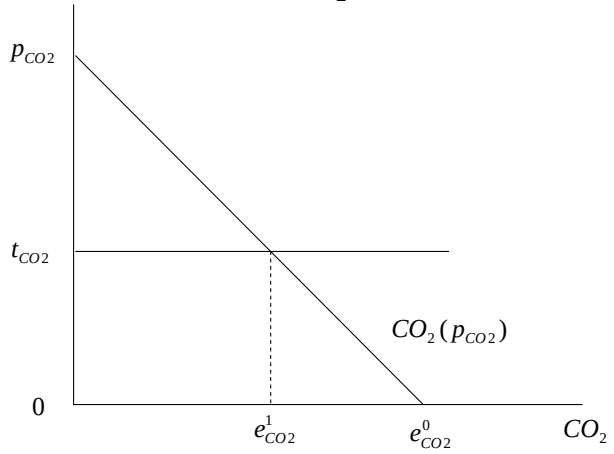
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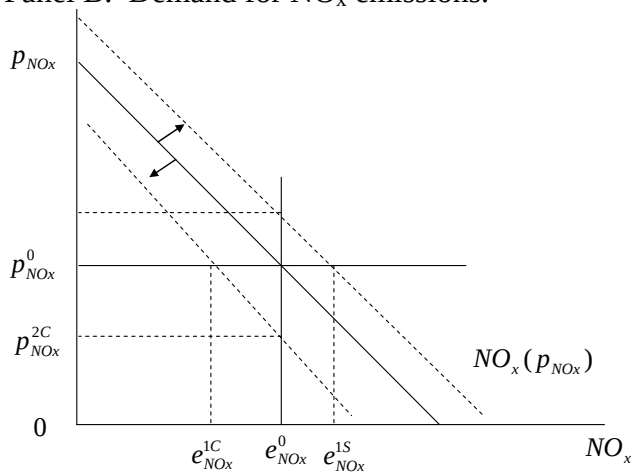
Figures and Tables

Figure 1. Graphical model of spillovers from climate policy.

Panel A. Demand for CO_2 emissions.



Panel B. Demand for NO_x emissions.



Panel C. Supply and demand for electricity.

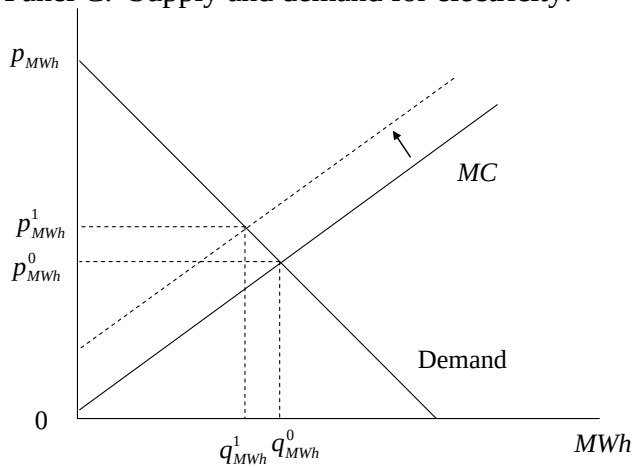


Table 1: Main Results. California results for NOx, CO2, and SO2 emissions and Megawatt hours.

Panel A: Including other regulatory controls.

	ln(NO_X)		ln(CO_2)		ln(SO_2)		ln(MWh)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nonattain	-0.473**	-0.219*	-0.254	0.028	-0.304	-0.020	-0.314
	(0.209)	(0.132)	(0.202)	(0.047)	(0.170)	(0.129)	(0.205)
ln(MWh)		0.809**		0.900**		0.896**	
		(0.016)		(0.010)		(0.012)	
CO nonattain	0.158	-0.006	0.296	0.113	0.251	0.076	0.203
	(0.211)	(0.159)	(0.183)	(0.085)	(0.153)	(0.134)	(0.164)
NO2 nonattain	0.073	0.017	0.109	0.047	0.247	0.211**	0.069
	(0.260)	(0.135)	(0.277)	(0.034)	(0.247)	(0.080)	(0.291)
8hr Oz nonattain	0.172	0.045	0.182	0.041	0.495**	0.334	0.157
	(0.185)	(0.119)	(0.182)	(0.035)	(0.247)	(0.223)	(0.218)
ARP NOx Early Elect	0.068	-0.197**	0.242	-0.053	0.319	-0.003	0.328
	(0.511)	(0.098)	(0.624)	(0.046)	(0.630)	(0.067)	(0.651)

Panel B: Omitting other regulatory controls.

	ln(NO_X)		ln(CO_2)		ln(SO_2)		ln(MWh)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nonattain	-0.516**	-0.221*	-0.326*	0.003	-0.371**	-0.037	-0.365*
	(0.203)	(0.131)	(0.190)	(0.030)	(0.170)	(0.132)	(0.200)
ln(MWh)		0.809**		0.900**		0.897**	
		(0.016)		(0.010)		(0.013)	

Notes: 8,239 monthly observations for 178 generating units. (8,188 observations for the SO_2 regressions.)

Dependent variable is log of emissions or log of MWh of generation.

Regressions additionally control for market-year-month fixed effects, generating unit fixed effects, and generating unit linear trends.

Controls for other regulations: (CO, NO2, and 8-hour ozone nonattainment and ARP NOx Early Election) are not jointly significant in six of the seven regressions.

** indicates significance at the 5% level and * indicates significance at the 10% level.

Appendices

Appendix 1: Theoretical results

Let input demands—which are functions of input and output prices and are derived from profit maximization—be $CO2$ and NOx. By Hotelling's lemma, the input demands are the derivatives of the profit function. By the symmetry of the Hessian matrix of the profit function, the cross-derivatives of the input demands are equal. If $dNOx/dp_{CO2} = dCO2/dp_{NOx}$ is greater (less) than zero, then NO_X and CO_2 are *gross substitutes (complements).*

Similarly, let conditional input demands—which are functions of input prices and the output level and which are derived from cost minimization—be $CO2^c$ and NOx^c. By Shepard's lemma, the conditional input demands are the derivatives of the cost function. By the symmetry of the Hessian matrix of the cost function, the cross-derivatives of the conditional input demands are equal. If $dNOx^c/dp_{CO2} = dCO2^c/dp_{NOx}$ is greater (less) than zero, then NO_X and CO_2 *net substitutes (complements).*

Since profit maximization implies cost minimization, the factor demands must equal the conditional factor demand where the output level is given by the supply function. Differentiating these identities for NOx and $CO2$ with respect to p_{CO2} gives the following "Slutsky" relationships:

$$\frac{dCO2}{dp_{CO2}} = \frac{dCO2^c}{dq}\frac{dq}{dp_{CO2}} + \frac{dCO2^c}{dp_{CO2}} \tag{5}$$

and

$$\frac{dNOx}{dp_{CO2}} = \frac{dNOx^c}{dq}\frac{dq}{dp_{CO2}} + \frac{dNOx^c}{dp_{CO2}}. \tag{6}$$

Equation 5 shows that the total change in NO_X emissions resulting from a change in the price of those emissions can be decomposed into an *output* and a *substitution* effect. The output effect, $\frac{dCO2^c}{dq}\frac{dq}{dp_{CO2}}$, is the change in emissions that results because the firm may choose to produce a different level of output (with different emissions) under the new input prices. The substitution effect describes the change in emissions which results from the changing relative prices of inputs while holding output constant. Intuitively, the substitution effect arises because the cheapest way of attaining a given output level may require more (different) capital or fuel or CO_2 emissions when the relative price of NO_X emissions increases.

Similarly, equation 6 decomposes the spillover effect (cross-price effect) into an output effect and a substitution effect. Note that the cross-price output effect is similar to the own-price output effect, except for the different marginal emissions rate.

Theory imposes some restrictions on the signs of these effects. These restrictions are:

Proposition 1 *Cross price effects are symmetric, i.e.,* $\frac{dCO2}{dp_{NOx}} = \frac{dNOx}{dp_{CO2}}$ *and* $\frac{dCO2^c}{dp_{NOx}} = \frac{dNOx^c}{dp_{CO2}}$. *Own price effects are non-positive for both the factor demand and the conditional factor demand, e.g.,* $\frac{dCO2}{dp_{CO2}} \leq 0$ *and* $\frac{dCO2^c}{dp_{CO2}} \leq 0$. *Output effects are always non-positive for the own prices, e.g.,* $\frac{dCO2^c}{dq}\frac{dq}{dp_{CO2}} \leq 0$. *Cross price (substitution and output) effects can be either positive or negative for both the factor demands and conditional factor demands.*

Proof of Proposition 1:

The symmetry of the cross-price effects is derived above. Since the profit function is convex, its Hessian matrix is positive definite, so its main diagonal elements must be positive. Since

the factor demands are the additive inverses of the first derivatives of the profit functions, the positive definite Hessian implies that the own-price effects are negative. Similarly, since the conditional factor demands are the derivatives of the concave cost function, the own-price substitution effects must be negative.

To show that the own-price output effect must be negative, decompose the output effect into:

$$\frac{dCO2^c}{dq}\frac{dq}{dp_{CO2}} = \frac{dCO2^c}{dq}\frac{dq(P=MC)}{dMC}\frac{dMC}{dp_{CO2}}$$

where MC is the marginal cost. Since quantity decreases when marginal cost increases, $\frac{dq(P=MC)}{dMC}$ is negative. For an inferior input, an increase in the input price can decrease marginal cost. But since

$$\frac{dCO2^c}{dq} = \frac{d^2c}{dqdp_{CO2}} = \frac{dMC}{dp_{CO2}}$$

the first and last factors must have the same sign even if the input is inferior. Thus the own-price output effect is negative.[33]

Since the cross-price effects are the off-diagonal elements of the matrix they can be either negative or positive. Moreover, if one of the inputs is an inferior input, then the cross-price output effect can be positive. ■

Proposition 1 provides three testable implications for the econometric estimation. Namely, own price effects should be non-positive for both the factor demand and the conditional factor demand, and the own output effect should be non-positive. For estimates that do not conform with these predictions, either the model suffers some specification error or attainment status is not a valid proxy for the price of NO_X emissions.

Although cross-price output effects can be positive, the proof of Proposition 1 makes clear that they can only be positive in the case of an inferior input. If all inputs are normal, then all output effects must be negative. Thus, the only way for two normal inputs to be gross substitutes (*i.e.,* for a regulation to increase emissions of a nontarget pollutant) is for them to be net substitutes and for the output effect to be sufficiently small that it does not outweigh the substitution effect.

Appendix 2: Data

Appendix Table 1 presents summary statistics of the data aggregated to the month and to the day. The first three rows are for the primary dependent variables: NO_X , CO_2, and SO_2 emissions. The monthly means are approximately 20 times the daily means, implying that units are generating 20 days per month on average. SO_2 emissions are particularly noisy (the coefficient of variation is about 15). Most generating units in California are gas-fired and thus have negligible SO_2 emissions, so the large coefficient of variation is driven by a few units with exceptionally high SO_2 emissions. The proxy for the price of NO_X emissions, nonattainment of the 1-hour ozone CAAAs standard, is positive for 86% of the monthly sample and 84% of the daily sample. This slight difference arises because the exclusion of months or days with zeroes for the dependent variables puts a different weight on each hour. About 30% of the observations are from the northern California electricity market (North Path 15). The market-year-month fixed effects control for differences across the two markets. Approximately 45% of the observations are of units which were also in nonattainment of the CAAAs' carbon monoxide

[33]This argument follows Nicholson's well-known text.

(CO) standard. The regressions control for these other programs. There is no unit-level variation in PM nonattainment, so this control is dropped from the regression, *i.e.,* is perfectly collinear with the unit fixed effects. None of the units is affected by the NO_X budget program (NBP) or the Ozone Transport Commission (OTC). None of the units is affected by the Acid Rain Program provisions affecting NO_X , although a four units at three plants did choose early election into the NO_X program.[34] All of the units were Phase 2 units under the Acid Rain Program affecting SO_2 (Title IV of the CAAAs). Since these regulations affected all units beginning in 2000, this control is dropped from the regressions, *i.e.,* is perfectly collinear with the market-year-month fixed effects.

Appendix Figures 1 shows average monthly NO_X emissions, CO_2 emissions, and generation over the sample years for four groups of units in California: two *control* groups (those units either always or never in attainment) and two *treatment* groups (those units declared in nonattainment in 1999 and those units redesignated as attainment in 2004).[35] Panel A shows that average monthly NO_X emissions from units generally fell over the sample. The monthly averages are mostly above the sample mean of 24,000 lbs. since the largest group (those units always in nonattainment) contains 139 of the 178 units. Average emissions from the units always in nonattainment only declined slightly over the sample, however average emissions of the 14 units always in attainment declined dramatically between 2000 and 2003. The NO_X emissions from the 11 units that were redesignated in nonattainment in 1999 also show a steep decline in emissions after 2000. Note that these units initially had higher emissions than the controls which were always in attainment, but then in 1999 and after had lower emissions. This suggests that the redesignation may have lowered emissions at these units. However, the units which were redesignated as in attainment in 2004 do not show a noticeable up tick in 2004 as might be expected in response to relaxed regulations.

Similar patterns are evident in the average monthly CO_2 emissions and generation shown in Panels B & C. In particular, a decline is seen in CO_2 emissions and generation from 2001-2003 for some groups. There does not seem to be as strong a decline over time as shown for the NO_X emissions. Comparing the CO_2 emissions at units always in attainment with those designated nonattainment in 1999, we again see lower emissions and generation after 1998 at the units which were designated nonattainment. The pattern is not as clear, since these units then have higher emissions after 2001. The regressions will estimate whether emissions were higher or lower controlling for other confounds.

Appendix 3: Robustness tests

Appendix Tables 3-6 present the robustness of the results to different specifications. Appendix Table 3 splits the sample into two time periods: before and after 2001. Identification of the result in Panel A is based on the 1999 redesignation of the San Francisco Bay Area to nonattainment status, while identification in Panel B is based on the redesignation to attainment of San Diego in 2004. Following the 1999 redesignation to nonattainment, the Bay Area Air Quality Management District was required to submit a State Implementation Plan (SIP) for how it would regain attainment status. The plan did not require new power plant controls (BA AQMD 2001). Thus, it is perhaps not surprising that the results in Panel A do not satisfy the testable predictions from theory. The results in Panel B, however, do satisfy the testable predictions and are quite

[34]The three power plants were AES Alamitos, Etiwanda Generating Station, and Riverside Canal Power Company. The indicators are only positive between 1997 and 1999.

[35]The two control groups had 14 units and 139 units. The two treatment groups had 11 units and 14 units.

similar in sign and magnitude to the main results in Table 1. When San Diego was designated as attainment in July 2003, the state was required to file a maintenance plan to prevent backsliding, however, other requirements associated with nonattainment designation for 1-hour ozone were relaxed.[36]

Appendix Table 4 splits the sample into old plants (those with average generator age before 1980) and new plants (those with average generator age after 1995). Note that no plants had an average generator age between 1980 and 1995 reflecting the lack of new construction of large power plants in California over this time frame. Appendix Table 4 shows that the results in Table 1 come primarily from the changes at older plants and the results in Panel A are quite similar in sign and magnitude to the results in Table 1. In particular, the gross CO_2 spillovers are significant at the 5% level as is the effect on output. The results in Panel B are not consistent with the testable predictions.

Appendix Table 5 presents analysis based on different levels of aggregation. Panel A presents results based on aggregating the data to the plant level. This reduces the number of observations by more than half and thus increases the standard errors. In addition, this analysis does not control for changes at the plant level, such as additions or retiring of units, which may be correlated with attainment designation. The preferred specifications directly control for these changes with the unit fixed effects and additionally control for differential trends within a plant with the unit-specific linear trends.

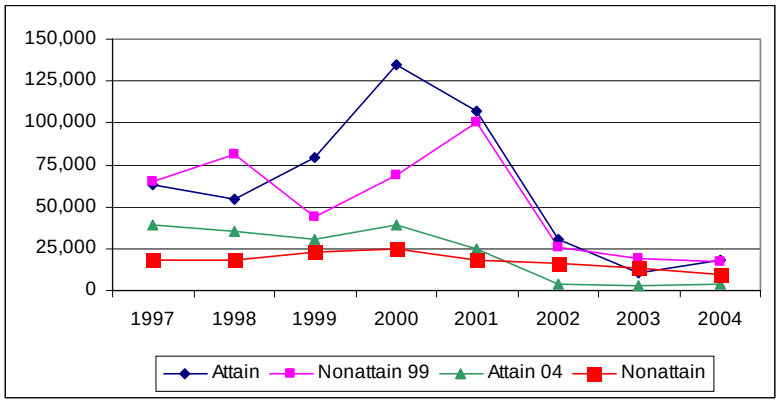
Panel B of Appendix Table 5 presents the results based on aggregating the hourly data to the day instead of the month. The signs and magnitudes of the results are quite similar to the preferred results in Table 1. Additionally, the standard errors are more precise leading to statistical significance of the gross spillover effects for both CO_2 and SO_2 as well as a significant effect on output. These regressions additionally control for a quadratic function of temperature, which is statistically significant.

Appendix Table 6 omits the unit-specific linear trends from the specification. The signs of the estimates are generally consistent with those in the preferred specification; however, the magnitudes of the own price effects are somewhat smaller. This specification also shows a marginally significant reduction in CO_2 emissions and a significant reduction in output from nonattainment designation.

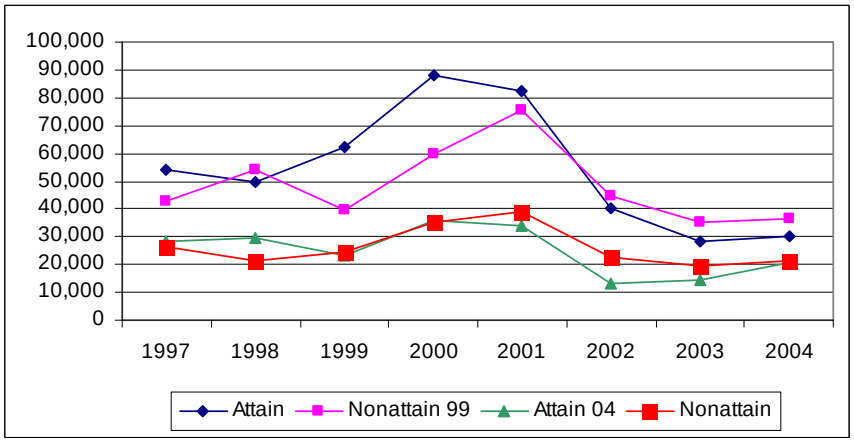
[36]San Diego was designated as in nonattainment of the 8-hour ozone standard in 2004. The main regressions control for this designation.

Appendix Figure 1.

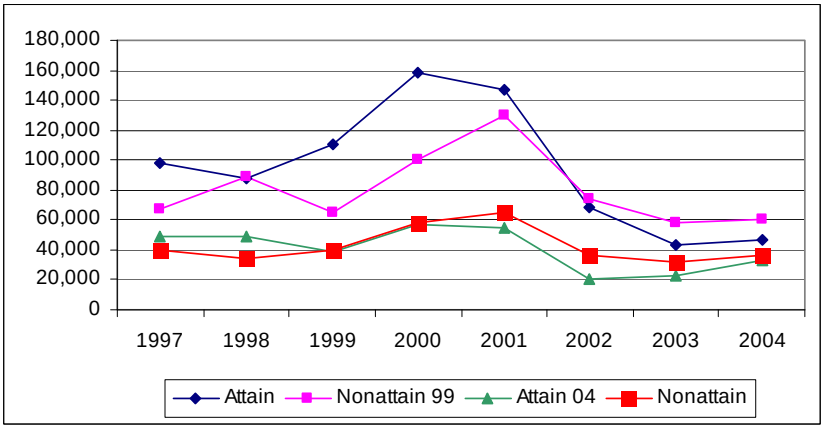
Panel A: NO_x emissions at power plant units in California by attainment status.



Panel B: CO_2 emissions at power plant units in California by attainment status.



Panel C: Generation at power plant units in California by attainment status.



Notes: "Attain" are the 14 units which are in attainment throughout the sample; "Nonattain 99" are the 11 units in the San Francisco Bay Area which were redesignated as nonattainment in 1999; "Attain 04" are the 18 units in San Diego which were redesignated as attainment in 2004; and "Nonattain" are the 135 units which are in nonattainment throughout the sample.

Appendix Table 1: Power plants in California counties with changes in attainment status for the 1-hour ozone standard from 1997-2004.

County	Re-designation	Power Plants (# units, mean year online)
Contra Costa	Nonattainment Aug. 10, 1998	Contra Costa Power Plant (2, 1964) Pittsburg Power Plant (7, 1958)
San Francisco	Nonattainment Aug. 10, 1998	Hunters Point (1, 1958) Potrero Power Plant (1, 1973)
San Diego	Attainment July 28, 2003	Cabrillo Power I (Encina) (5, 1965) Duke Energy South Bay (4, 1966) Cal Peak Power - Border (1, 2002) Cal Peak Power - El Cajon (1, 2002) Cal Peak Power - Enterprise (1, 2002) Escondido Power Plant (2, 2001) Chula Vista Power Plant (2, 2002) Larkspur Energy Facility (2, 2001)

Notes: Data on attainment status from http://www.epa.gov/air/oaqps/greenbk/anay.html. Power plant data from EGRID. Mean year online averages the starting years of the generators within the power plant. The five units at Hunters Point are combined since only one reports positive output.

Appendix Table 2: Means and standard deviations for California by unit aggregated to the month and day.

	Monthly	Daily
NOx lbs	24,073	1,297
	(58,973)	(2,614)
CO2 tons	30,111	1,623
	(38,140)	(1,526)
SO2 lbs	783	42
	(12,439)	(583)
Megawatt hours	49,823	2,689
	(67,057)	(2,740)
1-hour Ozone nonattainment	0.860	0.842
	(0.347)	(0.365)
North Path 15	0.310	0.346
	(0.462)	(0.476)
CO nonattainment	0.473	0.442
	(0.499)	(0.497)
NO2 nonattainment	0.083	0.082
	(0.276)	(0.274)
8-hr Ozone nonattainment	0.178	0.154
	(0.382)	(0.361)
PM nonattainment	0.599	0.573
	(0.490)	(0.495)
ARP: NOx Early Elect	0.008	0.006
	(0.089)	(0.076)
ARP: SO2 Phase 2	0.746	0.735
	(0.435)	(0.441)
Average temperature (NP15)		58.761
		(10.189)
Average temperature (SP15)		65.040
		(9.509)
N	8,239	152,642

Appendix Table 3: Early and late. California results for NOx, CO2, and SO2 emissions and Megawatt hours.

Panel A: Before 2000: 1997 to 2000. 3,022 observations with 96 units.

	$\ln(NO_X)$		$\ln(CO_2)$		$\ln(SO_2)$		ln(MWh)
Nonattain	0.250	-0.098	0.387	0.020	0.291	-0.081	0.416
	(0.277)	(0.150)	(0.239)	(0.077)	(0.245)	(0.139)	(0.252)
ln(MWh)		0.836**		0.884**		0.896**	
		(0.027)		(0.017)		(0.019)	

Panel B: After 2000: 2001 to 2004. 5,217 observations for 174 units.

	$\ln(NO_X)$		$\ln(CO_2)$		$\ln(SO_2)$		ln(MWh)
Nonattain	-0.450*	-0.274*	-0.265	-0.063	-0.782**	-0.587**	-0.224
	(0.252)	(0.140)	(0.244)	(0.040)	(0.229)	(0.146)	(0.246)
ln(MWh)		0.787**		0.907**		0.900**	
		(0.021)		(0.015)		(0.017)	

Note: Regressions additionally control for other regulations, for market-year-month fixed effects, for generating unit fixed effects, and for unit-specific linear trends.

Appendix Table 4: Old and new plants. California results for NOx, CO2, and SO2 emissions and Megawatt hours.

Panel A: Old plants (starting year before 1980). 5,566 observations with 89 units.

	$\ln(NO_X)$		$\ln(CO_2)$		$\ln(SO_2)$		ln(MWh)
Nonattain	-0.715**	-0.297*	-0.462**	-0.011	-0.325*	0.124	-0.511**
	(0.230)	(0.159)	(0.198)	(0.020)	(0.174)	(0.140)	(0.222)
ln(MWh)		0.817**		0.883**		0.887**	
		(0.018)		(0.012)		(0.013)	

Panel B: New plants (starting year after 1995). 2,673 observations with 89 units.

	$\ln(NO_X)$		$\ln(CO_2)$		$\ln(SO_2)$		ln(MWh)
Nonattain	0.154	0.090	0.044	-0.037	-0.536	-0.615*	0.085
	(0.445)	(0.279)	(0.507)	(0.053)	(0.517)	(0.364)	(0.495)
ln(MWh)		0.754**		0.957**		0.926**	
		(0.037)		(0.022)		(0.030)	

Note: Regressions additionally control for other regulations, for market-year-month fixed effects, for generating unit fixed effects, and for unit-specific linear trends.

Appendix Table 5: Plant and daily. California results for NOx, CO2, and SO2 emissions and Megawatt hours with generating unit fixed effects and fixed effect trends.

Panel A: By plant. 3,552 observations for 71 generating plants.

	$\ln(NO_X)$		$\ln(CO_2)$		$\ln(SO_2)$		ln(MWh)
Nonattain	-0.110	-0.159	0.155	0.098	-0.021	-0.081	0.062
	(0.419)	(0.180)	(0.366)	(0.076)	(0.303)	(0.192)	(0.353)
ln(MWh)		0.803**		0.924**		0.899**	
		(0.033)		(0.020)		(0.024)	

Panel B: Daily observations. 152,642 observations for 178 units.

	$\ln(NO_X)$		$\ln(CO_2)$		$\ln(SO_2)$		ln(MWh)
Nonattain	-0.536**	-0.285**	-0.230*	0.053	-0.341**	-0.077*	-0.346**
	(0.172)	(0.136)	(0.118)	(0.063)	(0.095)	(0.043)	(0.099)
ln(MWh)		0.727**		0.818**		0.794**	
		(0.020)		(0.010)		(0.013)	

Notes: Regressions additionally control for other regulations, for market-year-month fixed effects, for generating unit fixed effects, and for unit-specific linear trends. Daily regressions additionally include a quadratic control for regional temperature.

Appendix Table 6: No trends. California results for NOx, CO2, and SO2 emissions and Megawatt hours without generating unit-specific linear trends.

	$\ln(NO_X)$		$\ln(CO_2)$		$\ln(SO_2)$		ln(MWh)
Nonattain	-0.288	-0.067	-0.222*	0.022	-0.267	-0.019	-0.270**
	(0.191)	(0.166)	(0.120)	(0.034)	(0.169)	(0.128)	(0.121)
ln(MWh)		0.820**		0.906**		0.907**	
		(0.019)		(0.010)		(0.012)	

Notes: 8,239 monthly observations for 178 generating units. Regressions additionally control for other regulations, for market-year-month fixed effects, and for generating unit fixed effects.