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Abstract

In addition to global climate benefits, carbon mitigation improves local air quality by reducing emissions of hazardous co-pollutants. Using data on large industrial point sources in Europe, we estimate how changes in carbon dioxide emissions affect emissions of the three co-pollutants SO_X, NO_X, and PM_{10} for samples of 727 to 2,653 facilities for the years 2007 to 2015. We find substantial and significant co-pollutant elasticities of 0.7 for SO_X and NO_X, and 0.5 for PM_{10}, which are robust to different estimation approaches. Large CO_2 emitters and the energy sector are characterized by higher-than-average co-pollutant elasticities. For climate policy induced CO_2 emission reductions we find co-pollutant elasticities in the energy sector of 1.2 for SO_X, 1.0 for NO_X, and 0.8 for PM_{10}. Using these estimates to calculate monetary air quality co-benefits suggests that conventional European Environmental Agency estimates of carbon damages that omit co-benefits significantly underestimate the benefits of carbon mitigation.

Keywords

Co-pollutants, air quality co-benefits, climate mitigation, industrial air pollution

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1. Introduction

Carbon combustion simultaneously releases carbon dioxide (CO_2) and air pollutants such as sulfur oxides (SO_X), nitrogen oxides (NO_X), and particulate matter (PM). More stringent climate policies therefore also generate air quality and public health co-benefits. Omitting these co-benefits may lead to substantial underestimation of the economic benefits from carbon mitigation. To estimate the full social cost of carbon, or what Shindell (2015) terms the "social cost of atmospheric release," air quality co-benefits need to be incorporated along with climate benefits.

A crucial difference between CO_2 and co-emitted air pollutants – also termed co-pollutants – is that CO_2 is a uniformly mixed pollutant: a ton of emissions has the same climate impact independent of the location of release, and hence abatement is most efficient wherever its marginal costs are lowest, again independent of the location. Co-emitted air pollutants, by contrast, are non-uniformly mixed: the environmental and health damages are proximate to the location of release, and hence the total health damages depend on the number of people exposed (see, e.g., Muller and Mendelsohn 2007). For pollutants of the latter type, spatially differentiated policies have been recommended that take into account variations in damages, and hence abatement benefits, as well as in abatement costs (Tietenberg 1995; Muller and Mendelsohn 2009; Muller 2012; Boyce and Pastor 2013).

Air quality co-benefits of carbon mitigation policies in the form of positive public health externalities are important for two reasons. First, they can be sufficiently large that carbon mitigation policies are "in countries' own interests," helping to surmount collective action problems at the international level (Parry et al. 2015). If national compliance with international climate agreements were driven primarily by non-climate benefits of mitigation, and therefore would be undertaken even without the climate rationale, the additionality of international agreements may be limited (Zhang and Wang 2011). Second, variations across polluters in the extent of co-benefits per ton of carbon abatement imply that "one-size-fits-all" carbon mitigation policies may not be optimal (Muller 2012; Parry et al. 2015).

Despite the importance of air quality co-benefits from economic, public health, and environmental perspectives, there has been little empirical research on the relationship between CO_2 emissions and co-pollutants at the level of individual pollution sources. Most previous analyses are either simulation studies relying on ad hoc parameters to calculate the impact of carbon mitigation on co-pollutant emissions and their regional distribution, or are based on aggregate data that can return misleading results if the two types of pollutants are partially an outcome of different economic activities (i.e. caused by different sources).

Exceptions are Muller (2012) and Boyce and Pastor (2013), who calculate ratios of co-pollutant emissions and CO_2 at the level of pollution sources. These intensity ratios, however, implicitly assume a unit elasticity between carbon release and co-pollutant emissions rather than empirically estimating this relationship. The fact that CO_2 and co-pollutants are emitted by the same sources does not necessarily imply a unit elasticity relationship at the margin, whereby a one percent change in CO_2 emissions is accompanied by a one percent change in the same direction in co-pollutant emissions.

Variations in emissions of both greenhouse gases and air pollutants can be explained by scale effects (changes in economic output and thereby emissions), composition effects (changes in the sectoral composition of the economy), and technology effects that lead to a substitution across inputs, new emissions control technologies, or energy savings (Grossman and Krueger 1991; Copeland and Taylor 2004; Bollen and Brink 2014). While scale effects and composition effects do not affect the point source-level relationship between greenhouse gases and co-pollutants, technology effects can alter this relationship substantially (Holland 2010; Brunel and Johnson 2019). For example, end-of-pipe controls such as scrubbers can strongly reduce co-pollutants, while at the same time these devices need electricity to operate and therefore increase CO_2 emissions. An increase in the combustion temperature in natural gas-fired power plants reduces CO_2 but increases NO_X emissions. Co-pollutant and CO_2 emissions can also be complements; e.g. fuel switching from coal to natural gas reduces both CO_2 emissions as well as SO_2, since natural gas has lower sulfur content than coal. For these reasons, the relationship between CO_2 and co-pollutants is likely to vary strongly across facilities and an empirical estimate of its size at the source level is warranted.

A practical impediment to such an analysis has been the fact that in many countries, CO_2 and co-pollutant emissions are reported in separate databases that cover overlapping but different sets of facilities, lacking common codes for facility identification. This separation reflects the fact that regulatory policies for CO_2 and conventional pollutants often were formulated independently of each other. In this study, we take advantage of a novel European dataset, the European Pollutant Release and Transfer Register (E-PRTR), which provides annual facility-level data on CO_2 as well as co-pollutants starting in the year 2007. These data allow us to estimate the elasticities of co-pollutant emissions with respect to CO2 emissions.

An analysis of European industrial facilities is of particular interest against the background of the implementation of the world's first international emissions trading scheme for carbon (EU ETS) in 2005, which sets an overall cap for carbon emissions in the participating European countries (28 EU countries plus Iceland, Liechtenstein and Norway), but allows carbon trading across countries and sectors. At the same time, the European Union is continuously attempting to improve local air quality through taxes and total emissions caps on co-pollutants. Climate policy and air quality goals, however, are debated and formulated largely independently of each other. Spatial and sectoral heterogeneity in air quality co-benefits would therefore imply that spatially differentiated policies could provide strong efficiency as well as equity improvements.

To the best of our knowledge, this study is the first to estimate co-pollutant elasticities from panel data at the point-source level, which is needed not only for a precise assessment of the overall magnitude of air quality co-benefits of climate mitigation, but also for the efficient design of differentiated policies. We provide estimates of co-pollutant elasticities, based on all CO_2 variations in the data, and based on climate policy-induced variations.

We find evidence of substantial and statistically significant co-pollutant elasticities of around 0.7 for sulfur oxides (SO_X) and nitrogen oxides (NO_X), and 0.5 for particulate matter (PM_{10}) when we use all CO_2 variations in the sample. These results are robust to a variety of alternative specifications and estimation approaches. We find considerable variation in the magnitude of co-pollutant elasticities across CO_2 polluter size and economic sectors, and little variation over time, and by regional population density. Large CO_2 polluters and the energy sector are characterized by relatively high co-pollutant elasticities. Using changes in regulatory stringency to identify climate policy-induced changes in CO_2 emissions, we estimate co-pollutant elasticities in the electricity sector of 1.2 for SO_X, 1.0 for NO_X, and 0.8 for PM_{10}. Using these estimates to calculate monetary co-benefits suggests that conventional European Environmental Agency estimates that omit air quality co-benefits significantly underestimate the benefits of carbon mitigation.

The remainder of the paper is organized as follows. Section 2 reviews the literature on co-pollutants of carbon emissions and air quality co-benefits of carbon mitigation. Section 3 describes the data. Section 4 presents our identification strategy. Section 5 reports the results of our analysis. Section 6 monetizes the co-pollutant damage estimates and compares them to European damage cost estimates for CO_2 that are based on climate damages alone. Section 7 concludes.

2. Existing literature on co-pollutants and air quality co-benefits

Policy-induced variations in pollutants can generate spillovers on other pollutants. These spillovers can be positive if the two types of pollutants are complements, i.e. a reduction in one pollutant is associated with a reduction in the other, or negative if they are substitutes, i.e. if a decline in one pollutant leads to an increase in the other, generating a trade-off between two different environmental goals (Holland 2010). Two types of pollutants frequently studied together are greenhouse gases and local air pollutants. Both are released through the combustion of fossil fuels but are regulated separately using different environmental policy instruments (Brunel and Johnson 2019). The literature on air quality co-benefits of climate policy, on the one hand, consists largely of simulation studies that suggest large positive spillovers from climate policy on air quality and public health. On the other hand, the mostly empirical studies on climate benefits of air pollution regulation tend to find no clear evidence of spillovers. In this section we briefly review the related literature, and highlight what our study adds to it.

A growing body of literature has indicated that carbon mitigation can yield significant air quality co-benefits. The majority of studies on this topic have simulated specific carbon mitigation policy options and compared them to a reference-case scenario. Monetization of these co-benefits yields impacts per ton of CO_2 that are comparable to widely cited "social cost of carbon" (SCC) estimates of climate damages, and sometimes much larger. Many of these studies use aggregate data, and assume a unit-elasticity relationship between CO_2 and co-pollutants. Here we review several recent studies that illustrate representative findings.[4]

Shindell et al. (2016) find that a policy mix designed to reduce US carbon emissions by 2.7% per year would avert 36,000 (11,000 to 96,000; 95% CI) annual premature deaths from air pollution in the period 2016 to 2030. Monetizing the averted mortality by means of the US EPA's value of a statistical life (VSL, updated to 2010), the authors conclude that the total social cost of atmospheric release, combining co-benefits plus climate damages valued at the SCC, both at mid-range (3%) discounting, is three to four times greater than the SCC alone. The authors note that inclusion of other air quality benefits, such as impacts on medical spending and worker productivity, would further increase this ratio.

Parry et al. (2015) analyze a number of co-benefits of carbon mitigation, including not only air quality improvements but also other impacts, such as reduced traffic accidents and reduced fossil fuel subsidies, at the country level for the world's 20 largest CO_2 emitters in the year 2010. Air quality improvements from reduced coal combustion generate the largest co-benefits. They express their results as "second-best domestic CO_2 prices": second-best in that "no country presently has anything like fully corrective charges" for these externalities; and domestic in that the prices exclude global climate benefits. The average price for all 20 countries is \$57.5/tCO_2. For the six EU member countries included in the study, the price ranges from \$15 in Italy to \$90 in Poland; in Germany, France, the UK, and Spain it is \$45-55.

In an analysis of air quality co-benefits of carbon mitigation in the US, Thompson et al. (2014) model three policy scenarios – one targeting the electricity sector, one targeting transportation, and an economy-wide cap-and-trade program – and compare their costs with the mortality reductions the policies would induce. They find that monetized human health benefits would

[4] For reviews of earlier literature see Bell et al. (2008), Pittel and Rübbelke (2008), Nemet et al. (2010), and West et al. (2013).

offset 26% to 1,050% of the cost of carbon mitigation, with the highest net benefits accruing in the cap-and-trade scenario due to abatement cost minimization. They conclude that carbon mitigation policies initially “can be motivated based on air pollution co-benefits” (p. 921), but caution that as policy stringency increases, marginal abatement costs may rise to the point that they no longer are fully offset by co-benefits.

In a global simulation that takes into account trans-boundary movement of co-pollutants and interactions between climate change and air quality, West et al. (2013) calculate the averted mortality that would result from applying an international carbon price aimed to limit temperature increase in the year 2100 to 2.5°C. Using high and low VSLs and alternative concentration-response functions, they find worldwide average air quality and health co-benefits of \$50-380/tCO_2. Comparing these to carbon mitigation costs, they find that the co-benefits alone would exceed marginal abatement costs in 2030 and 2050.

Simulation studies also have assessed the air quality co-benefits of carbon mitigation policies specifically in electric power generation. In an early contribution, Burtraw et al. (2003) analyzed the impact of a \$25/t carbon tax on power plant emissions in the United States, and concluded that NO_X-related health benefits in the United States would be \$8/t of carbon reduced. Additional savings of \$4-7/t would accrue from reduced costs of compliance with existing SO_2 and NO_X emission caps. The authors concluded that these ancillary benefits alone would justify the average \$12/t cost of carbon reductions in response to a \$25/t tax.

Analyzing the Obama administration’s Clean Power Plan, that aimed to reduce CO_2 emissions from electric power plants in 2030 by 32% against the 2005 level, Driscoll et al. (2015) concluded that air quality improvements would prevent an estimated 3,500 (780-6,100; 95% CI) annual premature deaths by 2020. A follow-up study by Buonocore et al. (2016) that monetized the health co-benefits concluded that the plan would yield gross co-benefits of \$29 billion in 2020 (\$2.3-68 billion; 95% CI, in 2010 dollars) and net co-benefits of \$12 billion (–\$15 to \$51 billion, 95% CI).

While the above studies assess the magnitude of air quality co-benefits at the country or sectoral level, Groosman et. al (2011) investigate variations in air quality co-benefits across US states simulating the long-term impacts of a representative climate policy for the transport and electric power sector for the years 2010-2030. They find substantial variations in co-benefits across states. The largest per capita co-benefits can be found in states east of the Mississippi river, which are affected most strongly by the policy-induced reduction in coal-fired electric power generation (either directly, or because they are downwind of coal-fired power plants in other states). Reduced SO_2 emissions from electric power generation account for almost two-thirds of the total co-benefits.

Simulation studies like those reviewed above have been widely used to model the relationship between carbon mitigation and air quality co-benefits, but there has been relatively little empirical research analyzing how CO_2 and co-pollutant emissions are related to each other at the point-source level. To the best of our knowledge, the only exceptions are Muller (2012) and Boyce and Pastor (2013), who use facility-level data to calculate ratios of co-pollutant emissions and damages to CO_2 emissions in the US.

Muller (2012) computes co-pollutant emissions per ton of CO_2 for more than 10,000 sources, distinguishing among different facility types in the electric power generation sector and different vehicle types in the transport sector. Using a spatially disaggregated model of air pollution impacts (Muller and Mendelsohn 2007), he multiplies the ratio of co-pollutant to CO_2 emissions by the marginal damage per ton of co-pollutants to derive the monetary damages per ton of CO_2. The results indicate that co-benefits from carbon mitigation vary widely across source types. In the electricity sector, for example, co-pollutant damages from bituminous coal-fired power plants are \$87/tCO_2, whereas for natural gas-fired plants the corresponding figure is smaller than \$3/tCO_2.

Boyce and Pastor (2013) construct a dataset on CO_2 and co-pollutant emissions for 1,540 industrial facilities in the US by merging information from three US Environmental Protection Agency databases: the National Emissions Inventory 2008, the Toxics Release Inventory 2007, and the Greenhouse Gas Reporting Program 2010. Comparing the ratios of co-pollutant emissions to CO_2 emissions across and within industrial sectors, and comparing results with and without population-weighted conversion of emissions into health damages, they find considerable variation. Comparing petroleum refineries to electric power plants, for example, although emissions of co-pollutants per ton of CO_2 are higher for power plants, population-weighted damages per ton of CO_2 are 3-10 times higher for refineries because they generally are located in more densely populated areas.

The abovementioned studies have analyzed air quality co-benefits of climate mitigation, whereas few studies have investigated climate benefits of air quality regulations. While the former literature is dominated by simulation studies, the latter largely consists of empirical examinations. Holland (2010) analyzes spillovers from increased regulatory stringency of NO_x emissions on NO_x, SO_x, and CO_2, emissions, as well as output in the electric power generation sector in California, using emissions data from the continuous emissions monitoring system for power plants. He finds negative effects of increased regulatory stringency on all pollutants and output, identified by the county-level change in attainment status under the Clean Air Act. The effects for CO_2 and SO_x emissions become statistically insignificant when controlling for output. Splitting the sample into newer and older plants, he finds that the results are driven by older plants. He concludes that positive spillovers from increased NO_x regulation exist, but that these are primarily due to reductions in output at older power plants.

Brunel and Johnson (2019) analyze if increased regulatory stringency, also identified by the county-level change in attainment status under the Clean Air Act, in the non-energy sector affects CO_2 emissions using emissions data from the National Emissions Inventory for local air pollutants and from the Greenhouse Gas Reporting Program for CO_2 and other greenhouse gases. They match non-attainment counties (the treatment group) with attainment counties that are similar in all variables except attainment status (the control group) using propensity scores. They find that counties with stricter air-pollution regulation do not have lower greenhouse gas emissions. Controlling for output and industrial composition, they can rule out that their findings are explained by a decline in production.

In conclusion, while co-benefits from climate policies are modeled and simulated in several articles, little empirical evidence so far exists on the magnitude of co-pollutant elasticities at the level of industrial facilities, a crucial input for the assessment of air quality co-benefits. The empirical investigations in the US by Muller (2012) and Boyce and Pastor (2013) report co-pollutant ratios without estimating co-pollutant elasticities.[5] There have also been no empirical studies on co-pollutant ratios or elasticities in Europe. Further, in contrast to the simulation studies of air quality co-benefits, the empirical studies by Holland (2010) and Brunel and Johnson (2019) provide no clear evidence of spillovers of increased regulatory stringency of air pollution on greenhouse gas reductions. This could potentially suggest that the empirical support for air quality co-benefits might be weaker than modeled in simulation studies.[6] In these respects, the present study aims to fill important gaps in the literature on the relationship between local air pollutants and greenhouse gases.

3. Data

We obtain data from the European Pollutant Release and Transfer Register (E-PRTR) database, a facility-level registry that includes information on CO_2 emissions and the major co-emitted pollutants, SO_X, NO_X, and PM_{10}. In contrast to similar registries elsewhere (such as the US Toxics Release Inventory), the E-PRTR includes CO_2 as well as other pollutant emissions, providing a consistent dataset for facility-level analysis. It includes facilities in all European Union member states plus Iceland, Liechtenstein, Norway, Serbia, and Switzerland, and is available annually from 2007 to 2015. Facilities are required by law to report their emissions to the E-PRTR if they exceed capacity thresholds and pollutant thresholds. Firms whose emissions are above the threshold for some pollutants but not others only report the pollutants for which they exceed the threshold. Hence we have different sample sizes for the three co-pollutants (see Online Appendix A1 for summary statistics).

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[5] To illustrate this point, note that we estimate for a panel $\ln(copoll_{it}) = \beta \ln(CO2_{it}) + \alpha_i + \lambda_t + \varepsilon_{it}$ (see section 4), where β is identified through variations over time at the point source level. Muller (2012) and Boyce and Pastor (2013) calculate for a cross-sectional sample co-benefit ratios, i.e. $\ln(copoll_i) - \ln(CO2_i) = \exp(\gamma_i)$. Thus, the implicit "coefficient" of $\ln(CO2_i)$ is restricted to equal 1.

[6] Alternatively, it could indicate the importance of asymmetric spillover effects of environmental policies. Sigman (1996) shows that stricter ambient air quality standards for chlorinated solvents are associated with reductions in the overall releases of these toxics and therefore also with a reduction in toxic waste. Taxes on toxic waste generation by contrast are associated with an increase in toxic emissions, because rising costs of transferring emissions off-site for waste management makes it relatively cheaper to emit them into the air locally.

Table 1 shows the reporting thresholds for each pollutant and the share of aggregate emissions in the EU that is generated by the large industrial facilities included in the E-PRTR dataset. Firms reporting to E-PRTR release 42% of total European CO_2 emissions (including emissions from mobile sources), making them a highly relevant target for climate policies. They also account for 57% of total SO_X emissions, 24% of NO_X, and 6% of PM_{10}. Their relatively low share in PM_{10} emissions is partly due to releases from other sources, but may also reflect an excessively high reporting threshold (Amec Foster Wheeler Environment & Infrastructure 2015).

Table 1: Data coverage

	CO_2	SO_x	NO_x	PM_{10}
Reporting threshold	0.1	0.00015	0.00010	0.00005
Number of E-PRTR facilities in 2012	2277	856	1835	379
Average E-PRTR facilities emissions 2012	0.79811	0.00266	0.00113	0.00029
Total E-PRTR emissions 2012	1817.143	2.274	2.076	0.109
Aggregate total emissions 2012	4300.398	4.007	8.653	1.885
% Coverage of all emissions	42.3	56.8	24.0	5.8

Note: All variables, except the number of facilities, are reported in million tons. For CO_2, all facilities above the CO_2 reporting threshold were included; for co-pollutants, all facilities above both the CO_2 and the respective co-pollutant reporting threshold are included.
Sources: EEA 2014a, European Union 2006, E-PRTR; authors' calculations.

Table 2 presents co-pollutant intensity ratios, i.e. average ratios of co-pollutant to CO_2 emissions based on the E-PRTR data and compares these to the ratios reported in the US studies by Muller (2012) and Boyce and Pastor (2013). The ratios in Europe appear to be similar to those in the US. In Appendix Table A2 we report the same ratios disaggregated by NACE activities (the statistical classification of economic activities in the European Community). Again, similar to Muller (2012) and Boyce and Pastor (2013), we find considerable variation across activities.

Turning to the time-series dimension of our data, a trend decline in aggregate emissions can be observed from 2007 to 2015 for CO_2 and the three co-pollutants, both economy-wide and in the subset of facilities in the energy sector (see Appendix Figures A1 and A2). There was a particularly sharp decline in industrial emissions between 2007 and 2009, likely caused in part by output declines in the Great Recession, a pattern that is not limited to industrial facilities

(EEA 2016). Emissions of co-pollutants declined more rapidly than those of CO_2, probably reflecting the use of new technologies in combustion (e.g. low NO_X burners), improved flue-gas abatement technologies, EU directives on the sulfur content of fuels, and other new regulations (EEA 2014b, EEA 2014c, EEA 2014d).[7] In the energy sector, fuel switching from coal to natural gas also contributed to the declines. As a result, co-pollutant intensity ratios – emissions of SO_X, NO_X and particulate matter per ton of CO_2 – declined over the period (see Figure A3).

Table 2: Average ratios of co-pollutant emissions to CO_2 emissions

	US data		European data
	Boyce and Pastor (2013)	Muller (2012)	(authors' calculations)
SO_X	0.0025	0.0037	0.0027
NO_X	0.0018	0.0014	0.0018
PM	0.0003	0.0001	0.0003

Note: Ratios are calculated as averages of individual facility-level ratios. For Boyce and Pastor (2013) the results of the average across industries (Table 1) were converted to tons. For Muller (2012) we report an unweighted average of six different facility types in the electric power generation sector. Both studies use SO_2 instead of SO_X and $PM_{2.5}$ instead of PM_{10}, which would be preferable but is not available in the E-PRTR.

These co-pollutant intensity ratios provide crucial but insufficient information to integrate air quality co-benefits into carbon mitigation policy, since they do not quantify how changes in CO_2 affect co-pollutants. Co-pollutant elasticities above or below unity are possible, and they may vary across pollution sources.

4. Identification strategies

To identify the effects of variations in CO_2 release on co-pollutants, we first estimate two-way fixed effects specifications, and subsequently comprehensively test the robustness of the results by including additional fixed effects, specifying different data-generating processes, accounting for unobserved factors potentially leading to endogeneity, and conducting an event-study analysis to assess the relevance of pre-existing trends. In the second step of our analysis, we

[7] The EU National Emission Ceilings Directive (NECD 2001/81/EC) and the Gothenburg protocol set national caps of SO_X and NO_X emissions. The first caps were set for 2010 and largely were met. Additionally, emissions of all three co-pollutants by large combustion plants (above 50MWh, including fossil-fuel power stations and other large thermal plants such as petroleum refineries) are regulated through caps and technology requirements, mainly for

examine heterogeneity in elasticities across economic activities, size of the polluting source, regional population densities, and over time, to inform the design of future carbon mitigation policies that incorporate co-benefits. In the final step, we limit the variation in CO_2 emissions to identify co-pollutant elasticities to climate policy-induced changes by applying an instrumental variables approach.

We begin by estimating a two-way fixed effects (FE) model, in each case for the maximum sample available:

$$\ln(copoll_{it}) = \beta \ln(CO2_{it}) + \alpha_i + \delta_t + \epsilon_{it} \tag{1}$$

where $copoll_{it}$ is emissions of the co-pollutant, i.e. SO_X, NO_X, or PM_{10}, at facility i and year t, and $CO2_{it}$ is the corresponding carbon dioxide emissions. We purge facility fixed effects (α_i) to capture unobserved heterogeneity between point sources and common time effects (δ_t). This specification is a generalized form of a difference-in-difference set-up with continuous treatment. The variables are expressed in natural logarithms (ln), so the coefficients can be interpreted as elasticities, showing the effect of a 1% change in CO_2 on the percent change in the respective co-pollutant. To account for within-group serial correlation and heteroscedasticity, we cluster standard errors at the facility level (Cameron and Miller 2015).[8]

We then move from this canonical model to more saturated ones. We allow the time effects to vary by industry in each country, i.e. estimate specifications with NACE-by-country-by-year fixed effects (θ_{nct}). This model allows flexibly controlling for industry specific shocks at the country level or effects of national environmental policies on specific industries, and will serve as the baseline specification for additional robustness checks. Specifically, we additionally include facility-specific time trends as regressors ($\eta_i t$) to capture heterogeneity between facilities. Second, we estimate a version of this model with facility fixed effects purged through first differencing, to guard against potential bias due to unit roots, which can be substantial, especially in small panels. Third, we assess the relevance of additional unobserved confounders.

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newly built plants. Special regulations for large combustion plants have been revised and strengthened multiple times since they were introduced in the 1980s (EEA 2017).

[8] To reduce the influence of outliers in our analysis that could be a result of reporting errors, we censor CO_2 and the co-pollutants at the respective 99th percentiles. This, however, has no relevant effect on our results.

For example, time-varying environmental preferences of facility owners might be correlated with CO_2. Specifically, if the error term of our specification is $\epsilon_{it} = \lambda_i^{'} F_t + u_{it}$, where $\lambda_i^{'} F_t$ are unobserved time-varying confounders that are correlated with CO_2, and u_{it} is an idiosyncratic error term, then the estimates would yield biased results. To account for this possibility, we apply the interactive fixed effects (IFE) method of Bai (2009), which uses principal components analysis to unravel patterns in the error term causing endogeneity, and decomposes them into common factors (F_t) and individual factor loadings (λ_i). The IFE model can be solved by iteration when the number of factors is specified.[9]

To confirm that our estimates are not driven by pre-existing trends, we apply an event-study approach (e.g. Dube et al. 2010) and estimate distributed lag versions of the baseline models with facility and NACE-by-country-by-year fixed effects, adding two leads and two lags of CO_2 emissions:

$$\ln(copoll_{it}) = \sum_{r=-2}^{5} \beta_r \ln(CO2_{it}) + \alpha_i + \theta_{nct} + \epsilon_{it} \qquad (2)$$

The leading (t+1 and t+2) and lagged effects (t-1 and t-2) can be interpreted as falsification tests, since we expect CO_2 and co-pollutants to be combusted simultaneously in t=0.

Finally, we identify co-pollutant elasticities for CO_2 reductions specifically induced by climate policy. Our identification is based on the OECD's environmental policy stringency index (Botta and Koźluk 2014). This index transforms quantitative and qualitative policy instruments for several subcategories into measures on a scale of 0 to 6 that are comparable across countries and over time. It focuses almost exclusively on the energy sector and is available at the country level for the years 1990 to 2012 (to 2015 for a few countries). We use subcategories of this index that target CO_2 emissions and are typically classified as climate policies to estimate a two-stage least squares (2SLS) version of equation 1 for the electricity sector, where CO_2 is instrumented by these climate policies. Thus, the identifying variation in CO_2 is based on exogenous policy changes that were implemented for other reasons than the reduction of co-pollutants. To be valid instruments, the climate policy indicators must be able to predict CO_2. Thus, in the first

[9] To determine the number of factors we follow Totty (2015) and use the cross-sectional dependence test suggested by Pesaran (2015) on the residuals of a model, and allow for additional factors until the null hypothesis of weak

step we establish that an increase in climate policies stringency in the energy sector is able to predict CO_2 emissions in the energy sector. Since the period under investigation includes the Great Recession, and because climate policies might be correlated with policies regulating co-pollutants, we test if the instrumental variable results are driven by these confounders in robustness specifications. Thus, we control for the logarithm of real national GDP, and the stringency of the respective co-pollutant policies in the energy sector (also from Botta and Koźluk 2014). Since policy-variation occurs at the national level, standard errors are clustered at the country-level in all 2SLS specifications.

5. Results

5.1 Co-pollutant elasticities for all CO_2 variations

Table 3 presents the results for the three co-pollutants, SO_X, NO_X, and PM_{10}. In the first specification (column 1) with facility and time fixed effects, the panels consist of 727 to 2,653 point sources, depending on the co-pollutant, for the time period 2007 to 2015, yielding sample sizes from 3,574 to 16,493 observations. The estimated elasticities are 0.75 for SO_X, 0.74 for NO_X, and 0.50 for PM_{10}, all highly statistically significant (for summary statistics, see Appendix Table A1).[10] Reassuringly, the inclusion of NACE-by-country-by-year fixed effects (column 2) gives results nearly identical to those of the two-way fixed effects models. The estimates of column 2 will serve as baseline results for further robustness checks.

First, we include facility-specific time trends in addition to NACE-by-country-by-time fixed effects in column 3. This has very little effect on the estimated elasticities and their significance levels compared to the baseline results in column 2. Second, we purge fixed effects trough first differencing (column 4), which again yields very similar results as in column 2.

cross-sectional dependence is accepted.

[10] We also estimated the relationship by OLS. For SO_X, NO_X, and PM_{10} we obtain a co-pollutant elasticity of respectively 0.64 (SE 0.02), 0.74 (SE 0.01), and 0.35 (SE 0.03). These estimates are quite similar to the baseline FE results. However, OLS estimates are biased if unobserved heterogeneity between firms is correlated with the explaining variables.

Table 3: Effect of a log-point increase in CO_2 on log co-pollutants

	Facility and time FE	Facility and NACE-by-country-by-time FE						
		Baseline	With facility-specific time trends	Facility FE purged by 1st differencing	Balanced sample	Bai's (2009) interactive FE	Facilities in all sub-samples	Precise measure-ment sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Dependent variable: $\ln(SO_X)$							
$\ln(CO_2)$	0.752***	0.727***	0.699***	0.679***	0.697***	0.713***	0.740***	0.770***
	(0.049)	(0.049)	(0.063)	(0.057)	(0.075)	(0.135)	(0.078)	(0.153)
Observations	7.820	7.820	7.820	6,248	4,320	4,320	2,890	679
No. of facilities	1.313	1.313	1.313	1.313	540	540	582	238
R^2	0.328	0.572	0.769	0.476	0.565		0.601	0.779
	Panel B: Dependent variable: $\ln(NO_X)$							
$\ln(CO_2)$	0.743***	0.730***	0.736***	0.715***	0.720***	0.690***	0.813***	0.833***
	(0.025)	(0.027)	(0.030)	(0.029)	(0.040)	(0.075)	(0.052)	(0.077)
Observations	16,493	16,493	16,493	13,343	9,088	9,088	2,890	1,905
No. of facilities	2,653	2,653	2,653	2,653	1,136	1,136	582	560
R^2	0.462	0.617	0.788	0.516	0.625		0.687	0.594
	Panel C: Dependent variable: $\ln(PM_{10})$							
$\ln(CO_2)$	0.499***	0.501***	0.497***	0.482***	0.581***	0.530**	0.557***	1.269***
	(0.056)	(0.068)	(0.079)	(0.073)	(0.117)	(0.256)	(0.074)	(0.126)
Observations	3,574	3,574	3,574	2,647	1,472	1,472	2,890	224
No. of facilities	727	727	727	727	184	184	582	74
R^2	0.248	0.567	0.778	0.497	0.604		0.571	0.928

Notes: All specifications include facility and time or NACE-by-country-by-time fixed effects. Standard errors in parentheses are clustered at the facility-level, or bootstrapped in the case of the dynamic auto-regressive models. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: E-PRTR, authors' calculations.

Third, we drop all facilities that are not in the sample over the whole period (column 5), first because this is an interesting robustness exercise by itself, and second because Bai's (2009) interactive fixed effects approach (see column 6) requires sufficiently long time periods and we want to assess how the results with factors change compared to the models without factors. This halves the sample sizes, but has little effect on the estimated elasticities. We then apply the interactive fixed effects estimator on the balanced panel, to investigate the effect of missing common factors that can be thought of as omitted variables. Comparing the IFE model with four factors (column 6) with the model for the balanced panel (column 5) yields very similar results, suggesting that unobserved factors are of little importance.[11]

Fifth, we limit the sample to observations of facilities that report emissions of all three co-pollutants (column 7). The results again are similar to those with the full sample. This finding becomes relevant when calculating co-benefits from co-pollutant elasticities in section 6.

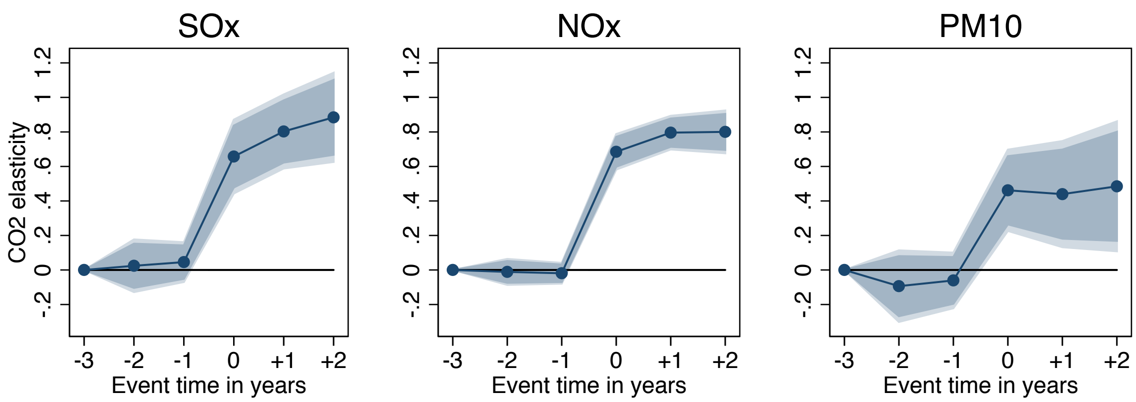
For some facilities pollutant emissions in the E-PRTR dataset are derived from direct monitoring of releases at the facility level, using internationally approved and standardized methodologies, and therefore are measured with a high degree of precision. Others are derived by applying emissions factors to other measured variables of the facility, such as fuel use or output, or by expert estimates for which detailed methodologies are not publicly available. To assess the consequences of possible reporting errors, we limit the sample to facilities where CO_2 and the respective co-pollutant are measured directly (column 8). This substantially reduces the sample sizes. The estimated co-pollutant elasticities for SO_X and NO_X are modestly larger than for the full sample. For PM_{10} the elasticity more than doubles, however, this result is based only on 220 observations and 74 facilities, and might better be interpreted cautiously.[12]

[11] Already the specification with zero factors included allows to accept the null hypothesis of weak cross-sectional dependence for all co-pollutant specifications according to the test by Pesaran (2015). Allowing for two, three, or four factors has very little effect on the point-estimates. This is reassuring since Moon and Weidner (2015) show that the regression parameters of the IFE model tend to stabilize if the correct number of factors is included and that it still performs well if more factors are allowed.

[12] While the results for the SO_X and NO_X samples are robust to different specifications, for PM_{10} they are not. For example, if we include simple year effects instead of NACE-by-country-by-year fixed effects, the estimated elasticity drops to 0.41 (SE 0.14).

The results of the event-study (see equation 2) are presented in Figure 1. The figure shows the cumulative time path of an increase in CO_2 on the co-pollutants for the full samples. We find the leading effects to be close to zero, confirming that our estimates are not driven by pre-existing trends. In the year that CO_2 is emitted (t=0), all three co-pollutant elasticities increase significantly, while additional impacts from lagged effects are small. The timing suggests a causal effect, with the magnitude of the estimated elasticities at t=0 being similar to the estimates reported in Table 3.

Figure 1: Cumulative response over time of a log CO2 increase on log co-pollutants



Notes: The figure shows the cumulative sum of the CO_2 coefficients form a distributed lag model beginning with the 2 year lead (see section 4, equation 2). All specifications include facility and NACE-by-country-by-time fixed effects. Standard errors are clustered at the facility-level. The dark shaded area represents 90%, the light shaded area 95% confidence intervals. The sample size is 3,603 observations for SO_X, 7,317 for NO_X, and 1,675 for PM_{10}. Source: E-PRTR, authors' calculations.

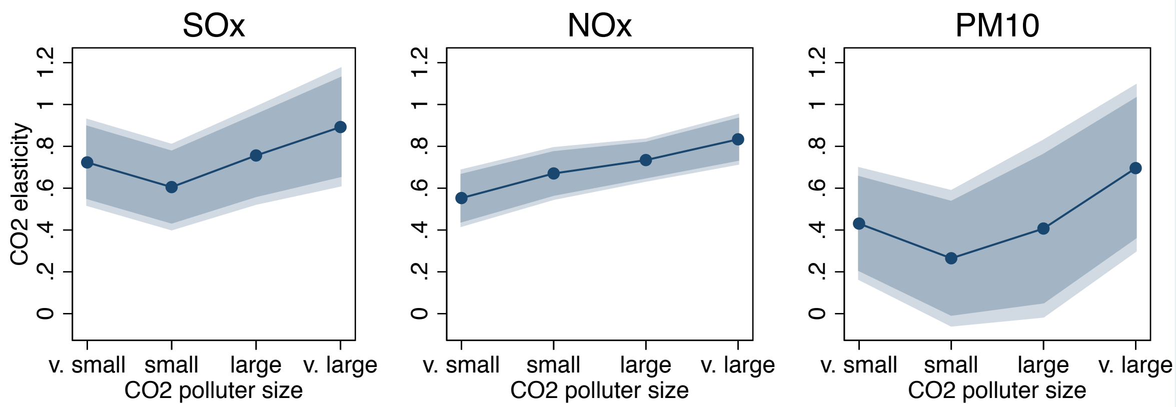
Overall, the results are highly robust to different specifications, estimation approaches, and samples. The estimates indicate that a 1% change in CO_2 emissions at the facility-level is associated with roughly a 0.7% change in the same direction in emissions of SO_X and NO_X, and with a 0.5% change in emissions of PM_{10}.

5.2 Heterogeneity in co-pollutant elasticities

We next assess whether and how co-pollutant elasticities vary by the size of polluters, economic sectors, population density of the region of location of the facility, and over time.

First, we estimate specifications that allow the co-pollutant elasticities to vary by four size classes of CO_2 emitters – very small, small, large, and very large – each capturing one-fourth of the respective sample observations. The results are presented in Figure 2. For all three co-pollutants, we find the highest co-pollutant elasticities in the very large CO_2 emitter quartile. This suggests that from the perspective of regulators, focusing on very large CO_2 polluters might yield the most air quality co-benefit returns.

Figure 2: Effect of a log-point increase in CO_2 on log co-pollutants for different CO_2 polluter sizes



Notes: We sort facilities according to CO_2 emitted, and then assign each facility to one of the following four groups, very small, small, large, or very large CO_2 polluter size, such that each group captures one-fourth of the respective sample observations. All specifications include facility and NACE-by-county-by-time fixed effects, a dummy for very small, small, large, and very large CO_2 polluters, and an interaction between these dummies and ln(CO_2). Standard errors are clustered at the facility-level. The dark shaded area represents 90%, the light shaded area 95% confidence intervals. The sample size is 7,820 observations for SO_X, 16,493 for NO_X, and 3,574 for PM_{10}.
Source: E-PRTR, authors' calculations.

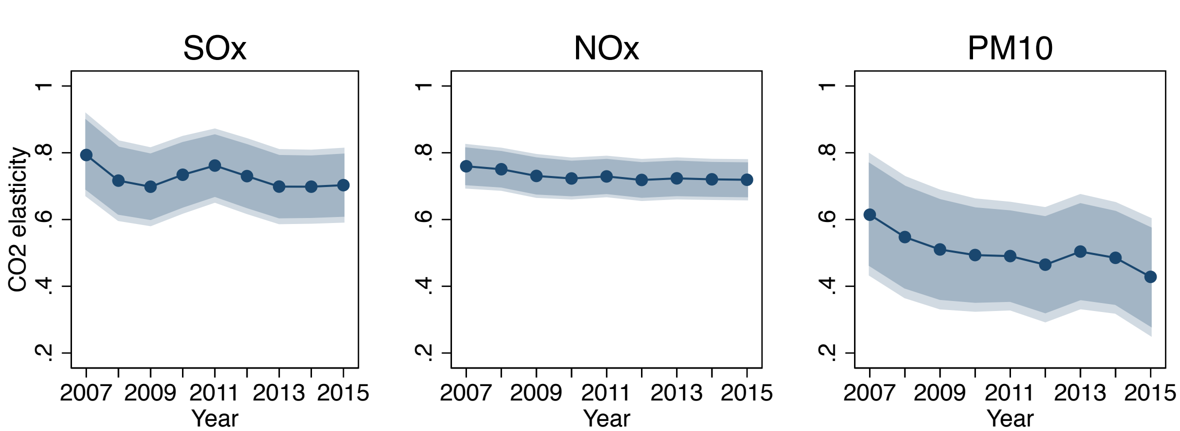
Next, we estimate elasticities by economic activity. Table 4 presents the results for the NACE activities with a sufficiently large number of observations.[13] We find substantial variations across activities, with relatively high elasticities in electricity production for all samples: approximately 0.9 for SO_X, 0.8 for NO_X, and 0.7 for PM_{10}. The production of electricity is the most important activity with respect to total CO_2 emissions (see last line of panel), and also has very high CO_2 emissions by facility for each pollutant. Thus, one reason for the results in Figure 2 is that energy-producing facilities are among the largest CO_2 emitters, and also have relatively

[13] We show results for sectors with at least 300 observations.

high co-pollutant elasticities. For the NO_X sample, also the extraction of crude petroleum and manufacture of other organic basic chemicals have above-average elasticities.

To assess heterogeneity over time, we estimate specifications that include interaction terms between year-dummies and CO_2. The results, graphically presented in Figure 3, show modest trend decreases in all three elasticities over the period 2007 to 2015.[14]

Figure 3: Effect of a log-point increase in CO_2 on log co-pollutants over time



Notes: Results from a specification including facility and NACE-by-country-by-time fixed effects, and interaction terms between year dummies and $\ln(CO_2)$. Standard errors are clustered at the facility-level. The dark shaded area represents 90%, the light shaded area 95% confidence intervals. The sample size is 7,820 observations for SO_X, 16,493 for NO_X, and 3,574 for PM_{10}.
Source: E-PRTR, authors' calculations.

If co-pollutant elasticities vary with regional population density, this would have implications on the number of people affected by health co-benefits.[15] To assess this possibility, we include dummy variables for quartiles of NUTS 2 areas ranked by population density, and interaction terms between these and CO_2. The results are presented in Figure 4. For SO_X and NO_X we find rather little differences across regions. For PM_{10} a sawtooth pattern emerges, with somewhat higher elasticities in regions with very low and high population density compared to regions with low and very high population density.

[14] In contrast, co-pollutant intensity ratios declined substantially over the period (see Appendix Figure A.3).
[15] Regional population density data at the NUTS 2 (Nomenclature of Territorial Units for Statistics) level were obtained for the year 2014 from EUROSTAT's regional database, as a ratio of total population divided by land area. The EU is divided into 276 NUTS 2 regions; in all three co-pollutant samples, a large majority of regions has at least one E-PRTR facility.

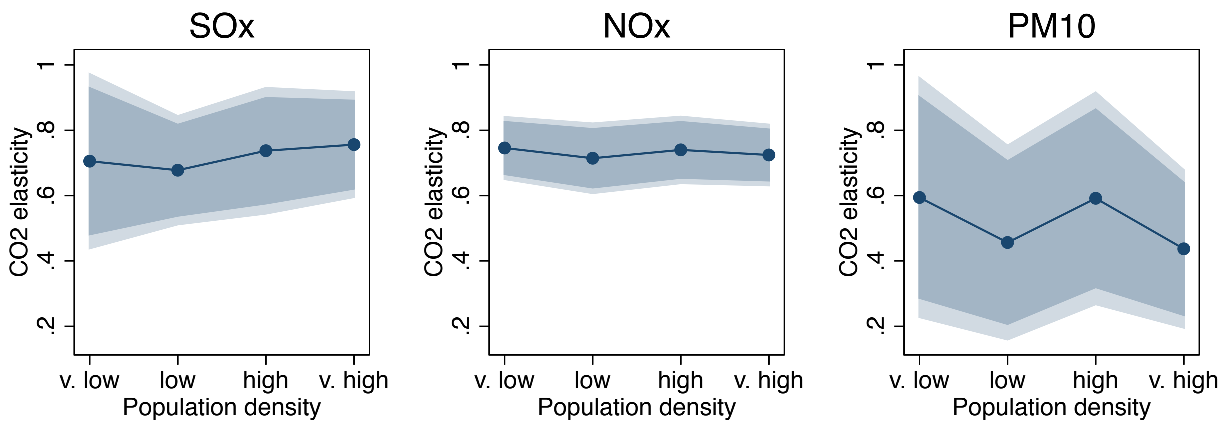
Table 4: Effect of a log-point increase in CO_2 on log co-pollutants for different NACE activities

	Extraction of crude petroleum	Manufacture of basic iron and steel and of ferro-alloys	Manufacture of cement	Manufacture of other inorganic basic chemicals	Manufacture of other organic basic chemicals	Manufacture of paper and paperboard	Manufacture of pulp	Manufacture of refined petroleum products	Production of electricity	Steam and air conditioning supply	Treatment and disposal of non-hazardous waste
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Dependent variable: $\ln(SO_x)$											
$\ln(CO_2)$		0.579***	0.330*					0.437***	0.868***	0.626***	
		(0.179)	(0.173)					(0.121)	(0.059)	(0.113)	
Observations		461	653					835	2,696	930	
No. of facilities		78	132					115	425	159	
R^2		0.555	0.436					0.667	0.539	0.486	
CO_2 (m t in 2012)		122.342	40.935					125.447	687.416	58.975	
Panel B: Dependent variable: $\ln(NO_x)$											
$\ln(CO_2)$	0.881***	0.507***	0.649***	0.631***	0.986***	0.451***	0.563***	0.665***	0.811***	0.711***	0.095
	(0.101)	(0.109)	(0.072)	(0.214)	(0.080)	(0.107)	(0.157)	(0.091)	(0.037)	(0.082)	(0.059)
Observations	722	674	2,022	315	555	793	302	884	5,126	1,434	824
No. of facilities	108	113	271	54	97	123	44	121	855	250	203
R^2	0.312	0.418	0.638	0.544	0.656	0.427	0.622	0.679	0.656	0.517	0.283
CO_2 (m t in 2012)	19.055	126.871	110.564	13.747	57.964	46.586	30.987	127.778	820.737	78.234	98.359
Panel C: Dependent variable: $\ln(PM_{10})$											
$\ln(CO_2)$		0.305***						0.101	0.658***		
		(0.114)						(0.168)	(0.086)		
Observations		338						301	1,354		
No. of facilities		61						59	268		
R^2		0.765						0.629	0.468		
CO_2 (m t in 2012)		93.244						57.935	450.104		

Notes: All specifications include facility and country-by-time fixed effects. Standard errors in parentheses are clustered at the facility-level. *** p<0.01, ** p<0.05, * p<0.1

Source: E-PRTR, authors' calculations.

Figure 4: Effect of a log-point increase in CO_2 on log co-pollutants by regional population density



Notes: We sort facilities according to population density in their region, and then assign each facility to one of the following four groups, very low, low, high, or very high population density, such that each group captures one-fourth of the respective sample observations. All specifications include facility and NACE-by-country-by-time fixed effects, a dummy for quartiles ranked by regional population density, and an interaction between these dummies and $\ln(CO_2)$. Standard errors are clustered at the facility-level. The dark shaded area represents 90%, the light shaded area 95% confidence intervals. The sample size is 7,820 observations for SO_X, 16,493 for NO_X, and 3,574 for PM_{10}.
Source: E-PRTR, authors' calculations.

In sum, we find some heterogeneity by CO_2 emitter size, that seems, however, be driven by the sectoral composition of the emitter size classes. We find strong heterogeneity by economic activity, where especially electricity production stands out with above average co-pollution elasticities for all three co-pollutants. Finally, we find rather little variation over time and by regional population density.

5.3 Co-pollutant elasticities in electricity production for CO_2 variations induced by climate policy

In this section we limit the variation in CO_2 emissions to those induced by changes in climate policy, in order to evaluate reductions in co-pollutants directly attributable to greenhouse-gas policies. We estimate two-stage least squares (2SLS) versions of equation 1, where CO_2 is instrumented with changes in environmental policy stringency that target CO_2 emissions. We use the following subcategories of the OECD Environmental Policy Stringency Index, that are typically classified as climate policies[16]: i.) trading schemes for CO_2, ii.) trading schemes for renewable energy, iii.) trading schemes for energy efficiency, iv.) taxes on CO_2, v.) feed-in tariffs for solar, and vi.) feed-in tariffs for wind.

To assess if these climate policies are suitable instruments, in the first step we assess if they predict CO_2 emissions. Since the OECD Environmental Policy Stringency Index focuses heavily on the energy sector, we present the results for the electric power sector only and for the remaining sectors. The results are shown in Table 5. The first specification (column 1) explains CO_2 emissions in electricity production with climate policies, purging facility and year fixed effects. Taxes on CO_2 are dropped from the specification due to a lack of variation, since most observations in our sample have a value of 0. Of the remaining five polices, all show a negative effect on CO_2 emissions. An F-test on their joint significance allows us to reject the null hypothesis that all coefficients are zero. Thus, climate policy stringency is found to significantly reduce CO_2 emissions in the average facility. The period under investigation includes the financial crisis of 2008/09, which had strong and persistent effects on economic output. To disentangle the effects of CO_2 emission reductions due to production declines in response to the Great Recession and reductions due to climate policies, we include the logarithm of real national GDP as confounder in column 2.[17] This specification leads to somewhat more precise estimates of the climate policy variables. CO_2 trading schemes and wind feed-in tariffs have statistically significant negative effects on CO_2 emissions. The F-test again confirms the joint significance of the policies.

Since these climate policies indicators were constructed to capture policies in the energy sector, it would add to the credibility of the instruments if they are unable to predict CO_2 in other sectors. The results in column 2 present results for similar specifications for the non-electricity sectors. Climate policies are found to be jointly insignificant. In what follows we therefore limit our investigation to electricity producing facilities.

[16] See e.g. here https://www.eea.europa.eu/themes/climate/policy-context or here: https://climatepolicyinfohub.eu/interactions-between-climate-policies-examples-europe [last accessed: 2019-05-05].
[17] Real GDP is from the annual macro-economic database of the European Commission (AMECO).

Table 5: Effect of climate policy stringency on log CO_2 for electricity production and other sectors

	Electricity production		Other sectors	
		with ln(real GDP)		with ln(real GDP)
	(1)	(2)	(3)	(4)
Green certificates trading schemes	-0.004	-0.026	0.020**	0.003
	(0.019)	(0.016)	(0.009)	(0.006)
CO_2 trading schemes	-0.030	-0.042**	0.002	-0.002
	(0.023)	(0.019)	(0.007)	(0.004)
White certificates trading schemes	-0.018	-0.016	-0.013	-0.006
	(0.024)	(0.021)	(0.010)	(0.005)
Wind feed-in tariffs	-0.017	-0.017*	-0.008	-0.001
	(0.010)	(0.009)	(0.005)	(0.003)
Solar feed-in tariffs	-0.007	0.001	-0.012	-0.012*
	(0.010)	(0.009)	(0.008)	(0.006)
F-test on joint sign. (p-value)	0.076	0.011	0.646	0.134
Observations	4,568	4,568	11,413	11,413
No. of facilities	840	840	2,111	2,111
R^2	0.146	0.151	0.057	0.078

Notes: Column 1 includes facility and time fixed effects, column 2 includes facility, time, and NACE fixed effects. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1
Source: E-PRTR, Botta and Koźluk (2014), AMECO, authors' calculations.

The results of the two-stage least squares estimation strategy for the energy sector, identifying co-pollution elasticities with exogenous climate policy changes, are presented in Table 6. For comparison, the first column shows results of the OLS model with facility and time fixed effects for the same samples. Column 2 shows results of the 2SLS regressions, including facility and time dummies, and instrumenting CO_2 with climate policies. Since policies vary at the national-level, standard errors are clustered at the country-level in the 2SLS specifications, which increases their size compared to clustering at the facility-level in column 1. The estimated co-pollutant elasticities for SO_x and NO_x are highly statistically significant, and substantially larger than the OLS estimates in column 1. The elasticity for PM_{10} is somewhat larger in size than the OLS estimate, but not precisely estimated.

To assess whether we are erroneously attributing effects on emissions of the Great Recession to stricter environmental policy, we control for real national GDP (in logarithms) in column 3.

This increases the precision of the estimates, and reduces the estimated elasticity for SO_x, but has little effect on the magnitude of the other results.

Following the approach of Belloni et al. (2014), there is little *a priori* reason to assume that these policies should enter as contemporaneous, independent, and linear variables. Since there might be complementarities between the policies, non-linarities, or lagged effects, a list of interactions, squared and cubic terms, and lags of the policy variables are also available as suitable instruments. This approach allows us to improve the first-stage estimates,[18] and to assess the sensitivity of the results. We allow for non-linear effects by adding bi- and trivariate interactions of all instruments and further include up to five-year lags of all indicators. To choose relevant instruments with true predictive power from this list, we apply the Least Absolute Shrinkage and Selection Operator (LASSO) (see Belloni et al. 2014).[19]

These LASSO-2SLS results are presented in column 4. Even though they are identified with different sets of instruments, they are quantitatively rather similar to the 2SLS results of column 3, with elasticities of 1.4 for SO_x, 1.1 for NO_x, and 0.9 for PM_{10}, but noticeably more precisely estimated, especially in the case of PM_{10}.[20]

[18] An F-test on the excluded instruments confirms strong first-stage results in all specifications. However, the testing procedure by Olea and Pflueger (2013), which is suitable for serially correlated and clustered errors, suggests otherwise. We obtain effective F-statistics and critical values that do not allow rejection of the null-hypothesis of weak instruments for any of the three co-pollutants in columns 2 and 3 (see last line of panel).

[19] LASSO is a machine-learning algorithm that chooses predictors to minimize the sum of the squared residuals plus a term that penalizes the size of the model to avoid overfitting. The latter term guards against overfitting and ensures feasibility of estimation by returning a small set of relevant instruments. We set lamda, the parameter that penalizes the size of the model, such that it returns a sparse list of picked instruments that perform well in the weak instruments test of Olea and Pflueger (2013). The picked instruments are: the second lag of cubic CO_2 trading schemes, and the fifth lag of white certificate trading schemes for the SO_x-sample; the first lag of quadratic green certificate trading schemes interacted with solar feed-in-tariffs, the fifth lag of white certificate trading schemes, and the first lag of wind feed-in-tariffs for the NO_x-sample; the fifth lag of CO_2 trading schemes, the fifth lag of CO_2 trading schemes interacted with wind feed-in-tariffs, the third lag of CO_2 trading schemes interacted with wind feed-in-tariffs, the fifth lag of white certificate trading schemes, the third lag of cubic white certificate trading schemes, and the first lag of squared solar feed-in-tariffs interacted with white certificate trading schemes for the PM_{10}-sample. The first-stage results are presented in Appendix Table A3.

[20] Applying the Olea-Pflueger test, we can confidently reject the null-hypothesis of weak instruments in the first-stage results for SO_x and NO_x, but not PM_{10}.

Table 6: Effect of a log-point increase in CO_2 instrumented by climate policy stringency on log co-pollutants for electricity production

	OLS	2SLS	2SLS with real GDP	LASSO-2SLS with real GDP	LASSO-2SLS with real GDP and co-pollutant policies	LASSO-2SLS with real GDP and co-pollutant policies (cubic)	LASSO-2SLS with real GDP and co-pollutant policies (cubic and lagged)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A: Dependent variable: $\ln(SO_x)$				
$\ln(CO_2)$	0.912***	1.803***	1.499***	1.424***	1.552***	1.455***	1.173***
	(0.068)	(0.379)	(0.265)	(0.206)	(0.243)	(0.184)	(0.096)
Observations	1,996	1,996	1,996	1,859	1,859	1,859	1,807
No. of facilities	338	338	338	313	313	313	301
R^2	0.491	0.212	0.382	0.428	0.381	0.381	0.515
Weak IV F-stat. > crit. value (10%)		no	no	yes	yes	yes	yes
			Panel B: Dependent variable: $\ln(NO_x)$				
$\ln(CO_2)$	0.837***	1.453***	1.387***	1.102***	1.071***	1.070***	0.969***
	(0.043)	(0.292)	(0.250)	(0.201)	(0.178)	(0.180)	(0.064)
Observations	3,947	3,947	3,947	3,461	3,461	3,461	3,369
No. of facilities	704	704	704	595	595	595	580
R^2	0.627	0.386	0.438	0.599	0.611	0.612	0.647
Weak IV F-stat. > crit. value (10%)		no	no	yes	yes	yes	yes
			Panel C: Dependent variable: $\ln(PM_{10})$				
$\ln(CO_2)$	0.677***	0.817	0.834	0.903**	0.888**	0.883**	0.886**
	(0.086)	(0.804)	(0.764)	(0.403)	(0.424)	(0.402)	(0.359)
Observations	952	952	952	893	893	893	878
No. of facilities	199	199	199	185	185	185	180
R^2	0.359	0.353	0.355	0.350	0.353	0.353	0.351
Weak IV F-stat. > crit. value (10%)		no	no	no	no	yes	yes

Notes: All specifications include facility and time fixed effects. Standard errors in parentheses are clustered at the facility-level (OLS) or country-level (2SLS). *** p<0.01, ** p<0.05, * p<0.1
Source: E-PRTR, Botta and Koźluk (2014), AMECO, authors' calculations.

Although air quality co-benefits so far have not been included in EU climate policy design, it is possible that industrial facility operators' responses to new climate policies took air quality co-benefits into account. For example, the implementation of the European emissions trading scheme (ETS) for carbon emissions overlapped partially with the introduction of emission limits on co-pollutants. By switching to non-carbon energy sources, facility operators could reduce emissions of CO_2 and co-pollutants simultaneously. To investigate whether policy stringency for co-pollutant emissions might be a relevant omitted variable, we re-estimate the LASSO specifications, adding controls for the stringency of taxes and emission limits for the respective co-pollutant. This information is also provided by the Botta and Koźluk (2014) dataset. We present three different versions. In column 5, we include linear and contemporaneous values of these regulatory confounders. The results are similar to those in column 4. In column 6, we also include squared and cubic terms. The results are again similar to those in column 4. Finally, in column 7 we additionally allow for up to five lags of the co-pollutant policies. The estimated co-pollutant elasticities for SO_x are modestly smaller compared to the results in column 4, 5, and 6, while they are very similar for NO_x and PM_{10}. We obtain elasticities of 1.2, 1.0, and 0.9 for SO_x, NO_x, and PM_{10}, respectively.[21]

Comparing the 2SLS co-pollution elasticities in column 7, based on variations in CO_2 due to climate policy, to the OLS elasticities in column 1, based on all CO_2 variations, it appears that climate policy-induced CO_2 reductions have somewhat larger co-pollutant elasticities for all three pollutants. This suggests that climate policies may have had their largest effects on technologically outdated plants and processes with high co-pollutant emissions. For example, climate policies like the EU ETS, promoting renewable energy sources, or wind and solar feed-in tariffs might induce fuel switching from coal to natural gas, wind, or solar. McGuiness and Ellerman (2008) show for power plants in the UK that the first phase of the EU ETS led to an increase in natural gas utilization by about 22 percent while coal utilization decreased by 17 percent. Similarly, the results for electric power firms in 10 European countries of Chan et al. (2013) suggest that the EU ETS led to fuel switching from coal to natural gas.

[21] The instruments pass the weak instruments test for all co-pollutant samples in columns 6 and 7.

6. Monetizing air quality co-benefits

To compute monetary estimates of human health benefits from reduced co-pollutant emissions per ton of CO_2 emission, we use a low and a high measure of the average damage costs per ton of industrial point-source emissions in the EU for the year 2012 for SO_X, NO_X, and PM_{10} (in 2005 EUR). These measures were estimated by the EEA (2014a) using the E-PRTR dataset, based on a pathway-impact model of exposure and health damages, monetized by means of the official value of statistical life (VSL) or value of a statistical life year (VSLY), with the VSL approach generally yielding the higher valuations.

To obtain the marginal air quality co-benefits from a ton of CO_2 reduction, we multiply the baseline co-benefit elasticities (Table 3) by average co-pollutant intensity ratios (Table 2) and by damage costs (EEA 2014a). The monetized co-benefits, shown in Table 6, amount to 19 to 57 EUR/tCO_2 for SO_X, 6 to 15 EUR/tCO_2 for NO_X, and 4 to 11 EUR/tCO_2 for PM_{10} (in 2005 EUR). The joint magnitude of these benefits is 29 to 82 EUR/tCO_2, a result consistent with magnitudes suggested by previous studies. Taking the average of the results for European countries reported by Nemet et al. (2010, Table A.1) and converting them into 2005 EUR yields overall co-benefits of about 50 EUR/tCO2 for all sectors. For facilities in electricity production, the joint co-benefits range from 33 to 95 EUR/tCO_2 for all CO_2 emissions, and from 36 to 104 EUR/tCO_2 for climate policy-induced changes in CO_2 emissions.[22]

For comparison, the EEA (2014a) estimates the climate damage costs from CO_2 emissions to range from 10 to 38 EUR/tCO_2 (again in 2005 EUR).[23] The monetized co-benefits therefore amount to 80 to 820% of CO_2 climate damage costs for the full sample, 90 to 950% of CO_2

[22] Since spatially disaggregated exposure data for industrial point-source releases are not available, the calculations in Table 6 do not consider the number of people exposed. However, since it is likely that on average the number of people exposed is higher in more densely populated areas, and since population density is significantly higher – by 21-25% for the different co-pollutant samples – in regions where electricity producers are located compared to the location of other industrial facilities, monetized co-benefits for the electricity producing sector might be understated. For the calculation of policy-induced co-benefits we use the lowest IV-estimate in Table 6. The results in Table 7 thus can be seen as a lower bound.

[23] The lower number reflects the modeled price of CO_2 in the EU Emissions Trading Scheme in 2020 in a scenario where current but no additional legislation is implemented (it is therefore similar to a business-as-usual scenario), and the higher number is the carbon price in 2030 projected to achieve a 40% reduction in greenhouse gas emissions compared to 1990 levels. The EEA (2014a) uses these carbon prices to quantify carbon emissions damages from industrial facilities as part of assessing the overall cost of industrial air pollution damages. Alternative estimates of the Social Cost of Carbon vary widely, depending on the discount rate and other assumptions (IPCC 2014).

damage costs for electricity producers, and 100 too 1,040% of CO_2 damage costs for policy-induced co-benefits in the electricity sector.[24] These results suggest that substantially higher carbon prices can be justified based on air quality co-benefits alone.

Table 7: Monetary co-benefits

	Co-pollutant elasticities from Table 3, 4, or 5	Average co-pollutant-to-CO_2 ratios for respective sample	Damage costs from EEA (2014a) in 2005 EUR/tCO_2		Monetary co-benefits in 2005 EUR/tCO_2	
			low	high	low	high
			All facilities			
SO_x	0.727	0.0027239	9,792	28,567	19.39	56.57
NO_x	0.730	0.0017541	4,419	11,966	5.66	15.32
PM_{10}	0.501	0.0003149	22,990	66,699	3.63	10.52
			Electricity production			
SO_x	0.868	0.0027523	9,792	28,567	23.39	68.25
NO_x	0.811	0.0019053	4,419	11,966	6.83	18.49
PM_{10}	0.658	0.0001981	22,990	66,699	3.00	8.69
			Electricity production – climate policy induced			
SO_x	1.173	0.0022408	9,792	28,567	25.74	75.09
NO_x	0.969	0.0018092	4,419	11,966	7.75	20.98
PM_{10}	0.817	0.0001520	22,990	66,699	2.85	8.28

Notes: The average damage costs for all industrial facilities were also used for the subsample of facilities in electricity production, since per ton co-pollutant damage cost estimates for electricity production are not available. Source: EEA (2014a) table 3.1, E-PRTR, authors' calculations.

7. Conclusions

The World Health Organization (2016, p. 11) characterizes air pollution as the "biggest environmental risk to health" around the world. The Lancet Commission on Health and Climate Change warns that climate change threatens to undermine half a century of progress in global health, and more optimistically foresees that response to climate change could be "the greatest global health opportunity of the 21st century" (Watts et al. 2105, p. 1861). An integrated analysis of CO_2 emissions and co-emitted air-pollutants is therefore of high academic and policy relevance.

[24] These calculations compare high (low) CO_2 damage costs with low (high) co-pollutant damage costs, adding up all three co-pollutant damages.

This paper's investigation of co-pollutant elasticities with respect to CO_2 emissions, based on facility-level data disaggregated across sources and across co-pollutants, fills an important gap in the literature. For industrial point sources in Europe as a whole, we find that in the time period 2007 to 2015 a 1% reduction in CO_2 emissions resulted in about a 0.7% reduction in SO_X and NO_X emissions, and a 0.5% reduction in PM_{10} emissions. In the electricity sector, which is the largest contributor to Europe's industrial carbon emissions, these elasticities were higher: a 1% reduction in CO_2 emissions is associated with a 0.9% reduction in SO_X, 0.8% reduction in NO_X, and a 0.7% reduction in PM_{10} emissions. Elasticities in the electricity sector for CO_2 reductions specifically induced by climate policies are still higher at 1.2%, 1.0%, and 0.8% for SO_X, NO_X, and PM_{10}, respectively. These findings provide useful inputs not only for assessing the magnitude of air quality co-benefits from carbon mitigation policies, but also for the design of spatially and sectorally differentiated policies that take into account variations in co-pollutant damages per ton of CO_2.

Monetizing the health impacts of co-pollutant emissions using EEA estimates of damage costs, we obtain air quality co-benefits of 29 to 104 Euros per ton of CO_2 for the three co-pollutants jointly. This is substantially higher than EEA estimates of climate damage costs per ton of CO_2. The implication of this finding is that higher carbon prices can be justified in Europe as a "no regrets" policy, independent of their climate benefits. Due to sectoral differences in co-pollutant intensities and elasticities, our results suggest that differentiated carbon mitigation policies may improve efficiency beyond that of uniform policies.

Potentially fruitful areas for future research include comparison of co-pollutant intensities and elasticities for industrial point sources to those for other emission sources, notably transportation. Facility-level studies in other countries and regions would shed light on whether and how European elasticities compare to corresponding sectors elsewhere. Finally, the fine degree of geographical resolution that can be obtained from facility-level data can be applied to the analysis of spatial differentiation in air quality co-benefits, an important policy issue from the standpoint of equity as well as efficiency.

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9. Appendix

Table A1: Summary statistics of the three samples used in the baseline regressions

Specification	Variable	Obs.	Mean	Std. Dev.	Min	Max
(1)	$\ln(SO_x)$	7062	13.915	1.297	11.918	17.461
(1)	$\ln(CO_2)$	7062	20.367	1.212	18.421	22.935
(2)	$\ln(NO_x)$	14826	13.246	1.111	11.513	16.433
(2)	$\ln(CO_2)$	14826	19.990	1.073	18.421	22.935
(3)	$\ln(PM_{10})$	3244	12.054	0.979	10.820	15.107
(3)	$\ln(CO_2)$	3244	20.816	1.218	18.421	22.935

Source: E-PRTR, authors' calculations.

Table A2: Average ratios of co-pollutant emissions to CO_2 emissions by NACE activity

	Production of electricity	Manufacture of basic iron and steel and of ferro-alloys	Manufacture of refined petroleum products	Manufacture of cement	Treatment and disposal of non-hazardous waste	Steam and air conditioning supply	Manufacture of paper and paperboard	Extraction of crude petroleum
SO_X	0.0028	0.0014	0.0028	0.0010		0.0035		
NO_X	0.0019	0.0012	0.0011	0.0018	0.0010	0.0013	0.0011	0.0034
PM_{10}	0.0002							

Note: Ratios are calculated as averages of individual facility-level ratios. Ratios are only reported for NACE sectors with more than 400 observations.
Source: E-PRTR, authors' calculations.

Table A3: First-stage results of the 2SLS specifications in Table 6, explaining ln(CO_2)

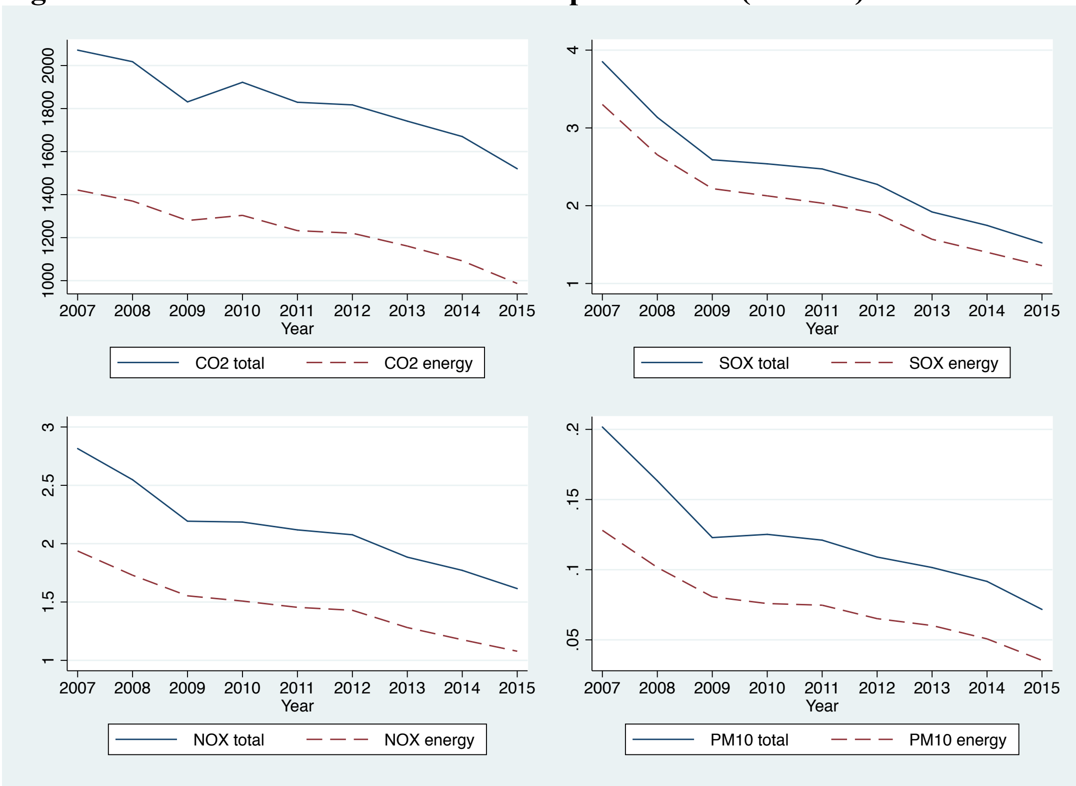
	2SLS	2SLS with real GDP	LASSO-2SLS with real GDP	LASSO-2SLS with real GDP and co-pollutant policies	LASSO-2SLS with real GDP and co-pollutant policies (cubic)	LASSO-2SLS with real GDP and co-pollutant policies (cubic and lagged)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: SO_x sample						
Green certificates trading schemes	0.019	0.015				
	(0.018)	(0.023)				
CO_2 trading schemes	-0.000	-0.002				
	(0.031)	(0.029)				
White certificates trading schemes	-0.052***	-0.052***				
	(0.016)	(0.015)				
Wind feed-in tariffs	-0.015	-0.016				
	(0.013)	(0.013)				
Solar feed-in tariffs	-0.009	-0.007				
	(0.014)	(0.015)				
(CO_2 trading schemes^3)$_{t-2}$			-0.001***	-0.001***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)	(0.000)
White certificates trading schemes$_{t-5}$			-0.116***	-0.124***	-0.116***	-0.124***
			(0.015)	(0.016)	(0.019)	(0.016)
Observations	1,996	1,996	1,859	1,859	1,859	1,807
No. of facilities	338	338	313	313	313	301
Weak IV F-stat. > crit. value (10%)	no	no	yes	yes	yes	yes
Panel B: NO_x sample						
Green certificates trading schemes	-0.006	-0.022				
	(0.015)	(0.013)				
CO_2 trading schemes	-0.021	-0.030*				
	(0.019)	(0.018)				
White certificates trading schemes	-0.019	-0.018				
	(0.019)	(0.017)				
Wind feed-in tariffs	-0.015*	-0.015*				
	(0.008)	(0.008)				
Solar feed-in tariffs	-0.007	-0.002				
	(0.008)	(0.008)				
(Solar feed-in tariffs x Green certificates trading schemes^2)$_{t-1}$			-0.001***	-0.001***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)	(0.000)
White certificates trading schemes$_{t-5}$			-0.069***	-0.067***	-0.057**	-0.041**
			(0.019)	(0.025)	(0.025)	(0.019)
Wind feed-in tariffs$_{t-1}$			-0.011**	-0.012***	-0.016***	-0.020***
			(0.005)	(0.004)	(0.006)	(0.005)
Observations	3,947	3,947	3,461	3,461	3,461	3,369
No. of facilities	704	704	595	595	595	580
Weak IV F-stat. > crit. value (10%)	no	no	yes	yes	yes	yes

Table A3 continued

	Panel C: PM_{10} sample					
Green certificates trading schemes	-0.002	-0.004				
	(0.022)	(0.026)				
CO_2 trading schemes	-0.016	-0.017				
	(0.019)	(0.018)				
White certificates trading schemes	-0.034***	-0.034***				
	(0.012)	(0.012)				
Wind feed-in tariffs	0.002	0.002				
	(0.013)	(0.012)				
Solar feed-in tariffs	-0.014	-0.013				
	(0.017)	(0.016)				
CO_2 taxes$_{t-5}$			-0.006	-0.007	0.008	-0.052
			(0.037)	(0.036)	(0.041)	(0.037)
(CO_2 taxes x Wind feed-in tariffs)$_{t-3}$			0.065***	0.065***	0.066***	0.058***
			(0.005)	(0.005)	(0.005)	(0.005)
(CO_2 taxes x Wind feed-in tariffs)$_{t-5}$			-0.067***	-0.067***	-0.069***	-0.055***
			(0.006)	(0.007)	(0.007)	(0.008)
White certificates trading schemes$_{t-5}$			-0.033*	-0.010	-0.036	0.098***
			(0.017)	(0.015)	(0.034)	(0.029)
(White certificates trading schemes^3)$_{t-3}$			-0.001***	-0.001***	-0.001***	-0.000
			(0.000)	(0.000)	(0.000)	(0.001)
(White certificates trading schemes x Solar feed-in tariffs^2)$_{t-1}$			-0.002***	-0.003***	-0.003***	-0.006***
			(0.001)	(0.001)	(0.001)	(0.001)
Observations	952	952	893	893	893	878
No. of facilities	199	199	185	185	185	180
Weak IV F-stat. > crit. value (10%)	no	no	no	no	yes	yes

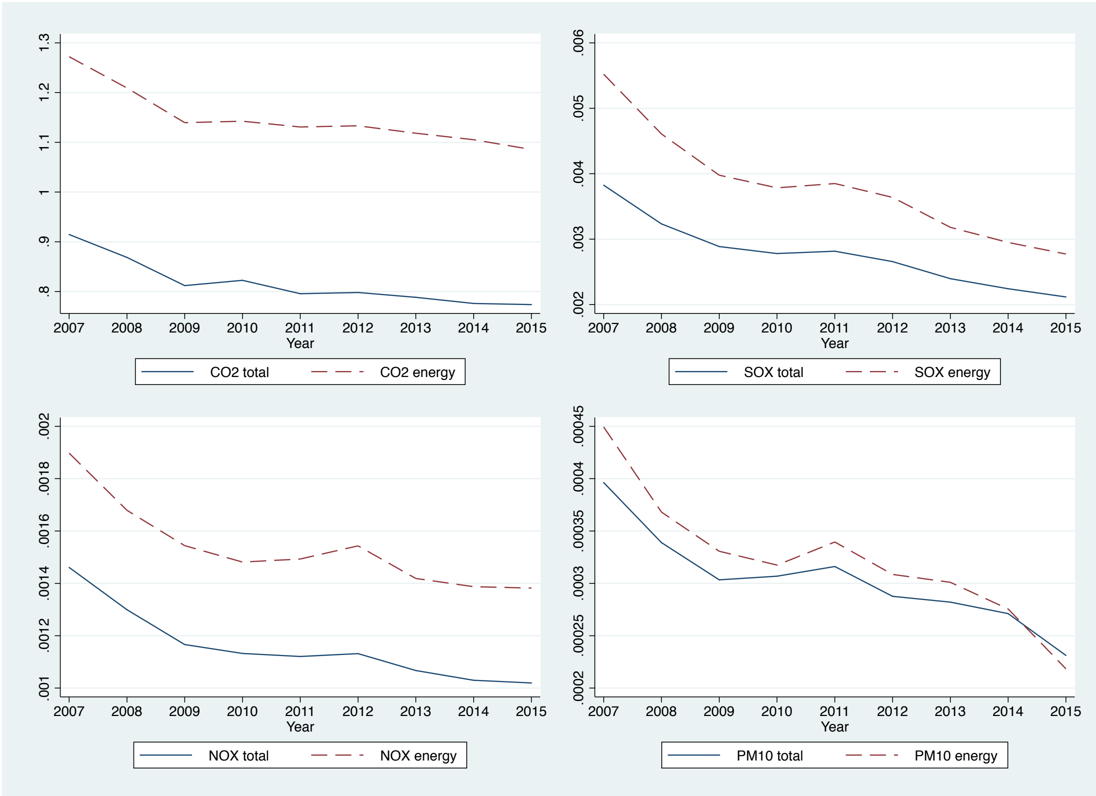
Notes: All specifications include facility and time fixed effects. Standard errors in parentheses are clustered at the country-level. *** p<0.01, ** p<0.05, * p<0.1
Source: E-PRTR, Botta and Koźluk (2014), authors' calculations.

Figure A1: Total annual emissions of sample facilities (in mio t)



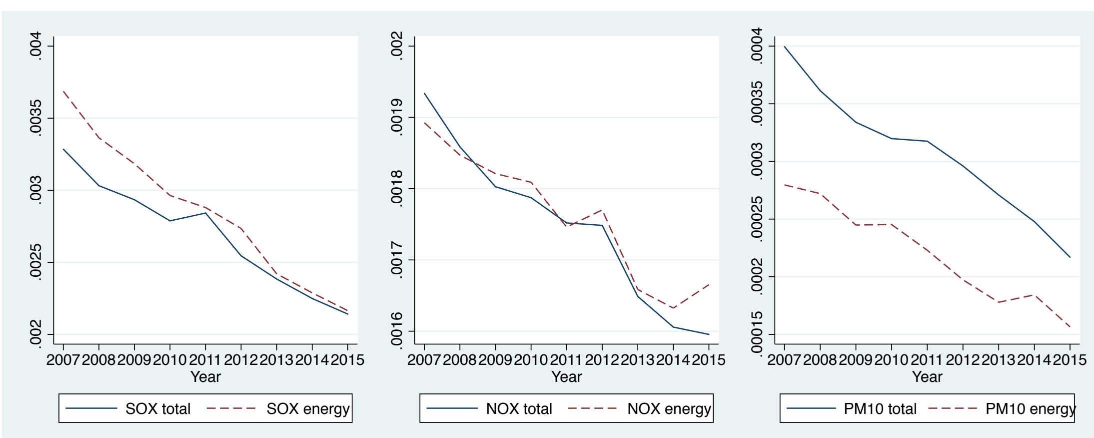
Source: E-PRTR, authors' calculations.

Figure A2: Average emissions per facility (in mio t)



Source: E-PRTR, authors' calculations.

Figure A3: Co-pollutant intensity ratios over time (average facility-level ratio between co-pollutant and CO_2 emissions)



Notes: Ratios are calculated as averages of individual facility-level ratios.
Source: E-PRTR, authors' calculations.