Two Birds, One Stone?
Local Pollution Regulation and Greenhouse Gas Emissions

Claire Brunel and Erik Paul Johnson*

April 2016

Abstract

In most countries, environmental regulation focuses on local pollution, which causes damages near the emission source, while regulation on global pollutants such as greenhouse gases (GHG) has been slow. Theoretically, local and global pollutants can either be substitutes or complements in production, implying that local pollution regulation may either intensify or reduce global warming concerns. We exploit new data on US GHG emissions and variation in local pollution regulation across US counties to estimate this relationship. We find no evidence that more stringent local pollution regulation changes GHG emissions. Therefore, local pollution regulation will not suffice to address global warming.

JEL Codes: Q52, Q53, Q54, Q58, H23

*Brunel: American University, School of International Service, 4400 Massachusetts Avenue NW, Washington DC 20016-8071, brunel@american.edu. Johnson: Georgia Institute of Technology, 221 Bobby Dodd Way, Atlanta, GA 30332, erik.johnson@econ.gatech.edu. This research was presented at Auburn University, Georgia Institute of Technology, the 2016 Midwest Economics Association Annual Meetings, and the Georgetown Center for Economic Research 2015 Biannual Conference. We would like to thank all seminar and conference participants for helpful comments. We would also like to thank Arik Levinson, Jake Mortenson, Juan Moreno-Cruz, Alison Weingarden, Andrew Whitten, and Caitlin Brown for comments and feedback. All remaining errors and omissions are our own.

Pollutants are classified into two broad categories, local and global, depending on their reach. Local pollutants affect the area in the vicinity of the source of emission. Global pollutants affect the whole globe. Since the environmental and political stakes are different for the two categories, local and global pollutants are generally regulated separately. In most countries, national regulation of global pollutants, especially greenhouse gases (GHG) has been slow, while local pollution regulation has become increasingly stringent. Regulating local pollution is in the best interest of national and sub-national governments since the costs and benefits are largely borne by and accrue to the same group of people. Moreover, since the reach of local pollution is limited, local pollution regulation can be implemented without international cooperation, making it easier to achieve than GHG regulation.

However, it is possible that the regulation of local pollutants also affects GHG emissions. If there is a reduction in GHG emissions due to local pollutant regulation, termed co-benefits, countries are reducing GHG indirectly as long as they continue to increase the stringency of local pollutant regulation. In this case, even countries that do not commit, or that commit too little, to GHG reductions would still be contributing to limiting global warming. However, if there are no co-benefits, or if local pollution regulation has a perverse effect on GHG, the lack of GHG progress to date is especially worrisome.

In this paper, we investigate whether local air pollution regulations in the United States have had an effect on GHG emissions. To our knowledge, this is the first study to empirically examine, across all US manufacturing industries, the trade-offs between local and global pollution when local pollution is regulated. Since GHG contribute to climate change, it is important to understand the underlying forces that lead to GHG emission changes. A firm required to lower emissions of local pollutants might respond in one of two ways. On the one hand, if there are spillovers to implementing reductions in local pollutant emissions, local air pollution regulation could be accompanied by a decrease in GHG emissions. Technologies intended to respond to local pollutant regulation could serve to concurrently reduce GHG emissions. For example, switching fuel source from oil to natural gas reduces both local and global pollution. Alternatively, firms might preemptively make all or most of their production processes cleaner if they expect further environmental regulation in the future. If this is the case, passing GHG regulation is less pressing since the regulation of local pollutants is already, at least partly, achieving a reduction in GHG emissions.

On the other hand, we might see an increase in GHG emissions as a result of local pollution regulation if local and global pollutants are substitutable. A firm might replace a production process that is intensive in local pollution with another that is intensive in GHG. For example, natural gas-fired industrial boiler could decrease their combustion temperature to reduce local pollutant emissions, but that leads to an increase in CO_2 emissions (Holland, 2012). In this case, mandating a decrease in one type of pollution encourages the deterioration of the environment through other, potentially more harmful, pollutants. Finally, there could be no effect of local pollution regulation on GHG emissions if for example a firm abides by the regulation by simply implementing end-of-pipe abatement technologies such as installing scrubbers, which do not affect GHG emissions. If the effect of local air pollution regulation is to increase GHG, or even if the effect is non-existent, global cooperation on GHG emissions should be a top priority.

We use spatial and temporal variation, including exogenous changes in air quality standards under the Clean Air Acts (CAA), to examine GHG emissions in counties that are subject to additional local pollutant regulation. The CAA have caused a dramatic reductions in local pollutant emissions (Chay and Greenstone, 2005; Shapiro and Walker, 2015). If local and global pollutants are complements, we should observe a similar decrease in GHG emissions across regulated counties. Figure 1 shows the unconditional trends in GHG emissions in counties that satisfy CAA air quality standards as well as in counties that do not meet the standards and therefore have to implement more stringent regulation. The graphs present the log of average firm emissions of GHG, and the vertical line indicates the date of the change in regulation. Regulated counties exhibit higher GHG emissions than unregulated ones, but the evolution over time is very similar across the two groups of counties, suggesting no spillovers from local pollution regulation on GHG emissions.[1] However, these graphs do not control for a number of factors that could conceal the effect of regulation on GHG. For example, the CAA concurrently retarded the level of manufacturing output in regulated counties (Greenstone, 2002). Moreover, it is not the case that all industries are affected by the regulation, so this aggregate figure could be hiding some important divergences across regulated and unregulated counties for key polluting industries.

Nonetheless, our econometric analysis suggests that the inference drawn from the unconditional graphs is correct: counties that have implemented more stringent regulation as a result of being in non-attainment under the National Ambient Air Quality Standards (NAAQS) do not exhibit GHG emission levels that are different from attainment counties in a systematic way. This conclusion is robust to using both a propensity score matching estimator and various fixed effects regressions which all produce precisely estimated zero effects. Notably, we account for changes to output levels and industrial composition, including the possibility of switching production to unregulated counties, and examine industry-specific patterns to verify that the zeros are not simply on net. Although we recognize that imperfect prox-

[1]Note that for lead, we do not have pre-implementation data.

ies might introduce some measurement error, in all specifications the results remain that local pollution regulation to date has not had ancillary benefits in terms of GHG reductions in the US manufacturing sector. In light of these conclusions, it is quite possible that efforts by China and others to control local air pollution will not necessarily translate into reductions in contributions to global pollution. In the absence of co-benefits, a world in which countries continue to focus on regulating local pollution while neglecting global pollution regulation will not suffice to address global warming concerns.

In the next section, we examine previous evidence about cross-pollutant substitution and evidence about the local pollutant benefits of greenhouse gas policies. Section 2 presents the new data that we bring to bear on this question. Sections 3 and 4 discuss the two empirical strategies used to estimate the cross-pollutant regulatory effects and the results of those specifications. Finally, Section 5 concludes.

1 Prior Evidence about Cross-Pollutant Substitution

Understanding the cross-effect of pollution regulation is important for several reasons. The presence of co-benefits can affect the choice of policy instrument to regulate the pollutants. Ambec and Coria (2013) shows that if the pollutants are complements, a mixed policy instrument where one pollutant is taxed and the other subject to a quota might be preferred, while if they are substitutes a pure price or quantity policy dominates. Co-benefits will also affect the scale of regulation to achieve the desired emission reductions. Parry et al. (2014) finds that the nationally efficient price of CO_2 can be quite large in countries with important co-benefits and that pricing those co-benefits reduces total CO_2 emissions significantly (around

11 percent globally). Moreover, whether pollutants are substitutes or complements will yield different optimal abatement levels (Moslener and Requate, 2007).

However, estimating the co-benefits presents some challenges. The literature examining the potential substitutability or complementarity between local and global pollution takes one of two forms. The first branch studies the local air-quality co-benefits of climate policies. The second, which is the focus of our paper, investigates the opposite direction: the ancillary benefits of local pollution regulation on GHG emissions.

Much of the literature to date focuses on the first channel: how climate policy affects air quality. Nemet et al. (2010) surveys 37 peer-reviewed studies of the modeled air-quality co-benefits of climate policies and finds that estimates vary widely, ranging from \$2/tCO_2 to \$128/tCO_2 in developed countries (see Appendix Table A1), and up to \$196/tCO_2 in developing countries. Some of these studies examine the health and agricultural benefits of climate policies in developing countries (Plantinga and Wu, 2003; Bollen et al., 2009; Bollen, 2009). Generally, the literature finds that there can be large differences in co-benefits of climate policies across countries, and within countries across sectors (Boyce and Pastor, 2013; Parry et al., 2014).

Other works focus on the spillovers of climate policy in specific sectors, typically the electricity sector, which represents two thirds of GHG emissions in the United States. Using an integrated assessment model, Burtraw et al. (2003) explores the ancillary benefits of reduced air pollution in the United States from GHG mitigation policies in the electricity sector. Muller (2012) develops a model of an optimal regulatory program for GHG emissions that accommodates the benefits due to reductions of co-pollutants in the transportation and electric power generation sectors. Van Harmelen et al. (2002) evaluates the avoided costs of regulating local pollution through climate policy. Beyond the narrow industrial focus which limits the external validity of the results, many of these studies suffer from the fact that industries currently subject to climate policy are also concurrently facing other environmental regulation such as local pollution regulation. In this context, identifying which changes in local pollution can be attributed to climate policy is a difficult task.

On the other hand, the literature on the existence of GHG co-benefits to local pollution regulation is more limited. Holland (2010) posits that due to the symmetry of input substitution, a change in GHG prices should have the same effect on local pollution than a change in local pollution prices would have on GHG emissions. This would suggest there is no need to study the question in both directions. However, the key issue is whether the measure of regulation accurately embodies the price of emissions or the change in that price. And for most available measures of regulatory stringency, this accuracy is contentious. Some measures do not capture price entirely while others encapsulate the price and much more, reflecting both the complexity of regulation and the challenges to measuring stringency (Brunel and Levinson, 2016). This implies that the correct magnitude of the GHG emission response to local pollution regulation cannot be inferred from the literature on climate policies' effect on local pollution. Therefore, it requires its own estimation.

In fact, Sigman (1996) examines the co-benefits of air pollution regulation on waste generation and vice-versa using data from the EPA's Toxic Release Inventories in the United States. The evidence suggests that air pollution control regulation reduce waste generation but, conversely, constraints on waste generation increase air emissions, suggesting that air and waste pollution can be complements or substitutes depending on which media is regulated.[2] This potential asymmetry implies that the

[2] Other examples of cross-media co-benefit analyses include Gibson (2015) which studies the co-benefits of the Clean Air Act on waste and water pollution.

above studies examining the effects of climate policies on local pollution may not be used to infer the co-benefits of local pollution regulation on GHG.

The most closely related paper to ours, Holland (2012), examines the response of CO_2 emissions to an increase in the stringency of NO_x regulation for power plants in California. He begins by presenting a theoretical framework where emissions are an input into the production process. An increase in the price of a pollutant due to more stringent regulation of that pollutant should therefore shift the demand for other inputs, including other pollutants. The shift in demand for other inputs could be either an increase or a decrease depending on whether the input is a substitute or complement. The empirical application uses a fixed effects regression to show that, following a tightening of NO_x regulation under the US Clean Air Act of 1990, almost all of the reduction in CO_2 emissions is due to a decrease in output which reduces both pollutants, rather than a complementarity between CO_2 and NO_x.

The focus on the California electricity sector presents an important drawback: the California electricity sector is heavily reliant on natural gas, which is not highly carbon-intensive. Therefore, Holland (2012) cannot capture the substitution from carbon intensive fuels (e.g., coal) to other fuels such as natural gas. Kolstad (2012) thus speculates that the substitution effects might be underestimated in Holland (2012).

In our paper, we change the scope of the analysis to focus on all manufacturing industries. As shown in Table 1, looking beyond the electricity sector is important because the share of non-electricity sectors in total US GHG emissions has increased from 27% to 34.4% in just five years. Additionally, for some GHG pollutants such as methane and N_2O, non-electricity sectors represent the vast majority of total emissions. Moreover, unlike the electricity sector, other industries are only subject to one piece of regulation for local air pollution - the US Clean Air Act - which avoids confounding effects of other regulation, a point we return to in the next section. Finally, we also expand the geographical scope of the paper since we have data on all counties in the United States.

2 Measuring Environmental Regulatory Stringency and Air Pollution

Our empirical strategy takes advantage of the spatial variation in the stringency of environmental regulation induced by the National Ambient Air Quality Standards, which set minimum air quality standards that each county in the US must meet, and combines this information with a new dataset from the US Environmental Protection Agency (EPA) on greenhouse gas emissions for industrial facilities.

2.1 Local Environmental Stringency

The Clean Air Act requires the EPA to set a minimum and uniform level of ambient air quality for six pollutants in all US counties. These standards, called the National Ambient Air Quality Standards (NAAQS), are the bar by which every county in the United States is evaluated annually to determine if the county has sufficiently clean air. All counties must attain the same air quality standards, but how they achieve this standard and how difficult it is to reach the threshold varies significantly across counties. Some counties need to impose costly emissions requirements because the composition of their industry is heavy in polluting industries or their geographical location traps air pollution in the county. Others will be able to achieve the standards with little to no effort. A county whose air quality falls below the NAAQS is designated as a "non-attainment" county and will be subject to increased regulatory scrutiny until local emissions are reduced and ambient air quality reaches the threshold or higher.

The NAAQS concern six pollutants, known as "criteria" pollutants: carbon monoxide (CO), ozone (O_3), particulate matter (PM), lead (Pb), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). Each year, the EPA makes an official determination of whether each county met each of the standards using air quality monitors and some atmospheric modeling.[3] Non-attainment determination therefore concerns a specific pollutant in a specific year for each county. Once a county is declared to be in non-attainment, the state must design a State Implementation Plan (SIP) that will bring non-attainment counties into compliance with the standard by regulating all major sources of pollution.

The number of counties in non-attainment for each year in our sample for each criteria pollutant standard does not change drastically from year to year suggesting that counties remain in non-attainment for relatively long periods of time (see Appendix Table A3). No counties were designated out-of-attainment for CO and NO_2 over our sample period, but the number of non-attainment counties varies across the other pollutants, with the lowest numbers of non-attainment countries for SO_2 and the highest for O_3.

One advantage to using the NAAQS as a signal of regulatory stringency is that the NAAQS are set by the federal government and apply nationally. They are not caused by or correlated with the economic activity in particular counties, and local

[3] A county can also be declared in non-attainment if it contributes to low ambient air quality in a neighboring county, hence the use of both monitor data and atmospheric modeling tools.

governments have little ability to affect non-attainment designations except by reducing pollution. Therefore, the standards represent plausibly exogenous variation in the level of stringency that a particular plant faces. Three pollutants experience a change of standard between 2010 and 2014: O_3, Pb, and SO_2 (see Appendix Table A4). Although for some pollutants the most recent change dates back to 2008 - prior to the start of our estimation period - the implementation of the rule change occurred after 2010 because of administrative, modeling, and legal delays. Since the rule change occurred a few years before implementation, these changes were highly anticipated and our results might be underestimated.

As states devise their SIPs by focusing on the major emitters, we are interested in the industries that are most likely to be targeted with additional regulatory attention when a county falls into non-attainment for a particular pollutant. We would expect regulators to focus on heavy manufacturing, chemicals, transportation, and other high emitters, while essentially ignoring industries that emit relatively little such as healthcare and other services. Beyond the usual high emitters, some industries pollute heavily in one criteria pollutant but not in others, so an industry regulated in one pollutant will not necessarily be regulated in another. Therefore, we need to identify high emitting industries for each pollutant.

We obtain data on national emissions of criteria pollutants from the 2011 National Emissions Inventory (NEI) for each 4-digit industry of the North American Industry Classification System (NAICS) in the United States. We designate an industry as a potential target of regulatory attention if it emits at least 7% of the national total of a particular pollutant.[4] Table 2 displays the industries that are the highest emitters of each criteria pollutant for which we have a regulation change. These

[4] The results are qualitatively the same with a less restrictive cutoff of 5%. We elect 7% following Greenstone (2002) and provide the results with a 5% cutoff in the Appendix.

comport with intuition: basic chemicals manufacturing, petroleum and coal products manufacturing, and pulp, paper and paperboard mills account for almost 50% of SO_2 emissions in the United States; oil and gas extraction is a major emitter of O_3. The portion of reporters that are high emitters and subject to regulation varies significantly across pollutants. Of the nearly 50% of reporters that could be subject to O_3 regulation because they are in high emitting industries, about 13% are in fact regulated because they are located in non-attainment counties (Appendix Table A5). But while approximately one third of reporters could be subject to SO_2 regulation, in practice less than 2% are indeed subject to regulatory scrutiny for SO_2 because very few counties are still in non-attainment for this pollutant.[5]

Therefore, the NAAQS data provides three sources of variation: cross-sectional variation between attainment and non-attainment counties; changes in attainment status over time; and within-county variation between high-emitting industries that are the target of regulation and the rest (Greenstone, 2002). Since non-electricity industries are only subject to the NAAQS for emission control, non-attainment status designation captures the extent of regulatory oversight of polluting industries outside of the electricity sector.[6]

[5] Some plants are regulated for more than one pollutant, see Appendix Table A6.

[6] Manufacturing industries are subject to additional environmental regulation more generally addressing pollution of other media. However, those regulations are orthogonal to NAAQS as they would affect facilities in both attainment and non-attainment counties. The electricity sector, on the other hand, is also regulated for local pollution by the Acid Rain Program, and for greenhouse gases by AB-32 in California and the Regional Greenhouse Gas Initiative (RGGI) in Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont.

2.2 Greenhouse gas emissions

We pair this information on local pollutant regulation with a new dataset that contains information on the emission of greenhouse gases. In 2010, the EPA began collecting data for the Greenhouse Gases Reporting Program. This dataset compiles GHG emissions from sources that emit at least 25,000 metric tons of carbon dioxide equivalent (CO_2e) per year.[7] As of 2014, the database covers over 8,000 facilities in 41 industries and is estimated to account for 85-90% of total GHG emissions in the United States (*GHGRP Overview Report 2014*, 2015). Of those, we use data on direct emitters that are not electricity generating units or fossil fuel extraction and transportation, which consist of 3,990 facilities representing 29 percent of direct emissions for 2014. The most polluting industries include: petroleum and coal products manufacturing, chemical manufacturing, primary metal manufacturing, nonmetallic mineral products manufacturing, paper manufacturing, and food manufacturing (see Appendix Table A2). Firms are required to report both total GHG emissions in tons of CO_2e as well as component parts of their emissions for six GHGs such as actual CO_2, methane, and nitrous oxide.[8]

In addition to GHG emissions, the Greenhouse Gas Reporting Program collects information about the ownership structure of each reporting facility. This information will allow us to examine how firms' ability to substitute production across facilities subject to differential local pollution regulation influences GHG emissions.

[7] The agricultural sector and land use changes are exempt from reporting.

[8] The other three gases combined represent less than 1% of emissions.

2.3 Other Data

We supplement these data on GHG emissions with information about county industrial composition and demographic information. We obtain data on industrial composition from the Quarterly Census of Employment and Wages (QCEW) compiled by the Bureau of Labor Statistics. The data is classified based on the NAICS. We aggregate the data at the 2-digit level to obtain total wages and total number of establishments per industry and year for each county. Other controls include population and income per capita data from the United States Census Bureau, as well county-level demographics from the American Community Survey, which averages estimates over 3 years for 2011-2013.

3 County GHG emissions and local pollutant regulation

Under the NAAQS each county receives an attainment or non-attainment designation for each criteria pollutant. Therefore, if GHG emissions are a complement (substitute) with that local pollutant we would expect aggregate GHG emissions to decrease (increase) with the imposition of additional regulatory stringency. However, GHG emissions are also correlated with other observable characteristics of the counties such as industrial composition that may affect the amount of regulatory stringency in that county. To identify counties that are similar to non-attainment counties except for their NAAQS attainment status, we employ a propensity score estimator.

We create a propensity score (probability of being in non-attainment) for each county and pollutant and use that score to match each non-attainment county (treatment) with an attainment county (control). The propensity score, p(Z), is the probability that treatment occurred given a set of characteristics Z which are relevant for the level of GHG emissions. In our case, Z includes a wide array of demographic and industrial composition variables. P(Z) is therefore a measure of how similar treatment and control groups are beyond the difference in regulatory stringency. The scores are then matched based on the nearest-neighbor strategy: a non-attainment county will be matched with replacement to the attainment county that has the closest propensity score.[9] The matching is done on a cross-section of the year counties were first designated for non-attainment for the new standard, so the year of the matching will be different for each pollutant. Once each treatment county is paired with a control county, we compare the means of the treatment and control groups for the three pollutants for which we observe changes in NAAQS.

To check that treatment and control groups are indeed similar enough that the control group can plausibly represent the counterfactual without regulation, we conduct some balancing tests. Appendix Tables A7 through A9 present the balancing test results for each of the standards when the dependent variable is total GHG and the matching is done on the most comprehensive set of controls variables at the county level: establishments by 2-digit industry, wages by 2-digit industry, population, average income per capita, educational attainment, native-born population, percent of population in the labor force, unemployment rates, poverty rates, median age, racial composition, and lagged GHG levels, as well as the squares of each of these variables.

Beyond the demographic characteristics, establishments and wages measure the

[9] Matching with replacement reduces bias, though it may increase variance.

size of each industry. Controlling for the industrial composition of each county serves to differentiate cleaner ambient air quality that is due to economic specialization in less polluting industries, from that due to more intensive or more efficient abatement efforts. Lagged GHG levels further restrict the matches to counties that emit similar levels of GHG in the year prior to the tightening of the local pollution regulation for each standard, so that any difference in GHG levels after the standard tightening can be attributed to the standard change. As can be seen in Appendix Tables A7 through A9, the mean for treated and control groups are not significantly different across the three pollutants, which constitutes evidence that control counties provide a reasonable counter-factual for our treated counties.

Propensity score matching provides us with some advantages in this context that other estimation methods would not confer. Firstly, propensity score matching allows us to determine attainment counties that are similar in observed attributes to non-attainment counties. This enables us to avoid averaging any treatment effect of being in non-attainment over counties that are drastically different from each other, including counties that are unlikely to ever be in non-attainment or attainment due to their industrial composition.

Additionally, propensity score matching estimators require few distributional assumptions and identify a restricted subsample of control observations that are most similar to the treatment group. However, some treated observations might not have a match. Since we conduct the analysis only on observations where the propensity scores overlap, observations outside of that range are discarded and we lose information. Figure 3 shows that some of our treated observations (green) cannot be matched to a control and are therefore dropped from the estimation. In all cases, these are the observations with the highest propensity scores, i.e. the counties that have the highest likelihood of being in non-attainment. These counties generally have pollution levels so high that they have consistently been in non-attainment since the introduction of the Clean Air Act. These counties cannot reasonably be expected to reduce local pollution levels below the NAAQS standards within the short period we study in this paper. These include for example the Los Angeles Basin. The question we ask in this paper is whether counties can substitute local for global pollution to abide by NAAQS *at the margin*, so dropping the counties with propensity scores close to 1 should not affect the estimation.

3.1 Matching Results

Table 3 columns 1-3 show the matching results using the complete set of matching variables for each pollutant, both for total GHG and for each of the top gases (CO_2, methane and N_2O). In all cases, the average treatment effect on the treated is not significantly different from zero. After the local pollution standard change, non-attainment counties emit the same quantities of GHG as attainment counties of the same industrial composition, demographics, and GHG levels prior to the change.[10] These results would suggest that a tightening of local pollution regulation has no effect on either total GHG emissions or emissions of CO_2, methane and N_2O separately.

Results from a propensity score matching estimation can be sensitive to the set of matching variables (Smith and Todd, 2005). In the next few columns, we test the robustness of the results to different sets of matching controls. In columns 4-6 we remove the quadratic terms in county demographics, columns 7-9 remove the quadratic terms in industrial composition, and columns 10-12 remove the lagged

[10] We do not observe lagged GHG values for the lead standard since it went into effect the first year we have GHG data.

GHG emissions. In general, the standard errors of the estimates are larger than the estimates themselves suggesting that there is no pattern to changes in county aggregate GHG emissions when a county enters non-attainment. The only significant result appears in column 6 for the effect of a change in lead regulation on total GHG emissions. However, none of the individual GHG components are significant and the estimate is not significant in any of the other specifications, thus we suspect it is likely a spurious correlation.

In case neighboring areas of attainment counties experience spillovers of regulation, we provide additional results assuming that all counties within a certain distance of the treated counties are also treated. Appendix Table A10 presents the results for county centroid distances of 30 and 60 miles, where the 60 mile perimeter generally includes all adjacent counties and some counties that do not directly border the non-attainment county. We observe little change in the results with no estimates being significantly different from zero.[11]

A few downsides of this strategy are worth mentioning. First, by aggregating all emissions up to the county level, we may be missing important heterogeneity within the county giving us estimates that are not statistically different from zero. Some industries are more likely to be subject to additional regulation from NAAQS than others and these industries may have different GHG emissions from others in the county. Figure 2, which presents the same graphs as Figure 1 but for industries that account for at least 7% of total emissions, shows that there might be a differential trend between GHG emissions of polluting industries in attainment and non-attainment counties for SO_2 and lead. In the next section we discuss a regression analysis at the industry-level.

[11] The results are in line with Auffhammer et al. (2009) which shows that neighboring counties of CAA treated counties are not affected by regulation for PM_{10}. Moreover, as stated before, counties can be classified in non-attainment when they cause pollution in neighbors.

Moreover, the matching is done at the county-level. We therefore lose some facility-specific information and facility-level dynamics in the process. Importantly, aggregating at the county-level prevents us from identifying the output effect: the fact that beyond changing production processes, another way we might observe a decrease in GHG following the implementation of local pollution regulation is if the regulation entices companies to switch the location of production to attainment counties. If some firms move production to other counties, thereby reducing GHGs, while others substitute local for global pollution which increases GHGs, the combined effect of substitution and output might be nil. Therefore, we turn to the regression analysis which allows more flexibility in the specification.

4 Facility GHG emissions and local pollutant regulation

In this section we exploit the fact that we have information on facility GHG emissions. Despite the fact that an entire county is designated in non-attainment status, all facilities in the county are not subject to the same additional regulatory scrutiny. Regulators likely only target the highest emitting facilities since this is where the largest difference can be made to bring the county into attainment. While we do not observe which facilities are subject to increased scrutiny, we use national industry-level emissions as a proxy for the likelihood that a facility faces local pollutant regulation. Using the 2011 National Emissions Inventory, we determine which industries (4-digit NAICS codes) emit more than 7% of national emissions of that pollutant and use this as a proxy for the likelihood that an industry is subject to additional regulatory scrutiny when the county is in non-attainment.[12]

Using this information, we estimate the effect of the NAAQS on GHG emissions in a similar fashion to Greenstone (2002) where we control for county-level shocks as well as industry-level shocks that may affect facility GHG emissions. There are two main ways through which GHG emissions might change following the tightening of NAAQS: either the firm changes its production processes and GHG emissions will decrease or increase depending on whether GHG and local pollution are complements or substitutes; or the firm changes the location of production from non-attainment to attainment counties. Our regression equation separates those two effects in the following way:

$$\begin{aligned} ln(GHG_{ijkt}) =& \boldsymbol{\beta_1 highpoll_{jt} * NA_{it}} + \boldsymbol{\beta_2 highpoll_{jt} * NA_{it}} * substitute_k \\ &+ \boldsymbol{\beta_3 X_{ijt}} + \gamma_{it} + \delta_{jt} + \omega_k + \epsilon_{ijkt} \end{aligned} \tag{1}$$

where GHG_{ijt} represent total GHG emissions (CO_2, methane, and N_2O) in metric tons of CO_2e for facility k of industry j in county i at time t.

Vector $\boldsymbol{NA_{it}}$ contains a separate indicator variable for each of the pollutants, where the indicator is equal to 1 if the county is in non-attainment for that pollutant and 0 otherwise. The interactions between non-attainment status and whether the industry is a high emitter that will be the target of regulation ($\boldsymbol{highpoll_{jt} * NA_{it}}$) capture variation in GHG specific to polluting plants (relative to non-emitters) in non-attainment counties (relative to attainment counties). Since high-emitting industries are the most likely to be regulated, if local pollution regulation affects GHG emissions $\boldsymbol{\beta_1}$ should be significant. This coefficient therefore captures the substitution or complementarity between local and global pollution. A positive and

[12] We exclude the oil and gas extraction industry and pipeline transportation of natural gas (NAICS codes 2111 and 4862 respectively) since our focus is the manufacturing industries.

significant β_1 for one of the pollutants would mean that plants regulated for that pollutant in non-attainment counties are increasing GHG emissions, suggesting a substitution between that local pollutant and global pollution. A negative and significant effect, on the other hand, would be indicative of a complementarity between local and global pollution in production. The effect for each pollutant is estimated holding the others constant, which is key since plants might be regulated for more than one of our pollutants (Greenstone, 2002).

The output effect, on the other hand, is represented by $\boldsymbol{\beta_2}$. The simplest way to switch production from non-attainment to attainment counties would be to relocate production to a different facility owned by the same firm but located in an attainment county. Although this would not affect the overall GHG levels in the United States, it would change GHG distribution across counties. If we do not control for the ability to switch production across countries, the output effect might be interpreted as a substitution. Ideally, we would like facility-level output, but we do not have that data. Therefore, we construct a variable $substitute_{kt}$ which is a dummy for whether at least one of the parent companies of the facility has other facilities in the dataset within the same 4-digit NAICS code that are located in attainment counties in year t. This variable is interacted with being a high emitter in a non-attainment county. Thus $\boldsymbol{\beta_2}$ captures variation in GHG specific to polluting plants (relative to non-emitters) in non-attainment counties (relative to attainment counties) for firms that can switch production across facilities (relative to those who cannot). A positive and significant $\boldsymbol{\beta_2}$ would suggest that firms with facilities producing polluting goods in non-attainment counties are indeed switching production towards facilities in unregulated attainment counties.

The vector $\boldsymbol{X_{ijt}}$ consists of control variables: number of establishments, annual average of monthly employment levels, and total annual wages by county and year, as well as for each facility the number of owners and of other production facilities the parent firm has in the same NAICS code. The first three variables control for the industrial composition of the county. The latter two controls are needed in case firms change their ownership structure as a result of regulation. A firm could for example purchase a facility in an attainment county, or merge with another firm that already has production facilities in attainment counties in order to transfer production.

The regression also includes industry-by-year fixed effects, county-by-year fixed effects, and facility fixed effects.[13] The industry-by-year fixed effects allow us to purge the estimates of unobservables that affect an entire industry, while the county-by-year fixed effects all us to purge the estimates of emissions changes that are common to highly-polluting and non-highly-polluting industries within a county. The facility fixed effects absorb facility characteristics that do not change over our sample period. These fixed effects mean that our estimates are identified by within county-year variation in GHG emissions across highly-polluting and non-highly-polluting industries and within industry-year variation across attainment and non-attainment counties.

The facility fixed effects reduce the degrees of freedom but they are essential to this regression since our datasets do not include any plant-specific characteristics. If non-attainment counties are more attractive to polluting plants and industries because of the presence of a natural resource or skilled workforce or simply contain larger production facilities, then non-attainment status would be correlated with systematic differences across plants. The facility fixed effects guarantee that the parameters of interest are identified from within-plant comparisons facing a change in regulation.

[13] All clean industries are combined into one group, while each polluting industry is on its own.

4.1 Facility Results

Table 4 shows the regression results. First and foremost, the striking conclusion is there does not appear to be any significant effect of local regulation on GHG emissions. This result is robust to including various controls and fixed effects, and holds whether the dependent variable is total GHG emissions or individual GHGs.

In column (1), we present the results of a simple equation relating the effect of being a high emitter in a non-attainment county to GHG emissions using all plants over the five years and including all sets of fixed effects. The next two columns correspond to specifications that include additional controls. Column (2) adds the number of establishments, annual average of monthly employment levels, and total annual wages by industry to account for industrial composition. Column (3) includes all controls in column (2) and the output effect, i.e. the interactions between being a high-emitter in a non-attainment county and having facilities in attainment counties where production can relocate. The coefficients on the first four variables are now the effect of regulation purged of the output effect, i.e. they represent the substitution effect alone. That effect is still indistinguishable from zero and nearly all of the point estimates are extremely close to zero.

The specifications in columns (4) and (5) add the number of owners for each facility and the number of other production facilities the parent firm has in the same 4-digit NAICS code. Ownership structure does not appear to have a significant effect on emissions. Columns (6) and (7) present the same specification as column (3) but with different sets of fixed effects: county, year, and facility for column (6), and county, year, industry, and facility for column (7). All of these specifications show the same general pattern that there is no effect of local pollutant regulation on greenhouse gas emissions regardless of the control variables included or the type of fixed effects. The specification in column (7) has two marginally significant coefficients on both of the ozone variables. The sum of these coefficients suggest that facilities owned by firms that can switch production do not change total greenhouse gas emissions. Still, there may be a complementarity effect on facilities that cannot switch production. However, the significance appears spurious and disappears with a more complete set of fixed effects.

In order to isolate the effect of local pollution regulation on greenhouse gas emissions without confounding this with the ability of firms to reallocate production across facilities, we examine only firms that have all of their facilities in non-attainment counties. While these firms are likely to be smaller than the average firm since many of them only have a single facility, they provide us with an estimate of the total effect of local pollutant regulation on greenhouse gas emissions. Column (8) displays the results of our preferred specification (column (3)) estimated on this sample. The coefficients are still not statistically significant, though the standard errors are higher due to the lower number of observations.

Up to this point, our analysis has focused on total GHG emissions and have not found systematic evidence of an effect of local pollution regulation on GHG emissions. However, there may be substitutability between local pollution and a specific type of GHG. Table 5 shows that even when we separate GHG into CO_2, methane, and N_2O, for our preferred specification (equivalent to column (3) in the previous tables), we still do not observe any effect.

Table 6 provides a series of robustness checks. Since polluting activities tend to be concentrated in urban areas, urban firms will be more severely impacted by regulation than rural firms, and their options for dealing with the regulation might be different. Urban firms, however, do not change their GHG emissions in response to local pollution regulation (column (1)). However, we see a decrease in GHG emissions for rural facilities in non-attainment counties (column (2)).[14] This is suggestive that for some firms ozone and GHG emissions may be complements; however this specification is asking a lot of the data since only 3% of facilities are in rural counties that are also in non-attainment for the ozone standard.

In addition to examining differential effects from urban and rural facilities, we consider the possibility that firms near attainment areas might be affected by the regulation even through they are not in a non-attainment county. Since states write an implementation plan to bring counties into compliance, it is possible that facilities in other counties within the same state are also subject to more stringent regulation in order to bring a neighboring county into attainment. Columns (3) and (4) of Table 6 display similar regression results where counties within 30 and 60 miles of non-attainment counties in the same state are also assumed to be subject to more stringent environmental regulation. Our results are not qualitatively different suggesting that we haven't diluted the treatment effect by including in our control group facilities located in attainment counties that are actually subject to additional regulation.

We further investigate if our estimates are averaging positive and negative effects across industries leading to a nil effect on average. It could be that some polluting industries are substituting local for global pollution, while others are decreasing all emissions, and yet others switch production to facilities in unregulated counties. Appendix Table A11 suggests that this is not the case. The lack of effect of local pollution regulation on GHG is persistent through each of the highly polluting

[14] We identify urban and rural areas using the US Department of Agriculture's 2013 Rural-Urban Continuum codes, available at http://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx.

industries (columns (1) through (8)) as well as for the group of industries that are regulated for at least one pollutant (column(9)).

Finally, we present results using a different cutoff for what is considered a high-emitting industry: 5% of total emissions rather than 7%. Appendix Table A12 indicates which industries are considered high emitters under this new threshold. Compared to Table 2, the following industries are added: cement and concrete product manufacturing, coal mining, nonmetallic mineral mining and quarrying, and sugar and confectionery product manufacturing. The regression results are qualitatively unchanged: there are some spurious significant coefficients mostly when the output effect is not controlled for, but our preferred specifications clearly show that local pollution regulations do not affect the level of GHG (Appendix Table A13).

In sum, we do not find evidence of either a substitutability or a complementarity between local and global pollution in production. We attempt to control as best we can given data constraints for other channels which could lead to an effect on emissions such as output decreasing, or the composition of production changing, including due to the production of polluting goods moving to unregulated counties. We also examine industry-specific results to check that the zero effect is not a net of some industries substituting while others treat local and global pollutants as complements. None of these options appear to be verified. Instead, we observe a persistent zero effect suggesting that regulating local pollution has not had an effect on national GHG emission levels of US manufacturing industries.

5 Conclusion

While many countries have made great strides in limiting environmental damages from local pollutants such as sulfur dioxide, ground-level ozone, and lead through increasing regulatory stringency, there has been relatively little direct regulation of greenhouse gases which have global consequences. Since the costs of local pollutant regulation are largely borne by the population of the country where benefits accrue, whereas the benefits of global pollutant regulation are spread more diffusely, it is likely that local pollutant regulation will continue to increase in stringency whereas it is less clear what meaningful efforts will be made to reduce GHG emissions.

In this paper, we explore whether local pollution regulation contribute to achieving reduction in GHG emissions due to a complementarity between local and global pollutants. Our results suggests that in the United States, increased stringency of local pollution regulation has not resulted in a statistically detectible concurrent decrease in GHG emissions for manufacturing industries. This result is robust to many specifications and different estimation methods. It cannot be explained by a decrease in production or by firms switching production to unregulated countries, and it is true on aggregate as well as for individual polluting industries. The good news is we do not either find that current local pollution regulation have had a perverse effect on GHG emission by substituting local for global pollution. Since current progress to control local pollution has not had ancillary benefits in terms of GHG reductions, action needs to be taken to directly address global pollutants rather than relying on local pollutant regulation.

References

Ambec, Stefan and Jessica Coria, "Prices vs quantities with multiple pollutants," *Journal of Environmental Economics and Management*, jul 2013, *66* (1), 123–140.

Auffhammer, Maximilian, Antonio M. Bento, and Scott E. Lowe, "Measuring the effects of the Clean Air Act Amendments on ambient concentrations: The critical importance of a spatially disaggregated analysis," *Journal of Environmental Economics and Management*, jul 2009, *58* (1), 15–26.

Bollen, Johannes, "Co-benefits of Climate Policy," Technical Report, Netherlands Environmental Assessment Agency 2009.

_ , Bob van der Zwaan, Corjan Brink, and Hans Eerens, "Local air pollution and global climate change: A combined cost-benefit analysis," *Resource and Energy Economics*, 2009, *31* (3), 161–181.

Boyce, James K. and Manuel Pastor, "Clearing the air: Incorporating air quality and environmental justice into climate policy," *Climatic Change*, 2013, *120* (4), 801–814.

Brunel, Claire and Arik Levinson, "Measuring the stringency of environmental regulations," *Review of Environmental Economics and Policy*, 2016, *10* (1), 47–67.

Burtraw, Dallas, Alan Krupnick, Karen Palmer, Anthony Paul, Michael Toman, and Cary Bloyd, "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*, 2003, *45* (3), 650–673.

Chay, K and M Greenstone, "Does Air Quality Matter? Evidence from the Housing Market," *Journal of Political Economy*, 2005, *113* (2), 376–424.
GHGRP Overview Report 2014

***GHGRP Overview Report 2014**, Technical Report, US Environmental Protection Agency, Greenhouse Gas Reporting Program 2015.*

Gibson, Matthew*, "Regulation-induced pollution substitution," Mimeo, 2015, pp. 1–63.*

Greenstone, Michael*, "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures," Journal of Political Economy, 2002, 110 (6), 1175–1219.*

Holland, Stephen P*, "Spillovers from Climate Policy," NBER Working Paper 16158, 2010.*

_ , "Spillovers from Climate Policy," in Don Fullerton and Catherine Wolfram, eds., The Design and Implementation of US Climate Policy, University of Chicago Press, 2012, pp. 79–90.

Kolstad, Charles*, "Comment on Spillovers from Climate Policy to Other Pollutants," in Don Fullerton and Catherine Wolfram, eds., The Design and Implementation of US Climate Policy, 2012, pp. 90–91.*

Moslener, Ulf and Till Requate*, "Optimal abatement in dynamic multi-pollutant problems when pollutants can be complements or substitutes," Journal of Economic Dynamics and Control, 2007, 31 (7), 2293–2316.*

Muller, Nicholas Z.*, "The design of optimal climate policy with air pollution co-*

benefits," Resource and Energy Economics, 2012, 34 (4), 696–722.

Nemet, G F, T Holloway, and P Meier*, "Implications of incorporating air-quality co-benefits into climate change policymaking," Environmental Research Letters, 2010, 5 (1), 014007.*

Parry, Ian, Chandara Veung, and Dirk Heine*, "How Much Carbon Pricing is in Countries' Own Interests? The Critical Role of Co-Benefits," IMF Working Paper WP-14-174, 2014.*

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

Shapiro, Joseph S. and Reed Walker*, "Why is Pollution from U.S. Manufacturing Declining? The Roles of Trade, Regulation, Productivity, and Preferences," NBER Working Paper 20879, 2015.*

Sigman, Hilary*, "Cross-Media Pollution: Respones to Restrictions on Chlorinated Solvent Releases," Land Economics, 1996, 72 (3), 298–312.*

Smith, Jeffrey A. and Petra E. Todd*, Does matching overcome LaLonde's critique of nonexperimental estimators?, Vol. 125 2005.*

Van Harmelen, Toon, Joost Bakker, Bert De Vries, Detlef Van Vuuren, Michel Den Elzen, and Petra Mayerhofer*, "Long-term reductions in costs of controlling regional air pollution in Europe due to climate policy," Environmental Science and Policy, 2002, 5 (4), 349–365.*

6 Tables

Table 1: US GHG emissions by sector, 2010 and 2014
(million metric tons CO_2e)

	2010		2014					
Sector	**GHG**	**%**	**GHG**	**%**	**Meth**	**%**	**N_2O**	**%**
Power plants	2,329	72.9	2,101	65.6	4	1.8	8	30.6
Non-electricity sector	867	27.1	1,102	34.4	219	98.2	19	69.4
Petroleum and natural gas systems	79	2.5	236	7.4	73	32.7	0	0.4
Refineries	178	5.6	175	5.5	1	0.3	0	1.8
Chemicals	164	5.1	177	5.5	0	0.1	17	60.5
Waste	111	2.8	113	3.5	102	45.6	0	1.3
Metals	99	3.5	103	3.2	0	0.0	0	0.1
Minerals	101	3.1	117	3.7	0	0.1	0	1.4
Pulp and paper	46	3.2	39	1.2	0	0.1	1	2.3
Other	89	1.4	142	4.4	43	19.2	0	1.6

Source: EPA GHGRP Data

Table 2: Percent of All Emissions by 4 Digit NAICS Code
Sectors that account for at least 7% of national emissions

	Criteria Pollutant			
2012 NAICS US Title	**O_3**	**Pb**	**SO_2**	
Basic Chemical Manufacturing				13.9
Nonferrous Metal (except Aluminum) Production		12.2		
Oil and Gas Extraction	16.6			
Petroleum and Coal Products Manufacturing	8.1			12.5
Pipeline Transportation of Natural Gas	14.2			
Pulp, Paper, and Paperboard Mills	9.1	17.6		
Support Activities for Air Transportation		47.8		

NAICS code 2211 (Electric Power Generation) excluded from calculations. Industries that emit either 7% of NOx or VOCs are counted in the ozone column. Oil and Gas Extraction and Pipeline Transportation of Natural Gas are excluded from the regression analysis.
Source: 2011 National Emissions Inventory

Table 3: Matching results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SO2	**Ozone**	**Lead**	**SO2**	**Ozone**	**Lead**	**SO2**	**Ozone**	**Lead**	**SO2**	**Ozone**	**Lead**
Total GHGs	0.01	0.16	1.36	-0.04	0.25	1.58	0.11	0.05	0.98	0.45	0.31	0.98
	(0.60)	(0.24)	(0.75)	(0.40)	(0.22)	(0.65)	(0.43)	(0.21)	(0.66)	(0.40)	(0.20)	(0.66)
CO_2	0.11	0.45	2.00	-0.21	0.43	1.94	0.32	0.24	1.63	0.08	0.42	1.63
	(0.90)	(0.40)	(1.49)	(0.81)	(0.36)	(1.12)	(0.70)	(0.32)	(1.13)	(0.70)	(0.33)	(1.13)
Methane	0.80	-0.18	-0.05	-0.22	-0.13	-0.07	0.52	-0.11	-0.23	0.24	0.03	-0.23
	(0.67)	(0.30)	(0.94)	(0.62)	(0.26)	(0.93)	(0.58)	(0.24)	(0.84)	(0.55)	(0.26)	(0.84)
N_2O	-0.15	0.12	0.76	-0.52	0.17	0.52	0.10	-0.16	0.35	-0.06	-0.03	0.35
	(0.46)	(0.14)	(0.48)	(0.47)	(0.15)	(0.43)	(0.30)	(0.16)	(0.48)	(0.33)	(0.14)	(0.48)
Industrial comp., county dem.	x	x	x	x	x	x	x	x	x	x	x	x
Lagged GHG emissions	x	x		x	x		x	x				
Quadratics of indust. comp.	x	x	x	x	x	x						
Quadratics of county dem.	x	x	x									

Standard errors shown in parentheses.

Table 4: Regression results:
Dependent Variable - Ln(Total GHG Emissions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High emitter × NA - Ozone	0.09	0.11	-0.02	-0.01	-0.01	0.27	-0.26	0.25
	(0.21)	(0.21)	(0.28)	(0.28)	(0.28)	(0.43)	(0.23)	(0.68)
High emitter × NA - Lead	0.08	0.08	0.10	0.09	0.09	-0.10	-0.12	0.78
	(0.14)	(0.14)	(0.20)	(0.20)	(0.20)	(0.08)	(0.08)	(0.64)
High emitter × NA - SO_2	0.03	0.03	0.02	0.02	0.02	-0.03	-0.04	0.17
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.05)	(0.05)	(0.13)
High emitter × NA - Ozone			0.16	0.17	0.17	0.11	0.22	
× Substitute production			(0.17)	(0.17)	(0.17)	(0.21)	(0.16)	
High emitter × NA - Lead			-0.05	-0.05	-0.05	0.08	0.08	
× Substitute production			(0.24)	(0.24)	(0.24)	(0.18)	(0.18)	
High emitter × NA - SO_2			0.02	0.02	0.02	-0.00	-0.00	
× Substitute production			(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	
ln(Establishments in same		0.04	0.04	0.04	0.04	-0.01	0.02	-0.03
county)		(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)	(0.12)
ln(Employment level)		0.02	0.02	0.02	0.02	0.02	0.03	0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
ln(Total annual wages)		-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of other facilities				-0.00	-0.00	-0.00	-0.00	
with same owner				(0.00)	(0.00)	(0.00)	(0.00)	
Number of owners					0.01	0.04	0.03	
					(0.04)	(0.04)	(0.04)	
Facility fixed effects	X	X	X	X	X	X	X	X
County × year fixed effects	X	X	X	X	X			X
Industry × year fixed effects	X	X	X	X	X			X
County fixed effects						X	X	
Year fixed effects						X	X	
Industry fixed effects							X	
Observations	18942	18942	18942	18942	18942	18942	18942	8109
R^2	0.95	0.95	0.95	0.95	0.95	0.93	0.93	0.94

Column (8) restricts the sample to only facilities at which owners do not own another facility in an attainment county. All standard errors are clustered at the county-level.

Table 5: Regression results by greenhouse gas

	(1) $\ln(CO_2)$	(2) ln(methane)	(3) $\ln(N_20)$
High emitter × NA - Ozone	0.00	0.01	0.27
	(0.26)	(0.17)	(0.13)
High emitter × NA - Lead	0.04	0.01	0.06
	(0.17)	(0.07)	(0.05)
High emitter × NA - SO_2	0.01	-0.33	-0.04
	(0.06)	(0.32)	(0.04)
High emitter × NA - Ozone	0.17	0.14	-0.00
× Substitute production	(0.17)	(0.09)	(0.10)
High emitter × NA - Lead	-0.05	-0.00	0.09
× Substitute production	(0.25)	(0.08)	(0.05)
High emitter × NA - SO_2	-0.09	0.19	-0.03
× Substitute production	(0.06)	(0.30)	(0.05)
ln(Establishments in same	0.07	-0.00	-0.01
county)	(0.05)	(0.04)	(0.02)
ln(Employment level)	0.04	0.01	0.01
	(0.03)	(0.02)	(0.01)
ln(Total annual wages)	-0.02	-0.00	-0.00
	(0.01)	(0.01)	(0.00)
Number of other facilities	0.00	-0.00	0.00
with same owner	(0.00)	(0.00)	(0.00)
Number of owners	0.01	-0.01	0.01
	(0.04)	(0.02)	(0.02)
Observations	15452	18550	14091
R^2	0.98	0.98	0.97

Estimates include county-by-year, industry-by-year, and facility fixed effects. Standard errors are clustered at the county-level.

Table 6: Regression results - Robustness checks

	Urbanization		Neighbors	
	(1) Urban	(2) Rural	(3) 30 miles	(4) 60 miles
High emitter × NA - Ozone	0.06	-0.57	0.09	0.11
	(0.33)	(0.11)	(0.22)	(0.20)
High emitter × NA - Lead	0.09		0.09	0.09
	(0.20)		(0.20)	(0.20)
High emitter × NA - SO_2	0.01	0.10	0.03	0.13
	(0.10)	(0.10)	(0.08)	(0.11)
High emitter × NA - Ozone	0.17	-0.44	0.12	0.14
× Substitute production	(0.19)	(0.11)	(0.16)	(0.11)
High emitter × NA - Lead	-0.06		-0.05	-0.05
× Substitute production	(0.25)		(0.24)	(0.24)
High emitter × NA - SO_2	0.04		0.04	-0.09
× Substitute production	(0.08)		(0.07)	(0.12)
ln(Establishments in same	0.05	0.01	0.04	0.04
county)	(0.05)	(0.17)	(0.05)	(0.05)
ln(Employment level)	0.01	0.19	0.02	0.02
	(0.03)	(0.10)	(0.02)	(0.02)
ln(Total annual wages)	-0.00	-0.08	-0.01	-0.01
	(0.01)	(0.04)	(0.01)	(0.01)
Number of other facilities	-0.00	-0.00	-0.00	-0.00
with same owner	(0.00)	(0.00)	(0.00)	(0.00)
Number of owners	0.02	-0.04	0.01	0.01
	(0.04)	(0.13)	(0.04)	(0.04)
Observations	13449	5493	18942	18942
R^2	0.95	0.95	0.95	0.95

Estimates include county by year, industry by year, and facility fixed effects.
Standard errors are clustered at the county-level.

7 Figures

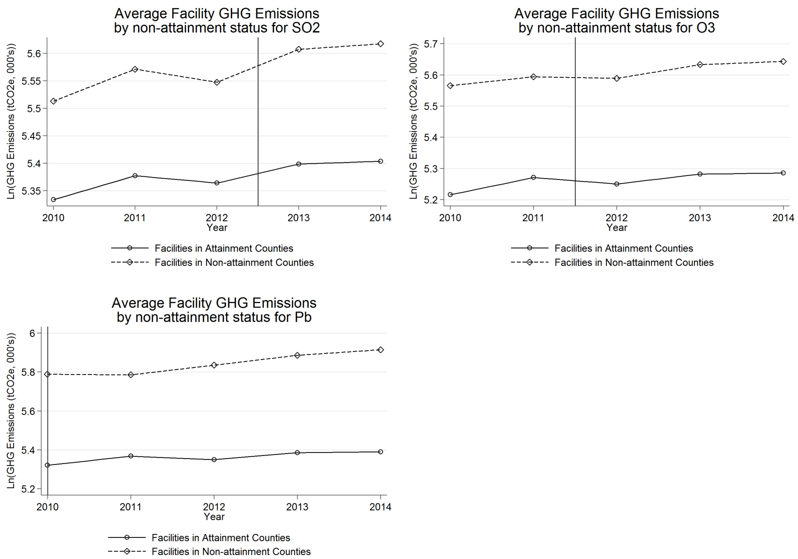


Figure 1: Average facility GHG emissions by non-attainment status, 2010-2014

Source: EPA GHG Inventory

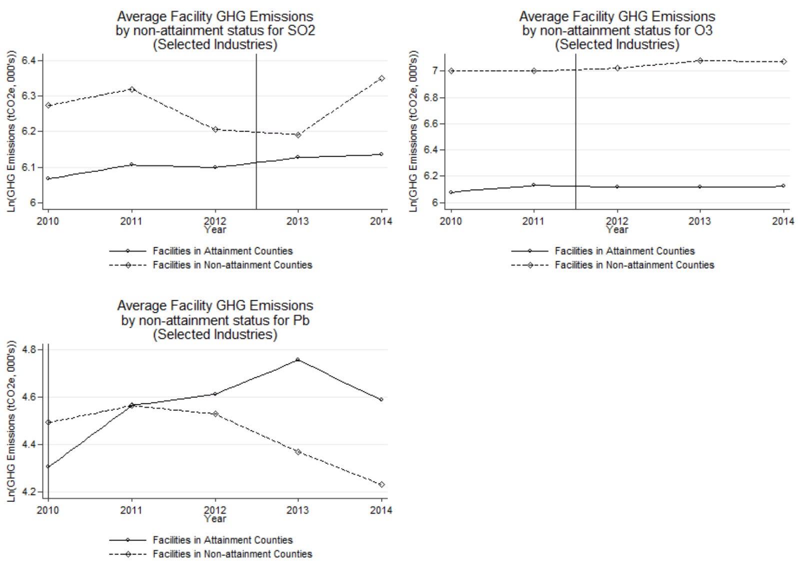
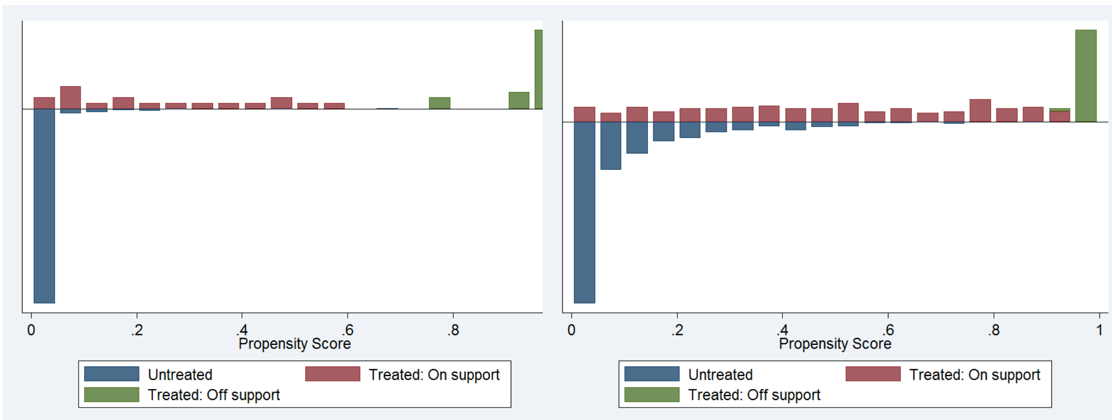
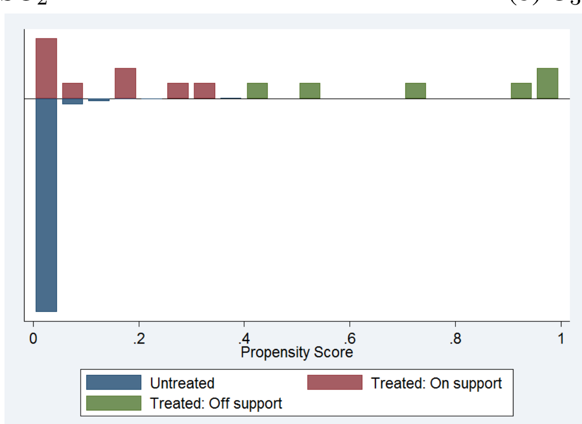


Figure 2: Average facility GHG emissions by non-attainment status for selected industries, 2010-2014

Source: EPA GHG Inventory



(a) SO_2 (b) O_3



(c) Pb

Figure 3: Range of propensity scores for treatment and control groups

Source: Authors' calculations

A Appendix Tables

For Online Publication

Table A1: Studies estimating the co-benefits of climate change mitigation in developed countries.

				Value of co-benefits (2008\$/tCO_2)		
	Study	**Geography**	**Sectors**	**Mid**	**High**	**Low**
1	Ayres and Walter (1991)	US	All	68	n.e.	n.e.
2	Ayres and Walter (1991)	Germany	All	128	n.e.	n.e.
3	Pearce (1992)	Norway	All	68	n.e.	n.e.
4	Pearce (1992)	UK	All	80	n.e.	n.e.
5	Alfsenet al (1992)	Norway	All	51	60	42
6	Holmeset al (1993)	US	Electric	4	n.e.	n.e.
7	Dowlatabadi et al (1993)	US	Electric	4	n.e.	n.e.
8	Goulder (1993)	US	All	44	n.e.	n.e.
9	Barker(1993)	UK	All	50	82	18
10	Barker (1993)	US	All	103	n.e.	n.e.
11	Barker (1993)	Norway	All	98	125	71
12	Viscusi et al (1994)	US	Electric	116	n.e.	n.e.
13	Rowe (1995)	US	Electric	31	n.e.	n.e.
14	Boyd et al (1995)	US	All	53	n.e.	n.e.
15	Palmer and Burtraw (1997)	US	Electric	6	n.e.	n.e.
16	EPA (1997)	US	Electric	31	n.e.	n.e.
17	Mccubbin (1999)	US	Electric	49	89	10
18	Caton and Constable (2000)	Canada	All	13	n.e.	n.e.
19	Syri et al (2001)	EU-15	All	n.e.	n.e.	n.e.
20	Han (2001)	Korea	All	80	91	69
21	Syri et al (2002)	Finland	All	n.e.	n.e.	n.e.
22	Bye et al (2002)	Nordic countries	All	18	26	11
23	Burtraw et al (2003)	US	Electric	17	18	15
24	Proost and Regemorter (2003)	Belgium	All	n.e.	n.e.	n.e.
25	Joh et al (2003)	Korea	All	2	n.e.	n.e.
26	van Vuuren et al (2006)	Europe	All	n.e.	n.e.	n.e.
27	Bollen et al (2009)	Netherlands	All	n.e.	n.e.	n.e.
28	Tollefsen et al (2009)	Europe	All	n.e.	n.e.	n.e.

Source: Nemet, Holloway and Meier (2010)

Table A2: Number of Direct Emitters that Reported (2014)

3-digit NAICS Industry	**Number of Reporters**	**Percent of total direct emissions**
Accommodation	5	0.01
Administration of Economic Programs	1	0.00
Administration of Environmental Quality	2	0.01
Administration of Human Resource Program	2	0.01
Administrative and Support Services	5	0.07
Air Transportation	2	0.00
Ambulatory Health Care Services	1	0.00
Amusement, Gambling, and Recreation Industries	1	0.01
Beverage and Tobacco Product Manufacturing	29	0.05
Chemical Manufacturing	624	6.29
Computer and Electronic Product Manufacturing	52	0.19
Crop Production	3	0.01
Educational Services	112	0.32
Electrical Equipment, Appliance, and Component Manufacturing	15	0.02
Executive, Legislative, and Other General Government Support	3	0.00
Fabricated Metal Product Manufacturing	25	0.03
Food Manufacturing	307	1.13
Funds, Trusts, and Other Financial Vehicles	1	0.00
Furniture and Related Product Manufacturing	1	0.00
Heavy and Civil Engineering Construction	4	0.01
Hospitals	24	0.03
Justice, Public Order, and Safety Activities	3	0.00
Machinery Manufacturing	18	0.03
Merchant Wholesalers, Durable Goods	2	0.00
Merchant Wholesalers, Nondurable Goods	3	0.00
Mining (except Oil and Gas)	191	1.97
Miscellaneous Manufacturing	4	0.01
National Security and International Affairs	50	0.10
Nonmetallic Mineral Product Manufacturing	319	3.14
Paper Manufacturing	211	1.34
Petroleum and Coal Products Manufacturing	172	6.80
Pipeline Transportation	4	0.01
Plastics and Rubber Products Manufacturing	33	0.05
Primary Metal Manufacturing	246	3.23
Printing and Related Support Activities	3	0.00
Religious, Grantmaking, Civic, Professional, and Similar Organizations	20	0.03
Real Estate	3	0.01
Religious, Grantmaking, Civic, Professio	2	0.00
Support Activities for Agriculture and Forestry	2	0.00
Support Activities for Mining	121	0.24
Support Activities for Transportation	8	0.01
Textile Mills	10	0.02
Textile Product Mills	6	0.01
Transportation Equipment Manufacturing	85	0.13
Utilities	91	0.30
Warehousing and Storage	7	0.01
Waste Management and Remediation Service	1137	3.07
Wood Product Manufacturing	20	0.02
Total	3990	28.70

Source: EPA GHGRP Data

Table A3: All non-attainment counties

NAAQS Standard	2006	2007	2008	2009	2010	2011	2012	2013	2014
1-Hr Ozone (1979)	217	217	217	217	217	217	217	217	217
8-Hr Ozone (1997)	415	299	293	268	247	235	216	210	181
8-Hr Ozone (2008)			0	0	0	0	225	225	225
Lead (1978)	2	2	2	2	2	2	2	2	2
Lead (2008)			0	0	17	21	21	21	22
Sulfur Dioxide (1971)	8	7	7	7	7	7	7	7	7
Sulfur Dioxide (2010)					0	0	0	38	38
Total	642	525	519	494	490	482	688	720	692

Table A4: Most recent change in standards for criteria pollutants under the Clean Air Act.

Date of final rule	Date of implementation	Pollutant	Primary or Secondary	Averaging Time	Level	Form
2008	2012	O_3	Both	8-hour	0.075 ppm	Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years
2008	2010	Pb-TSP	Both	3-month period	0.15 $\mu g/m^3$	Not to be exceeded
2010	2013	SO_2	Primary	1-hour	75 ppb	99th percentile, averaged over 3 years
				Annual and 24-hour		Revoked

Source: http://www.epa.gov/ttn/naaqs/

Notes: There was no change in carbon monoxide regulation between 2010 and 2013. The 2010 standard for nitrogen dioxide was not implemented before 2013, and the latest PM standard change was enforced starting in 2009.

Table A5: Percent of GHG reporters that are at risk for regulation or regulated under NAAQS

	At risk of regulation				**Regulated**			
	O_3	**Pb**	**SO_2**	**N**	**O_3**	**Pb**	**SO_2**	**N**
2010	45.2	0.6	39.5	5700	13.1	0.2	0.3	5700
2011	44.2	0.6	36.2	6298	12.3	0.2	0.3	6298
2012	44.9	0.6	35.7	6459	13.5	0.2	0.3	6459
2013	45.2	0.6	35.1	6478	13.0	0.2	1.9	6478
2014	45.6	0.6	33.8	6639	12.6	0.3	1.9	6639

All industries. 7% of national emissions cutoff.

Table A6: Number of plants that are regulated for multiple criteria pollutant

Number of Pollutants	Plants at risk to be regulated for multiple pollutants	Plants that are regulated for multiple pollutants
0	3133	4787
1	1259	368
2	0	42
3	438	10
4	377	0
Total	**5207**	**5207**

Data are for 2014 only. 7% of national emissions cutoff.

Table A7: Balancing results - SO_2

Variable	Mean Treated	Mean Control	Difference p-value	Variable	Mean Treated	Mean Control	Difference p-value
Nb of establishments NAICS11	17.1	12.2	0.257	Avg annual pay NAICS11	1.00E+006	8.90E+005	0.857
Nb of establishments NAICS23	216.5	185.5	0.581	Avg annual pay NAICS23	4.20E+007	3.50E+007	0.727
Nb of establishments NAICS31	11.3	7.2	0.155	Avg annual pay NAICS31	3.50E+005	81330	0.203
Nb of establishments NAICS32	28.0	27.8	0.975	Avg annual pay NAICS32	1.10E+007	1.20E+007	0.928
Nb of establishments NAICS33	46.8	42.8	0.751	Avg annual pay NAICS33	1.50E+007	3.10E+007	0.463
Nb of establishments NAICS42	102.8	105.9	0.949	Avg annual pay NAICS42	3.10E+007	2.90E+007	0.932
Nb of establishments NAICS44	193.9	171.2	0.616	Avg annual pay NAICS44	4.70E+007	4.30E+007	0.799
Nb of establishments NAICS45	72.2	64.1	0.644	Avg annual pay NAICS45	8.20E+006	6.70E+006	0.767
Nb of establishments NAICS49	20.7	17.4	0.394	Avg annual pay NAICS49	1.10E+007	8.40E+006	0.586
Nb of establishments NAICS51	26.4	24.6	0.843	Avg annual pay NAICS51	6.90E+006	8.70E+006	0.779
Nb of establishments NAICS52	104.2	103.6	0.985	Avg annual pay NAICS52	2.90E+007	4.40E+007	0.657
Nb of establishments NAICS53	68.6	58.3	0.618	Avg annual pay NAICS53	5.90E+006	5.70E+006	0.946
Nb of establishments NAICS54	174.0	157.0	0.770	Avg annual pay NAICS54	4.10E+007	3.50E+007	0.764
Nb of establishments NAICS55	10.2	10.6	0.904	Avg annual pay NAICS55	9.50E+006	1.10E+007	0.835
Nb of establishments NAICS56	104.5	96.8	0.827	Avg annual pay NAICS56	2.10E+007	1.60E+007	0.687
Nb of establishments NAICS61	41.3	33.9	0.426	Avg annual pay NAICS61	3.50E+007	3.40E+007	0.967
Nb of establishments NAICS62	244.4	190.9	0.262	Avg annual pay NAICS62	8.10E+007	6.30E+007	0.525
Nb of establishments NAICS71	39.4	32.9	0.613	Avg annual pay NAICS71	5.50E+006	5.10E+006	0.867
Nb of establishments NAICS72	177.0	157.8	0.622	Avg annual pay NAICS72	3.70E+007	3.30E+007	0.774
Nb of establishments NAICS81	190.6	181.3	0.852	Avg annual pay NAICS81	2.00E+007	1.60E+007	0.643
Nb of establishments NAICS92	49.1	51.1	0.792	Avg annual pay NAICS92	3.60E+007	5.40E+007	0.332
Nb of establishments NAICS99	3.5	3.1	0.858	Avg annual pay NAICS99	1.00E+005	91863	0.855
Nb of establishments NAICS11^2	467.5	271.6	0.298	Avg annual pay NAICS11^2	4.10E+012	4.50E+012	0.928
Nb of establishments NAICS23^2	74763.0	59172.0	0.722	Avg annual pay NAICS23^2	5.00E+015	3.60E+015	0.745
Nb of establishments NAICS31^2	209.3	107.2	0.314	Avg annual pay NAICS31^2	8.10E+011	4.40E+010	0.199
Nb of establishments NAICS32^2	1058.9	1363.4	0.630	Avg annual pay NAICS32^2	5.30E+014	8.50E+014	0.685
Nb of establishments NAICS33^2	3143.1	3547.1	0.827	Avg annual pay NAICS33^2	7.40E+014	8.40E+015	0.332
Nb of establishments NAICS42^2	24003.0	37074.0	0.684	Avg annual pay NAICS42^2	5.00E+015	5.80E+015	0.902
Nb of establishments NAICS44^2	55553.0	45657.0	0.712	Avg annual pay NAICS44^2	4.60E+015	5.20E+015	0.894
Nb of establishments NAICS45^2	7676.1	6767.9	0.820	Avg annual pay NAICS45^2	2.40E+014	2.80E+014	0.911
Nb of establishments NAICS49^2	553.9	420.5	0.500	Avg annual pay NAICS49^2	3.00E+014	3.00E+014	0.996
Nb of establishments NAICS51^2	1236.6	1406.7	0.881	Avg annual pay NAICS51^2	2.30E+014	6.00E+014	0.523
Nb of establishments NAICS52^2	18949.0	23985.0	0.768	Avg annual pay NAICS52^2	2.90E+015	1.90E+016	0.393
Nb of establishments NAICS53^2	8764.9	6415.9	0.660	Avg annual pay NAICS53^2	1.10E+014	1.20E+014	0.968
Nb of establishments NAICS54^2	58520.0	52867.0	0.892	Avg annual pay NAICS54^2	6.70E+015	4.00E+015	0.603
Nb of establishments NAICS55^2	184.9	258.7	0.678	Avg annual pay NAICS55^2	3.70E+014	8.00E+014	0.526
Nb of establishments NAICS56^2	20105.0	20733.0	0.968	Avg annual pay NAICS56^2	1.70E+015	9.60E+014	0.603
Nb of establishments NAICS61^2	2557.3	1723.6	0.394	Avg annual pay NAICS61^2	4.10E+015	3.60E+015	0.891
Nb of establishments NAICS62^2	86466.0	47205.0	0.216	Avg annual pay NAICS62^2	1.70E+016	7.80E+015	0.408
Nb of establishments NAICS71^2	3258.7	2184.8	0.627	Avg annual pay NAICS71^2	1.00E+014	5.40E+013	0.481
Nb of establishments NAICS72^2	45673.0	35909.0	0.605	Avg annual pay NAICS72^2	2.50E+015	2.40E+015	0.925
Nb of establishments NAICS81^2	55738.0	54119.0	0.953	Avg annual pay NAICS81^2	1.50E+015	6.70E+014	0.461
Nb of establishments NAICS92^2	2772.5	3204.5	0.639	Avg annual pay NAICS92^2	3.20E+015	6.50E+015	0.329
Nb of establishments NAICS99^2	32.4	68.9	0.559	Avg annual pay NAICS99^2	2.90E+010	7.60E+010	0.514
Population	79184.0	74385.0	0.768	Population^2	8.50E+009	7.70E+009	0.818
Income p.c. average	22.9	22.3	0.705	Income p.c. average^2	546.6	516.8	0.690
Median age	40.9	40.7	0.932	Median age^2	1702.9	1707.6	0.981
Ninth grade, pct	3.9	4.2	0.783	Ninth grade, pct^2	22.1	29.7	0.600
Some college, pct	21.5	21.2	0.794	Some college, pct^2	480.5	457.0	0.666
Associate degree, pct	8.6	8.9	0.705	Associate degree, pct^2	76.4	85.7	0.493
College, pct	13.4	13.5	0.926	College, pct^2	194.9	200.2	0.889
Graduate degree, pct	7.0	7.4	0.594	Graduate degree, pct^2	54.2	57.8	0.733
Unemployment rate	5.0	4.9	0.883	Unemployment rate^2	25.5	25.4	0.981
Poverty rate	10.8	11.3	0.600	Poverty rate^2	123.8	134.2	0.647
Black, pct	4.4	4.1	0.850	Black, pct^2	50.6	28.9	0.461
Asian, pct	1.1	1.1	0.920	Asian, pct^2	1.9	1.7	0.799
Hispanic, pct	5.1	3.4	0.247	Hispanic, pct^2	55.5	19.1	0.146
Lagged GHG emissions	6.0	5.9	0.902				

Table A8: Balancing results - O_3

Variable	Mean Treated	Mean Control	Difference p-value	Variable	Mean Treated	Mean Control	Difference p-value
Nb of establishments NAICS11	65.187	88.591	0.104	Avg annual pay NAICS11	2.30E+007	3.60E+007	0.243
Nb of establishments NAICS23	708.49	681.79	0.694	Avg annual pay NAICS23	2.50E+008	2.40E+008	0.631
Nb of establishments NAICS31	46.269	44.979	0.797	Avg annual pay NAICS31	1.60E+007	1.10E+007	0.105
Nb of establishments NAICS32	1.285	1.2021	0.680	Avg annual pay NAICS32	1.20E+005	1.50E+005	0.757
Nb of establishments NAICS99	46.627	98.373	0.000	Avg annual pay NAICS99	1.80E+006	3.20E+006	0.016
Nb of establishments NAICS11^2	21245	30409	0.475	Avg annual pay NAICS11^2	1.30E+016	1.30E+016	0.927
Nb of establishments NAICS23^2	1000000	840000	0.391	Avg annual pay NAICS23^2	2.00E+017	1.60E+017	0.510
Nb of establishments NAICS31^2	4854.2	4156.5	0.535	Avg annual pay NAICS31^2	1.50E+015	6.10E+014	0.035
Nb of establishments NAICS32^2	6.2694	4.5907	0.486	Avg annual pay NAICS32^2	7.00E+011	1.20E+012	0.594
Nb of establishments NAICS99^2	12488	37126	0.001	Avg annual pay NAICS99^2	1.90E+013	5.70E+013	0.055
Population	310000	300000	0.782	Population^2	2.00E+011	1.80E+011	0.574
Income p.c. average	26.6	26.3	0.730	Income p.c. average^2	759.7	752.3	0.877
Median age	38.9	38.4	0.274	Median age^2	1530.2	1498.7	0.363
Ninth grade, pct	4.7	5.8	0.010	Ninth grade, pct^2	33.9	55.1	0.016
Some college, pct	20.7	21.4	0.095	Some college, pct^2	442.2	469.8	0.084
Associate degree, pct	8.2	8.5	0.188	Associate degree, pct^2	70.3	75.8	0.088
College, pct	17.4	16.9	0.318	College, pct^2	337.7	311.3	0.224
Graduate degree, pct	10.2	9.8	0.464	Graduate degree, pct^2	124.4	113.7	0.337
Unemployment rate	5.7	5.7	0.689	Unemployment rate^2	35.1	34.2	0.644
Poverty rate	9.9	10.6	0.166	Poverty rate^2	117.0	132.0	0.260
Black, pct	9.3	8.1	0.277	Black, pct^2	216.1	162.8	0.324
Asian, pct	2.7	2.4	0.211	Asian, pct^2	14.2	9.1	0.060
Hispanic, pct	11.6	16.7	0.004	Hispanic, pct^2	324.4	668.7	0.006
Lagged GHG emissions	5.3	5.2	0.404				

Table A9: Balancing results - Pb

Variable	Mean Treated	Mean Control	Difference p-value	Variable	Mean Treated	Mean Control	Difference p-value
Nb of establishments NAICS53	47.444	45	0.910	Avg annual pay NAICS53	4.10E+006	2.10E+006	0.487
Nb of establishments NAICS54	329.11	440.22	0.616	Avg annual pay NAICS54	1.10E+008	1.20E+008	0.933
Nb of establishments NAICS55	18	20.333	0.818	Avg annual pay NAICS55	2.80E+007	4.00E+007	0.688
Nb of establishments NAICS56	170.33	186.44	0.844	Avg annual pay NAICS56	3.90E+007	3.10E+007	0.758
Nb of establishments NAICS61	73.778	66.222	0.796	Avg annual pay NAICS61	1.30E+008	6.20E+007	0.335
Nb of establishments NAICS62	361.78	323.11	0.758	Avg annual pay NAICS62	1.80E+008	1.10E+008	0.347
Nb of establishments NAICS71	6.4444	8.2222	0.563	Avg annual pay NAICS71	0	1.00E+006	0.122
Nb of establishments NAICS99	4.3333	10.556	0.287	Avg annual pay NAICS99	1.10E+005	3.80E+005	0.239
Nb of establishments NAICS53^2	4838.3	3073	0.632	Avg annual pay NAICS53^2	6.50E+013	1.70E+013	0.420
Nb of establishments NAICS54^2	2.30E+005	4.50E+005	0.547	Avg annual pay NAICS54^2	3.90E+016	4.40E+016	0.904
Nb of establishments NAICS55^2	724	812.78	0.913	Avg annual pay NAICS55^2	2.80E+015	7.00E+015	0.556
Nb of establishments NAICS56^2	52037	63938	0.806	Avg annual pay NAICS56^2	5.30E+015	2.40E+015	0.571
Nb of establishments NAICS61^2	10055	6409.6	0.594	Avg annual pay NAICS61^2	4.70E+016	1.10E+016	0.309
Nb of establishments NAICS62^2	2.00E+005	1.60E+005	0.696	Avg annual pay NAICS62^2	6.10E+016	2.70E+016	0.310
Nb of establishments NAICS71^2	68.444	113.33	0.478	Avg annual pay NAICS71^2	0	4.00E+012	0.146
Nb of establishments NAICS99^2	80.111	305	0.368	Avg annual pay NAICS99^2	3.20E+010	5.20E+011	0.282
Population	1.40E+005	1.20E+005	0.591	Population^2	3.40E+010	2.00E+010	0.474
Income p.c. average	23.0	23.9	0.674	Income p.c. average^2	553.8	578.9	0.807
Median age	39.2	37.9	0.460	Median age^2	1553.6	1446.8	0.441
Ninth grade, pct	3.4	2.7	0.311	Ninth grade, pct^2	13.9	8.3	0.303
Some college, pct	20.9	21.9	0.539	Some college, pct^2	446.7	489.2	0.504
Associate degree, pct	8.4	8.7	0.861	Associate degree, pct^2	75.9	84.1	0.733
College, pct	15.8	17.9	0.541	College, pct^2	281.2	383.8	0.460
Graduate degree, pct	9.1	10.4	0.398	Graduate degree, pct^2	89.3	121.1	0.351
Unemployment rate	5.4	5.1	0.530	Unemployment rate^2	30.2	26.9	0.537
Poverty rate	10.3	9.0	0.383	Poverty rate^2	115.8	88.3	0.386
Black, pct	7.3	2.4	0.225	Black, pct^2	167.2	11.9	0.309
Asian, pct	1.3	1.1	0.746	Asian, pct^2	3.2	1.5	0.473
Hispanic, pct	3.2	3.9	0.577	Hispanic, pct^2	15.1	21.9	0.639

Table A10: Matching results - All counties within perimeter of attainment county considered as treated

	30 miles			60 miles		
	(1)	(2)	(3)	(4)	(5)	(6)
	SO2	**Ozone**	**Lead**	**SO2**	**Ozone**	**Lead**
Total GHGs	0.05	-0.01	0.00	-0.06	-0.27	0.00
	(0.26)	(0.19)	(0.29)	(0.24)	(0.20)	(0.23)
CO_2	-0.13	0.17	-0.17	-0.52	-0.04	0.13
	(0.44)	(0.36)	(0.50)	(0.37)	(0.31)	(0.40)
Methane	0.45	-0.11	0.08	0.03	-0.45	-0.20
	(0.48)	(0.28)	(0.43)	(0.30)	(0.26)	(0.34)
N_2O	0.16	-0.08	-0.07	0.15	0.04	0.01
	(0.14)	(0.17)	(0.19)	(0.14)	(0.12)	(0.16)
Industrial comp., county dem.	x	x	x	x	x	x
Lagged GHG emissions	x	x		x	x	
Quadratics of Indust. comp.	x	x	x	x	x	x
Quadratics of Demographics.	x	x	x	x	x	x

Standard errors shown in parentheses.

Table A11: Regression results - By industry

	(1) Baseline	(2) Pulp & paper	(3) Petro. Man.	(4) Chem. Man.	(5) Nonferr. Metal	(6) Air Trans.	(7) Not clean
High emitter × NA - Ozone	-0.01	-0.45	0.53				-0.24
	(0.28)	(0.29)	(0.59)				(0.22)
High emitter × NA - Lead	0.09				-0.01	0.26	-0.15
	(0.20)				(0.30)	(0.27)	(0.15)
High emitter × NA - SO_2	0.02	-0.00	-0.07	0.05			-0.01
	(0.09)	(0.08)	(0.10)	(0.12)			(0.27)
High emitter × NA - Ozone	0.17	0.37	0.03				0.25
× Substitute production	(0.17)	(0.25)	(0.21)				(0.25)
High emitter × NA - Lead	-0.05				-0.10		-0.09
× Substitute production	(0.24)				(0.29)		(0.27)
High emitter × NA - SO_2	0.02	-0.09	-0.11	0.26			-0.08
× Substitute production	(0.07)	(0.11)	(0.11)	(0.15)			(0.10)
ln(Establishments in same	0.04	0.07	0.03	0.06	0.07	0.07	0.11
county)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.25)
ln(Employment level)	0.02	0.02	0.01	0.01	0.01	0.01	0.13
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.13)
ln(Total annual wages)	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00	-0.05
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
Number of other facilities	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.01
with same owner	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Number of owners	0.01	-0.01	0.00	-0.00	-0.01	-0.01	0.23
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.27)
Observations	18942	15769	15609	16866	14918	14780	4192
R^2	0.95	0.94	0.95	0.94	0.94	0.94	0.96

Estimates include county by year, industry by year, and facility fixed effects.
Standard errors are clustered at the county level.

Table A12: Percent of All Emissions by 4 Digit NAICS Code
Sectors that account for at least 5% of national emissions

	Criteria Pollutant		
2012 NAICS US Title	**O_3**	**Pb**	**SO_2**
Basic Chemical Manufacturing	6.7		13.9
Cement and Concrete Product Manufacturing	6.3		5.2
Iron and Steel Mills and Ferroalloy Manufacturing		5.8	
Nonferrous Metal (except Aluminum) Production		12.2	
Oil and Gas Extraction	16.6		
Petroleum and Coal Products Manufacturing	8.1		12.5
Pipeline Transportation of Natural Gas	14.2		
Pulp, Paper, and Paperboard Mills	9.1	17.6	
Support Activities for Air Transportation	6.2	47.8	

NAICS code 2211 (Electric Power Generation) excluded from calculations. Industries that emit either 5% of NOx or VOCs are counted in the ozone column. Oil and Gas Extraction and Pipeline Transportation of Natural Gas are excluded from the regression analysis.
Source: 2011 National Emissions Inventory

Table A13: Regression results:
Dependent Variable - Ln(Total GHG Emissions)
5% cutoff for polluting industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High emitter × NA - Ozone	0.05	0.06	0.02	0.03	0.03	0.13	-0.14	0.05
	(0.09)	(0.09)	(0.11)	(0.11)	(0.11)	(0.19)	(0.10)	(0.23)
High emitter × NA - Lead	0.00	0.00	0.11	0.10	0.10	-0.01	-0.02	0.79
	(0.10)	(0.10)	(0.19)	(0.19)	(0.19)	(0.14)	(0.14)	(0.64)
High emitter × NA - SO_2	0.07	0.08	0.05	0.05	0.05	-0.02	-0.02	0.17
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.05)	(0.05)	(0.13)
High emitter × NA - Ozone			0.06	0.06	0.06	0.06	0.10	
× Substitute production			(0.11)	(0.11)	(0.11)	(0.12)	(0.10)	
High emitter × NA - Lead			-0.17	-0.17	-0.17	-0.06	-0.06	
× Substitute production			(0.24)	(0.23)	(0.23)	(0.19)	(0.19)	
High emitter × NA - SO_2			0.05	0.05	0.05	0.01	0.01	
× Substitute production			(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	
ln(Establishments in same		0.05	0.05	0.06	0.06	-0.01	0.03	0.01
county)		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.12)
ln(Employment level)		0.02	0.02	0.02	0.02	0.01	0.03	0.02
		(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)
ln(Total annual wages)		-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of other facilities				-0.00	-0.00	-0.00	-0.00	
with same owner				(0.00)	(0.00)	(0.00)	(0.00)	
Number of owners					0.01	0.04	0.02	
					(0.03)	(0.04)	(0.03)	
Facility fixed effects	X	X	X	X	X	X	X	X
County × year fixed effects	X	X	X	X	X			X
Industry × year fixed effects	X	X	X	X	X			X
County fixed effects						X	X	
Year fixed effects						X	X	
Industry fixed effects							X	
Observations	18942	18942	18942	18942	18942	18942	18942	8109
R^2	0.95	0.95	0.95	0.95	0.95	0.93	0.93	0.94

Column (8) restricts the sample to only facilities at which owners do not own another facility in an attainment county. All standard errors are clustered at the county level.