How Effective are Emission Taxes in Reducing Air Pollution?

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October 2022

Preliminary version

ABSTRACT

This paper examines the role of environmental taxes in reducing emission output. Using unique satellite data to observe levels of nitrogen dioxide (NO2), we leverage an emission tax introduction in 2013 in the Autonomous Community Valenciana. We find that this environmental tax reduced NO2 levels by 1.2%. While the effect does not depend on prevalence of dirty versus clean firms in an area, we find that the NO2 burden is reduced more substantially in areas with a higher density of firms and in areas with innovative and large firms.

Keywords: Environmental taxation, emissions, greenhouse gases, nitrogen oxide

JEL classification: H22, H23, H32

Jacob and Zerwer acknowledge funding by the German Research Foundation (Deutsche Forschungsgemeinschaft), Project-ID 403041268 – TRR 266 Accounting for Transparency. We acknowledge the free use of tropospheric NO2 column data from the OMI sensor from http://www.temis.nl. We thank Lisa Hillmann, Barbara Stage, and seminar participants at the WHU – Otto Beisheim School of Management for helpful comments and suggestions.

1 Introduction

Rising sea levels, more frequent and intense climate-induced extreme events, and environmental damage show that there is a price to be paid on the emission of greenhouse gases such as carbon dioxide (CO2) or methane (IPCC, 2022). While the debate about CO2 is omnipresent, other anthropogenic emissions such as NOx are less discussed in public despite their potential harm. NOx is predominantly produced by combustion industrial production processes. For this reason, NOx and CO2 emissions are strongly linked and NOx is a robust proxy for combustion CO2 (Reuter et al., 2019; Liu et al., 2020; Hakkarainen et al., 2021). In addition to several negative health effects attributed to high NOx emissions such as coughing, wheezing, asthma, and other respiratory infections (EPA, 2022a), especially environmental effects can be significant when NOx levels are high. NOx interacts with water, oxygen and other chemicals in the atmosphere and can lead to acid rain (EPA, 2022a). This harms sensitive ecosystems such as lakes or forests and contributes to the nutrient pollution in coastal waters.

While the international community was able to agree on limiting global warming and stopping environmental damage caused by greenhouse gases and air pollutants, the paths to achieving this goal and especially the distribution of associated costs and efforts for necessary action measures is unclear. One frequently discussed path towards reduced emissions are emission taxes as "their principal rationale is that they are generally an effective tool for meeting domestic emission mitigation commitments" and "provide a clear incentive for redirecting energy investment towards low-carbon technologies" (IMF, 2019). As most NOx emissions can be attributed to industrial emissions (EPA, 2022b), firms are often seen as driver of innovation in clean technology to curb emissions (e.g., Krass et al., 2013 or Brown et al., 2022). Hence, taxing polluting firms seems to be a viable option for policy makers. However, empirical evidence on the effectiveness of taxes in reducing emissions is scarce.

In this paper, we thus examine how emission taxes on industrial NOx pollution affect NO2 levels, the most common NOx form. Understanding whether tax policy is effective in achieving this goal is important since environmental and health damages due to NOx can be severe while economic costs can be higher than intended (Jacob and Zerwer, 2022). In theory, the effect of emission taxes on emission levels appears straightforward. With an emission tax, firms face a new cost directly related to their emission output, which should reduce emission levels (Rafaty et al., 2020). This is a standard response considering Pigouvian pollution pricing and an adjustment of the market failure arising from pollution (Metcalf, 2019). However, since the price of emission taxes may be passed on by 'dirty' firms to 'clean' firms as evidenced by 'clean' firms cutting investments as much as 'dirty' firms in response to an emission tax (Jacob and Zerwer, 2022), the effectiveness of an emission tax in curbing emissions is ex ante unclear. This is, while a net decrease of emissions following the introduction of a respective tax seems likely, it is unclear where and under which circumstances emissions are cut more or less.

Prior research on emission levels and their relationship with emission taxes faces several data-related limitations. Due to the lack of data and presumably also lack of variation in policy, earlier studies analytically model the emission response (e.g., Goto, 1995, Nakata and Lamont, 2001, Wissema and Dellink, 2007, Lu et al., 2010). Later empirical studies use emission data that are at the sector level or an even more aggregated level such as at country level (e.g., Davis and Kilian, 2011, Lin and Li, 2011 Metcalf and Stock, 2022, Best et al., 2020, Bayer and Aklin, 2020, Pretis, 2022). As a result, there is large variation in the estimated effects, ranging from zero aggregate effects (e.g., Pretis, 2022) to very large effects for certain sectors or plants (Andersson, 2019, Rafaty et al., 2020). Moreover, studies using more granular data at the plant or measuring station level only approximate emissions synthetically using input factors such as fuel or electricity (Petrick and Wagner, 2014, Martin et al., 2014, Dussaux, 2020), cover only a comparably small area due to a limited number of measuring stations (Abrell et al., 2011, Klemetsen et al., 2016), and are prone to uncertainties through a possible lack of representativity of the spatial positions of the stations given the high spatial variability of atmospheric constituents (Zhu et al., 2020). Plant level data also have the disadvantage that the data do not fully capture the entire economic activity leading to emissions. These data do not cover emissions from commercial traffic which also contribute to overall emissions and therefore should not be neglected, especially when informing the policy debate. Hence, it is still an open empirical question whether and to what extent emission taxes can curb emissions.

In this paper, we overcome these challenges and examine emission levels by using granular data and a tax reform in a Spanish Autonomous Community. First, we use satellite data from the Ozone Monitoring Instrument (OMI) (Levelt et al., 2006) over the period 2009-2016 that allow us to measure the NO2 burden at the very local level. We use data on yearly average tropospheric NO2 column densities on an equidistant grid layered on Spain of 0.125° latitude and 0.125° longitude spatial resolution (equivalent to areas of about 10 × 10 kilometers (km), or about 6.2 times 6.2 miles) (Boersma et al., 2011). Such satellite-based observations of tropospheric NO2 column densities have been extensively used to infer NOx emissions (e.g., Silvern et al., 2019 and references therein; Voigt et al., 2022). Second, we leverage the introduction of an emission tax in the Spanish region of the Valencian Community in 2013 that taxes the amount of SOx and NOx emitted. The Comunidad Valenciana is our treatment group and matched regions of the rest of Spain comprise our control group. This setting has several advantages. First, it is the only tax reform on NOx emissions during our sample period in Spain. Second, despite being local, the emission tax is economically significant contributing an additional €30 million in annual revenue to the local budget (Europa Press, 2012), added about 13% to local firms' tax bills, and triggered investment cuts (Jacob and Zerwer 2022). Third, the within-country setting allows us to explore differences in emission levels across Spain while holding general economic conditions and regulations on a national level constant.

In our difference-in-differences (DiD) analysis, we show that the local emission tax leads to a significant reduction of NO2 levels during the observed period. That is, NO2 levels in a 10 × 10 km area located in the treatment group of the Valencian Community are cut by around 1.2% due to the emission tax. Given that similar emission initiatives that introduced taxes on *input* factors such as gasoline or other fuels led to a cut in CO2 emissions of 1% to 7.3% (Martin et al., 2014, Rafaty et al., 2020) or the fact that emission taxes reduced firm or plant level emissions by up to 45% (e.g., Klemetsen et al., 2016), our finding seems to be economically significant. However, it also indicates that when using granular data on emission *output* levels, the estimated effect is rather at the lower end of prior estimates. The finding of reduced NO2 levels is robust to different alternative tests and estimation methods.

In addition to the average response, we also explore the heterogeneity in the response across regions. The objective of these tests is twofold. First, these tests can inform policymakers which regions benefit most, and which benefit least from changing NOx taxes. Second, these tests help us assessing some of the mechanisms through which emission taxes can reduce emission levels. In our first tests, we show that emissions are reduced more in areas with high industrial activity. First, defining industrial activity by the actual number of firms in an area, in areas with many firms, emissions are reduced by about 2.5% while there is no change in emission in areas with only a few firms. Second, defining industrial activity by the degree of urbanization, emissions are reduced by about 5% in urban areas with high industrial activity while there is almost no change in rural areas where less firms are active in our sample. This is consistent with the expectation that areas with many firms have more potential to reduce emissions than areas with fewer firms given that NOx emissions mostly result from industrial activity.

We also show that when splitting the sample into areas with more 'clean' versus 'dirty' firms, we do not see a significantly stronger reduction for areas with more 'dirty' firms. We find a similar but this time significant reduction in areas with 'clean' firms. Hence, while emission policies are designed to make the polluter pay targeting ‘dirty’ firms, this result suggests that emission taxes affect not only those firms that are mainly responsible for emissions, but also hits cleaner sectors. One explanation is that ‘dirty’ firms can pass on the emission tax burden to ‘cleaner’ firms, who also respond to emission taxes by cutting investments (Jacob and Zerwer, 2022). It thus appears as if emission taxes hit all industrial areas at least partially, irrespective of the actual prevalence of ‘dirty’ firms in that area.

Next, we test for a difference in the response of areas with more versus fewer firms with high intangibles to test for the notion that emission reduction often is stronger for firms with R&D activity and technological innovation. Consistent with this prediction, we find that those areas with more innovative firms cut emissions more than areas with fewer or less innovative firms. This indicates that innovation and R&D activity indeed seems to be key when it comes to cutting emissions and meeting targets. We also test for the notion that larger firms potentially have more resources and thus more potential to reduce emissions post reform. We confirm this idea and find a negative and significant effect for areas with larger firms. This effect is statistically different from the effect for areas with smaller firms.

We contribute to the literature in two ways: First, we add to the literature on emission taxes using the merits of homogeneously gridded and integrated satellite-based data. To measure emissions, previous literature either modelled emission data or used proxies or sensor data that were highly aggregated to administrative units or sectors (see, e.g., Omrani et al., 2020 or Zhen et al., 2019). If firm level data are used, firm level emissions focus on information on free allocation of emissions allowances (Abrell et al., 2011) or firm data only comprise limited information at the firm or plant level (Klemetsen et al., 2016). We overcome these limitations by using highly granular spatial NO2 emission data coupled with data on local economic activity to capture a holistic picture of economic activity related to the emissions. Another advantage of using NO2 data is that this tracer for anthropogenic combustion processes remains rather local and close to the sources as it dissolves locally after a few hours and is hardly advected into other regions, thereby limiting the risk of emission leakage (Antweiler and Gulati, 2016).[2] With this data, we contribute to studies measuring emissions at an aggregate level by showing that emission taxes can reduce emissions (Pretis, 2022). However, our estimate is below country level estimates (Metcalf and Stock, 2022). Importantly, our estimate is much smaller than plant level or sector specific emission effects (e.g., Andersson, 2019, Klemetsen et al., 2016), indicating the importance to also capture effects beyond the actual plant or the specific potentially emission intense industry. Plant or sector level tests may overstate the aggregate response as emissions that stem from buildings, commercial traffic, and transport need to be considered when exploring the effectiveness of environmental initiatives even though industrial processes are the main contributor to overall emission levels.

Second, we contribute to the literature on the real effects of environmental and social responsibility for firms. Previous research shows that investors react to positive and negative corporate social responsibility (CSR) events (Krüger, 2015) and that 'dirty' firms are punished through divestment (Oehmke and Opp, 2020). Further, a firm's market value, productivity, or sales growth can depend on CSR standards and their realization (Flammer, 2015, Dowell et al., 2000). Matsumura et al. (2014) also find that firms that do not properly disclose their emissions under the existing environmental, social, and governance (ESG) regime face a higher capital market discount. While the literature on the real effects of ESG mostly observes the effects of existing corporate standards as well as disclosure requirements, we add to this debate by considering environmental taxes and, more importantly, environmental outcomes in the form of NO2 emissions. With our finding that an emission tax, decreases the NO2 burden, but at rather modest levels, we contribute to an understanding of the real effects of environmental

[2] Our Spanish setting also overcomes potential identification of existing studies that, for example, leverage the implementation of a carbon tax in British Columbia that shares a border with Washington (US), Alberta and Yukon (both Canada) (Pretis, 2022, Lawley and Thivierge, 2018, Erutku and Hildebrand, 2018, Rivers and Schaufele, 2015). Policies in Canada might spill over to the US and vice versa.

taxes, particularly on the key air pollutant NO2 with many detrimental effects for human beings and the environment but also being a robust proxy for combustion CO2.

Finally, we add to the policy debate about the effectiveness of emission taxes. By showing that emission taxes lead to only a modest decrease of emissions that varies based on intensity of industrial activity, technological innovation as well as firm size but that this effect is not fully related to the prevalence of cleaner versus dirtier industries, we provide a basis to discuss the addition of innovation stimulation policies as well as policies directly targeting specific areas (e.g., industry areas) more directly to the standard policy toolkit to reach net-zero targets.[3] This is particularly important as existing literature shows that emission taxes can be costly for 'dirty' and for 'clean' firms (Jacob and Zerwer, 2022). Thus, a careful design of emission taxes and a combination with other measures can help optimize the desired outcomes. In particular, if policymakers intend to target dirty industries, tax policy may not be the first best solution.

2 Institutional Background

2.1 NOx and its Effects

Nitrogen oxides (NOx = NO + NO2) are primarily emitted when fossil fuel is burned (EPA, 2022a). This can be by the emission from cars, trucks, or other vehicles, from buildings (e.g., heating), but mainly comes from industrial emissions of industrial production processes. Indeed, data from EPA (2022b) show that only 1-5% of U.S. NO2 emissions come from non-industrial processes. In Spain, around 91% of NO2 emissions come from industrial process emissions and agricultural soils, 4% from transportation, 3% from buildings, and 1% each from other industrial combustion and the power industry (Figure 1; European Commission, 2022). Thus, our assumption that most of the NO2 emissions stem from industrial activity seems to be plausible as firms are the largest contributor to NO2 emissions.

[3] Net-zero targets are targets set by many countries after the Paris Agreement to reach net-zero for CO2 and other greenhouse gas emission within a certain time i.e., to produce as much CO2/greenhouse gases as remove from the atmosphere. As of March 2022, 33 countries and the European Union have set such a target, either in law or in a policy document. More than 100 countries have proposed - or are considering - a net zero target (ECIU, 2021).

In addition to several negative health effects being attributed to high NOx emissions, environmental effects can also be significant when NOx levels are high (EPA, 2022a). NO2 and other NOx interact with water, oxygen, and other chemicals leading to acid rain (EPA, 2022a). The latter can harm ecosystems and contributes to the nutrient pollution in coastal waters. Thus, in recent years, policy makers have developed several approaches to tackle high NOx levels and reduce potential negative consequences. Policy responses range from softer forms such as air quality monitoring, modeling, and reporting to putting a hard price on pollution by introducing emission taxes or other pricing schemes. Particularly the later form of taxes on emissions have gained increasing popularity in recent years. For instance, while Sweden, Italy and Denmark were early adopters by introducing a charge on NOx in 1992 (IEA, 2017) and 1998 (EU Commission, 2015, 2016) respectively, other countries such as Estonia, Norway, and other Eastern European countries adopted similar taxes only in the early 2000s.

The quantity of NOx emitted by firms depends largely on the firm size and industry, the availability of abatement technologies as well as the explicit and implicit price of emissions. Moreover, NOx is a ground level greenhouse gas, which is not very stable and therefore cannot be transported too far by wind. Under average conditions, NO2 lasts in the atmosphere for only a few hours up to one day. This local and temporary preciseness can be also seen in other research using the same data that shows “the weekend effect” by emissions going down on Saturdays or Sundays (Bucsela et al., 2007). Thus, NO2 has the advantage that it can be easily attributed to a specific location and to the local economic activity without measuring any additive effects from earlier emissions or emissions generated at a different location and is a good proxy to estimate potential effects of emission policies.

2.2 Exploiting Regional Environmental Taxes in Spain

To explore the effect of NOx emission taxes on actual NOx emission levels, we leverage the introduction of a local emission tax in 2013 in the Spanish Comunidad Valenciana (see also

Jacob and Zerwer, 2022 for more details). Following the new law introduced as of January 1, 2013, SOx and NOx within the community are taxed between €9 and €50 per ton, depending on firm-specific consumption levels. In Figure 2, we illustrate the exact timeline of the introduction of the tax (see, also, Jacob and Zerwer, 2022).

To observe a potential change in emissions, this setting is advantageous for several reasons. First, it is the only tax reform on NOx emissions during our observed period in Spain. While other local emission taxes have been introduced during the early 2000s, the introduction in the Valencian Community allows us to compare it to the rest of Spain without confounding emission reforms. Other local environmental reforms took place during our sample period in Spain. However, none of them is related to emissions. We control for these reforms in a separate test. Especially as existing studies struggle to find an appropriate control group (see for instance Bayer and Aklin, 2022) as most emission reforms are at the federal level, leveraging a regional reform is advantageous. Second, despite being local in nature, the Valencian emission tax is economically significant. It is estimated to have raised close to an additional €30 million in annual revenue (Europa Press, 2012). The reform increased corporate tax bills by, on average, 13%[4] (and more for some firms) and caused substantial compliance and consulting costs; it also triggered investment responses (Jacob and Zerwer 2022).

Due to its economic significance, we expect the reform to affect emission levels, also because industrial activity is the main driver of NO2 emissions. This might not be the case for a marginal tax increase. Third, the within-country setting allows us to explore differences in emission levels across Spain while holding general economic conditions and regulations on a federal level constant. Since only few areas share borders with other countries, i.e., France or

[4] To calculate this amount, we follow Jacob and Zerwer (2022) who calculate the absolute tax burden using the rates given by law and then compare it with the total tax burden of firms. As we include all type of firms (and not only standalone firms), the average firm in our sample has a lower overall tax burden, resulting in the 13% costs.

Portugal, the potential for spillover effects is limited. Thus, it appears that our setting is suitable for our purpose of exploring the effect of an NOx emission tax on actual emission levels.

3 Data Preparation and Merging

3.1 Satellite Data

To measure daily and area-specific NO2 levels in Spain for the years 2009 to 2016, we use sensor data from the Ozone Monitoring Instrument (OMI) on board of NASA's AURA satellite (Levelt et al., 2006). OMI is a nadir-viewing spectrometer on a polar sun-synchronous orbit with a local equator crossing time at 1:45pm local time. With its wide swath and daily global coverage, it has been providing observations of tropospheric NO2 vertical column densities since 2004 at a spatial resolution of 13 km × 24 km at nadir. In this study, we apply gridded tropospheric NO2 vertical column densities (QA4ECV version 1.1) at an equidistant spatial sampling of 0.125° × 0.125° (Boersma et al., 2011). The NO2 values are vertically integrated throughout the troposphere with the unit µmol/m^2.

Tropospheric NO2 is a representative short-lived tracer for anthropogenic emissions from transport, energy production, and industrial processes into the boundary layer (Müller et al., 2022) with small possible contributions from natural emissions from lightning (Perez-Invernon et al., 2022) and soil (Lu et al., 2021). Therefore, tropospheric NO2 is extensively used to infer NOx emissions (Silvern et al., 2019, Kaynak et al., 2009), quantify lockdown effects during the COVID-19 pandemic (Voigt et al., 2022, Liu et al., 2021), examine economic impacts (Montgomery and Holloway, 2018, Bichler and Bittner, 2022), and identify urban pollution islands and their long-term trends (Erbertseder et al., 2015, Georgoulias et al., 2019). As substantiated by Goldberg et al., (2021) and Geddes et al., (2016) there is a strong correlation of tropospheric NO2 with surface NO2 concentrations.

As there is a certain influence on NO2 variability by meteorological conditions, we follow prior literature and use a yearly time period for integration to reduce the volatility possibly caused by weather and similar factors (Huang et al., 2017; Song et al., 2019; Müller et al., 2022). The average uncertainty of the satellite-based NO2 observations due to the tropospheric air mass factor over Europe is quantified by 18 to 26% per pixel (Boersma et al., 2018). However, a detailed error analysis for individual retrievals exhibits a strong variation of these estimates (Boersma et al., 2004). Parameters such as cloud fraction, surface albedo, surface pressure, and the a priori NO2 profile shape contribute to the overall error budget. Since the yearly mean is calculated from daily observations (with sample size n) and the standard error decreases by $1/\sqrt{n}$, the overall error can be strongly reduced using annualized data. Regarding the systematic error of the NO2 data, a negative bias is evident compared to ground-based measurements (Celarier et al., 2008). However, since we analyze relative variations from year-to-year, this systematic error does not impact our findings.

Compared to in-situ measurements from ground-level stations, a major advantage of satellite-based observation is the area-wide coverage and consistency of high spatial resolution. NO2 values are homogeneously integrated with the same spatial resolution. Hence, they represent the same conditions and are less prone to issues of representativity as is the case for measurement stations (Zhu et al., 2020). This ensures the spatial comparability of the data across space. Out equidistant sample further reduces the influence of artificial and inconsistent spatial units such as administrative boundaries. In other studies, fuel or energy data is used as input. This bottom-up approach for quantifying emissions allows a sector specific analysis.

While the data have clear advantages, the data come at a cost of several disadvantages. For example, uncertainties remain on the spatiotemporal variability of the resulting emission because many assumptions need to be made on the emission rates and emission factors (e.g., when and where what amount of fossil fuel is combusted at which temperature and at which efficiency). The satellite observations, however, enable a quantification of the resulting total NO2 burden from all emitting sources, which cannot be disentangled in sector-level data.

Moreover, optical measurements from satellite rely on backscattered solar radiation. Hence, no data is available during night or under cloudy conditions. While in-situ measurements on the ground are direct measurements, the quantities are indirectly obtained from satellite through the retrieval of trace gas amounts from measured spectra. Despite the necessary assumptions during the retrieval of atmospheric quantities, the characterization of uncertainties and error propagation has improved significantly in the last decades. While in-situ measurements can be performed continuously during day and night, the repetition rate of satellite observations is confined to the orbit type. However, one clear advantage of satellite observations vis-à-vis in-situ measurements is that our approach captures all overall NO2 concentration and not just one specific source (e.g., a chimney). Ultimately, it is the local overall NO2 concentration that is relevant for health damages and pollution, thereby speaking directly to policy goals.

3.2 Firm Level Data and Merging Databases

To measure and to control for local economic activity, we append our satellite data with aggregated firm data. For our firm data, we use all available data on Spanish firms from Bureau van Dijk's Amadeus database over the period 2009-2016. Our analysis is based on all unconsolidated financial statements. In contrast to consolidated balance sheet information, as provided, for example, in Compustat Global, unconsolidated data allow us to locate the activity of a single firm to match economic activity with the spatial emission data. We start with all available firms and exclude firms with total assets below €50,000, fixed assets below €5,000, and those that do not report earnings before interest and taxes. We also exclude observations with negative sales, total assets, or cash as these observations are most likely misreporting. To match our firm and emission data, we use geocoding to add the geographic longitude and latitude to all available postcodes of the Spanish Amadeus firm data. We consider full postcode level data (in contrast to full address data) to be sufficiently granular to match our datasets. Since 5-digit Spanish postcode areas are fairly small, these postcodes ensure a precise matching of firm and emission location. We use the OpenCage STATA code that matches the closest longitude and latitude to a given postcode (where we use the midpoint). In a second step, we locate postcodes to the pixel resolution of our satellite data so that we can assign each postcode to the 10 × 10 km from the satellite data. In a third step, we weight our main economic variables by sales to ensure that our firm level economic control variables reflect the local economic activity. Finally, we add additional regional variables such as population and car registration based on two-digit postcodes as more granular data are not available. We obtain this data from the Instituto Nacional de Estadística (Spanish National Statistics Institute).

This gives us a full panel data set of emission data as well as economic and demographic control variables. We also make one final modification: We exclude all areas without any meaningful economic activity, that is, any area of 10 × 10 km with fewer than five firms. We choose five firms as this is below the bottom quartile of the existence of industrial activity. After these steps, we arrive at our final sample of 15,374 observations from 1,957 areas.

4 Empirical Setting

4.1 Estimation Strategy

We exploit the local emission tax refom in a DiD approach. As shown in Figure 3, the treatment comprises the Autonomous Community Valenciana identified per two-digit postcode (i.e., observations with the two-digit postcode equal to 03, 46, or 12). As our control group, we use all other Autonomous Communities of Spain. We thus estimate the following equation:

$$Emissions_{i,t} = \alpha_0 + \beta_1 Treatment_i \times Post_t + \gamma X_{i,j,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t} \quad (1)$$

where the dependent variable, $Emissions_{i,t}$, is the natural logarithm of the amount of emission measured in μmol/m² per area i in year t. While it is common in the literature to simply use the absolute amount as our main dependent variable (for instance, see Müller et al., 2022), we use the natural logarithm of the absolute amount of NO2 content as our main dependent variable for two reasons. First, the raw emission values are highly skewed (skewness is above 2.3).

Second, the log transformation allows us to more easily interpret the coefficient estimate as a percent change (with some simple calculations). The dummy variable *Treatment* is equal to one for area i in the Valencian Community where the emission tax was introduced in 2013 and zero otherwise. The dummy variable *Post* is equal to one for years 2013 to 2016, and zero otherwise. Since our regression sample starts in 2009, we use four pre-reform and four post-reform years. The main variable of interest is the DiD coefficient, namely the interaction *Treatment* × *Post*. We expect to find that relative to areas in other places of Spain, the areas in the Community Valenciana decreased their emissions after the reform ($\beta_1 < 0$).

The baseline regression also includes a vector of control variables ($X_{i,j,t-1}$), building on prior economic literature on investment decision (e.g., Badertscher et al., 2013, Shroff et al., 2014, Shroff, 2017, Fox et al., 2022) but also literature using similar emission data (Müller et al., 2022). We further include area fixed effects (α_i) as well as year fixed effects ($\alpha_{ind,t}$) to account for time-invariant area characteristics and general yearly trends. The control variables are lagged by one year. Specifically, we control for *Firm Size* (defined as the natural logarithm of aggregate sales), *Number Firms* (defined as the natural logarithm of the number of firms within an area), *Population* (defined as the natural logarithm of the absolute population count), and *Past Emissions* (defined as a dummy variable being equal to one if above median emissions in past years). We also include weighted averages of the following firm characteristics in an area year: *Investment* (defined as change in fixed assets scaled by total assets), *Sales Growth* (defined as the natural logarithm of sales), *Profitability* (defined as net income scaled by total assets) and *Tangibility* (defined as fixed assets over total assets). As at least a small part of NO2 emissions is caused by cars and emissions from road traffic (European Environment Agency, 2022), we control for its intensity by including *Car Registrations* (defined as car registrations per inhabitants). We cluster standard errors at the area level.

Another important research design choice relates to entropy balancing. Because emission level data is noisy and because regions differ in their economic activity, we ensure that the treated 10 × 10 km areas are comparable to the 10 × 10 km control areas prior to the emission tax introduction. For this reason, we balance our sample using pre-treatment emissions of 2009, 2010 and 2011, the dummy variable for areas with above median emission in the past, firm size, and the area size in terms of number of firms as well as the firm control variables that differ the most between the two groups, namely, car registrations, sales growth, investment, profitability, and tangibility. The approach of using matching difference-in-difference estimators, including matching on past outcomes, is frequently used to ensure the treatment and control group are more comparable and the resulting estimator less biased and popular for research evaluating policy measures (see, e.g., Blundell and Costa Dias, 2000, Girma and Görg, 2006, Ham and Miratrix, 2022), particularly when it comes to environmental policies (see, for instance, Boampong, 2020). According to these authors, combining matching estimators with a difference-in-difference design can "improve the quality of non-experimental evaluation results significantly" (Blundell and Costa Dias, 2000, p. 438). We thus include three lags of pre-treatment outcomes to reduce the potential bias and to increase the reliability of the estimates (see, e.g., Ham and Miratrix, 2022). The final weights in our tests are illustrated in Figure 4. Matched areas are mostly located in the Autonomous Communities of Galicia, Castilla y Leon, Castilla la Mancha, Andalucía and the upper part of Catalunya. In contrast, the cities of Madrid and Barcelona and surroundings are assigned only very small weights. This is plausible as the areas around Madrid and Barcelona with over 5 million inhabitants each differ from Valenciana and its biggest cities Valencia and Alicante. Instead, the control group covers areas around Seville, Malaga, Murcia, Bilbao, or Oviedo, which are more comparable to Valencia or Alicante in terms of total population than Madrid or Barcelona.

4.2 Descriptive Statistics

Table 1 reports statistics for the variables of our sample of 15,374 observations used for the baseline analysis. The variable definition can be found in the Appendix. All area level control variables are winsorized at the first and 99th percentiles. Areas, on average, have emissions of 28.12 µmol/m². The average (median) area has investment of 4.6% (3.7%), sales growth of 4.2% (3.8%) and a profitability of 2.8% (2.3%). Panel C presents evidence of how the area of our treatment and control group compare. For most variables, we see a difference between areas located in Valenciana and those in the rest of Spain. For instance, areas in Valenciana have on average more firms within a single area, have higher past emissions and a higher profitability. For this reason, we use a balanced sample in all our tests as discussed above. Table 1, Panel D shows descriptive statistics for the balanced panel.

4.3 Identifying Assumptions

Next, we assess the parallel trend assumption prior to the introduction of the emission tax in 2013. The underlying assumption for our chosen empirical approach is that, absent of the reform in 2013, emission levels in our treatment (Valencian community) and our control group (rest of Spain) would have evolved similarly. While we cannot test this argument after the reform, we conduct a parallel trend test for the pre-reform years 2009 to 2012. Figure 5 shows the difference in emission levels between areas located in the Valencian Community and the other areas as well as the 95% confidence intervals. The figure suggests that prior to the reform, we see a parallel trend of our treatment and control group allowing us to proceed with our empirical approach (which is due to our entropy balancing approach).

5 Results

5.1 Graphical Evidence of the Emission Reductions

We start our analysis by illustrating the NO2 data in a map of Spain over time. Figure 6 shows average yearly NO2 levels across Spain from 2009 until 2016. Darker grey areas indicate areas with high emission levels (with black being the maximum of 80 µmol/m²) and light grey represent areas with fewer emissions (with white being the minimum of 0 µmol/m²). As expected, one can clearly see the largest cities such as Madrid or Barcelona as indicated by the darker shades. While there is an overall trend of reduced emissions over time (more light grey areas and less dark spots), particularly the Comunidad of Valenciana seems to have less emissions after the introduction of the emission tax.

This can also be seen when zooming into the Autonomous Community Valenciana and the neighboring provinces in Figure 7. The figure shows the difference of Valencian emissions to the Spanish yearly average NO2 levels for the years before (2009, 2010, 2011), during (2012, 2013) and after (2014, 2015, 2016) the tax reform. We set the maximum for the difference to the average emissions this time to 15 µmol/m² and the minimum to -25 µmol/m² to observe differences on a more granular level. While NO2 levels are generally quite high in the pre-reform years (darker grey areas) with a peak in 2012, the graphical evidence suggests that there is a reduction in NO2 emissions in post reform as indicated by a lightening of the grey areas, in particular, in the treated areas (highlighted in red) of each map. Hence, it appears as if there are lower NO2 levels in the Valencian Community after the tax reform.

5.2 Baseline Results

In Table 2, we test the emission level response in a regression analysis of areas located in the Valencian Community (treatment group) versus the entropy-balanced rest of Spain (control group) from Equation (1). In column 1, we estimate the regression using year and area fixed effects, but without control variables. The DiD coefficient (*Treatment* × *Post*) is negative and significant at the 10% level. Once we include controls, the estimate remains very similar. The results indicate that emissions in an area are cut by around 1.2% following the introduction of the emission tax in 2013. Given that similar emission initiatives that introduced taxes on *input* factors such as gasoline or other fuels led to a cut in CO2 emissions between 1% and 7.3%

(Rafaty et al., 2020, Martin et al., 2014) or the fact that emission taxes reduced firm or plant level emissions by up to 45 % (e.g., Klemetsen et al., 2016), our finding, while being economically significant, is at the lower end of prior estimates.[5] Put differently, our findings indicate that when actual emission *output* levels on a granular level, the estimated effect are much smaller than plant or sector-level data. One potential reason is that our data a able to capture all other sources of NOx emissions such as commercial traffic and transportation. To inform policymakers, it is, however, critical and important to obtain a holistic picture of emissions and to account for all potential sources of emissions.

5.3 Sensitivity and Robustness Tests

5.3.1 Alternative Dependent Variables

We further test the robustness of our results by using two alternative dependent variables in our main specification. First, we use the absolute amount of NO2 as common in the literature using similar data (see, for instance, Müller et al., 2022). The results are presented in column 1 of Table 3. The coefficient remains negative and significant. Second, we lag the treatment status by one year (column 2) to capture adoption effects that may take time. Also, for this dependent variable the DiD coefficient of *Treatment* × *Post* remains negative and significant. While the size of the two coefficients is not comparable due to their different nature, the statistical significance is not affected.

5.3.2 Alternative Model Specifications

Next, we test the robustness of our findings to alternative model specifications as we restrict our analysis to certain requirements. First, we further strengthen the assumption that areas are required to have at least five firms to requiring at least 10 firms[6] (column 3 of Table 3). The

[5] Previous literature mostly focused on the introduction of an emission tax on input factors such as fuel or gasoline. For instance, it observes the carbon tax on gasoline in British Columbia in Canada (Rivers and Schaufele, 2015, Lawley and Thivierge, 2018, Pretis, 2022), a carbon tax on transport fuels in Sweden (Andersson, 2019)

[6] In untabulated tests, we also use alternative number of firm restrictions (e.g., allowing to only have one firm per area). Robustness is also not affected by these changes.

DiD coefficient of *Treatment* × *Post* remains negative and significant. The estimate suggests a decrease in emissions of about 1.2% after the reform in 2013 for the treatment group. Second, as areas are not completely independent of each other and share e.g., common administrative institutions, we use standard errors clustered at the five-digit postcode level. The main coefficient in column 4 of Table 3 remains negative and significant indicating that our main finding is also robust to this design choice.

5.3.3 Exclusion of other Spanish Regions

As there are many local taxes in Spain[7], we test the robustness of our main results by excluding those regions that had any kind of tax reform during 2012 to 2014 from our control group. These local tax reforms cover, for example, the introduction of a tax on empty housing in Catalonia in 2015 or a gambling/bingo tax in Asturias in 2014 as well as all areas that had an environmental tax reform in the given time period. These reforms can relate to water, waste, or any other environment related product or the reform served a general environmental purpose.[8] The result of this analysis is shown in column 5 of Table 3. The DiD coefficient remains negative and significant, and even slightly increases in size and indicating a reduction of emissions reform by 1.6%. Overall, these tests indicate that the 2013 emission tax introduction in Valenciana led to a decline in NO2 levels between 1.2% to 1.6%. Hence, these results continue to indicate that the overall response was rather modest in comparison to prior estimates, in particular when using plant-level data (e.g., Klemetsen et al., 2016).

5.3.4 Placebo test

Next, we perform a placebo test to address concerns that our findings capture unobservable local trends. Specifically, we run a test for rural areas without any (for us measurable) industrial activity and compare these areas to all other areas (i.e., urban areas or rural areas with industrial

[7] A full list of all existing Spanish regional taxes can be obtained from the website of the Ministry of Finance and Public Administration (2022) under "Tributos Propios Autonomico" including all historic versions.
[8] For instance, Galicia introduced in December 2014 a tax for environmental compensation of mining activities in the Autonomous Community. Extremadura introduced a tax on landfill waste disposals introduced in 2012.

activity). The advantageous feature of this approach is that areas that can be classified as rural without industry are a pseudo treatment group. There should be no response for these areas. However, we expect to find a negative overall effect for all other areas as urban or rural industrial areas should exhibit a reduction in emissions. Results of this test are presented in Table 4. As expected, the coefficient for rural areas without industry is non-significant and very close to zero. Importantly, we find that for all other areas, there is a modest effect of emission taxes on emission levels (2.4%). This effect is statically different from the coefficient of rural areas with industry and non-rural areas, supporting our main inferences.

6 Exploring the Heterogeneity in the NO2 Emission Level Response

We next examine differences in the response to the emission tax. The objective of these tests is to inform policymakers and academics which regions benefit most from changing NOx taxes and in which regions, emission taxes may not have any or a much smaller effect on emissions. Moreover, these tests can help us assessing (some of) the mechanisms through which emission taxes can reduce emission levels. Finding evidence of reduced emission levels when expected by theory can further corroborate the causal interpretation of our findings.

6.1 Estimation Approach

To navigate through these tests, we first present the empirical approach to test for heterogeneity. We consider industrial activity (proxied by number of firms, urbanization or past emission levels) and firm characteristics (i.e., intangible assets and firm size). Using these characteristics, we perform a triple difference (DDD) analysis based on the following equation:

$$\begin{aligned} Emissions_{i,t} = {} & \alpha_0 + \beta_1 Treatment_i \times Post_t \\ & + \beta_2 High\ Split\ Variable_j \times Treatment_i \times Post_t \\ & + \beta_3 Split\ Variable_j \times Post_t + \gamma X_{i,j,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where *Emission* is defined as above. We again include all lagged controls as well as area and year fixed effects. The *Split Variable* is a dummy variable equal to one if it falls in the high category of the respective split (e.g., area with high industrial activity) and is zero otherwise (e.g., area with low industrial activity). In this model, the interaction *Treatment* × *Post* is the emission effect in the low category of the split variable and the DDD coefficient *High Split Variable* × *Treatment* × *Post* captures the difference between the high and the low group of the respective split variable. All other interactions of the DDD model are either absorbed by the fixed effect structure or are included in the regression but are not tabulated for brevity.

6.2 Role of Industrial Activity and Emissions

As a first channel, we test whether the industrial activity in an area impacts the reduction of emissions post reform. Emission taxes are designed to make the 'polluter pay' and to target 'dirty' firms or larger industries as these contribute more to overall emissions. In contrast to this, the relationship between emissions and the price of emissions may in fact be non-linear (Nordhaus, 1993). For instance, if a firm before the introduction of an emission tax already operates away from the average economy's emissions (i.e., with much higher emissions), taxes are expected to only have a small effect on emissions as cheaper abatement options already have been exploited (Rafaty et al., 2020). Similarly, a firm operating at emission level average or below would react more strongly and reduce emissions more. We test for these conflicting views by exploring the economic number of firms within an area (industrial activity measured by presence of firms), degree of urbanization (industrial activity measured by urbanization) and by looking at past emission levels (industrial activity measured by emissions).

6.2.1 Presence of Firms

We start by measuring the industrial activity through the presence of firms. Taking the number of firms, we use *Large Industry Area* as our split variable in equation (2). The dummy *Large Industry Area* is equal to one if an area is in the top quartile in terms of number of firms in an area and zero otherwise. We conduct the split in 2011 to avoid that the reform affects the location of firms in our sample period. Given that large industry areas are often seen as the main contributors to pollution, we expect a larger decrease in industrial areas relative to areas with fewer firms. In other words, we expect β_2 to be negative.

The results are shown in Table 5, Panel A. In column 1, we present the overall effect of the interaction *Treatment* × *Post,* which is the coefficient β_1. This coefficient shows the reduction of emissions for areas with a low number of firms (*Large Industry Area* = 0). The coefficient is close to zero and not significant, indicating a zero response of areas without much industry. In column 2, we show the overall effect for large industry areas (*Large Industry Area* = 1) which is calculated as $\beta_1 + \beta_2$ (*Treatment* × *Post* + *Large Industry Area* × *Treatment* × *Post*). The results are consistent with the idea that we see a larger reduction in large industry areas given their previously high pollution levels as the coefficient is negative and significant and larger than the baseline estimate (about 2.5% post reform reduction of emissions). Importantly, the two coefficients are significantly different from each other (t-stat = -2.09). We subject this finding to similar robustness tests as our main findings. These tests are reported in Panel A of Table A.1 in the Online Appendix and obtain qualitative similar findings.

6.2.2 Urbanization

We next use the degree of urbanization to test for industrial activity within an area. Urban areas generally can be characterized by the presence of more firms than rural areas due to advantages in infrastructure, labor markets, and closeness to consumers. For instance, in our sample, in urban areas, which we define an area as a city if its population is 50,000 or above following the Worldbank's approach (2020), we have an average of 612 firms per area whereas in rural areas we only have 147 firms per area. Thus, also the degree of urbanization can serve as a proxy for industrial activity. We then define an area to be a city with a population of 50,000 or above (*City* = 1) and areas with a population below this threshold to be rural (*City* = 0). When more firms are in an area as indicated by the degree of urbanization, we again expect a stronger response in contrast to rural areas. That is, the coefficient β_2 is expected to be negative.

The results of this analysis are presented in Table 5, Panel B. While we see a negative but nonsignificant coefficient for rural areas in column 1, the overall effect for cities in column 2 is higher and statistically different from the coefficient of rural areas. This indicates that indeed emissions are cut more strongly in urban areas. The reduction in emissions in urban areas (about 2% of our sample) amounts to 4.8%. We subject this finding to several robustness tests using the absolute amount NO2 as an alternative dependent variable, adjusting the threshold of firms required to be 15[9] and using standard errors clustered at the two-digit postcode level (Table A.1, Panel B). These tests generally support the idea of a stronger effect for urban areas.

6.2.3 Emissions of Firms

Since the split by the number of firms or degree of urbanization does not account for the actual pollution caused by a firm or industry, we next sort areas into those with 'dirty' versus 'clean' industrial activity. Since the emission tax is levied on the absolute emissions of NOx by a firm into the atmosphere (BOE, 2013), one could expect polluters to cut emissions more strongly than relatively 'clean' firms. To test this, we use *High Emissions* as our split variable. We base this measure on the industry composition in an area in 2011. Each firm is first sorted into 'dirty' and 'clean' industries based on industry-level NOx emissions scaled by aggregate sales obtained from Eurostat (2021). Industries above the median of industry-level NOx emissions are defined 'dirty'. We then calculate the sales-weighted percent of firms that are classified as 'dirty' in an area. This measure provides us an area-specific measure of the prevalence of dirty versus clean firms. We then use this percent and define a dummy variable *High Emission* of the percent of dirty firms in an area is above the median. Since the overall level of economic activity can affect the reform response (see Panel A), we perform the sorting into high versus low emission areas within quintiles of the number of firms per area. This ensures that the cutoff to define dirty and clean areas considers the size of the area. Moreover,

[9] In untabulated tests, we show the robustness to using all areas even without any firms

we modify equation (2) and include size quintiles times year fixed effects. These two modifications ensure that we sort on the extent of dirty versus clean firms within similarly sized areas and we compare areas with similar number of firms that differ in the density of dirty versus clean firms.[10] If dirty firms react more strongly consistent with the polluter pays principle, we expect the β_2 to be negative.

The results are presented in Table 5, Panel C. We include group size fixed effects to account for time-invariant characteristics of areas with more firms relative to areas with fewer firms. In column 1, we show the coefficient for 'clean' areas (*β1*, *Treatment* × *Post*). Column 2 shows the coefficient for 'dirty' areas (*β1* + *β2*, *Treatment* × *Post* + *High Emissions* × *Treatment* × *Post*). The results show negative coefficients for 'clean' and for 'dirty' areas. However, the estimate is only significant for 'clean' areas, and the two effects are not statistically different from each other (t-stat = 0.25). This supports the notion that it may not only be the polluters that pay for the emission tax, but that also clean industries respond to emission taxes (as, e.g., evidenced by the cut in investment among these firms; Jacob and Zerwer 2022). These results are similar when using absolute NO2 emission as the dependent variable, when using our dependent variable NO2 to split into 'dirty' and 'clean' or when using standard errors clustered at the five-digit postcode level (see Panel C, Table A.1 of the Online Appendix). Overall, these results show that emission taxes do not necessarily only target polluters, but also 'clean' firms.

6.3 Role of Firm Characteristics

Second, reducing emissions and moving to a zero-emission economy most likely depends on specific firm characteristics that foster and fund technological innovation and new product and process development. Existing literature considers R&D spending and innovation central to reducing emissions and meeting given targets (Metcalf, 2019, Acemoglu et al., 2012, 2016). Further, Brown et al. (2022) and Krass et al. (2013) show that emission taxes can stimulate

[10] We note that our results are similar when we split based on past emission levels (results untabulated).

R&D spending and incentivize the adoption of environmentally friendly technology. This environmentally friendly technology in turn can help firms reduce their emissions through, for example, innovative filter technologies or similar adaptions. Thus, more innovative firms are expected to decrease emissions more than their non-innovative counterpart. This idea is also supported by Gerlagh and Lise (2005) who show that carbon taxes are indeed only effective if they induce technological change. We test this idea by looking at intangible assets (as a proxy for R&D activity) as well as firm size (as a proxy for the availability of resources).

6.3.1 Intangible Assets

Since our firm level data do not contain information on R&D spending, we can only use firms' stock of intangible assets to test this notion. Specifically, we create the split variable *Intangibles* which is equal to one if an area is in the top tercile of the ratio of intangibles over fixed assets in 2011 and zero otherwise. As we expect firms with more innovations to be able to cut emissions more effectively, we expect β_2 to be negative. Results are presented in Table 6, Panel A. The coefficient for areas with low intangible to fixed asset ratios is slightly negative, but not significant ($\beta 1$). In contrast, the overall effect for areas with high intangibles to fixed assets is negative and significant ($\beta_1 + \beta_2$). This effect, however, is slightly not significantly different from the coefficient for areas with a low intangible ratio (*t*-stat = 1.50). We again perform several robustness tests in Panel D of Table A.1, Online Appendix, using the absolute amount of NO2 as the main dependent variable, requiring 15 firms per area, and using standard errors clustered at the five-digit postcode level. Our inferences remain robust in these tests and, more importantly, the difference between low and high intangible areas becomes significant supporting the above interpretation of results. Overall, the results support the idea that firms that innovate and invest in environmentally friendly technologies are better equipped to cut emissions following the reform in contrast to their non-innovative counterparts.

6.3.2 Firm Size

We also use firm size to test for differences across regions. We build our split variable *Firm Size* on the natural logarithm of sales. *Firm Size* which is equal to one if an area's average sales are in the top quartile in 2011, and zero otherwise. As larger firms potentially have more resources to adapt new technology and thereby adjust to the new price of emissions, we expect the coefficient β_2 to be negative. Results are presented in Panel B of Table 6. The coefficient for areas with small firms is small and not significant (β_1, *Treatment* × *Post*). In contrast, the coefficient for areas with larger firms is negative and significant ($\beta_1 + \beta_2$, *Treatment* × *Post* + *Firm Size* × *Treatment* × *Post*) and significantly different from the coefficient for areas with smaller firms. The estimates suggest that a post-reform emission reduction of 2.3%. This supports the idea that indeed firms that are bigger and potentially have more resources to adapt, react more strongly after the introduction of the new emission tax. Again, this result is robust to similar robustness tests as above as shown in the Online Appendix, Table A.1, Panel E.

7 Policy Implications and Conclusion

This paper investigates the impact of an emission tax on emission levels, leveraging a local tax on NOx emissions in Spain in 2013 and unique multitemporal satellite data on levels of NO2. Our results show that the local Spanish emission tax can reduce the actual NO2 burden by about 1.2%. The effect depends on the industrial activity and technological innovativeness. Large industry areas with many firms, highly urbanized areas as well as areas with a high degree of innovative or larger firms reduce emissions more in response to the emission tax reform than, for example, rural areas or areas with smaller firms. However, we also find that areas with more dirty industries exhibit no significantly different reduction in NO2 levels as areas with cleaner industries. This result contrasts the 'polluter pays' principle and suggests that emission taxes might not target necessarily only dirty firms but that the effects spill over to cleaner firms, explaining also the rather modest aggregate response.

Our findings thus have important implications for the debate of the optimal design of emission taxes. While the emission tax seems to be effective by leading to a net decrease in emissions, it does not directly target those firms that are mainly responsible for emissions, but hits predominantly industrial areas. This is because 'dirty' firms may pass on taxes to 'clean' firms (Jacob and Zerwer 2022). However, the cut in emissions seems to be particularly accelerated via innovation and technology improvements. Thus, while introducing emission taxes is the first step towards achieving zero emission targets, there is a need to combine it with other complementary policy measures to support R&D investments and innovation to accelerate the reduction as well as a more targeted design to make the real polluters pay.

We acknowledge that our analysis has several limitations. First, while the local setting of the Valencian Community has many advantages, our findings may not generalize to other countries and settings. This can be explored in future research. Second, the reform in our setting has been almost 10 years ago. Advancements in abatement technologies since then are highly likely. Thus, future research could focus on a more recent setting. Third, as we measure the integrated NO2 amount from satellite the contributions from different sectors are mixed and a direct correlation to emissions from industry can only be made by several assumptions, although we can still see that industrial concentration and urbanization plays an important role in the tax effect on emissions. Fourth, due to our empirical matching approach, treatment and control group give only with limited weight to hot spots such as Barcelona or Madrid. While our findings give a some indication about a potential response for more urbanized areas, we cannot make direct statements about large city hubs. Fifth, while complementary policy options in addition to an emission tax might be meaningful to target specifically polluting firms, we cannot make any statements about the effectiveness of such policies. Future research could concentrate on the combined effect of emission taxes and other environmental policy measures.

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Appendix A: Variable Definitions

This table shows the descriptions for all the regression variables.

Variables	Description	Level
ln(NO2)	Natural logarithm of NO2 column density in μmol/m².	Area
NO2	NO2 column density in μmol/m².	Area
Treatment	Dummy variable equal to 1 for areas located in Valenciana, and 0 otherwise. The area location is based on longitude and latitude data.	2-digit post code
Post	Dummy variable equal to 1 for 2013, 2014, 2015 and 2016 and 0 otherwise.	Area
Firm Size	The natural logarithm of sales.	Area
Number Firms	The natural logarithm of firms within an area.	Area
Population	The natural logarithm of absolute population count.	2-digit post code
Car Registrations	Car registrations per inhabitants. If the number of cars per inhabitant is not available for an area, we use the regions average.	2-digit post code
Past Emissions	Dummy variable equal to 1 for areas with above median emission in the past and 0 otherwise.	NACE Code
Investment	Change in fixed assets from year *t* - 1 to *t* plus depreciation scaled by total assets in year *t* - 1.	Area
Sales Growth	The natural logarithm of sales in year *t* minus the natural logarithm of sales in *t* - 1.	Area
Profitability	Net income in year *t* scaled by total assets in year *t* - 1.	Area
Tangibility	Fixed assets in year *t* over total assets in year *t*.	Area
Large	Dummy variable equal to 1 for areas with number of firms in the top 25th quartile, and 0 otherwise.	Area
Dirty	Dummy variable equal to 1 for areas with emissions in the top 25th quartile, and 0 otherwise.	Area
Intangible	Dummy variable equal to 1 for areas with intangible assets (scaled by fixed assets) above median, and 0 otherwise.	Area
Urban	Dummy variable equal to 1 for areas with population above the Worldbank city definition (50k inhabitants), and 0 otherwise.	Area

Figure 1:

This figure illustrates the sources of NO2 emissions in Spain between 2009-2016 as % of the total average over the years.

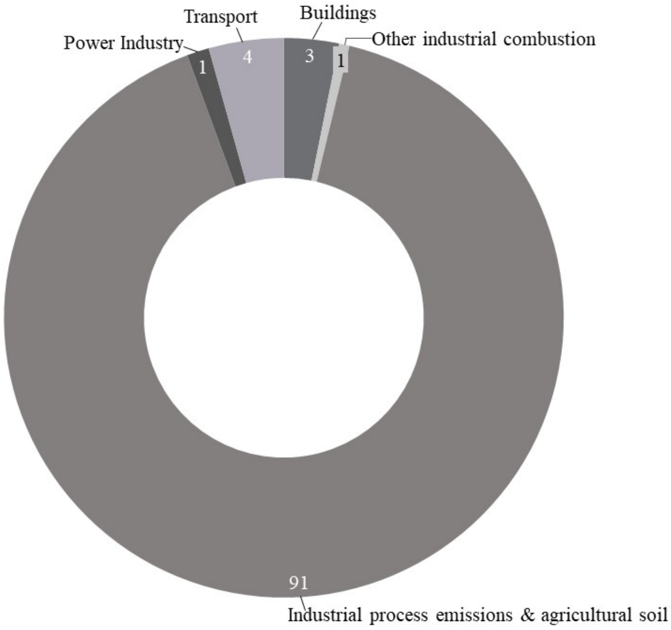

Figure 2: Introduction Timeline Valencian Emission Tax (Jacob and Zerwer, 2022)

This figure illustrates the overall sequence of the introduction of the new emission tax in the Spanish Community Valenciana beginning with the policy announcement on September 28, 2012.

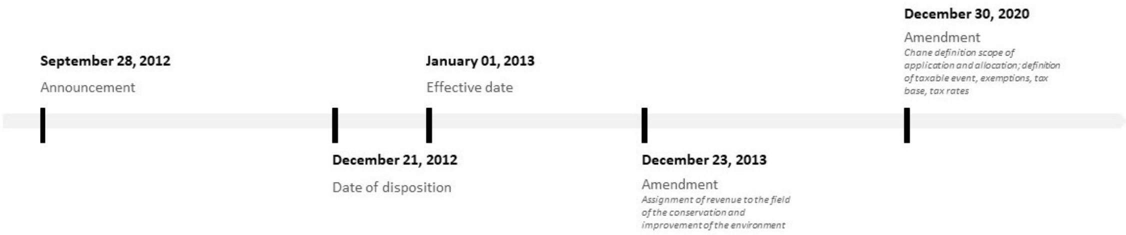

Figure 3: Treatment and Control Group, Map of Spain

This figure illustrates the choice of our treatment (dark grey area) and control group (light grey area).

Figure 4: Weights, Map of Spain

This figure illustrates the used weights for the main analysis.

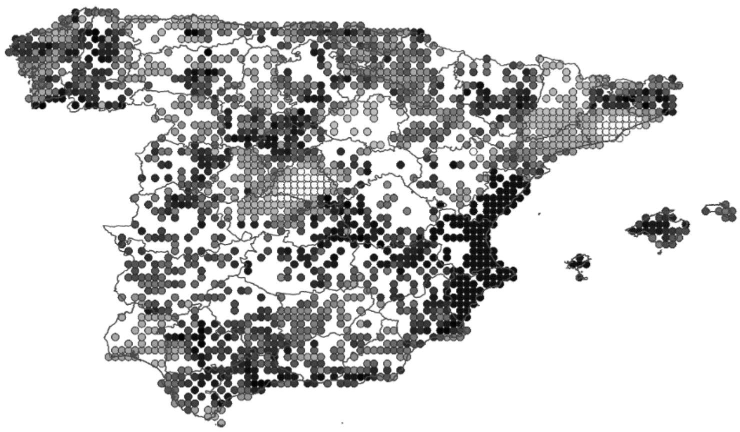

Figure 5: Parallel Pre-Trends

This figure illustrates the difference in NO2 emissions over the period 2009-2012 between the treated group (areas in Valenciana) and the control group (areas in the rest of Spain).

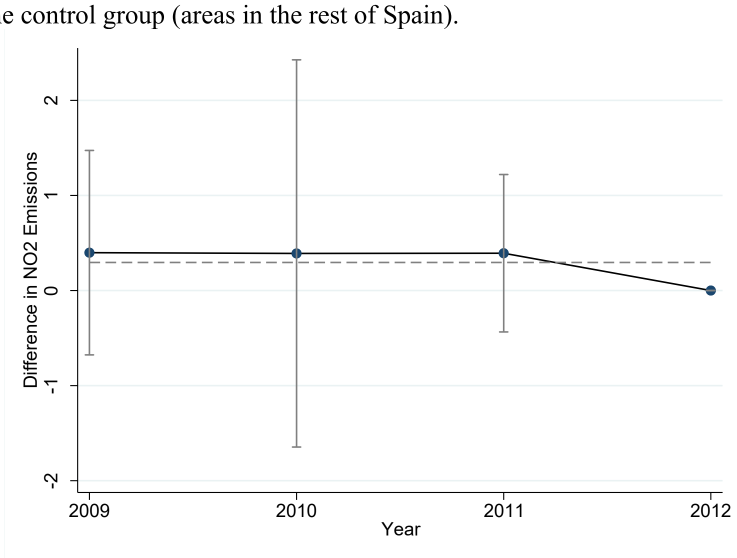

Figure 6: Emission Levels over Time across Spain

This figure illustrates the yearly average of NO2 levels across Spain from 2009 until 2016. Darker grey values indicate higher NO2 contents.

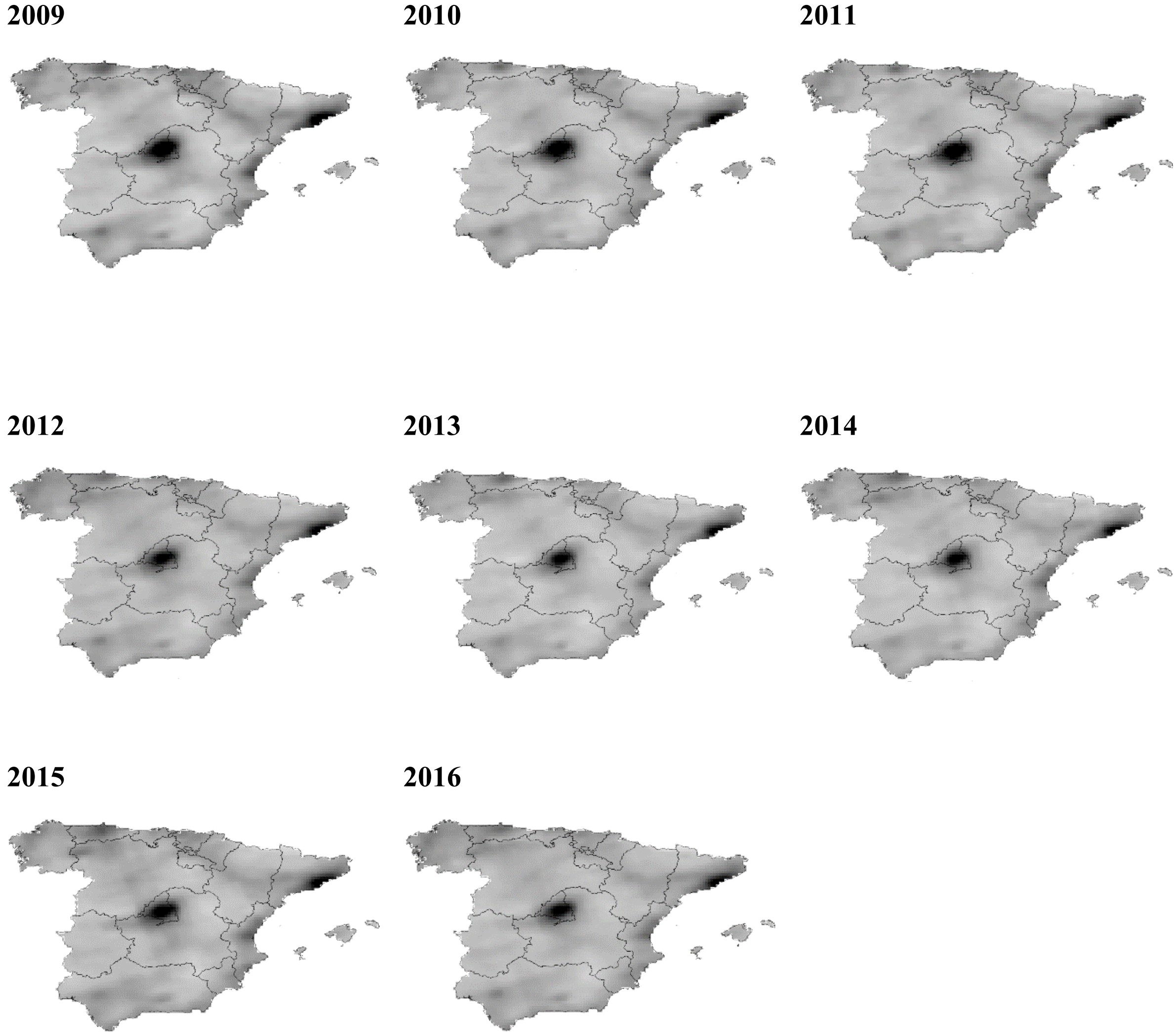

Figure 7: Emission Levels over Time in Valenciana and bordering Provinces

This figure illustrates the yearly average emission levels in Valenciana and the bordering provinces from 2009 until 2016.

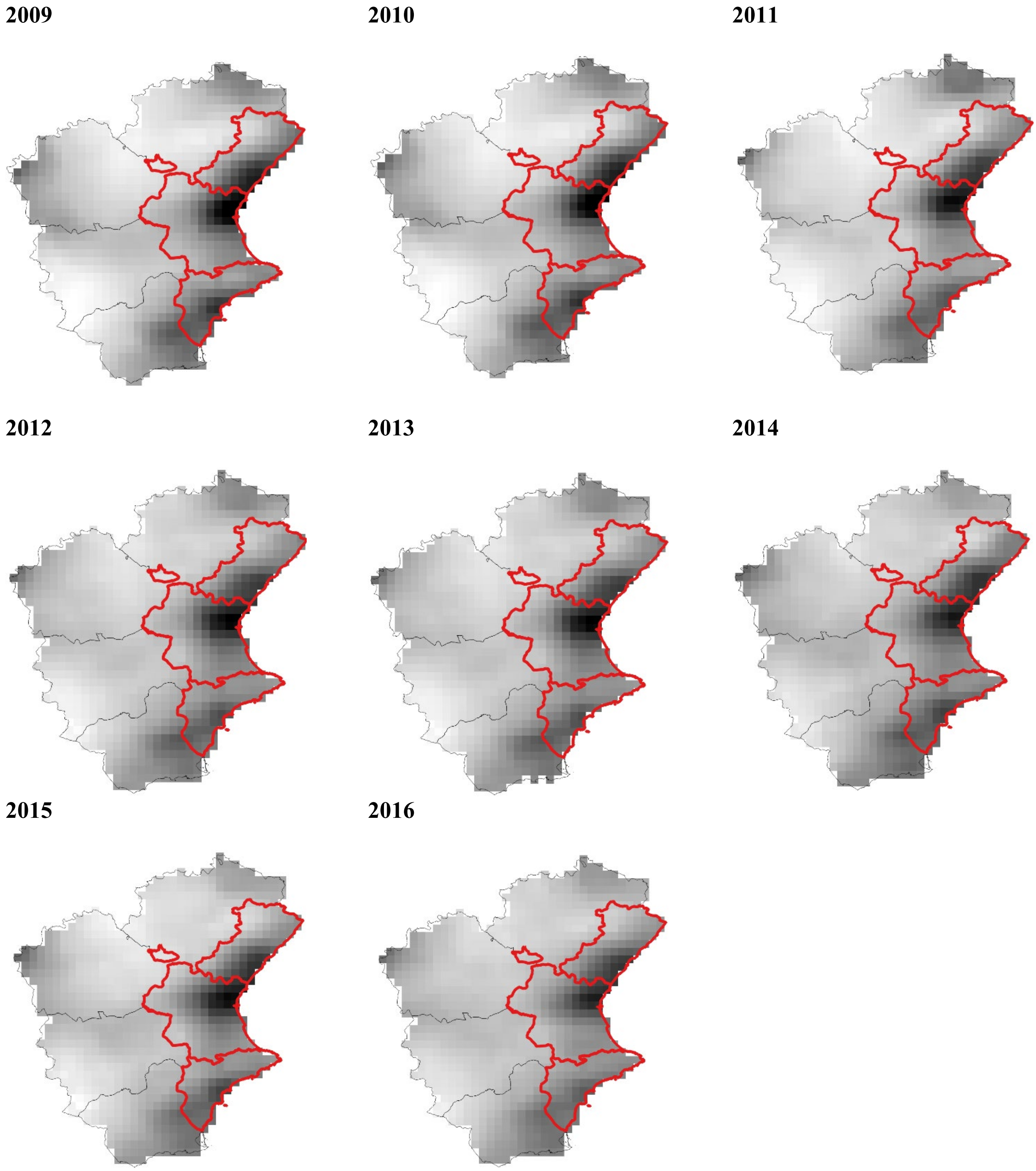

Table 1: Descriptive Statistics

This table presents descriptive statistics for our main variables for 15,374 observations from 1,957 areas from 2009 to 2016. The Appendix defines the variables. Panel A and B show a general overview of statistics. Panel C shows the difference in mean between the treatment and the control group. Panel D shows again the difference in mean between the treatment and control group, this time for our balanced panel.

Panel A: Dependent Variables					
	Mean	**St. Dev.**	**25th Perc.**	**Median**	**75th Perc.**
ln(NO2)	3.2923	0.2861	3.0886	3.2808	3.4551
NO2	28.1160	9.0636	21.9468	26.5963	31.6609
Panel B: Other Firm Variables					
Firm Size	17.5777	1.8756	16.1924	17.4057	18.8663
Number Firms	3.8544	1.4038	2.7081	3.5835	4.8040
Population	7.2969	1.7633	6.0051	7.3671	8.5222
Car Registrations	1110.9580	3006.1750	105.7044	286.6482	889.9471
Past Emissions	0.1776	0.1803	0.0487	0.1165	0.2493
Investment	0.0459	0.0464	0.0211	0.0368	0.0578
Sales Growth	0.0420	0.1445	-0.0260	0.0379	0.1001
Profitability	0.0275	0.0357	0.0090	0.0232	0.0419
Tangibility	0.3810	0.1149	0.3110	0.3676	0.4370

Panel C: Difference between Treatment and Control			
	Treatment = 0	**Treatment=1**	**Difference**
ln(NO2)	3.2796	3.4767	-0.1971***
NO2	27.7684	33.1937	-5.4252***
Firm Size	17.5040	18.6538	-1.1498***
Number Firms	3.7949	4.7229	-0.9280***
Population	7.2500	7.9828	-0.7328***
Car Registrations	1107.888	1155.808	-47.9197
Past Emissions	0.1768	0.1896	-0.0129**
Investment	0.0461	0.0442	0.0019
Sales Growth	0.0416	0.0489	-0.0073*
Profitability	0.0270	0.0348	-0.0078***
Tangibility	0.3825	0.3589	0.0236***
Panel D: Difference between Treatment and Control (balanced)			
	Treatment = 0	**Treatment = 1**	**Difference**
ln(NO2)	3.5402	3.5358	0.0044
NO2	36.0965	35.6481	0.4485
Firm Size	18.4323	18.4489	-0.0166
Number Firms	4.5272	4.5481	-0.0209
Population	7.2966	7.9573	-0.6609***
Car Registrations	750.0697	848.8609	-98.7912
Past Emissions	0.1855	0.1935	-0.0080
Investment	0.0431	0.0407	0.0023
Sales Growth	0.0405	0.0424	-0.0019
Profitability	0.0279	0.0308	-0.0029**
Tangibility	0.3576	0.3531	0.0045

Table 2: Emission Taxes and Emission Levels, Main Results

This table presents the main results of our analysis using an entropy balanced panel. The primary dependent variable is the natural logarithm of NO2 emissions. The primary independent variable is the interaction between *Treatment* and *Post*. In column (2), all control variables are lagged by one year. We report robust standard errors clustered at the area level for both column (1) and (2). The entropy balanced approach balances on selected control variables as well as emissions of 2009, 2010 and 2011. We include year and area fixed effects.*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Treatment × Post	-0.0106*	-0.0115*
	(0.0062)	(0.0069)
Firm Size		-0.0033
		(0.0050)
Number Firms		-0.0086
		(0.0202)
Population		-0.0626**
		(0.0279)
Car Registrations		0.0000
		(0.0000)
Past Emissions		0.0766***
		(0.0239)
Investment		0.0375
		(0.0369)
Sales Growth		0.0080
		(0.0091)
Profitability		-0.0715
		(0.0679)
Tangibility		-0.0874*
		(0.0519)
Area FE	Yes	Yes
Year FE	Yes	Yes
Balanced	Yes	Yes
Observations	15,374	15,374
Adj.-R^2	0.9518	0.9527

Table 3: Emission Taxes and Emission Levels, Robustness Tests

This table shows the results of our robustness tests. In columns (1) and (2), we use alternative dependent variables. In column (3), we adapt the model specifications to only allow for areas with at least 10 firms. In column (4), we use standard errors clustered at the five-digit postcode level. In column (5), we exclude all areas with local reforms during the pre-reform years. All regressions include area and year fixed effects as well as lagged controls. We report robust standard errors clustered at the area level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Excl. Regions			None		With other local tax reforms
Specification	Baseline		#Firms>10	SE Cluster	Baseline
Dep. Variable	NO2	Future NO2		ln(NO2)	
Treatment × Post	-0.4512*	-0.4960**	-0.0122*	-0.0119*	-0.0156**
	(0.2742)	(0.2419)	(0.0071)	(0.0072)	(0.0062)
Area FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Balanced	Yes	Yes	Yes	Yes	Yes
Observations	15,374	15,374	12,780	15,374	14,160
Adj.-R²	0.9457	0.9333	0.9508	0.9526	0.9507

Table 4: Placebo Test

This table shows the results of estimating Equation (2) for a rural area without industry versus a rural area with industry & non-rural areas (placebo test). In Panel A, we interact *Treatment*, *Post* and *Treatment × Post* with a placebo dummy variable which is equal to one for rural areas without industry and zero otherwise. All regressions use area and year fixed effects as well as lagged controls. We report robust standard errors clustered at the area id level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Breakdown by	**Population and # Firms**	
	Rural with Industry & Non-Rural (1)	Rural without Industry (2)
Treatment × Post	-0.0244***	0.0014
	(0.0083)	(0.0083)
Difference	*0.0258***	
[t-stat]	*[2.29]*	
Controls	Yes	
Area FE	Yes	
Year FE	Yes	
Observations	15,393	
Adj.-R²	0.9528	

Table 5: Emission Taxes and Emission Levels, Role of Industrial Activity and Emissions

This table shows the results of estimating Equation (2) for # firms in an area, degree of urbanization as well as emission levels. In Panel A, we interact *Treatment*, *Post* and *Treatment* × *Post* with the dummy variable *Large Industry Area* that is equal to one if an area is in the top quartile in terms of number of firms in an area and zero otherwise. In Panel B, we interact *Treatment*, *Post* and *Treatment* × *Post* with the dummy variable *City* which is equal to one if an area is above the defined population threshold of 50,000 inhabitants and zero otherwise. In Panel C, we interact *Treatment*, *Post* and *Treatment* × *Post* with the dummy variable *High Emissions* representing the percent of dirty firms in an area is above the top quartile. All three splits are executed in 2011. All regressions use area and year fixed effects as well as lagged controls. We report robust standard errors clustered at the area id level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Breakdown by Number Firms		
Split Variable	**Number of Firms in Area**	
	Few	Many
	(1)	(2)
Treatment × Post	0.0000	-0.0250***
	(0.0084)	(0.0091)
Difference	*-0.0249***	
[t-stat]	*[-2.09]*	
Controls	Yes	
Area FE	Yes	
Year FE	Yes	
Observations	15,374	
Adj.-R^2	0.9528	

Panel B: Breakdown by Urbanization		
Split Variable	**Degree of Urbanization**	
	Rural	Urban
	(1)	(2)
Treatment × Post	-0.0096	-0.0484***
	(0.0065)	(0.0132)
Difference	*-0.0389****	
[t-stat]	*[-2.72]*	
Controls	Yes	
Area FE	Yes	
Year FE	Yes	
Observations	15,393	
Adj.-R^2	0.9526	

Panel C: Breakdown by Emission Levels		
Split Variable	**% Firms in High Pollution Industry**	
	Clean	Dirty
	(1)	(2)
Treatment × Post	-0.0126**	-0.0098
	(0.0063)	(0.0099)
Difference	*0.0028*	
[t-stat]	*[0.25]*	
Controls	Yes	
Area FE	Yes	
Year FE	Yes	
Group Size FE	Yes	
Observations	15,374	
Adj.-R^2	0.9563	

Table 6: Emission Taxes and Emission Levels, Role of Firm Characteristics

This table shows the results of estimating Equation (2) for the intangible ratio of firms as well as firm size. In Panel A, we interact *Treatment*, *Post* and *Treatment* × *Post* with the dummy variable *Intangibles* which is equal to one if an area has an above median ratio of intangibles over fixed assets and zero otherwise. The split is executed in 2011. In Panel B, we interact *Treatment*, *Post* and *Treatment* × *Post* with the dummy variable *Firm Size* equal to one if an area's average firm size in the top quintile in 2011 and zero otherwise. The split is again executed in 2011. All regressions use area and year fixed effects as well as lagged controls. We report robust standard errors clustered at the area id level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Breakdown by Intangibles		
Split variable	**Intangible Assets**	
	Low	High
	(1)	(2)
Treatment × Post	-0.0040	-0.0220**
	(0.0080)	(0.0094)
Difference	*-0.0180*	
[t-stat]	*[-1.50]*	
Controls	Yes	
Area FE	Yes	
Year FE	Yes	
Observations	15,374	
Adj.-R^2	0.9528	

Panel B: Breakdown by Firm Size		
Split variable	**Firm Size**	
	Small	Large
	(1)	(2)
Treatment × Post	0.0033	-0.0225**
	(0.0088)	(0.0104)
Difference	*-0.0258**	
[t-stat]	*[-1.95]*	
Controls	Yes	
Area FE	Yes	
Year FE	Yes	
Observations	15,377	
Adj.-R^2	0.9523	

Online Appendix

Table A.1: Robustness Checks Cross-Sections

This table shows the various robustness checks we perform for our heterogeneity analysis. Panel A shows the robustness checks for the *Large Industry Area* split by using NO2 as an alternative dependent variable (columns (1) and (2)), estimating the regression for areas with at least 15 firms (columns (3) and (4)) as well as using standard errors clustered at the postcode level (columns (5) and (6)). Panel B shows the robustness tests for *Cities*. Again, we use NO2 (columns (1) and (2)), estimating the regression for areas with at least 15 firms (columns (3) and (4)) and standard errors clustered at the postcode level (columns (5) and (6)). Panel C shows the robustness tests for *High Emissions.* In columns (1) and (2), we use NO2 as the dependent variable. In columns (3) and (4), we use our dependent NO2 variable to perform the split into dirty and clean. In columns (5) and (6) we use standard errors clustered at the postcode level. Panel D shows the robustness tests for *Intangibles*. In columns (1) and (2), we again use NO2 as our dependent variable. In columns (3) and (4) we require again 15 firms per area. In columns (5) and (6) we use standard errors clustered at the postcode level. Panel E shows the robustness tests for *Firm Size*. Again, we use NO2 (columns (1) and (2)), estimating the regression for areas with at least 15 firms (columns (3) and (4)) and standard errors clustered at the postcode level (columns (5) and (6)). All regressions use area and year fixed effects as well as lagged controls. We report robust standard errors clustered at the area id level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Robustness Checks Industrial Activity (# Firms)

	Dependent variable		**Model specification**			
	NO2		**# Firms >15**		**SE Cluster**	
	Small	Large	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	0.0703	-1.0270***	0.0060	-0.0235***	-0.0000	-0.0250***
	(0.3697)	(0.3465)	(0.0092)	(0.0088)	(0.0097)	(0.0089)
Difference	*-1.0973***		*-0.0296***		*-0.0249***	
[t-stat]	*[-2.22]*		*[-2.41]*		*[-1.97]*	
Controls	Yes		Yes		Yes	
Area FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Observations	15,374		11,005		15,374	
Adj.-R^2	0.9461		0.9493		0.9528	

Panel B: Robustness Checks Industrial Activity (Population)

	Dependent variable		**Model specification**			
	NO2		**# Firms >15**		**SE Cluster**	
	Rural	City	Rural	City	Rural	City
	(1)	(2)	(1)	(2)	(1)	(2)
Treatment × Post	-0.3571	-1.9592***	-0.0085	-0.0458***	-0.0096	-0.0484***
	(0.2636)	(0.6485)	(0.0071)	(0.0131)	(0.0110)	(0.0150)
Difference	*-1.6021***		*-0.0374***		*-0.0388****	
[t-stat]	*[-2.32]*		*[-2.53]*		*[-2.93]*	
Controls	Yes		Yes		Yes	
Area FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Group Size FE	Yes		Yes		No	
Observations	15,393		11,018		15,393	
Adj.-R^2	0.9456		0.9490		0.9526	

Panel C: Robustness Checks Industrial Activity (Emissions)						
	Dependent variable		Model specification			
	NO2		Dummy Split		SE Cluster	
	Clean	Dirty	Clean	Dirty	Clean	Dirty
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	-0.5485**	-0.3458	-0.0098***	-0.0143	-0.0126*	-0.0098
	(0.2291)	(0.4181)	(0.0055)	(0.0133)	(0.0076)	(0.0093)
Difference	*0.2027*		*-0.0045*		*0.0028*	
[t-stat]	*[0.45]*		*[-0.23]*		*[0.24]*	
Controls	Yes		Yes		Yes	
Area FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Group Size FE	Yes		Yes		No	
Observations	15,374		15,374		15,374	
Adj.-R^2	0.9505		0.9563		0.9566	

Panel D: Robustness Checks Firm Characteristics (Intangible Assets)						
	Dependent variable		Model specification			
	NO2		# Firms >15		SE Cluster	
	Low	High	Low	High	Low	High
	(1)	(2)	(1)	(2)	(1)	(2)
Treatment × Post	-0.0749	-0.9455***	0.0026	-0.0249*	-0.0040	-0.0220**
	(0.3473)	(0.3650)	(0.0081)	(0.0098)	(0.0090)	(0.0095)
Difference	*-0.8705**		*-0.0275***		*-0.0180***	
[t-stat]	*[-1.77]*		*[-2.24]*		*[-1.43]*	
Controls	Yes		Yes		Yes	
Area FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Observations	15,374		11,005		15,374	
Adj.-R^2	0.9459		0.9493		0.9528	

Panel E: Robustness Checks Firm Characteristics (Firm Size)						
	Dependent variable		Model specification			
	NO2		# Firms >15		SE Cluster	
	Low	High	Low	High	Low	High
	(1)	(2)	(1)	(2)	(1)	(2)
Treatment × Post	0.2537	-1.0218***	0.0062	-0.0219**	0.0033	-0.0225**
	(0.4279)	(0.3893)	(0.0114)	(0.0101)	(0.0092)	(0.0102)
Difference	*-1.2755***		*-0.0280**		*-0.0208*	
[t-stat]	*[-2.27]*		*[-1.93]*		*[-1.60]*	
Controls	Yes		Yes		Yes	
Area FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Observations	15,377		11,008		15,377	
Adj.-R^2	0.9450		0.9479		0.9523	