The heterogeneous effects of environmental taxation on green technologies

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April 27, 2022

Abstract

This paper analyses the effectiveness of environmental taxation in stimulating the adoption of end-of-pipe and cleaner production technologies across manufacturing and mining firms between 2008 and 2014. We perform simple and categorical treatment matching of firms to study the heterogeneous effects of different taxation levels. We assess the effects between firms forced to pay environmental taxation (treated) and those that did not have to pay such taxes (controls), as well as between different levels of environmental taxation (small, medium, large). We find that low levels of environmental taxation are ineffective at stimulating green technology adoption. As the taxation level increases, so does the associated effect on green technology investment. Additionally, we find that even low levels of environmental taxation can be effective when combined with public financing. In this case, the effect is stronger than that of providing public financing alone.

Keywords: environmental taxation, doses, policy-mix, green technologies

JEL Codes: H21; H23; H25

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[1]Acknowledgments: The research leading to these results has received funding from RecerCaixa (RecerCaixa project 2016: The climate change challenge: policies for energy transition). We also acknowledge financial support from the Chair of Energy Sustainability (IEB, University of Barcelona) and from the Ministry of Science, Innovation and Universities (Project RTI2018-100710-B-I00, PGC2018-096316-b-i00, MCIU/ AEI /FEDER, EU) and FEDER(UNCB15-EE-3636)

[2]Acknowledgements: We would like to thank Pierpaolo Parrotta for his insightful comments and support throughout the research process as well as our three reviewers for their excellent constructive feedback. We would like to also thanks participants of the PhD Workshop in Economics at University of Barcelona, and Department Seminar at ZEW Mannheim.

1 Introduction

Governments and researchers around the world recognise that environmental taxes, especially carbon pricing, are not only effective initiatives to stimulate cost-effective pollution mitigation, improve the quality of air/water, and consequently reduce negative health impacts, but are also important stimulants for low-carbon, energy-efficient innovation (WB, 2018). Indeed, countries have become increasingly bold in introducing various environmental taxes, despite industry lobbying and dramatic newspaper headlines [1]. Among the ones that have become the most successful in Europe are the NOx tax in Sweden which decreased emissions by over 30%, and the landfill tax in the UK, which helped reduce the amount of waste sent to landfills from 50 million tonnes in 2001 to 12 million tonnes in 2015 [2]. In Spain, environmental taxes are still opposed and applied only at the regional level. Admittedly, several regional governments in Spain have tried to push new ones into existence; for example, Catalonia introduced a new vehicle tax in 2020 [3].

To assess the desirability of such taxes, it is important to understand how they affect firm behaviour. With this aim, scholars have studied the effect of environmental regulation on several outcomes, commonly finding inconclusive evidence. The current state of literature is clear about the positive effects that environmental taxes have on firms' innovative activities in cleaner technologies (Acemoglu, Aghion, et al., 2012; Acemoglu, Akcigit, et al., 2016; Aghion et al., 2016), pollution reduction (Greenstone, 2004; Mardones and Flores, 2018; Stoerk, 2018), and technology adoption (Bakhtiari, 2018), but with respect to the effect on firms' competitiveness and employment (Yamazaki, 2017), results are still inconclusive, as pointed out by Jaffe et al. (1995) and more recently by Dechezleprêtre and Sato (2017). In their review, they underline that the recent empirical literature on firms' competitiveness, proxied by trade flows and industry locations (entries and exits), still find little evidence to support the claim that environmental regulation has large adverse effects on firms. The study by Martin et al. (2014) also underlines another conclusion, namely, the surprising scarcity of rigorous impact analysis of environmental policies due to unavailable firm-level data.

Considering this data obstacle, this paper contributes to the literature on the effectiveness of environmental market-based instruments by studying the effect of environmental taxation, with and without public financing, on firms' investment in end-of-pipe and cleaner production technologies. To this end, this study uses a novel panel dataset of 2,562 Spanish industrial firms across 30 sectors between 2008-2014 collected by the Spanish Institute of Statistics through the annual 'Survey of Environmental Protection Expenditures.'

The manufacturing sector is an important contributor to air pollution and waste in Spain. In 2017, air pollution alone represented 47% of the non-methane volatile organic compounds, 43% of all sulphur dioxide emitted, 37% of carbon monoxide, 15% of nitrogen oxides, and 15% of total particles (PM2.5). The aggregated cost of industrial pollution in Spain is estimated at approximately EUR 6.5-10.0 billion . The industrial sector is also the third largest source of greenhouse gas (GHG) emissions,

[1] https://www.theguardian.com/environment/2017/sep/04/emissions-carbon-tax-profits-polluters-Paris-targets, 07.02.2020

[2] https://meta.eeb.org/2017/11/23/the-5-most-successful-environmental-taxes-in-Europe/; 07.02.2020

[3] https://www.electrive.com/2019/11/01/catalonia-introduces-carbon-tax-for-polluting-vehicles/, 07.02.2020

accounting for 21% of the total (INE, 2017; OECD, 2015). Spain is a good representative of environmental pollution at the European level , and among the 28 member states, it produces 8% of all total GHG emissions, which is substantial (EC, 2019). On top of that, Spain is an interesting example of a state which does not have a consolidated environmental policy in the form of environmental taxation at the national level. Instead, regional governments of Autonomous Communities (ACs) can introduce such environmental taxes, should they wish to. This results in a relatively high heterogeneity of implementation and subsequent environmental tax rates across regions in Spain, making it a good setting for empirical investigation.

Thus, this study exploits the regional heterogeneity of environmental tax implementation by using a panel dataset of 2,562 Spanish manufacturing and mining firms. First, we investigated how different levels of environmental taxes (air pollution, waste, and others) affect investment in green technologies. To this end, we divided firms into four categories: those that did not pay any environmental taxes in the past, and three groups paying *low*, *medium*, and *high* levels. Furthermore, we performed categorical treatment matching of firms to study the heterogeneous effects of different taxation levels. We matched firms on observable characteristics such as size, sector, previous green investment, and organizational capabilities, and performed categorical treatment matching to compare the effects of not only paying low, medium, or high environmental taxes, but also between low and medium, low and high, and medium and high levels of environmental taxation. Consequently, we assume that once we match firms on observables, most of the differences between taxation levels arise from regional differences in tax implementation. Second, this study uses the propensity score matching (PSM) technique to investigate the effects of a policy mix between environmental taxes and public financing in the form of subsidies and fiscal incentives.

Our main estimates indicate that on average, low levels of environmental taxation do not induce the adoption of green technologies. However, as the level of environmental taxation increases, the effect becomes statistically significant and increases. Additionally, we find that, even at low levels, environmental taxation can be effective if combined with public financing. In this case, the effect was stronger than that of providing public financing alone. However, the synergistic effect disappeared at high levels. High taxation alone is sufficient to encourage firms to adopt green technologies.

The remainder of this paper is organised as follows. Section 2 offers a literature review, while Section 3 describes the heterogeneity of Spanish environmental taxes at the regional level. Section 4 presents the data and descriptive statistics, and Section 5 describes the empirical model and methodology used. Section 6 discusses the empirical findings. Finally, we conclude and present policy implications in Section 7.

2 Literature Review

This study contributes to the large body of literature on the impact of environmental policy on firm behaviour. [4] Within this field, considerable attention has been given to the drivers of green technology adoption — the literature on eco-innovations (Demirel and Kesidou, 2011; Triguero et al., 2013)—

[4]For a review of the current literature on the impact of environmental regulation on competitiveness, please see Dechezleprêtre and Sato (2017) .

but due to insufficient data those usually focus on correlations. In fact, to date, there seems to be an insufficient number of rigorous empirical studies on the effects of market-based instruments, such as those conducted by (Martin et al., 2014).

While the role of environmental taxes, especially carbon taxes, on innovative activity is demonstrated theoretically, the role that environmental taxes might have on the adoption of green technologies is not supported by the empirical literature. Even if it seems intuitive that environmental taxes will motivate companies to invest in cleaner technologies to reduce their emission fees, it is not clear whether firms actually invest in cleaner technologies as a result of those taxes, or what level of the environmental tax is high enough to motivate firms to invest. Martin et al. (2014) were the first ones to study the causal inference of a carbon tax on a manufacturing sector in the UK. In their study, they find evidence in favour of implementing a carbon tax, as in the case of the UK, where a moderate tax on energy encouraged electricity conservation, and reduced energy intensity without affecting employment, productivity, or gross output. This study aims to fill the gap in the environmental economics literature by focusing on instrument choice regarding the adoption of new technologies. While the effectiveness of environmental taxes in inducing innovation and adoption of technologies has been addressed before, it is still far from conclusive on the appropriate level of such taxes, which is crucial from the policymaking perspective.

Within this context, this study attempts to fill a gap at the nexus of behavioural and environmental economic literature, shedding light on monetary incentives. The literature has shown that monetary incentives (extrinsic motivation) sometimes go in the opposite direction to the expected effects and undermine voluntary actions (intrinsic motivation). Specifically, Gneezy and Rustichini (2000a,b) stated that the effect of monetary compensation on performance is not monotonic. In the experiments carried out, a larger monetary incentive resulted in higher performance; however, offering small amounts of money did not increase the performance of participants significantly more than that of those offered no compensation. Similarly, Frey and Jegen (2001) underlined that crowding-in and crowding-out effects are empirically relevant phenomena and can, in some cases, be substantially larger than the traditional relative price effect. In our context, a policy instrument such as environmental taxation (a penalty) could produce an inverse crowding-out effect in firms' efforts to green the production transition (investment and adoption of green technologies). Implicit monetary incentives may displace a firm's willingness to adopt clean technologies. By contrast, subsidies are voluntary tools that express the decision of firms to be involved in environmental protection activities. Our study fills this gap in the literature in the context of environmental policy and firm behaviour.

Even more scarce is evidence on the effectiveness of a policy mix between environmental policy instruments, although in recent years, it has started to develop dynamically. Most scholars have focused on the complementarities of policy mixes (Mohnen and Röller, 2005), on a combination of policies that form a composite set to see how they interact (Costantini et al., 2017; Flanagan et al., 2011; Uyarra et al., 2016), and whether their interaction is highly effective (Cunningham et al., 2013; Fischer et al., 2003; Guerzoni and Raiteri, 2015; Hascic et al., 2009; Marino et al., 2016; Popp, 2006; Reichardt and Rogge, 2016). That said, there exists only one theoretical paper on the combination of environmental taxes with investment subsidies for green technologies. Christiansen and Smith (2015) agree that firms can arrive at a much more efficient outcome if the regulator combines emission tax with an investment subsidy or some other type of environmental regulation. They believe that existing uncertainty about the future hinders firms' decisions. In this study, we focus on the effects of environmental taxation on investment in green technologies. In addition, we examine their effects in combination with public financing.

Furthermore, since the seminal paper by Almus and Czarnitzki (2003), researchers have increasingly used matching as an empirical method to investigate the effectiveness of market-based policy instruments and to investigate causal inference rather than assessing simple correlations, such as subsidies, at stimulating innovative performance across firms (Guerzoni and Raiteri, 2015; Marino et al., 2016). However, matching techniques admittedly pose several challenges for internal validity owing to sample selection, data limitations, and others. Within the context of public policy and green innovation papers, Guerzoni and Raiteri (2015) argue that matching methodologies may suffer owing to uncontrolled unobservable variables that can act as 'hidden treatments' in the analysis. Marino et al. (2016), while studying the additionality of subsidies on firms' investment in R&D, tried to tackle this existing bias by addressing sources of unobserved heterogeneity. To control for firm-specific time-invariant characteristics, they first take the differences in the outcome variable. They also perform matching between the treated and control groups in each observational year to ensure that comparisons include all observable within-firm changes occurring on an annual basis. Following their methodology, we use simple and categorical treatment matching to study the heterogeneous effects of environmental taxation, with and without public financing.

We have identified several gaps in the aforementioned literature and would like to answer the following research questions. Are low taxation levels ineffective in inducing green technologies? [5] Is there a positive relationship between the taxation level and green investment? Do the effects of environmental taxes differ for different types of green investment? Does the policy mix between environmental taxes and public financing be more effective than the use of a single instrument?

3 Heterogeneity of environmental taxes in Spain

The Kyoto Protocol might not have been a successful endeavour at the international level, but it did put environmental pollution in the spotlight. As a result of it, in the 1990s, the European Commission (EC) for the very first time had advised universal adoption of several environmental taxes across the member states. Many countries followed up on the advice such as the Netherlands, Ireland, and Slovenia [6], but also outside the EU, such as Switzerland [7], all implementing third-generation green taxes, with their revenues financing energy efficiency investments and climate change mitigation. Spain,

[5] As presented by anecdotal stories, firms generally prefer to pay taxation at low levels rather than invest in green technologies. This might be related to the marginal cost of investment in green technology being higher than the marginal benefit from reducing pollution levels and the resulting reduction in environmental taxation. Alternatively, it can also be connected to the behavioural economics literature which suggests that monetary incentives may displace the potential willingness of firms to adopt clean technologies (Gneezy and Rustichini, 2000a,b).

[6] The Netherlands introduced a surcharge on energy taxation in 2013, date accessed: 01.03.2020, available online: https://ec.europa.eu/energy/sites/ener/files/documents/nl2016energyefficiency annualreport1en.pdf

[7] Switzerland introduced a tax on CO2 emissions in 2008, date accessed: 01.03.2020, available online: https://lenews.ch/2018/10/28/switzerland-leads-the-world-on-taxing-carbon/

however, did not follow this recommendation at the central level, making it voluntary for the regional governments of ACs to introduce (or not) such taxes at the regional level (Freire-González and Ho, 2018).

Almost 30 years later, Spain made remarkable progress in its overall environmental performance. Yet, it is also fair to say that significant challenges remain. While the carbon intensity has decreased significantly (OECD, 2015), water and waste pollution still pose a challenge. Spanish CO_2 emissions were reduced at a modest rate of -3.2% in 2018 compared to an increase of 7.4% in the previous year (Eurostat, 2018, 2019). Simultaneously, Spain is still recovering from the financial crisis of 2008, and the EC once again urged the country to implement more ambitious environmental policy instruments. More specifically, to increase green taxes at the regional level and reduce subsidies 'damaging' the environment (EC, 2017). The EC also points out that revenues from environmental taxes in Spain are the lowest in the EU-27 (accounting for 1.8% of GDP in comparison to the EU's average of 2.46%). Finally, within its report, the EC calls for the introduction of a national tax on waste or harmonising the current regional taxes, arguing that positive effects could easily be accelerated if Spain had a consolidated national environmental policy. Admittedly, many agree that the Spanish government makes only limited use of environmental taxes and calls for a more decisive green tax reform (Böhringer et al., 2019; Labandeira, Labeaga, and López-Otero, 2019).

As mentioned earlier, despite the lack of initiative at the central level, a few regional governments decided to introduce a range of industry-related environmental taxes. These taxes were introduced mainly with the purpose of developing regional autonomy regarding taxation and to increase public revenues without having, in many cases, a real environmental objective (Gago, Labandeira, Labeaga, et al., 2019). Regional governments used the legal space to introduce new taxes that could only be created in the field of taxation that was not previously occupied by the central government (Sole-Olle, 2013). Regional environmental taxes that apply to industrial firms include, apart from taxes on water use and sanitation charges, taxes on air pollution emissions (Figure 1), waste generation and storage, and installations and activities that have an environmental impact (Figure 2). It appears that the impact of regional environmental taxation is limited. Researchers blame not only the low rates of those taxes that were not designed appropriately but also inequality in treatment and coordination problems between different governance levels (Gago, Labandeira, Labeaga, et al., 2019; Gago, Labandeira, Picos, et al., 2007; Labandeira, Labeaga, and Rodriguez, 2004).

[Figures 1 and 2 around here]

Differences in environmental taxation between regions are substantial, and some ACs have been more active than others in this field (Gago, Labandeira, Labeaga, et al., 2019; OECD, 2015). Although ACs have progressively introduced environmental taxes, there are still many without any environmental tax. Additionally, there is substantial heterogeneity in the time of introduction, existence of environmental taxes, and their rates across regions. Some regions have introduced all types of environmental taxes we are concerned with, that is, air pollution tax, waste tax, and taxes on activities that have an environmental impact, while some regions, such as Cantabria and Madrid, have taxes only on waste. More information on the dates of the introduction of specific taxes in different regions is provided in Table 1.

[Table 1 around here]

Local air pollution tax on industrial firms was introduced in five regions starting with Galicia in 1995, while similar taxes have been introduced in Castilla-La Mancha, Andalusia, Murcia, and Aragon in 2001, 2003, 2005, and 2007, respectively. All five regions are among the less developed ones, although some more developed regions have also introduced environmental taxes. Specifically, Valencia (2012) and Catalonia (2014) approved laws to introduce air pollution taxes, although in Catalonia, revenues from these taxes began in 2015. The amount collected for these taxes in our period of analysis, 2008-2014, is around 22,5 million euro annually. The Galician air pollution taxation could be a good example for the rest when it comes to the extent of taxation — they charge on the emissions of sulphur oxides and nitrogen oxides — substances known to lead to acid rains. Further, some of the revenue is transferred to a contingency fund for environmental catastrophes (Gago, Labandeira, Picos, et al., 2007). Air pollution taxes in all autonomous regions are similar in the way they are constructed, although with different rates and exemptions (Gago, Labandeira, Labeaga, et al., 2019). Specific taxes on different combinations of emissions above a certain threshold are considered. Once the threshold is reached, the tax rate is applied per tonne. That said, air pollution taxes have often been criticised for two main reasons. First, they are believed to be too low to have any real effect on the adoption of eco-innovation among firms, although many argue that since they deal with local pollutants (such as SO and NOx), the heterogeneity of tax rates is justified in this aspect of the environmental tax. Second, many believe that imposing additional carbon taxes at the regional level is difficult to justify, given that Emission Trading System (ETS) is already present in several sectors and emissions are diffusive in nature (Gago, Labandeira, Labeaga, et al., 2019; OECD, 2015).

With regard to waste taxation, the industrial sector has improved slightly in terms of waste reduction. In 2010 the amount of industrial waste amounted to 49.2 million tonnes, 22% less than in 2000 but 27% more than in 2009 (OECD, 2015). This decrease is explained by a reduction in mostly non-hazardous waste generated by extractive industries and the manufacturing sector. Only five regions introduced some kind of waste collection charges or taxes on the landfilling of industrial waste, and collected approximately EUR 6,6 million annually in the 2008-2014 period.

Finally, between 2008-2014 five ACs introduced other taxes on activities that had an environmental impact. Extremadura was the first region to introduce such a tax in 1997, and Asturias, Castile and Leon, La Rioja, and Valencia soon followed and introduced similar taxes in 2011 and 2012. More recently, Aragon (2016) and Catalonia (2017) have also enriched their regional fiscal schemes through environmental taxes. All of these taxes are set at different rates and on different types of pollutants, but most of them focus on activities with environmental impact such as the production, storage, transportation, transformation, and supply of electricity and fuel. Although energy firms are particularly affected, income from these taxes is collected from all the manufacturing industries. The amount collected from industry and energy firms during our period of analysis was approximately 25 million euros annually.

4 Data

In this section, we report the data used to run our estimations. We also discuss descriptive statistics and preliminary evidence on the link between environmental taxation and the adoption of green technologies.

4.1 Data Source and Cleaning

The data used in this empirical analysis were collected by the National Statistics Institute of Spain (INE) for "*Survey on Industry Expenditure on Environmental Protection (SIEEP)*". The objective of the survey was to gather firm-level data on environmental protection expenditures across 30 manufacturing sectors in all regions of Spain. The primary activity of a company is defined as the one which gives the greatest added value. The sample was stratified according to the INE to provide representative results for all manufacturing sectors. SIEEP also provides information on the size (including all establishments hiring 10 or more remunerated employees) and several capital environmental expenditures, investments, and research data. The firm-level data are available between 2008 and 2014, creating an unbalanced panel dataset for 2,562 companies, where each company has at least four observations across seven years. Out of all 26 variables provided, we chose the most suitable for our investigation, which is briefly described below. INE ensures the quality of the data by employing a centralised collection unit (CCU), which is dedicated to obtaining all information from the questionnaire. Once the survey was created, errors and typographical errors were detected and corrected. Unclear answers were double-checked via phone interviews. A list of variables with their corresponding definitions is presented in Table 2. Unfortunately, merging the database with other databases was not possible. Nevertheless, this survey reports on several relevant firm characteristics.

[Table 2. around here]

4.2 Variables

For our dependent variables, we use investments in end-of-pipe technologies (lnEP) and cleaner production technologies (lnCP) in log terms as our two proxies for process eco-innovation. Both variables measure the total amount of money spent on adopting a given technology. As pointed out in the literature on eco-innovation drivers, since different eco-innovations have different characteristics, they might also react differently to treatment; therefore, it is important to distinguish between the types of green technologies that firms decide to adopt (Demirel and Kesidou, 2011; Frondel et al., 2007; Garcia-Quevedo, Martinez-Ros, et al., 2022; Horbach, 2008; Triguero et al., 2013). Consequently, in this analysis, we not only capture which firms decided to eco-innovate but also pay attention to the amount of money that they decided to invest in pollution abatement and energy-efficient technologies. End-of-pipe technologies are known to reduce air pollution without interference in the production process, while cleaner production technologies may either reduce air pollution and/or decrease energy consumption by changing the production process. For robustness, we also calculate a relative measure of our dependent variables: the natural logarithm of the amount invested in per capita terms. This is calculated as the investment per number of employees.

Our main variable of interest is our 'treatment': environmental taxation level, which is observed at the firm level for each year. These are the final amounts of environmental taxation paid by each firm every year. Given the heterogeneity and randomness of the implementation of environmental taxes across regions in Spain, we divide environmental taxation into three terciles. By this rule, we divide the amounts objectively to later compare the effects of, for example, jumping from a low to a medium level of taxation. Additionally, we also use a secondary treatment 'public aid', which is the amount of money that a firm has received in tax incentives, subsidies, grants, and other types of public financing in a given year. This variable aggregates all possible subsidies and credit taxes available in Spain at the national and regional levels, which contributes to reducing the cost of investing in environmental protection. During the analysis period, we can distinguish between tax credits and subsidies. Tax credits were introduced in Spain in 1996 at 10% of the firm's level of investment. Firms from any sector can obtain tax credits for their environmental protection investments. In 2006, a slow phase-out was announced, with an annual reduction of two percentage points every year until 2011. Nevertheless, in March 2011, this tax credit was re-introduced for four more years at a stable investment rate of 8 % as a measure to address the effect of the financial crisis. Finally, in 2015, it was removed with a change in the law on corporate taxation (Garcia-Quevedo and Jove-Llopis, 2021; Tchórzewska et al., 2020).

Regional and central governments provide support for environmental investments (OECD, 2015). For manufacturing firms, the most important factor comes from the central government in the form of subsidies, or subsidised loans. These are meant for general investments with a premium for environmental investments, and particularly to increase energy efficiency, within the framework of savings and energy efficiency action plans (Government of Spain, 2017). Specifically, one of the main instruments is the aid programme for energy efficiency measures in industrial enterprises. This programme provides grants to firms to support investments aimed at improving industrial equipment and process technology to reduce carbon dioxide emissions. The maximum amount of these grants is 30% of the corresponding eligible investment per application.

We also use a wide range of firms' pre-treatment characteristics, such as: lagged investment in CP and EP (following the literature on the persistence of innovation, such as the paper by Arqué-Castells, 2013), expenditure on environmental protection activities such as hiring employees dedicated to environmental protection [8], dummies associated with size and sectoral dummies. Several covariates typically appear in literature. In particular, the size dummies account for potential common demand and supply shocks or idiosyncratic shocks to a given company, whereas sectoral dummies are good for controlling the sectoral characteristics of production and pollution creation. We believe that other covariates might help control for firms' time-invariant characteristics, such as path dependency (Aghion et al., 2016). More specifically, size dummies are defined as follows: firms between 20 and 49, 50 and 99, 100 and 299, 300 and 500, and above 500 employees. This classification is justified by the Spanish manufacturing structure, which is dominated by medium-sized companies. With regard to

[8]We use the traditional definition of the so-called green jobs from the International Labour Organization (ILO) as occupations that help reduce the negative environmental impact at the company. In a broad sense, the EC (2018) specifies that 'a green job is one that directly deals with information, technologies, or materials that preserves or restores environmental quality. This requires specialised skills, knowledge, training, or experience (e.g. verifying compliance with environmental legislation, monitoring resource efficiency within the company, promoting and selling green products and services)'

sector dummies, we have access to 30 different sectors defined by the two-digit-industry NACE code, which we pool into 10 more general larger sectors with similar characteristics.

4.3 Descriptive Evidence

Figure 3 presents the averages of environmental taxes: aggregated, air-pollution, waste and other environmental taxes for each year and all observed firms. Consistent with what we stated in the section describing the Spanish heterogeneity of environmental taxation, we observe not only differences between year to year but also in the level of taxation for each type of pollution. We notice an increase in the level of taxation especially from 2011 on. Even though environmental taxes are relatively low in Spain, Spanish manufacturing firms still pay much more in those taxes than they receive in the form of public financing for green investment as can be seen in Figure 4. Additionally, we can see that in contrast to the increase in environmental taxation in 2011, the amount of public aid has decreased significantly in 2011. This might possibly be related to the planned phase-out of an investment tax credit in 2011, and the firms' inability to adjust their budgets, which decreased the amount of public aid received. With regards to the amount of money invested in both technologies between 2008 and 2014, we can see a jump between 2008 and 2010. However, between 2010 and 2014 the investment levels remain constant in spite of the financial crisis prevalent at that time (Figure 5). That being said, the percentages of firms deciding to adopt both green technologies decrease gradually and not in a drastic way as can be seen in Figure 6.

[Figures 3, 4, 5 and 6 around here]

The following descriptive statistics and results refer to the final sample. Table 3 describes the main variables employed in the analysis. It compares companies' expenditures when they are only under regional environmental taxation (1,983 firms), when they are only recipients of public financing in the form of subsidies, tax credits, and others (499 firms), and when they are recipients of both economic instruments (213 firms) and when they are recipients of none (firms 8,788). The first two are our treatment variables: environmental taxation and public aid. The next set are our outcome variables, which are represented as nominal values and log terms. The remaining listed variables are our pre-treatment covariates used for matching, such as lagged investment in cleaner production technologies (lagCP), lagged investment in end-of-pipe technologies (lagEP), and lagged amount of money spent on salaries for employees dedicated to environmental protection (lagGRexp). Most of the pre-treatment variables are similar when we compare the groups; however, it is worth noting that levels of investment are much higher when firms are under both policy regimes.

Tables 4 and 5 present a similar structure as the previous table and facilitate comparisons between the terciles of the distribution of firms under environmental tax only (*small environmental tax, medium environmental tax and large environmental tax*) and under both policy regimes, respectively. It turns out that firms paying larger amounts of environmental taxation are larger companies from highly polluting industries such as the chemical sector, and former large investors in green technology. When we compare Tables 4 and 5, it is easy to notice the results are consistent across two groups of companies. Additionally, we include the descriptive statistics of terciles of environmental taxation per capita for further robustness checks. The results in Table 6 look similar to those previously analysed in Table

4. This type of evidence is a promising start for our inference analysis and the synergistic impact of both policy instruments.

[Tables 3, 4 and 5 around here]

5 Methodology

This section discusses the estimation strategies implemented in our empirical assessment of environmental taxation in Spain in the absence of and in combination with public financing in the form of subsidies and investment tax credits. Employing recent advancements in program evaluation analysis, we have complemented general matching with categorical treatment matching — both propensity score and exact version (Caliendo and Kopeinig, 2008; Cunningham, 2020; Iacus et al., 2012). To provide some insights into the methodology, as well as to discuss the strengths and weaknesses of each method, we discuss them separately.

In the previous section, we thoroughly analysed regional differences in the rates of environmental taxation. In the following section, we will assume that once we match firms on their pre-treatment characteristics, such as size, sector, previous green investment activity, and organisational capabilities such as having green employees, the difference between their environmental tax arises from the regional heterogeneity of environmental taxation. To investigate the effect of environmental taxes on the adoption of green technology, it would be ideal to use borders between regions as environmental tax discontinuities; however, this type of data is very rarely accessible at such a level of geographic accuracy, in our case, unattainable. However, as is often the case with observable data, we are faced with numerous limitations. Given the lack of access to information on firms belonging to regions, we decided to use information on the heterogeneity of environmental tax rates in general.

In the first step, we use PSM, as proposed by Caliendo and Kopeinig (2008) and Rosenbaum and Rubin (1983). More specifically, we implement both simple and categorical treatment matching as used by Marino et al. (2016), which allows us to compare not only treated and non-treated but also different levels of treatment. We then run a categorical treatment matching model, which aids in the conclusion on the appropriate treatment level.

5.1 Propensity Score Matching

Technological policies have evolved rapidly over the years. However, the traditional problems of evaluating such policies, including endogeneity and sample selection (Afcha and García-Quevedo, 2016), remain. We believe that self-selection is not a threat to our study, as we assume plants are too difficult to move across the ACs, and thus, if a given local governance introduces a tax rate, the firm is forced to pay it (Duranton et al., 2011; Holmes, 1998). The second problem is endogeneity. It comes from the fact that the variables used to measure these effects of public interventions can be endogenously determined if we assume that firms are making a greater effort in case of existing environmental policy stringency.

Most recent studies have used non-parametric matching techniques to ensure the maximum degree of similarity between the control and treated groups. Matching techniques allow the comparison of two potential results: firms that were required to pay an environmental tax, T=1, and those that did not have to, T=0. Matching is based on the conditional independence assumption.

The data for the period 2008-2014 are treated as pooled data; thus, observations for the same firms in different years are considered independent observations. After describing the variables with missing values, PSM is run, thus providing a sample of treated and control firms matched on the set of variables.

We define PSM as the conditional probability of being treated, given a vector of covariates X:

$$p(X) = P(T = 1|X) = E(T|X) \tag{1}$$

where T is a dummy tax variable indicating exposure to the environmental taxation treatment that takes the values of T=(0,1). Then, the ATT is formulated as follows:

$$ATT = p(x)|T = 1E[Y(1)|T = 1, P(X)] - E[Y(0)|T = 0, P(X)] \tag{2}$$

where:
Y(1) represents the expected outcome for taxed firms (investment in green technologies)
Y(0) represents the outcome for non-taxed firms (investment in green technologies) and
X is the vector of covariates which include size dummies, sector dummies, lagged investment in CP technologies, lagged investment in EP technologies, and lagged green expenditures.

However, such a simplistic effect of environmental taxation does not consider the heterogeneous effects that may exist at different levels of environmental taxation, thus not informing us fully on the relationship between the policy instrument and firms' investment levels. In the next section, we implement categorical treatment matching to further investigate environmental taxation and extend the dummy tax variable to different levels of taxation: small, medium, and large.

5.2 Categorical Treatment Matching

Research shows that environmental taxation should increase investment in the development of green technologies (Aghion et al., 2016). However, the recommended level of environmental taxation that should be implemented is unclear (Acemoglu, Akcigit, et al., 2016). Additionally, coupling information on whether the firm has paid environmental taxation with the exact amount it has paid opens a new perspective of the analysis based on categorical treatment matching.

Categorical treatment matching evaluates the expected treatment category to which firms may belong given their pre-treatment characteristics. Estimations are based on a comparison of firms with similar scores, but belonging to two different categories. In our study, we define these categories as terciles of environmental taxation distribution (low, medium, and large). We expect terciles to provide us with an objective division of taxation expenditures paid by firms; therefore, we assume it is not subject to any potentially misleading categorisation criteria (in our robustness checks, we also look at the terciles of the distribution of the taxation per capita and we no longer match the size of the firm).

In fact, we face a trade-off between the number of groups analysed and the observations available in each group. The larger the number of groups analysed, given the available number of observations, the lower the efficiency of the estimates, ultimately risking the complete loss of feasibility due to the lack of a common support group.

As observed by Marino et al. (2016), the categorical treatment matching estimation method is very useful because it allows for comparisons not only between two categories of treated groups (e.g. small versus medium) but also between treated and untreated groups. This approach is not possible in continuous treatment/dose-response cases alone. Hence, categorical treatment matching aids in understanding whether the assessed average treatment effect masks the substantial heterogeneity between different taxation levels.

Similar to Marino et al. (2016), we use the variables Y^0, Y^1, Y^2, Y^3 for four mutually exclusive treatment categories, where the 0 category is exclusively composed of untreated, and the 1, 2 and 3 category are the small, medium, and large environmental taxation level payers. We can only observe the realisation of the potential outcome vector. The remainder are counterfactuals. Typically, to estimate different treatment effects, unconfoundedness and common support assumptions must be satisfied. On the one hand, the unconfoundedness assumption requires the treatment indicator to be independent of the realised outcomes; on the other hand, common support ensures that we find the correct match within the comparison group. This was performed by computing the propensity scores.

Implementation of categorical treatment matching consists of running the same number of logit estimations as the number of categorical effects we are interested in. Therefore, conditional on pre-treatment firm-level characteristics, it is possible to compute the treatment effects between different environmental tax category groups. In addition, to ensure the highest quality of the matching, counterfactuals are selected by the caliper method set at 0.1, which is the border for which matching is allowed. In our analysis, we use several different methods for controlling the quality of matching, and the results hold for all of them.

We also perform continuous treatment matching to arrive at an 'optimal' level of taxation within our analysis. As pointed out by Bia, Mattei, et al. (2007), dose-response matching is considered natural in the context of firm-level analysis because the treatment variable is naturally continuous rather than binary or categorical. Continuous treatment matching enables comparison of firms exposed to a specific level of investment and is generally quite attractive because it allows for smoothing of the treatment, which in turn allows for improvement in the precision of the inference. The estimation strategy is based on a weak unconfoundness assumption. Unfortunately, our treatment variable — environmental taxation — is not normally distributed, which excludes it from the possibility of implementing dose–response matching.

6 Results

This section presents the results of the simple and categorical matching evaluation schemes. Multiple treatment approaches have been used since we believe that the average treatment effect masks substantial heterogeneity across taxation level groups. Eventually, we decided on three main categories, and divided our treatment into terciles of the distribution of our treatment variable: environmental taxation. Our decision was not dictated by ex ante knowledge. By contrast, we believe that separating the treatment variable into terciles is an objective rule.

Validity of the matching

The next important step was to confirm the validity of matching. The main goal was to determine whether we could observe similarities in the joint distribution of covariates corresponding to the control and treated groups. To ensure that both groups are properly balanced, we followed a common procedure for estimating the standardised bias before and after matching (Rosenbaum and Rubin, 1983). In our case, the main values for the variables of interest did not present significant differences between the control and treated groups for any of the three levels of environmental taxation. For all our outcomes and treatments, the average bias was below the recommended level of 25%. The balancing tests and overlap plots for lnCP and lnEP outcome variables are in Figures 7-20 in the Online Supplementary Materials (OSM).

6.1 Heterogeneous Impacts of Environmental Taxation

This section presents the results of the simple and categorical matching evaluation schemes. Table 7 summarises the estimates obtained using simple and categorical treatment matching methods for our outcome variables: log level of investment in cleaner production technology (lnCP) and end-of-pipe technology (lnEP), as well as their corresponding amounts in per capita terms (lnCPpc and lnEPpc). For all these estimates, we report the average effect on the treatment. The caliper is equal to 0.1, and robust standard errors are shown in parentheses. All standard errors are robust to firm heteroscedasticity.

[Table 7 around here]

The tables are constructed to facilitate a comparison of the effects between the categories. In the columns, we refer to companies that do not pay environmental taxation (no tax), paid small amounts of tax (small), and a medium amount of tax (medium); subsequently, we can see what happens if such firms are matched with generally having to pay tax (tax), having to pay small amounts (small), medium amounts (medium), and large amounts of tax (large), which are presented in rows. Consequently, for each effect, we can match the firms on the observables and compare the effects. With regard to the simplest matching case, we can see a large and statistically significant effect of environmental taxation on the adoption of cleaner production technologies presented in Table 7 (lnCP). On average, tax firms invest approximately 182% more in cleaner production technologies than non-taxed firms. However, when we split the levels of taxation, it turns out that environmental taxation at low and medium levels (average of EUR 299 and EUR 2500 per year per firm) is ineffective in stimulating the adoption of green innovation, as suggested by the statistically insignificant coefficient of the treatment effect between non-taxed (no tax) and small-medium taxed (small, medium) firms. Several other conclusions can be drawn. First, as we increase the level of environmental taxation to large amounts, the effect becomes positive and statistically significant. Firms taxed at the middle level invest over 100% more in green technology than those not subject to environmental tax. Additionally, there are large positive effects of increasing the tax rates of firms that already pay some type of environmental taxation, suggesting that path dependency also exists in our sample of companies. Interestingly, the coefficients are statistically significant between large and small, and large and medium doses of taxation, but not between medium and large doses. The main results hold for amounts in cleaner production investment per capita (lnCPpc), showing that the relative amount of taxation drives the effect here.

We can observe similar results for end-of-pipe technologies (lnEP) presented in the bottom rows of Table 7. The effect of taxation, in general, is large and slightly less profound than in the case of cleaner production technologies. This is an interesting result because end-of-pipe technologies are generally considered inferior and much cheaper than cleaner production technologies. Therefore, when environmental taxation is introduced, firms are usually more willing to invest in cheaper alternatives. The effect of environmental taxation followed a pattern similar to that of the previous outcome variable. Tax is not effective at low levels; however, as we increase the level of taxation to medium amounts, the firm spends at least 50-92% more on end-of-pipe technologies. This effect increases even more when we tax firms in large amounts (117%). We observe a similar positive and statistically significant effect between firms taxed with small and large amounts (90%); however, it seems that between small and medium as well as medium and large amounts of taxation, we do not observe any increase in investment levels. This potentially suggests that once a firm has invested substantially in filters or scrubbers, it does not need or is not willing to purchase any new eco-innovations unless tax is increased considerably; thus, the marginal benefit is larger than the marginal cost from abating pollution by investment in end-of-pipe technology. Once again, our results hold when using the investment amount in per capita terms (lnEPpc).

Extensions: The Policy-Mix - Environmental Taxes and Public Financing

In the second step, we compare the effectiveness of environmental taxation versus public aid versus both policy instruments, as presented in Table 8. We examine the effects of environmental tax and public aid separately as well as in combination, thus investigating the policy mix between environmental taxation and public aid. We proceeded in two steps. Given the small number of observations under both policy regimes (213), we use as control groups both firms that were not taxed and firms that received only public aid. We proceeded with this double-matching procedure for two reasons. The comparison between the policy mix and public aid recipients, controls for self-selection in the public aid voluntary scheme by controlling for the amount of public aid received. However, given the small number of observations in this group, it is difficult to find a sufficient number of good matches, especially between the terciles of taxation. Consequently, it is difficult to interpret the results for the doses of environmental taxation. Using all non-public-aid recipients as a control group relaxes the restriction and increases the pool of potential matches, thus resulting in better quality matches. However, this approach suffers from issues of self-selection, which are eliminated in the other method. Therefore, it is beneficial to interpret the two side by side, as we have done here. For the purpose of interpretation, the general effect on the policy-mix vs. public aid should be considered, while for terciles of environmental taxation with public aid, non-taxed, non-public aid recipient firms should be used as controls to increase the pool of potential matches.

[Table 8 around here]

In general, both methods of policy-mix investigation point to the conclusion that the policy mix increases investment levels in both cleaner production and end-of-pipe technologies, as shown by the positive and statistically significant coefficients.[9] Further interpretation of the results is more complicated. It seems, however, that the combination of environmental taxation with public financing does not always bring about increased effectiveness. If the regulator decides to combine low or medium levels of environmental taxation with public aid, we do see increased effects for both green technologies. This is noted in the results, with non-taxed firms as the control group. However, once environmental taxation is sufficient, the additional support of public financing does not improve the investment levels significantly, and in some cases even decreases the coefficient (as in the case of cleaner production technologies). This leads us to conclude that combining large levels of taxation with public financing might be unnecessary, and either of the two individual policy instruments is sufficient incentive. The effect of a large amount of taxation in combination with public aid on end-of-pipe technologies is inconclusive. This is a platform for future research.

It seems unclear whether combining large levels of taxation with public financing adds significantly to the effect at all times. Relevant literature (Acemoglu, Aghion, et al., 2012; Greco et al., 2020) also supports this claim and has revealed that the combination of different tools could produce a policy mess instead of an improved effect, since the objectives/aims of each tool are very different. As Sorrell and Sijm (2003) suggested, when the policy mix lacks coherence, that is, different policy tools pursue different goals and are not well coordinated, the policy mix results in uncertainty for firms (Christiansen and Smith, 2015). Moreover, Costantini et al. (2017) provided evidence that the simple addition of an indiscriminate number of simultaneous policy instruments may reduce the effectiveness of the policy mix.

Extensions: No effect on Environmental R&D

Moreover, we performed the analysis using a variable related strongly to environmental innovation itself though not adopting the environmental technology in a given year: private environmental expenditure on research and development (lnRD). We find no positive or statistically significant effects of either environmental tax with or without the aid of public financing (see Tables 9a and 9b). This result suggests that while environmental taxation at current levels induces the adoption of green solutions, it does not encourage firms to engage in private environmental R&D. Again, this might suggest that even high levels of environmental taxation in Spain are not sufficiently high to induce private environmental R&D, and that specific instruments are needed.

[Tables 9a and 9b around here]

Extensions: Specific Taxes, Specific Technologies

In the next section, we examine whether significant differences exist compared to the main results when we consider more specific types of green investment, such as cleaner production technologies aimed at air pollution (lnCPair) and those aimed at reducing energy consumption alone (lnCPenc).

[9] Except for the coefficient on lnEP in the last estimation, which nonetheless is statistically significant at 89.9% level.

The estimates of the categorical treatment matching run for these two outcome variables are presented in Table 10. We can observe that for specific types of technologies, which we assume to significantly reduce air pollution and energy consumption, even low environmental taxation significantly increases investment in those technologies by more than 128% and 93%, respectively. Again, we are not surprised by this result that energy consumption-reducing technologies can be considered quite advanced and expensive; at the same time, both air pollution taxes and other environmental taxes are the ones creating the highest expenditure for companies. It, therefore, makes sense that when investigated separately, even small levels of taxation are successful in encouraging the adoption of specific green technologies. Similar to the main results, investment in green technologies continues to increase as we jump to large levels of environmental taxation . We can also see evidence of path dependence, as shown by positive statistically significant coefficients on the effects between different levels of taxation for cleaner production technologies aimed at air pollution reduction (lnCPair).

[Table 10 around here]

We ran a similar analysis on end-of-pipe technologies specifically reducing air pollution, which we interpreted as technologies such as filters and sulphur scrubbers; however, due to the small number of observations, we could not balance them perfectly and our average bias was above the recommended 25% level; consequently, we decided to exclude it from the analysis.

As explained in Section 2, qualitative assessments of environmental taxes in Spain pointed out that the impact of environmental taxes have been very limited because of their low rates and inappropriate design. Another study (Ventosa, 2018), with a descriptive analysis of the evolution of taxes and pollutants by region, concludes that environmental taxes have not helped reduce air pollution emissions in Spanish regions. In addition, Garcia-Quevedo and Jove-Llopis (2021) with an industry level analysis show that environmental taxes do not have positive effects on investment in environmental protection, with the objective of reducing energy consumption. Nevertheless, as they point out, their results should be considered mainly as relationships and not strictly as causal effects. To the best of our knowledge, there are no analyses that examine the effects of different levels of taxation, as we have carried out in this work, or that have estimated their effects in combination with public financing. The results of our estimations provide more detailed information on the design of environmental policies.

6.2 Robustness Checks

Robustness: Coarsened Exact Matching (CEM) We carried out several robustness checks to examine the sensitivity of our analysis. First, in the recent literature, PSM techniques have been increasingly criticised (King and Nielsen, 2019) for being blind to a large portion of the imbalance that could be eliminated by approximating full blocking. As recommended, we check whether the results hold when using CEM for both the natural logarithm of investment and investment in per capita terms (Cunningham, 2020; Iacus et al., 2012). Table 11 in the OSM presents the results. We observed the same patterns as in the case of PSM, and the coefficients were slightly more generous.

Robustness: Environmental Taxation per Capita Second, we used a modified treatment variable. Instead of using the direct environmental taxation level, which is endogenous to many factors and matches firms on their characteristics including size dummies, we created a new variable called environmental taxation per capita ($env\_taxpc = env\_tax/size$). Consequently, we checked the sensitivity of the results to the definition of the treatment variable, thus losing an important matching variable and therefore matching precision, for example, size. The descriptive statistics of the terciles of the distribution of environmental tax per capita are shown in Table 12 (in the OSM). We found that the results were generally robust. Taxation at low levels is ineffective at encouraging the adoption of green technologies, while it increases as we increase the level of environmental taxation per capita.

Robustness: Modified Database Third, we performed the main analysis of the modified database. First, we ran categorical treatment matching on the fully balanced panel, as shown in Table 13 in the OSM. In this case, the results hold for cleaner production technologies, whereas the results for end-of-pipe ones are slightly less robust. More specifically, we observe a positive and statistically significant coefficient on the medium level of taxation but not on a large level of taxation. In the second step, we also analysed the years 2010-2014 alone, which are the years of the financial crisis and, as such, financially challenging. We find that, in those years, even medium levels of taxation were successful in encouraging firms to adopt both types of green technologies.

Robustness: Modified Dependent Variable Finally, we performed categorical treatment matching using the growth of investment in cleaner production ($growthCP = lnCP[t] - lnCP[t-1]$) as well as growth of investment in end-of-pipe technologies ($growthEP = lnEP[t] - lnEP[t-1]$) to control for time-invariant firm characteristics. We believe that these results could inform us about the true effect on firms when controlling for firm fixed effects in our sample. We find that the results generally hold, as low levels of environmental taxation remain ineffective in inducing the adoption of green technologies, while medium level of taxation is the strongest, suggesting that while firms might invest in green technologies, they do not increase their levels from year to year, as shown in Tables 14a and 14b in the OSM. Additionally, it appears that the effectiveness of the policy mix between environmental taxation and public aid on the growth of CP and EP also increases (see Table 15 in the OSM). In this case, for end-of-pipe technologies, the effect is the largest for medium levels of environmental taxation with existing public financing; however, to increase the growth of cleaner production technologies, one needs only low levels of environmental taxation with available public financing (although other levels of taxation are successful as well). These estimations are performed using the old psmatch2 command in STATA, where the standard errors are not properly defined.

7 Conclusions

While there is an understanding that environmental taxes should be present to reduce industrial emissions and push green technology adaptation, empirical evidence is scarce. Additionally, we are not aware of any study on the impact of the policy mix between an environmental tax and public financing on manufacturing. In this study, we attempted to address these gaps.

This study aims to evaluate the effectiveness of environmental taxes in Spain at different levels of taxation, in the absence of and in combination with public finance, an equally important market-based instrument addressing the market failure of firms. The evaluation is performed to determine whether the implementation of such an environmental policy instrument in Spain is successful in encouraging the adoption of green technologies among industrial firms. With this goal in mind, we use an extensive panel data set of 2,562 firms between 2008 and 2014 and perform both inter-and intra-group assessments of the outcome of the policy. Our results are robust to different measures of the outcome variable, different ways of defining our treatment variable, and using our outcome variable in first differences, which controls for time-invariant firm characteristics.

Our results suggest that environmental taxation is effective in encouraging the adoption of both types of green technologies. That said, once we split our treatment into different categories, we find that low levels of environmental taxation do not induce further investments in process eco-innovations (EUR 299 per year). Therefore, we show that the average treatment effect masks substantial heterogeneity across taxation-level groups. The results also consistently show that increasing the amount of tax increases the subsequent adoption of green technologies. In the sample of fully supported environmental taxpayers, it seems that firms that are required to pay around EUR 2,500 per year already exhibit significantly higher investment in green technology than under lower amounts of taxation.

Additionally, our findings suggest that even low levels of environmental taxation (around EUR 665 per year) can be effective in inducing investment in green technology if combined with public financing. However, once again, the effect is largest when environmental taxation is at the medium level (EUR 7,378). That said, if the regulator is reluctant to increase the taxation level in fear of hurting firms' competitiveness, even low levels of taxation can be effective in combination with public support. Large environmental levels, though very effective on their own, are not strongly encouraged by a combination of public financing.

Overall, the findings suggest a substantial redesign of the modulation of environmental taxation. Although this result has shed some light on the heterogeneous effects of environmental taxation, further research is required to investigate the policy mix of environmental taxation with different types of public finance, such as subsidies and investment tax incentives.

This overall assessment indicated that an evaluation of the targets of environmental taxation is desirable, if not necessary, should Spain want to follow the EC's advice to consolidate national green taxes. The analysis is especially informative because our sample is representative of the time of downturns and economic stagnation given the financial crisis in place. If environmental taxation is seen as a valid policy instrument, public attention should inevitably be directed toward encouraging companies to invest in new energy-efficient technologies, especially since it will decrease their production costs substantially, while also preserving the environment.

Finally, it is clear that the Spanish government makes only a limited use of environmental taxation. Should they wish to implement such taxes at the national level, they could be very successful at both pushing the industry toward green technology adaptation and collecting significant revenues, which could later be recycled to environmental funds or redistributed back to firms in the form of subsidies for green investment, as suggested by Böhringer et al. (2019).

Our study has several limitations. Due to data restrictions, the first and most important limitation is the lack of a regional location for each firm. This makes it impossible to locate the region to which each firm belongs; and therefore, the exact tax rates firms are required to pay. We know the final amount of environmental taxation paid by the firm, but do not know the tax rate and the pollution level that translate into our resulting 'taxation paid.' This information would also help control for all time-invariant regional characteristics. Additionally, location information allows us to verify whether firms respond to location choice decisions through entries, and exist as a response to environmental taxes. However, we claim that the previous literature supports our assumption that while tax policy affects employment outcomes, it does not strongly affect location decisions (Duranton et al., 2011; Holmes, 1998; Rathelot and Sillard, 2008). Lastly, had it been allowed, merger with other databases would enrich our dataset with additional firm characteristics, which would then result in a more satisfactory matching.

It would be interesting for future studies to investigate if and how specific environmental taxes affect employment outcomes, more specifically, the size of firms, number of employees dedicated to environmental protection, and wages. Did the firms hire additional green workers, did they reduce regular staff, did environmental taxes affect Spanish competitiveness in manufacturing? It would also be beneficial to investigate whether the firms responded to the introduction of environmental taxation by altering the location of their plants. These questions remain a platform for further research.

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8 Figures and Tables

Figure 1: Regions of Spain with taxes directed at air-pollution. Source: self-made based on data from Ministry of Environment.

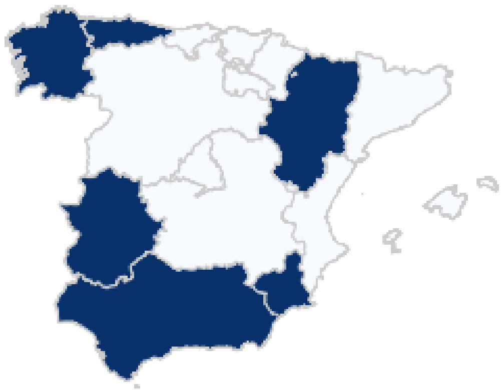

Figure 2: Regions of Spain with any environmental taxes. Source: self-made based on data from Ministry of Environment

Figure 3: Yearly average environmental taxes: aggregated, air-pollution, waste and others.

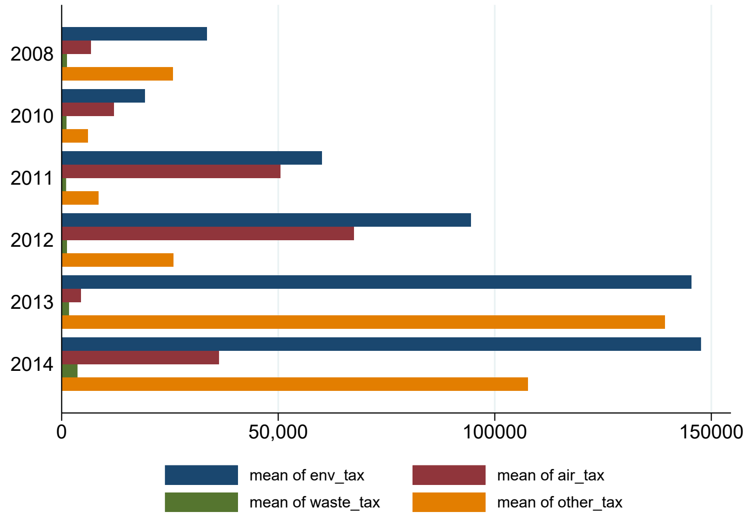

Figure 4: Yearly average aggregated environmental taxes and public financing.

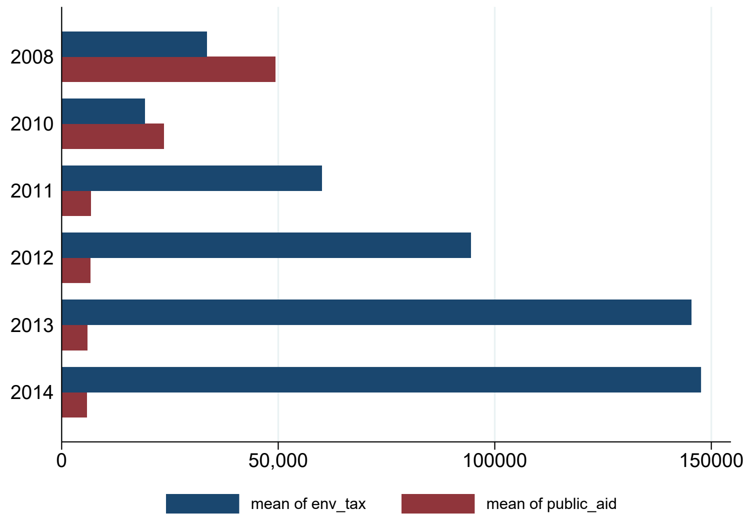

Figure 5: Yearly average aggregated investments in CP and EP technologies.

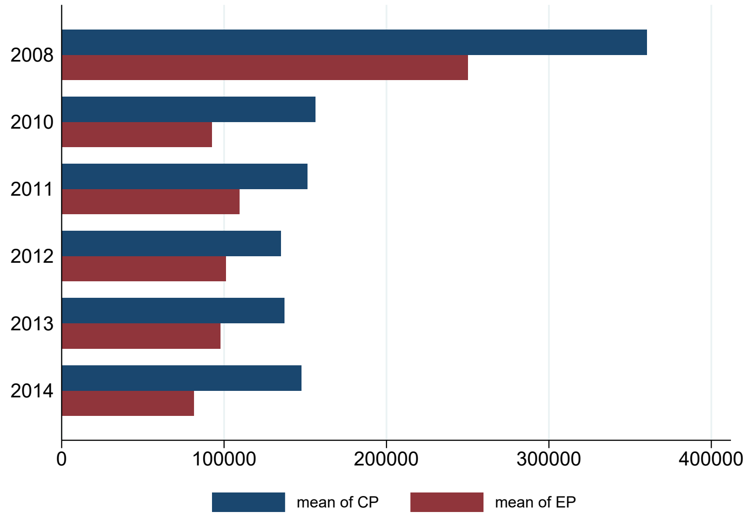

Figure 6: Yearly average percentage of firms investing in green technology adoption, both CP and EP.

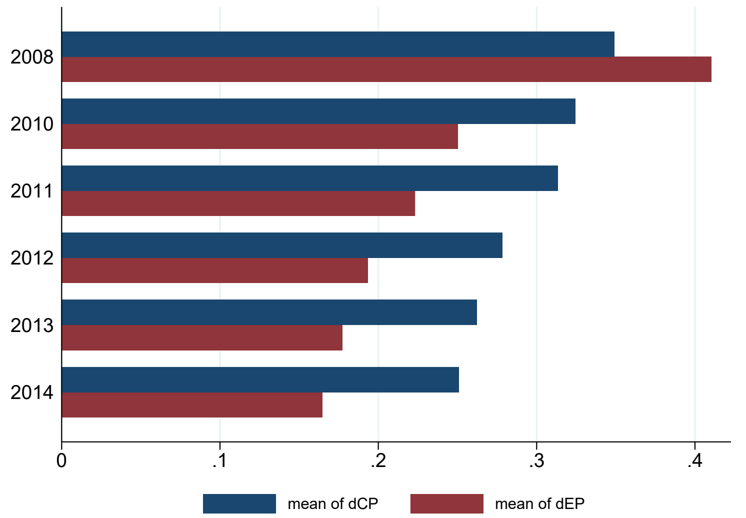

Table 1: Dates of introduction of environmental taxes across Autonomous Communities.

ACs	*air pollution tax*	*waste tax*	*other environmental tax*
Andalusia	2003	2005	
Catalonia	2014		
Madrid		2003	
Valencia	2012		2012
Galicia	1995		
Castile and Leon			2012
Basque Country			
Castilla-La Mancha	2000		
Canary Islands			
Murcia	2005	2005	
Aragon	2005		
Extremadura			1997
Bealearic Islands			
Asturias			2011
Navarra			
Cantabria		2009	
La Rioja			2012

Note: Environmental taxes that apply to industrial sectors. Dates refer to the year of approval of the referent laws. Source: Gago, Labandeira, Labeaga, et al. (2019) and OECD (2015)

Table 2: Variables, definitions and sources.

Treatment Variables:	**Definition**	**Source**
environmental taxation	sum of all environmental taxes (air pollution, waste and others, in euros)	INE
air pollution taxes	amount of air pollution tax paid by the firm in a given year (in euros)	INE
waste taxes	an amount of waste taxes paid by the firm in a given year (in euros)	INE
other environmental taxes	an amount of other environmental taxes paid by the firm in a given year (in euros)	INE
public aid	sum of all public financing for green technology adoption (subsidies, grants and tax credits, in euros)	INE
Dependent Variables:		
CP	amount of money spent in the adoption of cleaner production technologies (in euros)	INE
lnCP	natural logarithm of CP+0.001	INE
lnCPpc	natural logarithm of CP/size +0.001	INE
lnCPair	natural logarithm of CPair dedicated to air pollution reduction +0.001	INE
lnCPenc	natural logarithm of CPenc dedicated to energy consumption reduction +0.001	INE
EP	amount of money spent in the adoption of end-of-pipe technologies (in euros)	INE
lnEP	natural logarithm of EP+0.001	INE
lnEPpc	natural logarithm of EP/size +0.001	INE
RD	amount of money spent on environmental R&D (in euros)	INE
lnRD	natural logarithm of RD+0.001	INE
Control Variables:		
lagGRexp	lagged amount of money spent on environmental protection activities e.g. hiring green employees	INE
lagCP	lagged amount of money spent on cleaner production technologies	INE
lagEP	lagged amount of money spent on end-of-pipe technologies	INE
size dummies	20-49, 50-99, 100-299, 300-500 and >500 employees	INE
sectoral dummies	10 sectoral dummies aggregated together based on the NACE sectors at 2 digit level	INE

Table 3: Descriptive Statistics: Firms under environmental taxation, public aid, both instruments and none.

	Environmental Tax			*Just Public Aid*			*Both Policies*			*None*		
Variable	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*
Treatment Variable:												
Environmental Taxation	460506	5078692	1983	0	0	499	353489	3365070	213	0	0	8788
Public Aid	0	0	1983	188852	849631	499	374224	1815563	213	0	0	8788
Outcome Variables:												
CP	348815	2084006	1983	503504	2107823	499	1470506	3933342	213	85567	781029	8788
lnCP	-0.401	8,873	1983	5.279	9.205	499	8.167	8.654	213	-2.483	7.731	8788
EP	223943	1459807	1983	341587	2719085	499	617954	1579861	213	68423	655116	8788
lnEP	-1.469	8.391	1983	1.769	9.240	499	4.151	9.617	213	-3.558	6.943	8788
RD	3648	40428	1983	7231	49534	499	33445	185593	213	3072	53018	8788
lnRD	-5.978	3.764	1983	-5.538	4.678	499	-4.934	5.717	213	-6.270	3.163	8788
Pre-Treatment Variables												8788
lagCP	217238	1617921	1983	399123	2231087	499	531029	2391459	213	143120	1118740	8788
lagEP	168799	1136151	1983	185622	1388359	499	193891	803230	213	99627	990029	8788
lagGRexp	118151	313181	1983	109143	249221	499	148619	412704	213	79088	22642	8788
Size 1 (10 - 49)	0.04	0.20	1983	0.01	0.10	499	0.01	0.12	213	0.04	0.18	8788
Size 2 (50 - 99)	0.09	0.29	1983	0.09	0.28	499	0.05	0.21	213	0.15	0.36	8788
Size 3 (100 - 299)	0.57	0.50	1983	0.54	0.50	499	0.46	0.50	213	0.59	0.49	8788
Size 4 (300 - 499)	0.15	0.36	1983	0.18	0.39	499	0.26	0.44	213	0.13	0.33	8788
Size 5 (>500)	0.13	0.34	1983	0.17	0.38	499	0.19	0.40	213	0.09	0.28	8788

Table 4: Descriptive Statistics: Terciles of Environmental Taxation

	1st Tercile			*2nd Tercile*			*3rd Tercile*		
Variable	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*
Treatment Variable:									
Environmental Taxation	299	223	661	2500	1437	661	1378718	8728740	661
Public Aid	0	0	661	0	0	661	0	0	661
Outcome Variables:									
CP	40787	225340	661	96978	490529	661	908680	3504075	661
lnCP	-2.785	7.451	661	-0.960	8.478	661	2.540	9.714	661
EP	39602	298025	661	104894	1375362	661	527333	2068506	661
lnEP	-3.458	6.937	661	-2.015	7.867	661	1.065	9.526	661
RD	1540	17030	661	1479	13130	661	7926	66470	661
lnRD	-6.087	3.499	661	-5.994	3.635	661	-5.855	4.129	661
Pre-Treatment Variables									
lagCP	72812	414193	661	80788	461279	661	498115	2712573	661
lagEP	37906	249625	661	79886	711224	661	388606	1798558	661
lagGRexp	73645	178977	661	70416	119322	661	210393	485270	661
Size 1 (10 - 49)	0.05	0.23	661	0.02	0.13	661	0.06	0.23	661
Size 2 (50 - 99)	0.09	0.28	661	0.08	0.28	661	0.10	0.30	661
Size 3 (100 - 299)	0.64	0.48	661	0.60	0.49	661	0.46	0.50	661
Size 4 (300 - 499)	0.13	0.33	661	0.17	0.37	661	0.16	0.37	661
Size 5 (>500)	0.08	0.27	661	0.12	0.33	661	0.20	0.40	661

Table 5: Descriptive Statistics: Terciles of firms under both policy instruments: environmental taxation and public aid.

	1st Tercile			*2nd Tercile*			*3rd Tercile*		
Variable	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*
Treatment Variable:									
Environmental Taxation	665	554	71	7378	5706	71	1052424	5792351	71
Public Aid	102082	187274	71	257007	541771	71	763582	3067830	71
Outcome Variables:									
CP	277890	513274	71	935291	1714438	71	3198336	6236310	71
lnCP	6.713	8.662	71	7.541	8.965	71	10.249	8.029	71
EP	208204	549070	71	491544	1755060	71	1154115	1923386	71
lnEP	1.704	9.404	71	4.261	9.214	71	6.490	9.755	71
RD	32652	226335	71	317	2108	71	67367	225402	71
lnRD	-4.887	5.735	71	-6.261	3.111	71	-3.655	7.277	71
Pre-Treatment Variables									
lagCP	108960	395496	71	243054	765629	71	1241074	3975155	71
lagEP	78024	277670	71	124159	859928	71	379496	1041107	71
lagGRexp	69816	67363	71	97145	129752	71	278897	684299	71
Size 1 (10 - 49)	0.01	0.11	71	0.01	0.11	71	0.01	0.11	71
Size 2 (50 - 99)	0.03	0.17	71	0.06	0.23	71	0.06	0.23	71
Size 3 (100 - 299)	0.52	0.44	71	0.30	0.50	71	0.23	0.42	71
Size 4 (300 - 499)	0.25	0.43	71	0.29	0.46	71	0.23	0.42	71
Size 5 (>500)	0.18	0.39	71	0.14	0.35	71	0.25	0.44	71

Table 6: Descriptive Statistics: Environmental Taxation per capita. Robustness Check.

	Environmental Taxation per capita			*1st Tercile*			*2nd Tercile*			*3rd Tercile*		
Variable	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*	*Mean*	*St. dev*	*N*
Treatment Variable:												
Environmental Taxation	445672	4996849	2049	542	1172	659	3286	5916	658	1348391	8742766	658
Public Aid	0	0	2049	0	0	659	0	0	658	0	0	658
Outcome Variables:												
CP	371859	2158645	2049	79862	423654	659	122648	657478	658	836172	3475914	658
lnCP	-0.263	8.932	2049	-2.265	7.858	659	-1.033	8.465	658	2.027	9.624	658
EP	237440	1475100	2049	112865	1401125	659	71368	364406	658	485336	2053550	658
lnEP	-1.272	8.506	2049	-3.051	7.277	659	-2.163	7.866	658	0.728	9.384	658
RD	3863	41944	2049	1673	17141	659	2167	20459	658	7039	64749	658
lnRD	-5.9297	3.856	2049	-5.983	3.713	659	-5.936	3.765	658	-6.033	3.779	658
Pre-Treatment Variables												
lagCP	246796	1729986	2049	74441	413868	659	83097	464838	658	492001	2717242	658
lagEP	183381	1139028	2049	37655	243098	659	88095	853370	658	376401	1737961	658
lagGRexp	118247	310148	2049	73652	170000	659	80178	180248	658	200989	473328	658

Table 7: Main Results: The effect of environmental taxes on the outcome variables: absolute and in per capita terms.

lnCP	*no tax*	*small*	*medium*	*lnCPpc*	*no tax*	*small*	*medium*
tax	1.82***			*tax*	1.16***		
	(0.24)				(0.16)		
small	-0.13			*small*	1.02		
	(0.39)				(0.27)		
medium	0.27	1.22**		*medium*	0.34	0.79*	
	(0.43)	(0.60)			(0.29)	(0.39)	
large	1.08**	1.76**	1.33	*large*	1.30***	1.05*	0.71
	(0.47)	(0.72)	(0.86)		(0.33)	(0.54)	(0.49)

lnEP	*no tax*	*small*	*medium*	*lnEPpc*	*no tax*	*small*	*medium*
tax	1.52***			*tax*	0.99***		
	(0.23)				(0.17)		
small	0.39			*small*	0.34		
	(0.35)				(0.25)		
medium	0.92**	0.69		*medium*	0.50*	0.47	
	(0.40)	(0.55)			(0.27)	(0.37)	
large	1.17***	0.90***	0.73	*large*	0.97***	1.07**	0.12
	(0.45)	(0.32)	(0.82)		(0.32)	(0.45)	(0.45)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.1. Standard errors shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level.

Table 8: Extensions: Comparison of the effectiveness of public aid, environmental taxes alone as well as environmental taxes given that the firm has received public aid (outcome variables: lnCP & lnEP)

	Just environmental tax		*Just Public Aid*		*Both vs. None*		*Both vs. Public Aid*	
	lnCP	*lnEP*	*lnCP*	*lnEP*	*lnCP*	*lnEP*	*lnCP*	*lnEP*
tax	1.82***	1.52***	5.09***	3.57***	5.90***	5.19***	2.50**	1.61^
	(0.24)	(0.23)	(0.51)	(0.50)	(0.78)	(0.83)	(1.06)	(0.98)
small	-0.13	0.39	3.54***	2.43***	4.95***	5.21***	-0.36	-0.67
	(0.39)	(0.35)	(0.75)	(0.74)	(1.39)	(1.44)	(1.41)	(1.37)
medium	0.27	0.92**	7.61***	4.51***	8.51***	8.20***	-0.34	0.85
	(0.43)	(0.40)	(0.89)	(0.92)	(1.45)	(1.31)	(1.50)	(1.57)
large	1.08**	1.17***	7.93***	5.99***	4.42***	2.67	1.26	4.43***
	(0.47)	(0.45)	(0.88)	(0.85)	(1.46)	(1.70)	(1.62)	(1.73)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.1. Standard errors shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level. There are 1,983 observations of firms under environmental tax alone, 499 observations of firms under the public financing alone, 213 observations of firms under both policy regimes, and 8,878 observations of firms that have not been affected by environmental policy instruments.

Table 9: Extensions: No effect on private environmental R&D

(a) Treatment: environmental tax alone

	no tax	*small*	*medium*
tax	-0.01 (0.425)		
small	0.232 (0.141)		
medium	0.107 (0.147)	0.015 (0.542)	
large	0.285 (0.275)	0.176 (0.558)	0.075 (0.483)

(b) Treatment: both policy instruments

	no tax
tax	-0.209 (0.413)
small	0.281 (0.972)
medium	-1.067 (0.853)
large	0.395 (1.297)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.01. Standard errors shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level. This analysis was done with the old psmatch2 command.

Table 10: Extensions: The effect of specific environmental taxes on specific green investments.

lnCPair	no tax	small	medium	lnCPenc	no tax	small	medium
tax	1.28*** (0.19)			*tax*	0.93*** (0.19)		
small	0.02 (0.24)			*small*	-0.12 (0.26)		
medium	-0.07 (0.30)	0.16 (0.45)		*medium*	0.29 (0.31)	0.54 (0.44)	
large	1.45*** (0.40)	1.96*** (0.55)	0.71 (0.87)	*large*	1.03*** (0.34)	-0.14 (0.43)	0.22 (0.53)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.1. Standard errors shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level, * denotes significance at the 90% level.

A Online Supplementary Materials

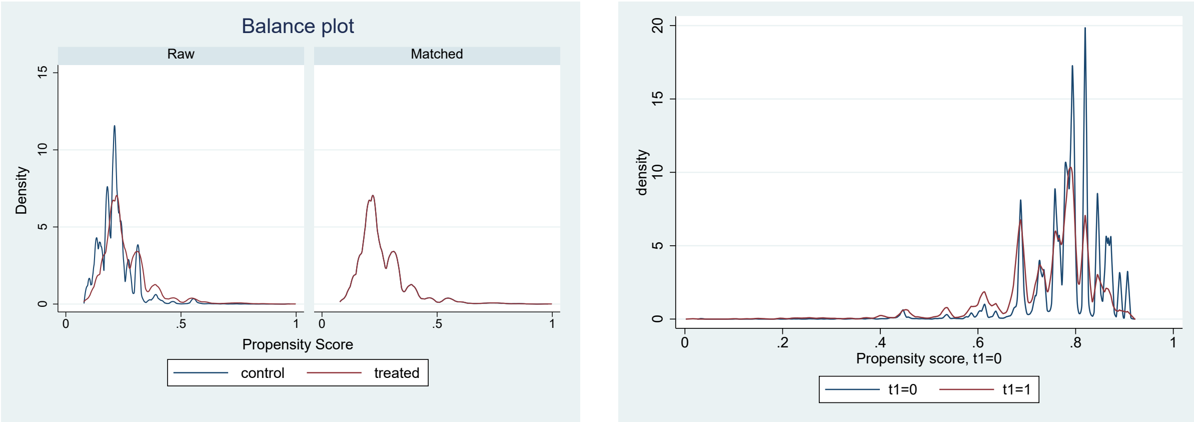

Figure 7: Balance and Overlap plots for lnCP, general tax dummy (tax).

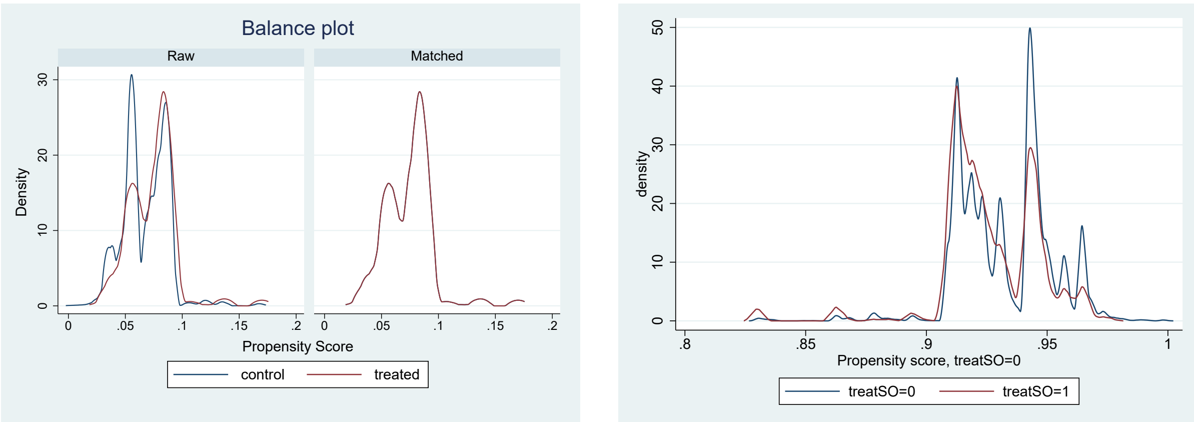

Figure 8: Balance and Overlap plots for lnCP, small tax tercile (small).

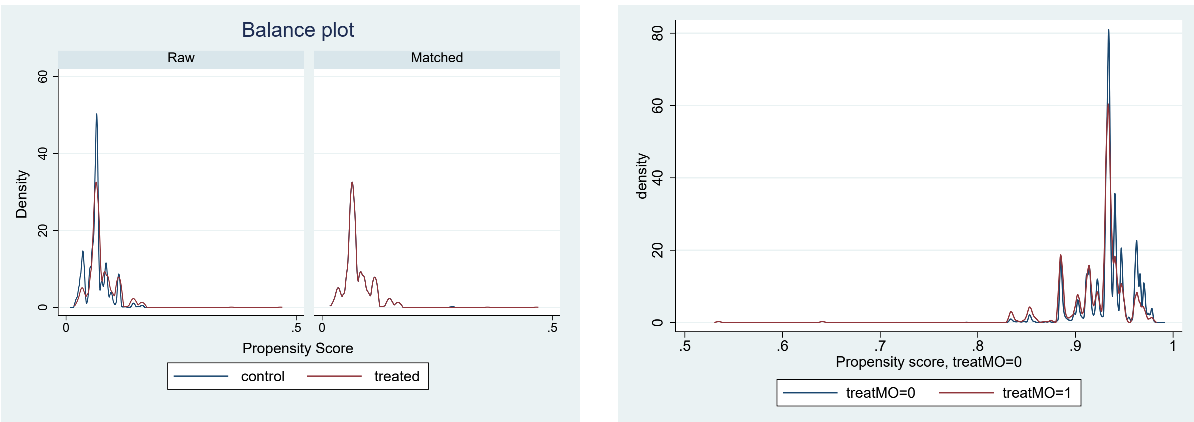

Figure 9: Balance and Overlap plots for lnCP, medium tax tercile (medium).

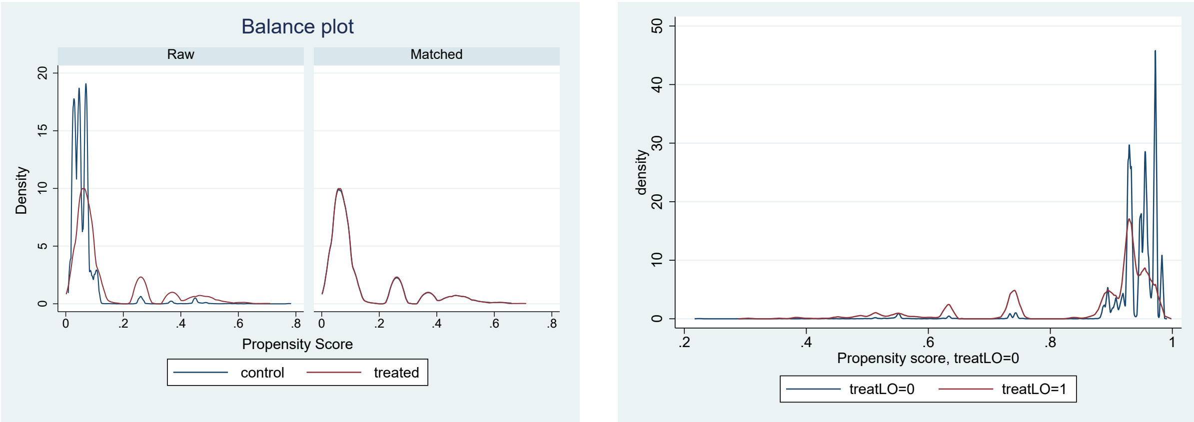

Figure 10: Balance and Overlap plots for lnCP, large tax tercile (large).

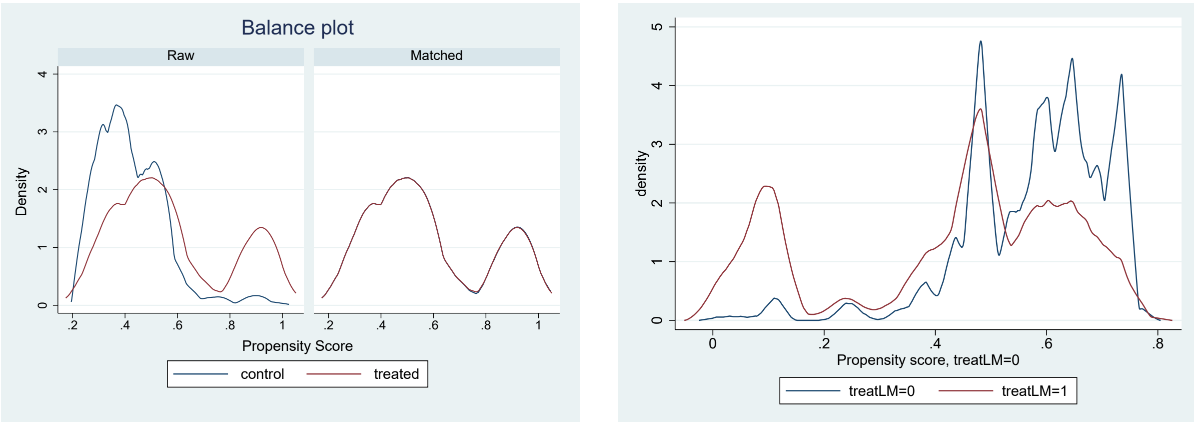

Figure 11: Balance and Overlap plots for lnCP, large vs medium tax tercile.

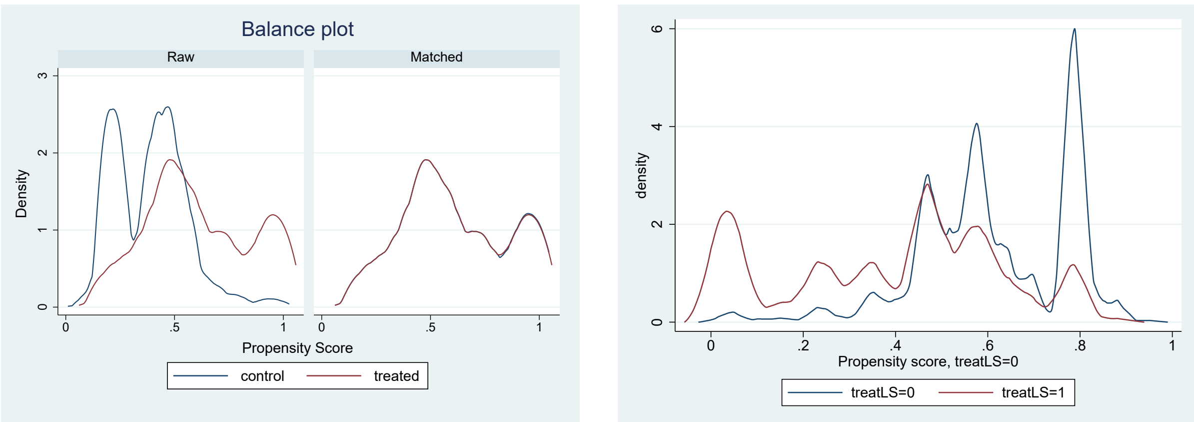

Figure 12: Balance and Overlap plots for lnCP, large vs small tax tercile.

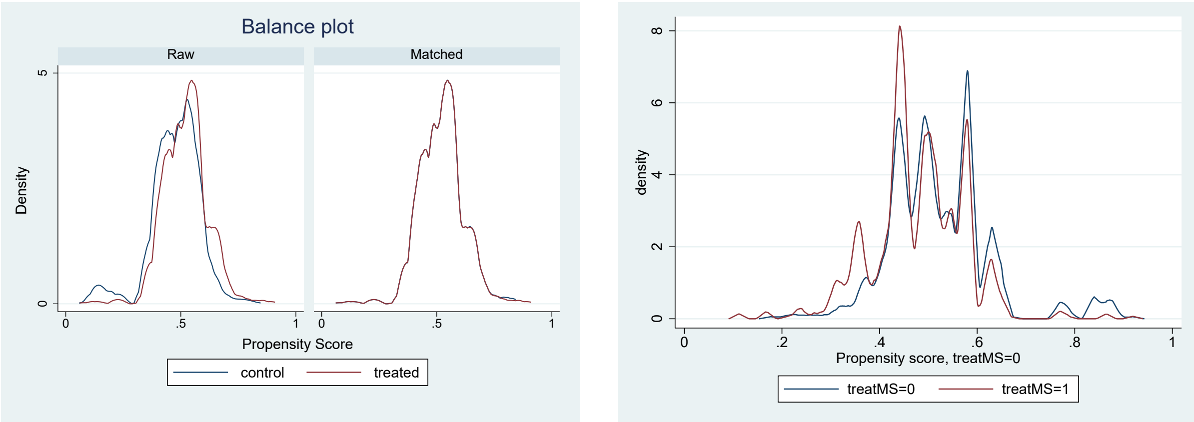

Figure 13: Balance and Overlap plots for lnCP, medium vs small tax tercile.

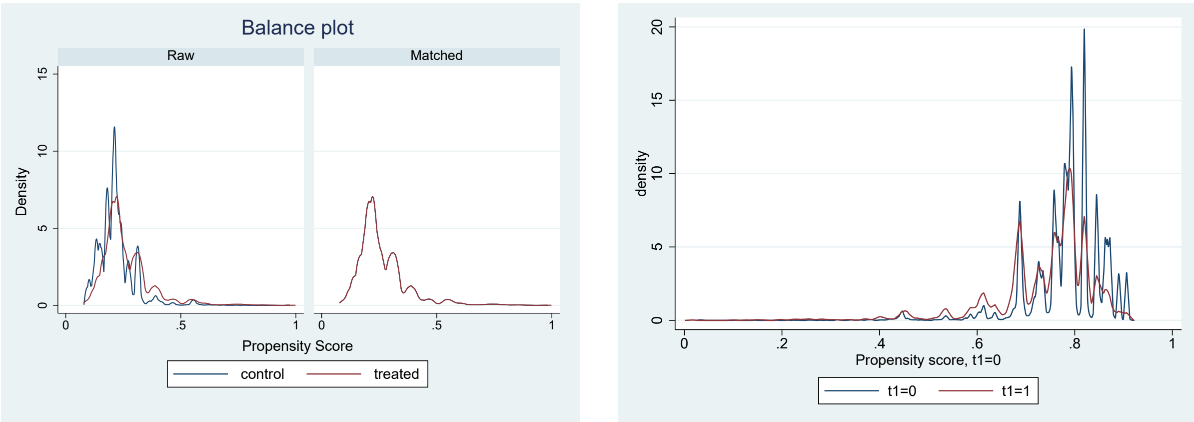

Figure 14: Balance and Overlap plots for lnEP, general tax dummy (tax).

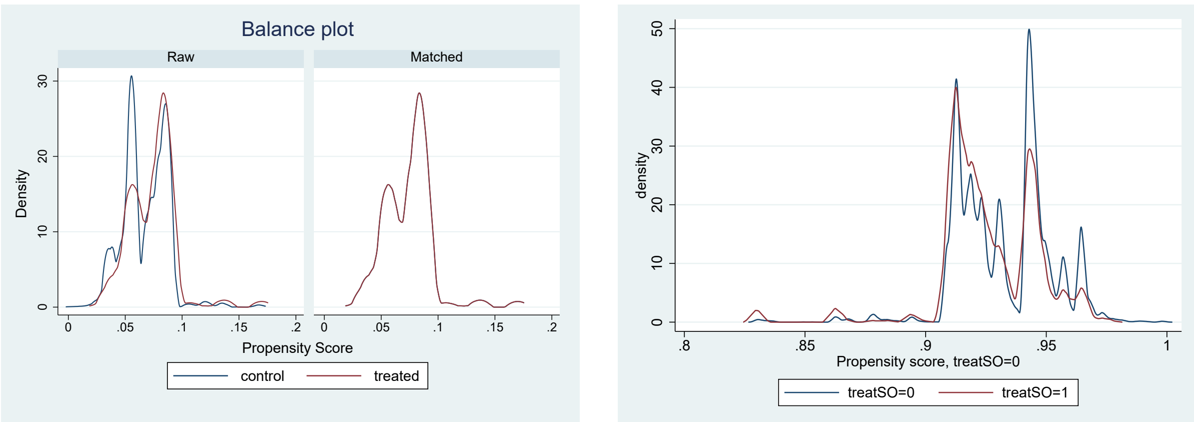

Figure 15: Balance and Overlap plots for lnEP, small tax tercile (small).

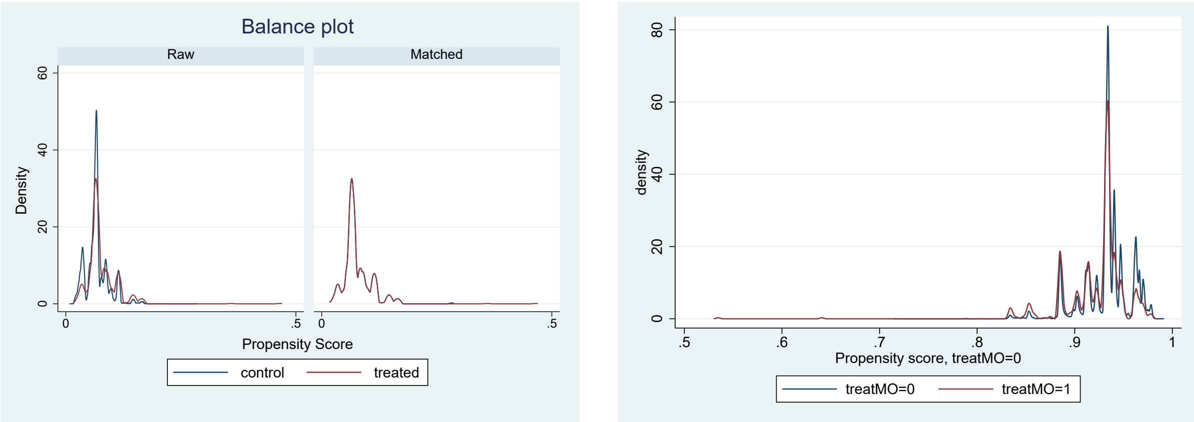

Figure 16: Balance and Overlap plots for lnEP, medium tax tercile (medium).

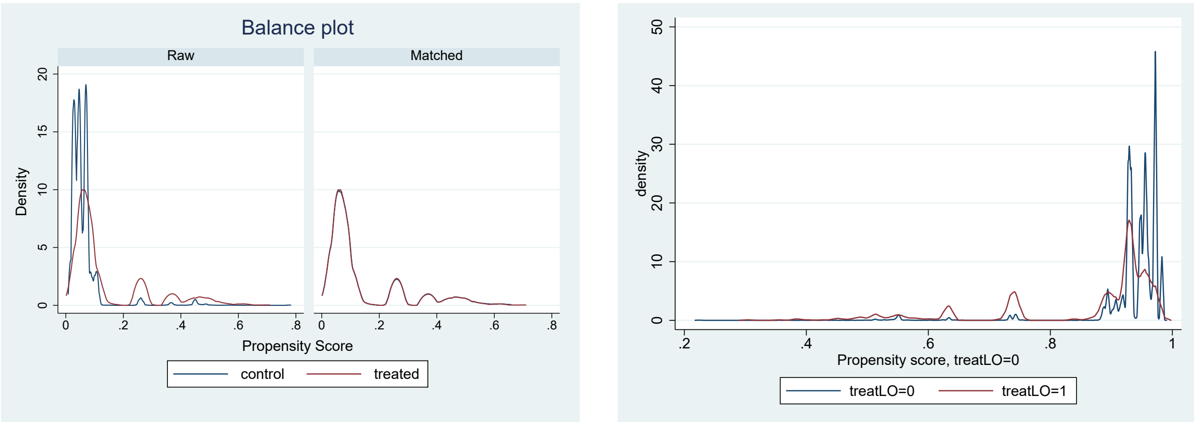

Figure 17: Balance and Overlap plots for lnEP, large tax tercile (large).

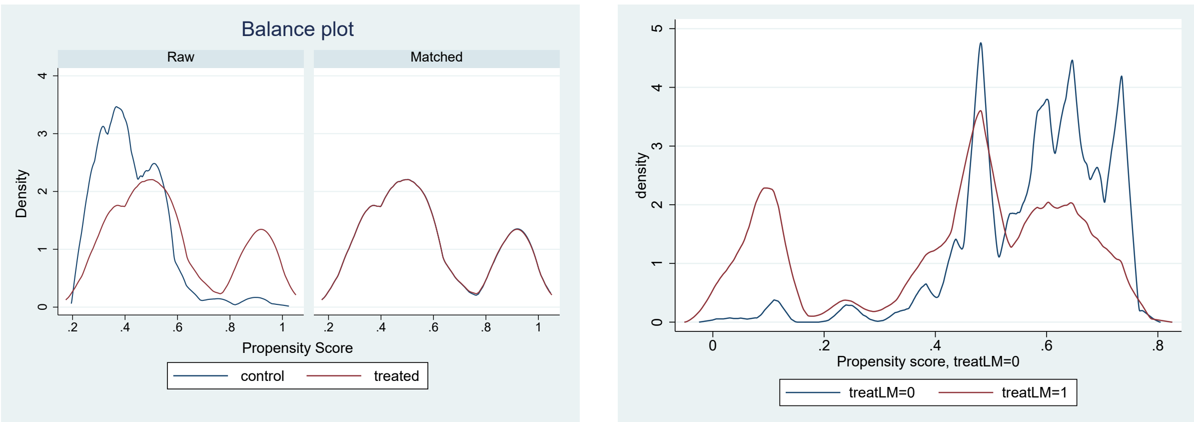

Figure 18: Balance and Overlap plots for lnEP, large vs medium tax tercile.

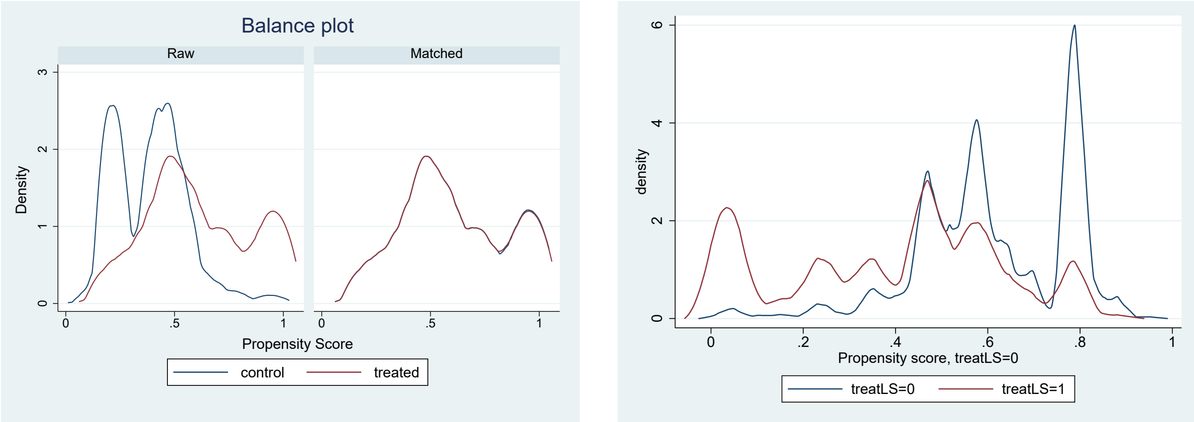

Figure 19: Balance and Overlap plots for lnEP, large vs small tax tercile.

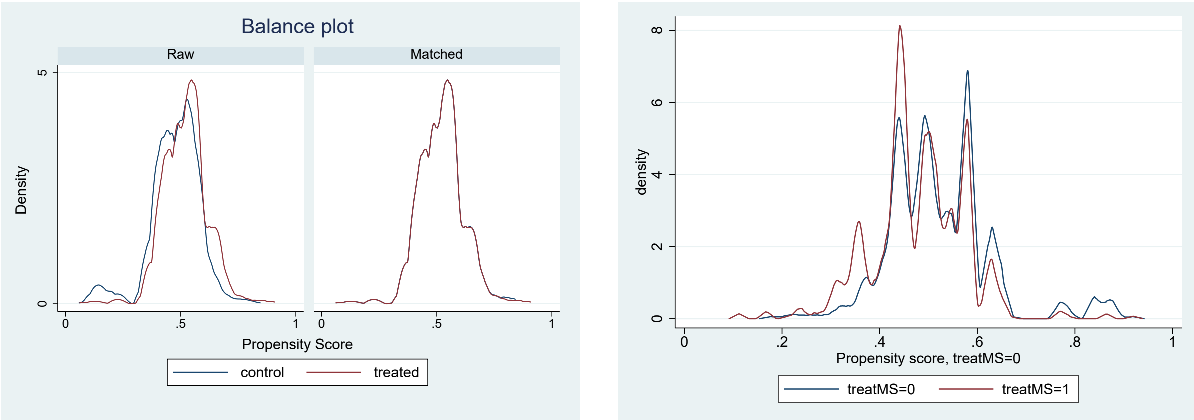

Figure 20: Balance and Overlap plots for lnEP, medium vs small tax tercile.

Table 11: Robustness Checks: CEM Results - The effect of environmental taxes on the outcome variables: absolute and in per capita terms.

lnCP	*no tax*	*small*	*medium*	*lnCPpc*	*no tax*	*small*	*medium*
tax	2.34***			*tax*	1.67***		
	(0.29)				(0.20)		
small	-0.21			*small*	-0.14		
	(0.37)				(0.26)		
medium	0.61	1.05*		*medium*	0.43	0.72*	
	(0.44)	(0.62)			(0.30)	(0.42)	
large	2.20**	2.16**	1.65**	*large*	1.64***	1.54**	1.23**
	(0.56)	(0.87)	(0.79)		(0.41)	(0.64)	(0.56)
lnEP	*no tax*	*small*	*medium*	*lnEPpc*	*no tax*	*small*	*medium*
tax	1.74***			*tax*	1.23***		
	(0.29)				(0.20)		
small	0.31			*small*	0.20		
	(0.36)				(0.25)		
medium	0.96**	0.82		*medium*	0.66**	0.57	
	(0.40)	(0.57)			(0.28)	(0.38)	
large	1.51**	0.74	0.22	*large*	1.02**	0.56	0.24
	(0.61)	(0.84)	(0.77)		(0.44)	(0.61)	(0.55)

Note: We hereby report the average treatment effect on treated. Standard errors shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level. Estimations are done with the default automatic coarsening algorithm. The standard errors are clustered at the firm level.

Table 12: Robustness Checks: Treatment in per capita terms.

	lnCP	lnEP
tax	1.85***	1.57***
	(0.28)	(0.23)
small	-0.47	0.10
	(0.41)	(0.36)
medium	0.71*	0.49
	(0.42)	(0.39)
large	1.04**	1.42***
	(0.47)	(0.47)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.1. Standard errors shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level.

Table 13: Robustness Checks: The effect of environmental tax on outcome variables in a balanced panel dataset and in years 2010-2014.

Balanced Panel

lnCP	no tax	small	medium	lnEP	no tax	small	medium
tax	1.72***			*tax*	1.02***		
	(0.32)				(0.34)		
small	-1.34**			*small*	-0.38		
	(0.62)				(0.54)		
medium	1.42**	1.56*		*medium*	1.01*	1.00	
	(0.60)	(0.91)			(0.52)	(0.80)	
large	2.06***	2.34**	1.88**	*large*	0.83	2.17	0.73
	(0.60)	(1.03)	(0.82)		(0.65)	(1.35)	(0.79)

2010-2014

lnCP	no tax	small	medium	lnEP	no tax	small	medium
tax	1.85***			*tax*	1.68***		
	(0.26)				(0.24)		
small	-0.27			*small*	0.57*		
	(0.40)				(0.33)		
medium	1.73***	1.01		*medium*	1.39***	0.54	
	(0.45)	(0.62)			(0.40)	(0.57)	
large	2.29***	1.78**	2.21	*large*	2.31***	2.78**	1.30
	(0.53)	(0.74)	(1.52)		(0.51)	(1.36)	(1.38)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.1. Standard errors are shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level.

Table 14: Robustness Checks: The effect of environmental tax on outcome variables in first differences.

(a) Outcome Variable: growthCP

	no tax	*small*	*medium*
tax	0.217***		
	(0.308)		
small	-0.358		
	(0.424)		
medium	1.195***	3.142***	
	(0.451)	(1.309)	
large	0.732	0.143	3.299**
	(0.560)	(1.386)	(1.374)

(b) Outcome Variable: growthEP

	no tax	*small*	*medium*
tax	1.109***		
	(0.281)		
small	0.327		
	(0.379)		
medium	1.992***	0.930	
	(0.406)	(1.231)	
large	1.546***	0.046	1.010
	(0.509)	(1.327)	(1.566)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.01. Standard errors are shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level. To perform those estimations we use the psmatch2 command.

Table 15: Robustness Checks: Outcome variables growthCP, growthEP, treatment: both environmental tax and public aid

	growthCP	*growthEP*
tax	10.853***	4.164***
	(1.264)	(1.489)
small	11.179***	0.836
	(1.699)	(2.042)
medium	11.074***	7.594***
	(1.926)	(2.217)
large	10.255***	3.594*
	(1.869)	(2.171)

Note: We hereby report the average treatment effect on treated. The caliper is equal to 0.01. Standard errors shown in parentheses. All standard errors are robust to firm heteroskedasticity. *** denotes significance at the 99% level, ** denotes significance at the 95% level and * denotes significant at the 90% level. To perform the estimations with use the psmatch2 command.