Effects of Carbon Mitigation on Co-pollutants at Industrial Facilities in Europe

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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 630 to 2,400 facilities for the years 2007 to 2015. We find substantial and statistically significant co-pollutant elasticities of about 1.0 for SO_X, 0.9 for NO_X, and 0.7 for PM_{10}. These elasticities vary by economic activity, and are substantially higher for the production of energy. For climate policy-induced CO_2 emission reductions we find elasticities in the energy sector of 1.2 to 1.8 for SO_X, 1.1 to 1.5 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 may 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.,

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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. 2014, 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. 2014, 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, composition effects, and technology effects (Grossman and Krueger 1991; Copeland and Taylor 2004; Bollen and Brink 2014). Scale effects are due to changes in economic output, and thereby emissions, that affect neither the economy-wide nor the point source-level relationship between greenhouse gases and co-pollutants. For example, in the electricity sector, a recession might be expected to reduce output, greenhouse gases, and co-pollutants rather proportionally, with a co-pollutant elasticity close to one. Composition effects reflect changes in the sectoral composition of the economy that change emissions at the aggregate level due to different co-pollution ratios of the various economic sectors. For example, an economy-wide recession might affect some sectors more than others. Thus, while point source-level co-pollutant ratios are unaffected, composition effects alter economy-wide ratios between greenhouse gases and co-pollutants.

Finally, technology effects refer to substitutions across inputs, new emissions control technologies, or energy savings, and can alter the point-source level relationship between greenhouse gases and co-pollutants substantially (Holland 2010; Brunel and Johnson 2019). For example, end-of-pipe controls such as scrubbers can significantly reduce co-pollutants, while at the same time these devices need electricity to operate and therefore increase CO_2 emissions.[1] An increase in the combustion temperature in natural gas-fired power plants reduces CO_2 per kilowatt but increases

1. For CO2, by contrast, no end-of-pipe technology is currently technically and economically feasible to implement at a larger scale.

NO_X emissions. Co-pollutant and CO_2 emissions can also be complements; e.g. fuel switching from coal or oil to natural gas reduces both CO_2 and SO_2 emissions, since natural gas has lower sulfur content (Holladay and Soloway 2016; Gillingham and Huang 2019). For these reasons, the relationship between CO_2 and co-pollutants is likely to vary 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 CO_2 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 (Cole et al. 2005). Despite continuous regulatory efforts over the last decades, air pollution is still high. Lelieveld et al. (2019) find a per capita mortality rate from air pollution exposure in Europe of 129 deaths per 100,000 inhabitants in the EU–28 and an average reduction in life expectancy by 2.2 years, due to a combination of low air quality and high population density. These excess pollution damages can be lowered through second-best carbon prices, which not only address climate, but also co-pollutant damages. The second-best carbon price would deviate from its Pigouvian level depending on the level of co-pollutant regulation. If marginal damages from co-pollutants are sub-optimally high, the carbon price should be set above its Pigouvian rate. Spatial or sectoral heterogeneity in air quality co-pollution elasticities would further imply that differentiated policies provide strong efficiency as well as equity improvements over a uniform carbon price.

To the best of our knowledge, this study is the first to estimate co-pollutant elasticities from panel data at the point-source level. This type of analysis 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 also based specifically on climate policy-induced variations, where the latter is most relevant for the assessment of air quality co-benefits.

We find evidence of substantial and statistically significant co-pollutant elasticities of around 1.0 for sulfur oxides (SO_X), 0.9 for nitrogen oxides (NO_X), and 0.7 for particulate matter (PM_{10}) for the average facility in the full sample. We find considerable variation in the magnitude of co-pollutant elasticities across economic sectors. The energy sector is characterized by relatively high co-pollutant elasticities of 1.6 for SO_X, and 1.0 for NO_X and PM_{10}. Identifying climate policy-induced changes in CO_2 emissions based on changes in regulatory stringency, we estimate co-pollutant elasticities in the electricity sector of 1.2 to 1.8 for SO_X, 1.1 to 1.5 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 the identification strategies. Section 5 reports the results of the empirical 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

Variations in emissions of one pollutant 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).

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 briefly review several recent studies that illustrate representative findings.[2]

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 is 3–4 times greater than the SCC alone. As the authors note, the inclusion of other air quality benefits, such as impacts on medical spending and worker productivity, would further augment this ratio.

Parry et al. (2014, 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.

Thompson et al. (2014) model three carbon policy scenarios in the US—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 achieve through air quality co-benefits. They find that monetized human health benefits would offset 26% to 1,050% of the cost of carbon mitigation, and conclude that carbon mitigation policies initially "can be motivated based on air pollution co-benefits" (p. 921).

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

In a global simulation, 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. 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.

Studies also have assessed the air quality co-benefits of carbon mitigation policies specifically in electric power generation. For example, analyzing the Obama administration's Clean Power Plan, which 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).

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 sole 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. 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, and compare co-pollutant emissions and damages across and within industrial sectors. Comparing petroleum refineries to electric power plants, for example, they find that 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, suggesting a co-pollutant elasticity of one.

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.[3] 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 mixed evidence of spillovers of increased regulatory stringency of air pollution on greenhouse gas reductions. This could potentially either suggest that the empirical support for air quality co-benefits might be weaker than modeled in simulation studies, or that spillover effects of environmental policies are asymmetric.[4] Finally, the differences in the findings of Holland (2010) and Brunel and Johnson (2019) might result from sectoral differences in spillovers, since the former study analyzes the energy sector, while the latter analyzes non-energy sectors. 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 samples for the three co-pollutants (see Appendix Table A1 for summary statistics) that exclude small polluters below either the CO_2 or co-pollutant reporting thresholds.

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 are shown in Ap-

3. To illustrate this point, note that we estimate for a panel $\ln(copoll_{it}) = \beta \ln(CO2_{it}) + \varepsilon_{it}$ (see section 4), where $copoll_{it}$ and $CO2_{it}$ are co-pollutant and CO2 emissions across facility i and year t, respectively. 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, where the implicit "elasticity" of CO2 is restricted to equal 1.

4. 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. The same asymmetry could apply to greenhouse gas and co-pollutant regulation, and therefore the findings of Holland (2010) and Brunel and Johnson (2019) might not hold true in the reverse direction.

pendix Table A2. 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, and also account for 57% of total SO_X emissions, 24% of NO_X, and 6% of PM_{10}. The 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).

Appendix Table A3 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 A4 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 the 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).[5] 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).[6] 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 Appendix Figure A3).

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 begin the discussion with the following difference-in-difference specification:

$$\ln\left(copoll_{ijct}\right)=\beta\ln\left(CO2_{ijct}\right)+\alpha_i+\delta_{jct}+\epsilon_{ijct} \tag{1}$$

where $copoll_{\text{ijct}}$ are emissions of the co-pollutant, i.e. SO_X, NO_X, or PM_{10}, at facility *i*, economic sector *j*, country *c*, and year *t*. $CO2_{ijct}$ are the corresponding carbon dioxide emissions at the same facility. 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

5. The data shown in Appendix Figures A1 and A2 suggest that CO2 is strongly correlated with the three co-pollutants. Further, standard cointegration-tests based on Kao (1999), Pedroni (1999; 2004), and Westerlund (2005) allow to soundly reject the null hypothesis of no cointegration for all combinations of CO2 with the three co-pollutants, confirming a long-run relationship between CO2 and the co-pollutants.

6. The EU National Emission Ceilings Directive (NECD 2001/81/EC) and the Gothenburg protocol set national caps of SOX and NOX 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 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).

co-pollutant. We purge facility fixed effects (α_i) to capture unobserved heterogeneity between point sources, and sector-by-country-by-year fixed effects (δ_{jct}) capturing year effects at the sectoral level in each country individually. Thus, any shock or policy is flexibly purged at the sector-by-country level. To account for within-group serial correlation and heteroscedasticity, we cluster standard errors at the facility level (Cameron and Miller 2015).[7]

In the first step of the empirical analysis, we estimate a distributed lag version of equation (1), adding two leads and two lags of CO_2 emissions, to assess the timing of the effects:

$$\ln\left(copoll_{ijct}\right) = \sum_{r=-2}^{2} \beta_r \ln\left(CO2_{ijct-r}\right) + \alpha_i + \delta_{jct} + \epsilon_{ijct} \tag{2}$$

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. Significant leading or lagged effects would highlight potential problems with this specification.

Based on these findings we then proceed with the analysis by addressing simultaneity bias due to the joint release of CO_2 and co-pollutants when burning carbon. We follow the standard approach in the literature and estimate two-stage least squares (2SLS) versions of equation (1) instrumenting CO_2 with its first lag (Reed 2015). Following the advice of Andrews et al. (2019) we also present the results of the weak instruments test by Montiel Olea and Pflueger (2013) that is suitable for clustered errors. This test incorporates a multiplicative correction that depends on the robust variance estimate. According to the rule-of-thumb suggested by Staiger and Stock (1997) and Andrews et al. (2019) a value of above 10 allows rejecting the null hypothesis of weak instruments. We also report the confidence sets based on the Anderson-Rubin statistic (Anderson and Rubin 1949) that are robust to weak identification and efficient in the just-identified case.

We present results of this specification for all facilities, various sub-samples including only facilities with data on all three co-pollutants, facilities with very precisely measured pollution emission data, and for single economic sectors. We also show results including only facility and common year effects, or facility, country-by-year and sector-by-year fixed effects.

From a policy perspective, co-pollutant elasticities of climate policy induced emission reductions might be most interesting. We therefore identify co-pollutant elasticities for CO_2 reductions specifically induced by climate policy 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 several 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 with facility and year fixed effects for the electricity sector, where CO_2 is instrumented by a vector of *n* climate policies. This specification has the following form:

$$\ln\left(copoll_{ict}\right) = \beta \ln\left(CO2_{ict}\right) + \alpha_i + \gamma_t + \epsilon_{ict} \tag{3}$$

with the first stage equation being:

$$\ln\left(CO2_{ict}\right) = \sum_{k=1}^{n} \pi_k \left(climate\ policies_{ct}\right) + \alpha_i + \gamma_t + \upsilon_{ict} \tag{4}$$

7. To reduce the influence of outliers in the analysis that could be a result of reporting errors, we censor CO2 and the co-pollutants at the respective 99th percentiles. This, however, has no relevant effect on the results.

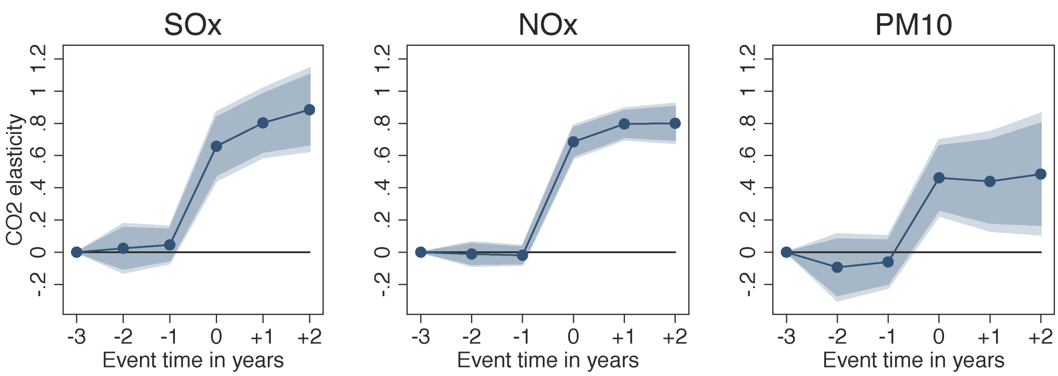
The identifying variation in CO_2 is based on exogenous policy changes that were implemented for other reasons than the reduction of co-pollutants. To be valid instruments, the climate policy indicators must be able to predict CO_2. Thus, in the first step we establish that an increase in climate policies stringency 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 potential confounders. Since policy-variation occurs at the national level, standard errors are clustered at the country-level in these specifications.

5. RESULTS

5.1 Co-pollutant elasticities

We begin the analysis by assessing the observed timing of the effects by estimating a distributed lag model (equation 2). The results are presented in Figure 1, which 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 pre-existing trends do not bias the results. 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 confirms the validity of the specification with purged facility and industry-by-country-by-year fixed effects.

Figure 1: Cumulative response over time of a log CO_2 increase on log co-pollutants



Notes: The figure shows the cumulative sum of the CO_2 coefficients from 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.

Table 1 presents the results of the 2SLS specifications addressing simultaneity bias with lagged CO_2 as instrument for the three co-pollutants, SO_X, NO_X, and PM_{10}. The panels consist of 628 to 2,404 point sources, depending on the co-pollutant, for the time period 2007 to 2015, yielding sample sizes from 2,946 to 13,709 observations. The estimated elasticities for the full sample (column 1) are 1.0 for SO_X, 0.9 for NO_X, and 0.7 for PM_{10}, all highly statistically significant (for summary statistics, see Appendix Table A1). The estimates based on the full samples perform well in the weak instrument test by Montiel Olea and Pflueger (2013) for SO_X and NO_X. Also for PM_{10}, where the effective F-statistic is slightly below 10, the weak instrument robust Anderson-Rubin confidence sets suggest large positive co-pollutant elasticities.

Table 1: Effect of a log-point increase in CO_2 on log co-pollutants in 2SLS models instrumenting CO_2 with its first lag

	Facility and industry-by-country-by-year FE				Facility, industry-by-year and country-by-year FE	Facility and year FE
	Full sample (1)	Balanced sample (2)	Facilities in all sub-samples (3)	Precise measurement sample (4)	Full sample (5)	Full sample (6)
			Panel A: Dependent variable: $\ln(SO_X)$			
$\ln(CO_2)$	1.010***	1.093***	1.007***	0.953***	0.948***	1.005***
	(0.151)	(0.198)	(0.212)	(0.168)	(0.141)	(0.150)
Observations	6,508	3,780	2,399	548	6,508	6,508
No. of facilities	1,176	540	510	189	1,176	1,176
CS_{AR}	[0.742, 1.351]	[0.725, 1.539]	[0.612, 1.554]	[–]	[0.708, 1.277]	[0.750, 1.354]
F_{Eff}	35.23	21.20	8.05	2.23	46.36	60.88
			Panel B: Dependent variable: $\ln(NO_X)$			
$\ln(CO_2)$	0.857***	0.872***	0.878***	1.145***	0.829***	0.858***
	(0.047)	(0.066)	(0.125)	(0.244)	(0.047)	(0.044)
Observations	13,709	7,952	2,399	1,533	13,709	13,709
No. of facilities	2,404	1,136	510	446	2,404	2,404
CS_{AR}	[0.770, 0.952]	[0.754, 1.017]	[0.606, 1.161]	[0.710, 1.772]	[0.742, 0.924]	[0.776, 0.948]
F_{Eff}	166.04	80.20	8.05	11.48	219.87	306.13
			Panel C: Dependent variable: $\ln(PM_{10})$			
$\ln(CO_2)$	0.709***	0.498**	0.690***	1.758***	0.630***	0.743***
	(0.193)	(0.236)	(0.195)	(0.243)	(0.189)	(0.196)
Observations	2,946	1,288	2,399	185	2,946	2,946
No. of facilities	628	184	510	60	628	628
CS_{AR}	[0.349, 1.207]	[–0.015, 0.975]	[0.280, 1.147]	[1.189, 1.459]	[0.294, 1.115]	[0.425, 1.325]
F_{Eff}	9.35	22.69	8.05	2.96	13.20	19.11

Notes: Specifications 1–4 include facility and NACE-by-country-by-year fixed effects. Specification 5 includes facility, NACE-by-year, and country-by-year fixed effects. Specification 6 includes facility and year 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.

We assess the robustness of these results by re-estimating this specification for various subsets of the sample. In column 2 we drop all facilities that are not in the sample over the whole period. This halves the sample sizes, but has little effect on the estimated elasticities. Only for PM_{10} the estimate is somewhat lower. In column 3 we limit the sample to observations of facilities that report emissions of all three co-pollutants. The results are similar to those in column 1.

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 are therefore 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 4). This substantially reduces the sample sizes. The estimated co-pollutant elasticities for NO_X and especially PM_{10} are significantly larger than for the full sample. For PM_{10} the elasticity more than doubles; however, this result is based on only 185 observations and 60 facilities.

Finally, columns 5 and 6 present results for the full samples with fixed effects purged at a less fine level. Instead of industry-by-country-by-year and facility fixed effects, column 5 includes country-by-year and industry-by-year fixed effects, next to facility fixed effects. Column 6 includes overall year and facility fixed effects. The results are very similar to those in column 1.

Overall, the results are robust to different specifications and samples. They indicate that a 1% change in CO_2 emissions at the facility-level is associated with roughly a 1.0% change in the same direction in emissions of SO_X, 0.9% of NO_X, and around 0.7% of PM_{10}.

5.2 Sectoral heterogeneity in co-pollutant elasticities

We further assess whether and how co-pollutant elasticities vary by economic sectors. Table 2 presents results by economic activity (NACE).[8] We find substantial variations across activities, with relatively high elasticities in electricity production for all co-pollutants: approximately 1.6 for SO_X, 1.0 for NO_X, and 1.0 for PM_{10}. The production of electricity is also the most important activity with respect to total CO_2 emissions (see last line of panel). For NO_X we also find high co-pollutant elasticities for the extraction of crude petroleum.[9]

5.3 Climate policy induced co-pollutant elasticities in electricity production

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 a two-stage least squares (2SLS) specification (see equation 3), where CO_2 is instrumented with changes in environmental policy stringency that target CO_2 emissions (equation 4). We use the following subcategories of the OECD Environmental Policy Stringency Index, that are typically classified as climate policies: 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.[10]

To assess whether these climate policies are suitable instruments, in the first step we test if they predict CO_2 emissions. Since the OECD Environmental Policy Stringency Index focuses predominantly on the energy sector, we present separate results for the electric power sector and for the remaining sectors. The results are shown in Table 3. 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 the sample have a value of zero. Of the remaining five polices, all show a negative effect on CO_2 emissions. An *F*-test on their joint significance allows to reject the null hypothesis that all coefficients are zero (see Bound et al. 1995). Thus, climate policy stringency is found to significantly reduce CO_2 emissions at the average facility. The period under investigation includes the financial

8. For reasons of robustness we only show results for sectors with at least 600 observations in Appendix Table A4.

9. We also assess if co-pollutant elasticities vary with regional population density, which would have implications on the number of people affected by health co-benefits. We thus split the sample into regions with fewer than 500 inhabitants per km2, and those with more than that. 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. 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. Population density varies between 3 and more than 7,000 inhabitants per km2, with a mean of about 300 and a median of about 150. The results are presented in Appendix Table A5. For SOX we find somewhat larger elasticities in more densely populated regions, and for NOX little difference, while for PM10 we find higher elasticities in regions with low population density. However, these differences are not statistically significant.

10. 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].

Table 2: Effect of a log-point increase in CO_2 on log co-pollutants for different NACE activities in 2SLS models instrumenting CO_2 with its first lag

	Extraction of crude petroleum (1)	Manufacture of cement (2)	Manufacture of paper and paperboard (3)	Manufacture of refined petroleum products (4)	Production of electricity (5)	Steam and air conditioning supply (6)	Treatment and disposal of non-hazardous waste (7)
				Panel A: Dependent variable: $\ln(SO_X)$			
$\ln(CO_2)$				0.320**	1.558***	1.078**	
				(0.149)	(0.289)	(0.474)	
Observations				724	2,266	777	
No. of facilities				112	390	142	
CS_{AR}				[0.054, –]	[1.089, 2.347]	[0.047, 2.110]	
F_{Eff}				45.56	15.10	19.59	
CO_2 (m t in 2012)				125.447	687.416	58.975	
				Panel B: Dependent variable: $\ln(NO_X)$			
$\ln(CO_2)$	1.900***	0.660***	0.501***	0.578***	0.970***	0.904***	0.070
	(0.638)	(0.145)	(0.159)	(0.109)	(0.067)	(0.157)	(0.125)
Observations	598	1,735	673	766	4,265	1,200	677
No. of facilities	97	264	113	117	789	224	180
CS_{AR}	[0.865, 4.098]	[0.333, 0.930]	[0.079, 0.835]	[0.392, 0.979]	[0.851, 1.116]	[0.588, 1.245]	[–0.192, 0.361]
F_{Eff}	10.55	32.31	48.67	56.47	95.60	27.70	24.98
CO_2 (m t in 2012)	19.055	110.564	46.586	127.778	820.737	78.234	98.359
				Panel C: Dependent variable: $\ln(PM_{10})$			
$\ln(CO_2)$					0.963***		
					(0.327)		
Observations					1,128		
No. of facilities					243		
CS_{AR}					[0.302, –]		
F_{Eff}					3.68		
CO_2 (m t in 2012)					450.104		

Notes: All specifications include facility and country-by-year 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.

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 control for the logarithm of real national GDP in column 2.[11] 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. Columns 3 and 4 present results for similar specifications for the non-electricity sectors. Climate policies are found to be jointly insignificant. In what follows we therefore limit the investigation to electricity producing facilities.

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 4. Column 1 shows results of the 2SLS regressions including facility and year dummies, and instru-

11. Real GDP is from the annual macro-economic database of the European Commission (AMECO).

Table 3: Effect of climate policy stringency on log CO_2 for electricity production and other sectors

	Electricity production		Other sectors	
	(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)
With ln(real GDP)	no	yes	no	yes
F-test on joint sign. (p-val)	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: All specifications include facility and year 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.

menting CO_2 with climate policies.[12] Since policies vary at the national-level, standard errors are clustered at the country-level, which increases their size compared to clustering at the facility-level. The estimated co-pollutant elasticities are 1.8 for SO_x, 1.5 for NO_x, 0.8 for PM_{10}. The estimates are highly statistically significant for SO_x and NO_x, but not precisely estimated for PM_{10}. The first-stage results are presented in Appendix Table A6.

Comparing these results to those for the energy sector in Table 2 (column 5) based on internal instruments, climate policy induced elasticities are found to be somewhat larger for SO_x and NO_x, and somewhat smaller for PM_{10}. These differences are not statistically significant, however.

To assess whether we may be erroneously attributing effects of the Great Recession on co-pollutants to stricter climate policy, we additionally control for real national GDP (in logarithms) in column 2. This increases the precision of the estimates, and reduces the estimated elasticity for SO_x to 1.5, but has little effect on 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-linearities, 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,[13] and to assess the sensitivity of the results to this alternative specification. 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

12. Even though the validity of the moment conditions is an identifying assumption that cannot be tested (see Parente and Santos Silva 2012), we follow standard convention and report the p-value of Hansen's *J*-test of overidentifying restrictions in the table. We cannot reject the null hypothesis that the instruments are uncorrelated with the error term in nearly all specifications.

13. An *F*-test on the excluded instruments confirms strong first-stage results. However, the testing procedure by Montiel Olea and Pflueger (2013), which is suitable for serially correlated and clustered errors, suggests otherwise. We obtain Feff-statistics below the rule-of-thumb cutoff of 10, which does not allow rejecting the null-hypothesis of weak instruments for any of the three co-pollutants in columns 1 and 2 (see last line of panel).

Table 4: Effect of a log-point increase in CO_2 on log co-pollutants in 2SLS models instrumenting CO_2 with climate policies

	2SLS with climate policies instruments (1)	= column 1 with ln(GDP) as control (2)	= column 2 with LASSO-picked instruments (3)	= column 3 with co-poll. policies (4)	= column 4 with up to cubic co-pollutant policies (5)	= column 5 with additionally lagged co-pollutant policies (6)
	Panel A: Dependent variable: $\ln(SO_X)$					
$\ln(CO_2)$	1.803***	1.499***	1.469***	1.571***	1.437***	1.241***
	(0.379)	(0.265)	(0.205)	(0.224)	(0.174)	(0.145)
Observations	2,030	2,030	2,112	1,867	1,867	1,917
No. of facilities	372	372	346	346	340	342
Hansen *J*-test (p-val)	0.532	0.111	0.104	0.210	0.185	0.278
F^{eff}	2.62	2.45	14.22	15.73	17.01	14.57
	Panel B: Dependent variable: $\ln(NO_X)$					
$\ln(CO_2)$	1.453***	1.387***	1.182***	1.157***	1.153***	1.066***
	(0.292)	(0.250)	(0.243)	(0.199)	(0.199)	(0.141)
Observations	4,015	4,015	3,559	3,361	3,361	3,311
No. of facilities	772	772	647	647	637	632
Hansen *J*-test (p-val)	0.104	0.289	0.198	0.117	0.295	0.054
F^{eff}	2.01	2.87	14.61	14.28	12.97	11.20
	Panel C: Dependent variable: $\ln(PM_{10})$					
$\ln(CO_2)$	0.817	0.834	0.806**	0.808*	0.798**	0.783*
	(0.804)	(0.764)	(0.416)	(0.406)	(0.396)	(0.418)
Observations	989	989	974	908	908	906
No. of facilities	236	236	220	220	216	216
Hansen *J*-test (p-val)	0.673	0.380	0.371	0.292	0.285	0.361
F^{eff}	1.55	1.61	225.78	216.17	219.60	108.21

Notes: All specifications include facility and year 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.

choose a sparse list of relevant instruments with true predictive power, we apply the Least Absolute Shrinkage and Selection Operator (LASSO) (see Belloni et al. 2014).[14]

The LASSO-2SLS results are presented in column 3. Even though they are identified with different sets of instruments, they are quantitatively similar to the 2SLS results of column 2, with elasticities of 1.5 for SO_x, 1.2 for NO_x, and 0.8 for PM_{10} that are noticeably more precisely estimated, especially in the case of PM_{10}.[15]

14. 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. The latter term, called lambda, guards against overfitting and ensures feasibility of estimation by returning a small set of relevant instruments. We set lambda such that LASSO picks not more than a handful of instruments for each sample. The picked instruments are: the second lag of cubic CO_2 trading schemes, the fifth lag of green certificate trading schemes, and the fifth lag of white certificate trading schemes for the SO_x-sample; the first lag of CO_2 trading schemes interacted with wind feed-in-tariffs, the second lag of green certificate trading schemes interacted with white certificate trading schemes and solar feed-in-tariffs, and the fourth and fifth lag of white certificate trading schemes for the NO_x-sample; the third and fifth lag of CO_2 tax interacted with wind feed-in-tariffs, the first lag of green certificate trading schemes interacted with white certificate trading schemes and solar feed-in-tariffs, and the third lag of cubic white certificate trading schemes.

15. The effective *F*-statistic suggested by Montiel Olea-Pflueger (2013) is above the critical value of 10 for all LASSO-2SLS models for all samples and thus allows rejecting the null-hypothesis of weak instruments in the first-stage results.

Although air quality co-benefits so far have not been incorporated into EU climate policy design, it is possible that industrial facility operators' responses to new climate policies nevertheless 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, and this may have affected decisions on how to respond to the climate policies. 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-pollutants.[16] We present three different versions. In column 4, we include linear and contemporaneous values of these regulatory confounders. The results are similar to those in column 3. In column 5, we also include squared and cubic terms. The results are again similar to those in column 3. Finally, in column 6 we additionally allow for up to five lags of the co-pollutant policies, and let LASSO pick the four most important predictors of the respective co-pollutant from this large list of about thirty co-pollutant policy terms. The estimated co-pollutant elasticities for SO_x and NO_x are modestly smaller compared to the results in columns 4 and 5, while they are very similar for PM_{10}. For the specifications controlling for co-pollution policies (columns 4 to 6), we obtain elasticities of 1.2 to 1.6 for SO_x, 1.1 to 1.2 for NO_x, and 0.8 for PM_{10}.

Comparing these results with the unit elasticity assumption applied in many studies (see Section 2), for the SO_x-sample we find that all of the estimates in Table 4 allow ruling out a unit elasticity at the 10% significance level, and all but the results in column 6 also at the 5% level. For the other pollutants, the estimates do not allow ruling out a unit elasticity. This suggests that the unit elasticity assumption might be a reasonably close approximation for NO_x and PM_{10}, but that it significantly underestimates the co-pollutant elasticity for sulfur oxides. In the next section we note that of the three co-pollutants, SO_x has by far the highest monetized air-quality co-benefits per ton of carbon emissions. These findings therefore suggest that assuming a unit elasticity can lead to a substantial underestimation of air quality co-benefits.

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 measure 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 of the two valuations.

To obtain marginal air quality co-benefits from a ton of CO_2 reduction, we multiply the climate policy induced co-pollution elasticity of Table 4 by the average co-pollutant intensity ratios of the electricity sector (Appendix Table A4) and by damage costs (EEA 2014a). We use the lowest estimate from Table 4 for these calculations, which thus might be seen as a conservative estimate. The monetized co-benefits, shown in Table 5, amount to 33 to 98 EUR/tCO_2 for SO_X, 9 to 24 EUR/tCO_2 for NO_X, and 4 to 10 EUR/tCO_2 for PM_{10} (in 2005 EUR). The joint magnitude of these benefits is 46 to 132 EUR/tCO_2, with SO_X accounting for more than 70% of the total.

Comparing this range to previous findings based on different methodologies, we take the average of the results from various studies for European countries reported by Nemet et al. (2010, Table A.1) and convert them into 2005 EUR. This yields overall co-benefits of about 50 EUR/tCO_2.

16. This information is also provided by the Botta and Koźluk (2014) dataset.

These results are not directly comparable since they are based on all sectors, whereas our estimates refer to the electricity sector, but this value lies within our estimated range.[17]

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).[18] The monetized air quality co-benefits therefore amount to 120% to 1,320% of this estimate of CO_2 climate damage costs.[19] These results suggest that substantially higher carbon prices can be justified based on air quality co-benefits alone.

Table 5: Monetary co-benefits of climate policy in electricity production

	Co-pollutant elasticities from Table 4	Average co-pollutant-to-CO_2 ratios in electricity production from Appendix Table A4	Damage costs from EEA (2014a) in 2005 EUR/t of co-pollutant		Monetary co-benefits in 2005 EUR/tCO_2	
			low	high	low	high
SO_x	1.241	0.0027523	9,792	28,567	33.45	97.57
NO_x	1.066	0.0019053	4,419	11,966	8.98	24.30
PM_{10}	0.783	0.0001981	22,990	66,699	3.57	10.35
Total					46.00	132.22

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 policy relevance.

This paper's investigation of co-pollutant elasticities with respect to CO_2 emissions is based on facility-level data, disaggregated across sources and across co-pollutants. It provides useful inputs not only for assessing the overall magnitude of air quality co-benefits from carbon mitigation policies, but also for the design of differentiated policies that take into account variations in co-pollutant damages per ton of CO_2. 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 1.0% reduction in emissions of SO_X, 0.9% of NO_X, and a 0.7% of PM_{10}. 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 1.6% reduction in SO_X and a 1.0% reduction in NO_X and PM_{10} emissions. Elasticities in the electricity sector for CO_2 reductions specifically induced by climate policies are at 1.2% to 1.8%, 1.1% to 1.5%, and 0.8% for SO_X, NO_X, and PM_{10}, respectively.

17. Technology effects are accounted for in our estimates, since policy-induced shifts are picked up in the empirical estimates.

18. 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).

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

These findings imply that assuming a co-pollutant elasticity of one may lead to an underestimation of overall co-benefits.

Monetizing the health impacts of policy induced co-pollutant emissions using EEA estimates of damage costs, we obtain air quality co-benefits of 46 to 132 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. Since co-pollutant emissions cause excess economic and health damages in the EU that are not sufficiently addressed by existing co-pollutant regulations, 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. Even if there is only one carbon price, however, the presence of positive spillovers from CO_2 regulation on underregulated co-pollutant emissions warrant a higher carbon price than one that only includes CO_2 damages.

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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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: 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 A3: Average ratios of co-pollutant emissions to CO_2 emissions

	U.S. 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.

Table A4: Average ratios of co-pollutant emissions to CO_2 emissions by NACE activity

	Production of electricity	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	0.0028			0.0035		
NO_X	0.0019	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 600 observations. Source: E-PRTR, authors' calculations.

Table A5: Effect of a log-point increase in CO_2 on log co-pollutants for differently populated regions in 2SLS models instrumenting CO_2 with its first lag

	Population density <500 per km^2 (1)	Population density > ≥500 per km^2 (2)
	Panel A: Dependent variable: ln(SO_X)	
ln(CO_2)	0.974***	1.109***
	(0.181)	(0.342)
Observations	5,053	1,455
No. of facilities	907	272
CS_{AR}	[0.652, 1.396]	[0.608, 2.368]
F^{eff}	20.23	12.89
	Panel B: Dependent variable: ln(NO_X)	
ln(CO_2)	0.851***	0.879***
	(0.057)	(0.087)
Observations	10,023	3,686
No. of facilities	1,764	646
CS_{AR}	[0.750, 0.975]	[0.717, 1.070]
F^{eff}	82.18	81.18
	Panel C: Dependent variable: ln(PM_{10})	
ln(CO_2)	0.743***	0.505
	(0.229)	(0.325)
Observations	2,364	592
No. of facilities	506	123
CS_{AR}	[0.335, 1.440]	[–0.281, 1.265]
F^{eff}	5.92	17.89

Notes: All specifications include facility and NACE-by-country-by-year 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.

Table A6: First-stage results of the 2SLS specifications in Table 4, explaining ln(CO_2)

	2SLS with climate policies instruments, facility and year FE (3)	= column 3 with GDP (4)	= column 4 with LASSO-picked climate policies instruments (5)	= column 5 with co-poll. policies (6)	= column 6 with up to cubic co-poll. policies (7)	= column 6 with up to cubic and lagged co-poll. policies (8)
			Panel A: SO_x sample			
Green certificates trading schemes	0.019	0.015				
	(0.020)	(0.026)				
CO_2 trading schemes	–0.000	–0.002				
	(0.034)	(0.032)				
White certificates trading schemes	–0.052***	–0.052***				
	(0.017)	(0.017)				
Wind feed-in tariffs	–0.015	–0.016				
	(0.014)	(0.014)				
Solar feed-in tariffs	–0.009	–0.007				
	(0.016)	(0.017)				
(CO_2 trading schemes^3)$_{t-2}$			–0.001*	–0.001**	–0.001***	–0.0004
			(0.0004)	(0.0004)	(0.0003)	(0.0003)
Green certificates trading schemes$_{t-5}$			–0.013	–0.018	–0.017	–0.046***
			(0.012)	(0.020)	(0.020)	(0.015)
White certificates trading schemes$_{t-5}$			–0.117***	–0.121***	–0.111***	–0.091***
			(0.019)	(0.016)	(0.018)	(0.021)
Observations	2,030	2,030	2,112	1,867	1,867	1,917
			Panel B: NO_x sample			
Green certificates trading schemes	–0.006	–0.022				
	(0.016)	(0.015)				
CO_2 trading schemes	–0.021	–0.030				
	(0.022)	(0.020)				
White certificates trading schemes	–0.019	–0.018				
	(0.021)	(0.019)				
Wind feed-in tariffs	–0.015	–0.015*				
	(0.009)	(0.009)				
Solar feed-in tariffs	–0.007	–0.002				
	(0.009)	(0.009)				
(CO_2 trading schemes x wind feed-in tariffs)$_{t-1}$			–0.003***	–0.003***	–0.004***	–0.004***
			(0.001)	(0.001)	(0.001)	(0.001)
(Green certificates trading schemes x white certificates trading schemes x solar feed-in tariffs)$_{t-2}$			–0.002***	–0.002***	–0.002***	–0.002***
			(0.0004)	(0.0003)	(0.0004)	(0.0003)
White certificates trading schemes$_{t-4}$			–0.020	–0.018	–0.019	–0.010
			(0.032)	(0.033)	(0.035)	(0.025)
White certificates trading schemes$_{t-5}$			–0.064*	–0.068*	–0.060	–0.043
			(0.034)	(0.039)	(0.044)	(0.036)
Observations	4,015	4,015	3,559	3,361	3,361	3,311

(continued)

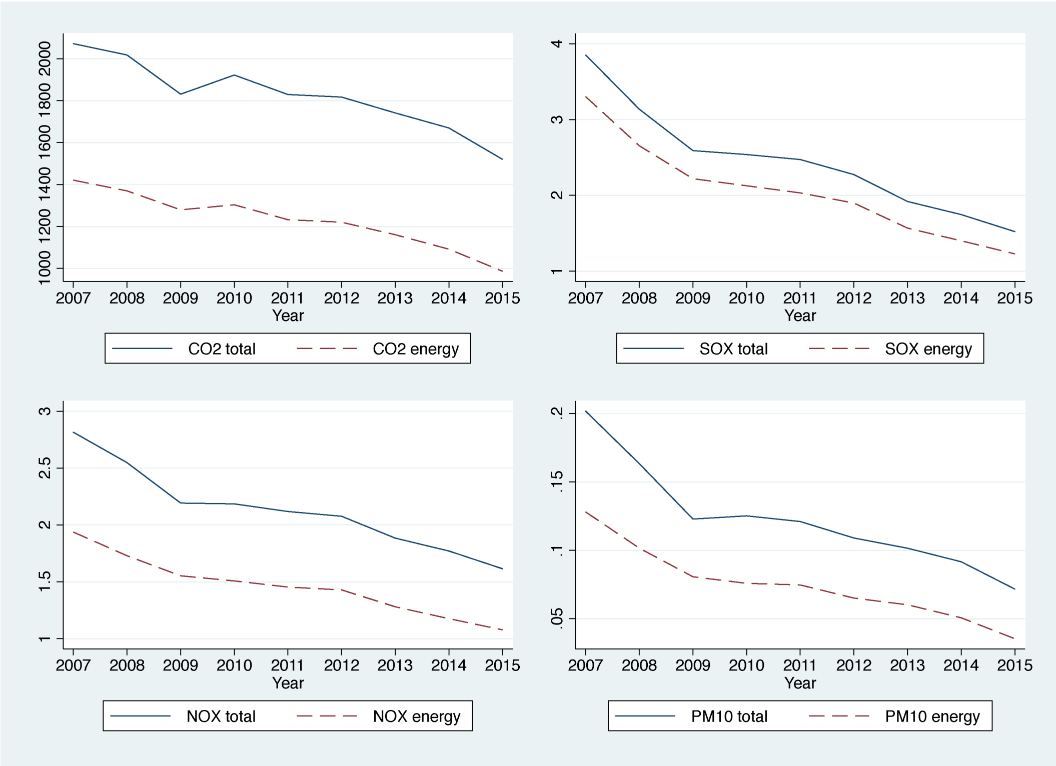
Table A6: First-stage results of the 2SLS specifications in Table 4, explaining ln(CO_2) *(continued)*

	2SLS with climate policies instruments, facility and year FE (3)	= column 3 with GDP (4)	= column 4 with LASSO-picked climate policies instruments (5)	= column 5 with co-poll. policies (6)	= column 6 with up to cubic co-poll. policies (7)	= column 6 with up to cubic and lagged co-poll. policies (8)
Panel C: PM_{10} sample						
Green certificates trading schemes	–0.002	–0.004				
	(0.025)	(0.030)				
CO_2 trading schemes	–0.016	–0.017				
	(0.022)	(0.020)				
White certificates trading schemes	–0.034***	–0.034**				
	(0.014)	(0.014)				
Wind feed-in tariffs	0.002	0.002				
	(0.014)	(0.014)				
Solar feed-in tariffs	–0.014	–0.013				
	(0.020)	(0.018)				
(CO_2 taxes x Wind feed-in tariffs)$_{t-3}$			0.065***	0.067***	0.067***	0.067***
			(0.005)	(0.006)	(0.006)	(0.005)
(CO_2 taxes x Wind feed-in tariffs)$_{t-5}$			–0.066***	–0.068***	–0.068***	–0.067***
			(0.003)	(0.004)	(0.004)	(0.004)
Green certificates trading schemes x white certificates trading schemes x solar feed-in tariffs)$_{t-1}$			–0.003***	–0.003***	–0.003***	–0.003***
			(0.0003)	(0.0002)	(0.0002)	(0.0002)
(White certificates trading schemes^3)$_{t-3}$			–0.002***	–0.001***	–0.002***	–0.001***
			(0.0001)	(0.0002)	(0.0002)	(0.0003)
Observations	989	989	974	908	908	906

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

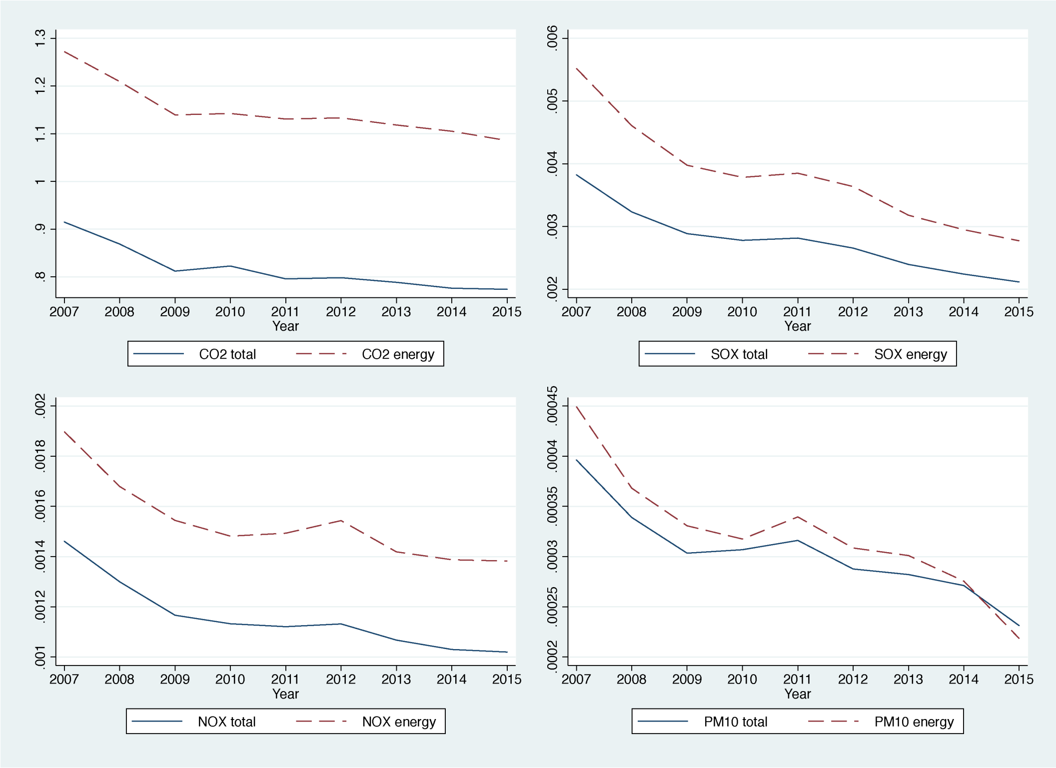
Source: E-PRTR, Botta and Koźluk (2014), authors' calculations.

Figure A1: Total annual emissions (in mio t) of sample facilities for the total economy and the energy sector



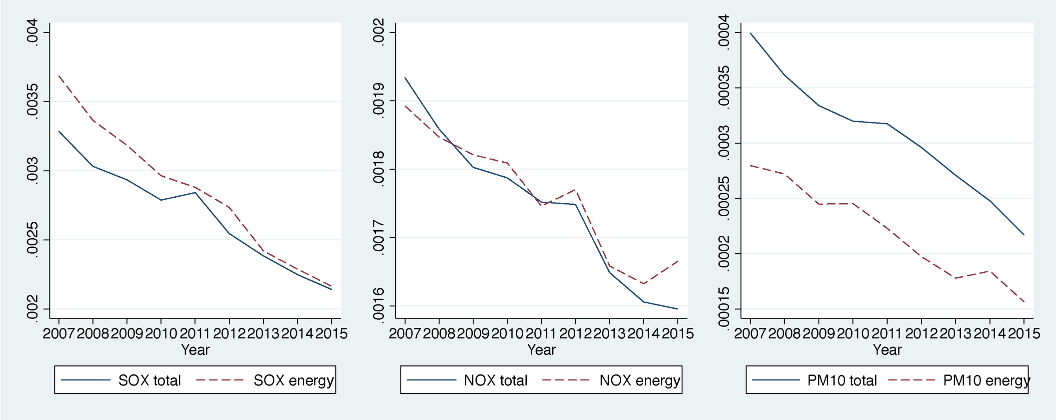
Source: E-PRTR, authors' calculations.

Figure A2: Average emissions (in mio t) per facility for the total economy and the energy sector



Source: E-PRTR, authors' calculations.

Figure A3: Co-pollutant intensity ratios over time for the total economy and the energy sector



Note: Co-pollutant intensity ratios are calculated as average facility-level ratio between co-pollutant and CO2 emissions.
Source: E-PRTR, authors' calculations.

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