NBER WORKING PAPER SERIES

SPILLOVERS FROM CLIMATE POLICY

Stephen P. Holland

Working Paper 16158
http://www.nber.org/papers/w16158

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2010

This paper was prepared for the NBER Conference "The Design and Implementation of U.S. Climate Policy" convened in Washington D.C., May 13-14, 2010. Special thanks to Severin Borenstein, James Bushnell, Chris Ruhm and Catherine Wolfram for helpful discussions. Thanks to the University of California Energy Institute (UCEI) for generous research support during this project. Thanks also to seminar participants at the University of North Carolina at Greensboro and at UCEI and to Michael Mills for valuable research assistance. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

Spillovers from Climate Policy
Stephen P. Holland
NBER Working Paper No. 16158
July 2010
JEL No. H23,Q0

ABSTRACT

Climate policy spillovers can be either positive or negative since firms change their production processes in response to climate policies, which may either increase or decrease emissions of other pollutants. Understanding these ancillary benefits or costs has important implications for climate policy design, modeling, and benefit-cost analysis. This paper shows how spillovers can be decomposed into 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. I then test for climate policy spillovers in electricity power generation. The estimates are consistent with ancillary benefits from climate policy arising primarily from reductions in output (primarily at older plants) rather than from changes in emissions rates.

Stephen P. Holland
Bryan School of Business and Economics
University of North Carolina, Greensboro
P.O. Box 26165
Greensboro, NC 27402-6165
and NBER
sphollan@uncg.edu

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 empirically 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 simulation 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," or 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, *e.g.,* 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, 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 SO_2 and NO_X as well as CO_2. Suppose climate policy caused dual fuel generating units to switch

[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] Theory texts illustrate the equivalence of the first two approaches by modeling "netputs" rather than "inputs" and "outputs". Modeling pollution abatement is less useful here since it requires the definition of a hypothetical emissions level, which is unclear when modeling 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.

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 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. In this case CO_2 and NO_X would be 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. Thus, climate policy could have ancillary benefits or ancillary costs.

Spillovers are illustrated in Figure 1 for the case of electricity production with emissions of 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 firm would increase use of an input if the value of the marginal product were greater than the input cost. Thus at the optimum the value of the marginal product equals the input cost. 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 a carbon cap or 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 environmental 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 $e^0_{NO_x}$ and there are no spillover benefits, 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 increases NO_X emissions) would need to outweigh the output effect (which decreases NO_X emissions).[10]

Appendix 1 illustrates the proper valuation of climate policy spillovers for benefit-cost analysis. Two results are noteworthy. First, spillovers can affect the optimal carbon price. In particular, if there are ancillary benefits, then the optimal carbon price would be set *higher* than the marginal damages. Second, spillovers should be included in benefit-cost analysis just as other benefits or costs are included. In fact, from a theoretical standpoint, spillovers are indistinguishable from changes in any other input, such as labor. However, care must be taken to evaluate environmental spillovers according to their damages since market prices are not available.

Appendix 2 extends the theoretical analysis in this section by deriving theoretical predictions. In particular, both the input demand and conditional input demand must be decreasing in

[9]Burtraw *et al.* (2003) note that the falling NO_X price may have benefits from avoided future control equipment.

[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.

the own price and output effects must be negative. These predictions will aid in the identification of empirical models.

3 Estimation Strategy

Spillovers resulting from responses to climate policy cannot be directly estimated 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 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.[11] 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 proxy for changes in NO_X prices, I use changes in attainment status under the CAAAs. Regions that fail to achieve an ambient air quality standard are deemed to be in nonattainment. Designation as nonattainment under the CAAAs triggers additional regulations, which vary according to each state's implementation plan (SIP).[12] In this study, attainment status for 1-hour ozone proxies for the price of NO_X , which is a primary ozone precursor. Since California had multiple changes into and out of attainment, the analysis focuses on California power plants .

The estimation strategy uses a fixed effects estimator. The basic estimating equation is:

$$\ln(\text{Emiss}_{it}) = \beta\text{Nonattain}_{it} + f_i + g_i t + \nu_{jt} + \epsilon_{it} \tag{1}$$

where Emiss_{it} is emissions (of NO_X , CO_2, or SO_2) from generating unit i at time t; Nonattain_{it} is a dummy variable indicating that unit i is in nonattainment for 1-hour ozone at time t; 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.

[11] Exploiting symmetry requires care since it only holds for marginal changes. See Appendix 2 for details on the symmetry of input substitution.

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

The parameter of interest, β, indicates the response of emissions to a change in attainment status. 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 is 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). The own and spillover conditional (net) effects can be estimated by controlling for output in [1], and the output effect can be estimated directly when output is the dependent variable.[13]

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.

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. Intuitively, the generating units with unchanged attainment status would serve as controls for the generators with changed attainment status (the treated group).[14] 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 multiple changes into and out

[13]By estimating $\ln(\text{Emiss}_{it}) = \beta^c \text{Nonattain}_{it} + \beta^{MWh} \ln(\text{MWh}_{it}) + f_i + g_i t + \nu_{jt} + \epsilon_{it}$ and $\ln(\text{MWh}_{it}) = \beta' \text{Nonattain}_{it} + f_i + g_i t + \nu_{jt} + \epsilon_{it}$ in addition to [1], all four derivatives in the Slutsky equation in Appendix 2 are estimated separately. However, the identity $\beta = \beta^{MWh}\beta' + \beta^c$ holds since the sample and all conditioning variables are identical.

[14]With change at one time in attainment status, the estimator would be similar to the well-known difference-in-differences estimator.

of attainment in California 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 estimated spillover effect could also be incorrectly identified 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.[15]

Identification is supported further by the testable predictions from theory. In particular, Appendix 2 shows that own price effects are non-positive for both factor demands and conditional factor demands and that output effects are non-positive. A nonpositive estimate of β in [1] with NO_X emissions as the dependent variable is consistent with the theoretical predictions. With CO_2 emissions as the dependent variable, there are no additional testable implications since cross price effects can be either negative or positive.

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.[16] The hourly generating-unit-level data are aggregated to the month for three reasons. First, a number of units report emissions in hours for which they report no output. Aggregation accurately captures emissions and output while incorporating any

[15] This argument does not hold for SO_2 emissions.
[16] For example, see Puller (2007), Holland and Mansur (2008).

start-up emissions from generating units. Second, if regulations caused a unit to be run fewer hours, disaggregated data would not capture this reduction with the proportional (log) estimating equations. Aggregation captures the zero production hours. 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. After dropping non-reports and data inconsistencies, the model identification is based on changes in attainment status at 29 of 178 generating units. The data are discussed further in Appendix 3.

5 Estimation Results

The results from estimating equation [1] are presented in Table 1. Each column reports the results from one of seven regressions. Column (1) reports estimates where $\ln(NO_X)$ is the dependent variable, *i.e.,* the NO_X factor demand, and 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. Panel B additionally controls for other regulations. Throughout, the unit fixed effects, unit-specific linear trends, and market-year-month fixed effects are highly significant but are not reported.

The estimates of the three testable implications, in columns (1), (2) and (7), are all negative. Thus, the regression results are consistent with the theoretical predictions. Moreover these results show that approximately half of the estimated 40% 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 30%, suggesting gross complementarity. Controlling for output, the point estimate is very near zero. This suggests that almost all of the reduction in CO_2 emissions can be attributed to output effects. Similarly, the results for SO_2, columns (5) and (6), also indicate gross complementarity almost entirely due to output effects. The coefficient for the output effect in column (7) estimates a 30% reduction in output with nonattainment designation.

The coefficients on output in (2), (4), and (6) imply emissions elasticities for the three pollutants of 0.8 to 0.9. These estimates are 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.

Panel B includes controls for other regulations. 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). Controlling for other regulations reduces the point estimates in Panel A but does not change the results dramatically.

Table 2 splits the sample into old and new plants based on the average age of the plant's units. These results show that the reductions in Table 1 come primarily from the reductions in output and emissions at older plants. Since newer plants are less polluting, they use the NO_X input more efficiently and thus did not reduce output in response to the change in attainment status.

The results are subject to three 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. Finally, the symmetry assumption requires care in interpreting the coefficients as spillovers from climate policy. Although the estimates are valid estimates of spillovers from ozone policy, they are only locally valid estimates of spillovers from climate policy.

6 Conclusion

Spillovers from climate policy are important for policy design, modeling and benefit-cost analysis. This paper 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. The estimates are consistent with ancillary benefits from climate policy arising primarily from reductions in output (primarily at older plants) rather than from changes in emissions rates.

References

[1] Bell, Michelle L., Devra L. Davis, Luis A. Cifuentes, Alan J. Krupnick, Richard D. Morgenstern, and George D. Thurston. 2008. "Ancillary human health benefits of improved air quality resulting from climate change mitigation" *Environmental Health* 7(41). doi:10.1186/1476-069X-7-41.

[2] Burtraw, Dallas, *et al.* 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: 650-673.

[3] Cifuentes, Luis, Victor H. Borja-Aburto, Nelson Gouveia, George Thurston, and Devra Lee Davis. 2001. "Assessing the Health Benefits of Urban Air Pollution Reductions Associated with Climate Change Mitigation (2000-2020): Santiago, So Paulo, Mxico City, and New York City." *Environmental Health Perspectives*, 109(Supplement 3): 419-425.

[4] Dessus, Sebastien and David O'Connor. 2003. "Climate Policy without Tears: CGE-Based Ancillary Benefits Estimates for Chile." *Environmental and Resource Economics* 25: 287-317.

[5] Dudek, Dan, Alexander Golub, and Elena Strukova. 2003. "Ancillary Benefits of Reducing Greenhouse Gas Emissions in Transitional Economies." *World Development* 31(10): 1759-1769.

[6] European Environment Agency. 2004. "Air quality and ancillary benefits of climate change policies." *EEA Technical report* No 4. ISSN 1725-2237.

[7] Elbakidze, Levan and Bruce A. McCarl. 2004. "Should We Consider the Co-benefits of Agricultural GHG Offsets?" *Choices* Fall 2004: 25-26.

[8] Feng, Hongli, Catherine L. Kling, and Philip W. Gassman. 2004. "Carbon Sequestration, Co-Benefits, and Conservation Programs" *Choices* Fall 2004: 19-24.

[9] Greenstone, Michael (2002). "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufacturers." *Journal of Political Economy* 110: 1175-1219.

[10] Greenstone, Michael. 2003. "Estimating Regulation-Induced Substitution: The Effect of the Clean Air Act on Water and Ground Pollution." *American Economic Review Papers and Proceedings* 93(2): 442-448.

[11] Groosman, Britt, Nicholas Z. Muller, and Erin O'Neill. 2009. "The Ancillary Benefits from Climate Policy in the United States." mimeo.

[12] Holland, Stephen P. 2009. "Taxes and Trading versus Intensity Standards: Second-Best Environmental Policies with Incomplete Regulation (Leakage) or Market Power." NBER WP# 15262.

[13] Holland, Stephen P. and Erin T. Mansur. (2008). "Is Real-Time Pricing Green? The Environmental Impacts of Electricity Demand Variance." *Review of Economics and Statistics* 90(3): 550-561.

[14] Joh, Seunghun, Yunmi Nam, Sanggyoo Shim, Joohon Sung and Youngchul Shin. 2001. "Empirical Study on Environmental Ancillary Benefits Due to Greenhouse Gas Mitigation in Korea" mimeo.

[15] Mazzi, Eric A. and Hadi Dowlatabadi. 2007. "Air Quality Impacts of Climate Mitigation: UK Policy and Passenger Vehicle Choice." *Environmental Science and Technology*, 41: 387-392.

[16] McCarl, Bruce A. and Uwe A. Schneider. 2001. "Greenhouse Gas Mitigation in U.S. Agriculture and Forestry" *Science* 294 (21 December): 2481-2482.

[17] Pattanayak, Subhrendu K., Allan Sommer, Brian C. Murray, Timothy Bondelid, Bruce A. McCarl, and Dhazn Gillig. 2002. "Water Quality Co-Benefits of Greenhouse Gas Reduction Incentives in U.S. Agriculture: Final Report." EPA Contract Number 68-C-01-142 and RTI Project Number 08249.001.004.

[18] Plantinga, Andrew J. and JunJie Wu. 2003. "Co-Benefits from Carbon Sequestration in Forests: Evaluating Reductions in Agricultural Externalities from an Afforestation Policy in Wisconsin" *Land Economics* 79(1): 74-85.

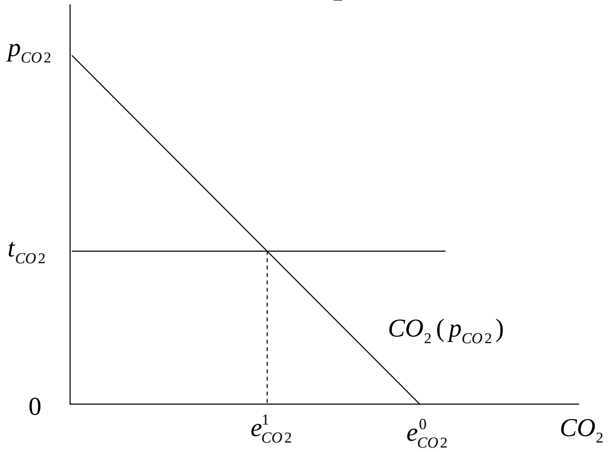
[19] Puller, Steven L. (2007) "Pricing and Firm Conduct in California's Deregulated Electricity Market." *Review of Economics and Statistics* 89(1): 75-87.

[20] Walsh, Michael P. 2008. "Ancillary Benefits for Climate Change Mitigation and Air Pollution Control in the World's Motor Vehicle Fleets" *Annual Review of Public Health* 29:1-9. doi: 10.1146/annurev.publhealth.29.091307.083257

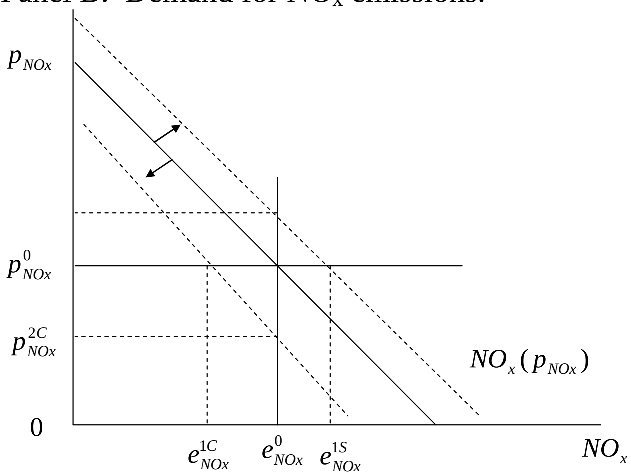
Figures and Tables

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.

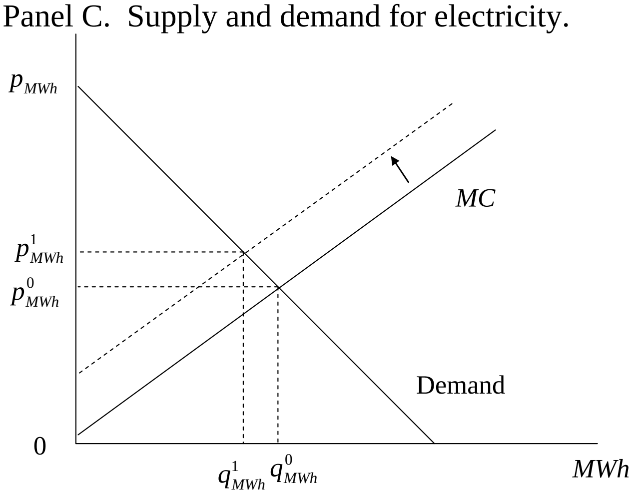


Table 1: Main Results. California results for NOx, CO2, and SO2 emissions and Megawatt hours.

Panel A: Parsimonious specification 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)	

Panel B: 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)

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.

Table 2: Old and new plants. California results for NOx, CO2, and SO2 emissions and Megawatt hours.

Panel A: Old plants (average start 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 (average start 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.

Appendices

Appendix 1: Valuation of spillovers

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 $U'(q)$ 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:

$$\frac{d}{dt_{CO2}}[U(q) - wk - \tau_{CO2}CO2 - \tau_{NOx}NOx]$$

$$= (U'f_1 - w)\frac{dk}{dt_{CO2}} + (U'f_2 - \tau_{CO2})\frac{dCO2}{dt_{CO2}} + (U'f_3 - \tau_{NOx})\frac{dNOx}{dt_{CO2}}$$

$$= (t_{CO2} - \tau_{CO2})\frac{dCO2}{dt_{CO2}} + (t_{NOx} - \tau_{NOx})\frac{dNOx}{dt_{CO2}}. \tag{2}$$

Equation [2] decomposes the change in social surplus from climate policy into a direct effect and a spillover effect. There are several things to note about [2]. 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 would 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:

$$\Delta U - w\Delta k - \tau_{CO2}\Delta CO2 - \tau_{NOx}\Delta NOx. \tag{3}$$

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.[17]

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

Appendix 2: 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 $\mathrm{NO_X}$ and $\mathrm{CO_2}$ 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 $\mathrm{NO_X}$ and $\mathrm{CO_2}$ *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:

$$\frac{dCO2}{dp_{CO2}} = \frac{dCO2^c}{dq}\frac{dq}{dp_{CO2}} + \frac{dCO2^c}{dp_{CO2}} \tag{4}$$

and

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

Equation 4 shows that the total change in $\mathrm{NO_X}$ 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 $\mathrm{CO_2}$ emissions when the relative price of $\mathrm{NO_X}$ emissions increases.

Similarly, equation 5 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

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

the first and last factors must have the same sign even if the input is inferior. Thus the own-price output effect is negative.[18]

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 3: Data

The primary level of analysis is the generating unit, which is defined by the EPA and may consist of one or more smokestacks, boilers and/or generators. Appendix Table 1 shows the power plants and number of units in the three counties with changes in attainment status reporting in the CEMS data before and after the change.[19] San Diego was declared to be in nonattainment of the new 8-hour ozone standard in 2004. The estimation controls for this redesignation. The redesignation months of August 1998 and July 2003 are dropped from the sample for all units.[20]

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.

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

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

[19] Six counties with changes in attainment status 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.

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

average age (year online) of the generators at plant, which is 1982, thus is a proxy for the age of the units. The fourteen units 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.[21]

Appendix Table 2 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 (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.[22] 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).[23] 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 at-

[21]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.

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

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

tainment, 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 4: Robustness tests

Appendix Tables 3-5 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, 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. 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 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.[24]

Appendix Table 4 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 4 presents the results based on aggregating the hourly data to the day instead of the month.[25] 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.

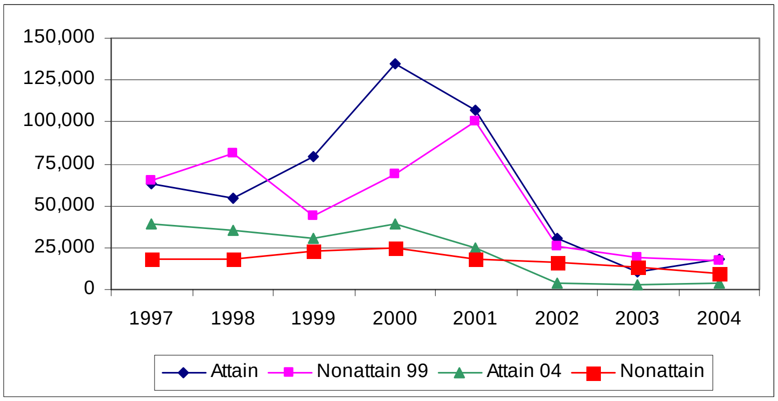
[24] San Diego was designated as in nonattainment of the 8-hour ozone standard in 2004. The main regressions control for this designation.

[25] 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 market-level 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.

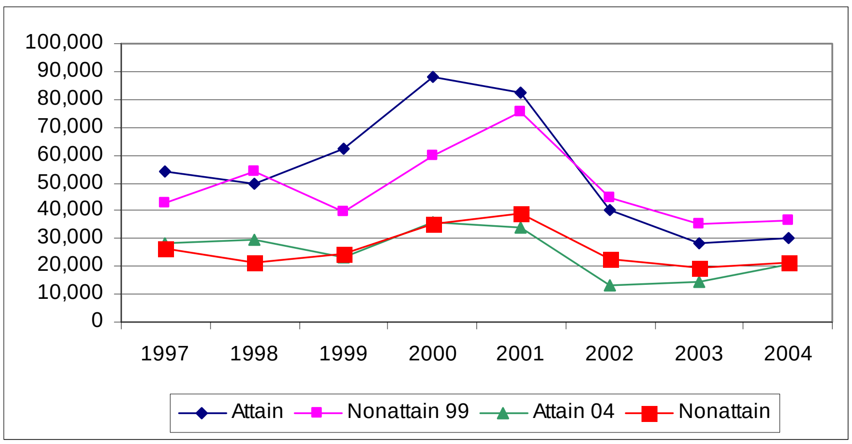
Appendix Table 5 omits the unit-specific linear trends from the specification. The signs of the estimates are generally consistent with those in the preferred specification; however, the magnitudes of the own price effects are somewhat smaller. This specification also shows a marginally significant reduction in CO_2 emissions and a significant reduction in output from nonattainment designation.

Appendix Figure 1.

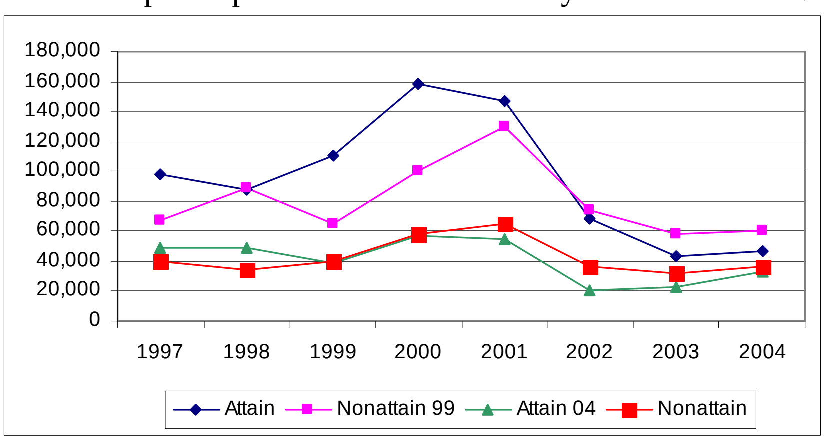
Panel A: NO_x emissions at power plant units in California by attainment status.



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: 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 5: 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.