Sudden re-introduction of environmental investment tax-incentive - how do firms respond? *

Preliminary Draft

K.B. Tchorzewska †

February 15, 2019

Abstract

This paper investigates the effect of a sudden re-introduction of environmental investment tax incentives on investment in green technologies, using a sample of 2,562 Spanish manufacturing companies between 2008 and 2014. Exploiting the sharp unexpected re-introduction of the tax deduction at 8% in 2011, we perform difference-in-difference analysis. We combine difference-in-difference with propensity score matching technique to find firms, which could be used as an appropriate control group. We find that due to the nature of the tax credit in place, its re-introduction resulted in a decrease in investment in pollution abating end-of-pipe technologies and has, instead, increased financing cleaner production technologies aimed at air pollution reduction. Studying the dynamic effects, we find that as time passes, air pollution end-of-pipe technologies are increasingly financed through those tax credits.

Keywords: Green technologies, Tax incentives, Panel Data, Quasi-Experiment

JEL Codes: O31; 038; Q55; Q58

*Acknowledgments: We acknowledge financial support from the Chair of Energy Sustainability (IEB, University of Barcelona) and from the Ministry of Economy and Competitiveness (Project ECO2015-69107-R, MINECO/FEDER, EU). The research leading to these results has received funding from RecerCaixa (RecerCaixa project 2016: The climate change challenge: policies for energy transition). I would like to thank Pierpaolo Parrotta for all the invaluable help throughout the research process as well as my advisor Jose Garcia Quevedo and Tatyana Deryugina for all the support of any kind. I would like to thank Spanish Institute of Statistics (INE) for their support and access to data.

†Department of Economics, Chair of Energy Sustainability and Barcelona Institute of Economics (IEB), University of Barcelona, e-mail: kinga.tchorzewska@ub.edu
1 Introduction

Environmental taxation, in spite of its cost effectiveness and efficiency, is still fiercely fought with by the industry. Firms commonly fear losing their revenues and the media coverage supports that image by publishing dramatic titles \(^1\). However, in the absence of environmental taxation or any other form of environmental pressure, firms are reluctant to invest in green technology: blaming high fixed costs and the resulting capital market failure. Are there any other policy instruments that could substitute environmental taxation, and incentivise firms’ adoption of green innovation? How effective are environmental investment tax incentives on the adoption of green technology?

Tax incentives in spite of being existent in the public policy reforms for years are not very well researched. Commonly included within the subset of subsidies are and not studied in detail. Yes, scholars do agree fiscal incentives increase investment Zwick and Mahon (2017) but the literature have focused mainly on the responsiveness and the effects of R&D tax incentives on the level of R&D (Bloom et al., 2002; Rao, 2016; Thomson, 2017) and innovation outcomes (e.g. level of patenting) (Dechezleprêtre et al., 2016; Howell, 2017) rather than firms’ adoption of innovation.

This paper aims at estimating the causal effect of the Environmental Investment (EI) tax credit using comprehensive firm level data, allowing us to control for firm fixed effects. The central outcome of interest for a policy such as EI tax incentives are the resulting investments in green technologies. The only source of for environmental protection expenditures of firms are confidential business surveys maintained by government statistical agencies. Access to these are restricted and subject to disclosure control, which also explains why studies of this kind are not common if existent at all. This paper uses administrative panel data of 2,567 Spanish manufacturing firms to shed more light on the issue. Because of the nature of EI tax credits, there is also considerable concern regarding its impact on innovativeness of firms itself (private environmental R&D) - fearing that it takes away the funds from the firms’

innovativeness abilities - as well as its economic outcomes - among them employment. Our
dataset provides one of the most reliable sources for this kind of information and we explore
these outcomes as well.

In the following paper we investigate if and how firms responded to an unexpected re-
introduction to environmental investment tax credit. The re-introduction of tax incentive
the financing of abating technologies became much more challenging, due to the stricter rules
on the tax credit itself, which though generous was much more directed at the energy efficient
technologies rather than pollution abating technologies. More specifically, in the first step
we perform the standard difference in difference analysis on the investment in green tech-
nologies, in the second step we analyse the dynamic effects, studying in detail the possible
enhancement/decay of the effect and lastly we study the heterogenous effects at the sectoral
level. We also, perform a simple difference-in-difference on private environmental R&D to
test whether re-introduction of the EI tax credit has possibly pulling away the money away
from the innovative activity.

To this aim we first match firms on similar pre-treatment characteristics to arrive at an
appropriate control group, which could help us to control for self-selection. Then, exploiting
the sudden policy change that have occured in March of 2011, we perform difference-in-
difference analysis. We try to uncover how the sharp re-introduction of the investment tax
credits in a harsher form has affected adoption of green technologies (energy efficient and
abating technology) among Spanish manufacturing firms.

Our results suggest that, as expected the investment in green technologies has decreased
significantly. One, due to the stricter form of the tax credit itself - firms were finding it
much more difficult to finance their pollution abating investments. Two, due to the unex-
pected re-introduction, much confusion within the regulation setting and possibly budgeting
adjustment period.

The paper is structured as follows. Section 2 presents the existing empirical literature
review. Section 3 introduces the Spanish institutional setting of environmental investment tax credits. Sections 4 and 5 explain the data and methodology used while Section 6 discusses the results. Section 7 concludes and presents policy recommendations.

2 Literature Review

Suprisingly, the empirical literature concerned with firms’ responsiveness to changes in environmental investment tax incentives is, to our knowledge, non-existent. Indeed, there is a consensus that fiscal incentives increase investment (Zwick and Mahon, 2017) but within the innovation literature (not even environmental) scholars have focused on the responsiveness and the effects of R&D tax incentives on the level of R&D (Bloom et al., 2002; Rao, 2016; Thomson, 2017) and innovation outcomes (e.g. level of patenting) (Dechezleprêtre et al., 2016; Howell, 2017) rather than firms’ adoption of innovation.

Even the literature studying the effectiveness of environmental investment tax incentives is quite scarce. Encouraging adoptions of green technologies can be done indirectly through introduction of environmental taxes (Pigou, 1920; Aghion et al., 2016) or directly through provision of subsidies or tax credits on environmental protection investments. The latter ones hopefully address the capital market failure firms can be faced with and would result in newer greener solutions to environmental challenges. Environmental investment tax credits specifically, in theory, lower the after tax costs of innovation both from capital and labour perspective by providing a tax deduction for all eligible environmental protection investments. It thereby reduces the costs of undertaking innovation and diminishes the barrier to innovate by providing an incentive (Meyer et al., 1993). The empirical evidence on the effect of production tax credit (Roach, 2015), renewable energy subsidies (Murray et al., 2014) and energy infrastructure subsidies (Metcalf, 2010) and are far from reaching an agreement. In fact, while the paper by Metcalf (2010) emphasized the crucial role that the production tax credit had played for wind energy investment in the US, the results of Roach (2015) are less optimistic, concluding that the production tax credit for wind were much more successful in the deregulated rather than in the regulated electricity markets. Alarmingly also, Murray et al. (2014) estimated that over $10 billion spent in tax incentives (production tax credit
and investment tax credit on renewable energy and use of biofuels) had small impact on reduction of greenhouse gases and have ultimately led to an increase of emissions in some cases. There exists also one paper on the effectiveness of environmental investment tax incentive on levels of investment and coal consumption (Mao and Wang, 2016). To this aim authors use an identification strategy by Greenstone (2002) on the panel data set of universe of Chinese firms between 2007-2011. Their results show that tax incentive does not seem to be popular, as the mechanisms hurt interests of firms, however, it does seem to protect the environment by limiting coal consumption - yet only among firms connected to the central government. That being said the literature on the effectiveness very often suffers from self-selection problems - certain firms’ natural willingness to apply for investment tax credits is not easily measured and so the papers do not effectively assess the causality of specific reforms. Papers using quasi-experimental analysis are non-existent. 

Another fear that also exists is concerned with the fact that even if tax credits do increase investment, the eligibility for the tax deduction is usually limited to known technologies and hence it decreases the use of private information that the environmental taxes take advantage of. Additionally, as tax deductions are not uniformly applied, they are usually sought by companies that would be interested in innovating anyway, and since they are funded from the public capital, tax deductions are criticized for being wasted on companies that do not need additional incentives to innovate. Indeed, literature has spent a lot of time and effort trying to evaluate innovation fiscal policies such as R&D tax credits and still cannot come to agreement on whether there is an evidence of an input additionality or crowding out (Marino et al., 2016).

That being said, as we have point out before there exist a few articles studying the causal effects of R&D tax incentives and subsidies on R&D investment (Bloom et al., 2002), and patenting activity of firms (Dechezleprêtre et al., 2016; Howell, 2017) using quasi-experimental approach. More specifically, Dechezleprêtre et al. (2016), for example, uses RDD approach and asset-based size threshold for eligibility of R&D tax subsidies to study the effect on patenting activities of British firms. They find a remarkable result showing
that the business R&D would be 10% lower in the absence of the tax relief scheme. (Howell, 2017), on the other hand, investigates R&D grants on patenting and commercialization - also using RDD. She finds that the effects are stronger for more financially constrained firms - hence, showing that R&D grants seem to address capital market failure. They also point out to the fact that certification, where the award contains information about firm quality, likely does not explain the grant effect on funding. Instead, the grants seem to reduce investor uncertainty by funding technology prototyping. But even those authors do not analyse the responsiveness of firms to a sudden change in the investment tax credit rate or its reintroduction/disappearance and their need to adjust their budgets.

Focusing on firms’ behavioural responses to fiscal incentives Zwick and Mahon (2017) estimates the effect of temporary tax incentives on equipment investment using shifts in accelerated depreciation. He finds that, the incentive worked increasing the investment even up to 16.9 percent, though small firms responded 95 percent more than big firms. Second, that firms respond strongly when the policy generates immediate cash flows. To that aim they use a big panel data and analyse it using difference-in-difference analysis Neicu et al. (2016) on the other hand study behavioural additionality effects to wage-based R&D with and without R&D subsidies. Firms are found to initiate additional R&D projects and tip the R&D-balance more towards research relative to development. The latter effect indicates that tax credits nudge firms’ behavior towards those activities characterized by the most severe market failures.... other papers on behavioural responses... however to our knowledge there are no papers on behavioural responses of firms regarding the budget ...tralal and the decay/enhancement of their budget adjustment over time.

Lastly, we cannot forget about increasing literature on environmental policies using the quasi-experimental approach (Calel and Dechezlepretre, 2016; Wagner et al., 2014; Martin et al., 2014). More specifically, Calel and Dechezlepretre (2016) as well as Wagner et al. (2014) use difference-in-difference in combination with matching to study the causal effect of EU ETS.
Having this in mind, the following paper plans to fill the gap in the literature on the firms’ responsiveness to tax incentive policy changes using quasi-experimental approach. Following Howell (2017); Zwick and Mahon (2017) we use difference in difference matching estimator as adopted by the Wagner et al. (2014); Calel and Dechezlepretre (2016). In the second stage, we perform the dynamic difference-in-difference for the first performed by Autor (2003). Thanks so this type of investigation, we not only can see how firms reacted to an un-expected reintroduction of an investment tax credit but also whether the effect persisted or died down over time. As a result we would like to test the four following hypothesis.

**Hypothesis 1:** Due to the unexpected nature of the re-introduction of the tax incentive, the investment in cleaner production technologies has decreased slightly as firms suffered budgetary adjustments. We expect the negative effect to decay over time as firms adjust their budgets.

**Hypothesis 2:** Investment in end-of-pipe technologies decreased much more for two reasons: budgetary adjustments and due to stricter tax incentive rules for financing mostly cleaner production technologies. The effect persists over time.

**Hypothesis 3:** We expect that as investment tax credit is re-introduced it might affect indirectly the private environmental R&D. Firms might decide to spend their money on adoption of green innovation rather their own private research and development to develop their own technologies. The effect decays over time.

**Hypothesis 4:** We expect that the re-introduction of the investment tax credit affects positively green employment, that could help with application process. The positive effect decays over time.
3 Environmental Investment Tax Incentive

Environmentally related tax credits in Spain had been a result of a central effort rather than a regional one (OECD, 2010) in comparison to for example environmental taxes. The Law 13/1996\(^2\) introduced two provision notes to the Spanish Corporate Income initially indefinitely: one related to a tax credit on research and development expenses another concerning a tax credit for eligible environmental protection investments (EI tax credit from now on) aimed at reducing pollution related to air, water and industrial waste. The tax credit was agreed to be equal to 10% of total investment in green technologies. In order for the investments to qualify for the tax credit, they had to go beyond what is legally required. However, it was discussed (Garcia 2004) - that the exact Spanish phrase "investments (...) for the improvement of existing regulation" might have been confusing and has subsequently led to implementation difficulties. As a consequence firms not only were investing in cleaner production technologies - which was recommended but were also using the tax incentive to finance end-of-pipe technologies (abatement technologies such as filters and scrubbers) (OECD, 2008)

The legal condition that the investment was to go beyond what is legally required implies that investments were (in principle) undertaken on a voluntary basis. In this sense the tax credit on environmental investments effectively reduced the price and payback period of investments, and increased its internal rate of return. To our knowledge there are no econometric studies analysing the effectiveness of the tax credit and therefore the "additionality" of part of these investments cannot be confirmed.

As mentioned before, EI tax credit was a result of a central effort rather than a regional one. That being said, the application of the tax credit depended upon the certificates issued by Autonomous Communities - where while the rules forms and procedures were similar they were not identical and so the application of the tax credit varied between regions. However, according to OECD (2008) despite the participation of regional authorities in the validation of environmental investments, regional dispersion of the tax credit was virtually the

\(^2\)Ley 13/1996, de 30 de Diciembre, del Impuesto sobre Sociedades
same regarding the number of declarations presented - and though higher in general for the amount deducted - in comparison to R&D&I tax credit its much lower. Additionally, INE 2008d has found a strong correlation between the environmental investments undertaken by industrial companies at regional level and the amounts deducted in each region - with the only exception being Madrid - probably suffering from the big-city-effect. That being said, the evidence points into an assumption that the regional differences were not substantial as to affect the firm level analysis.

This environmental tax incentive had been successfully used by firms for almost two decades until both of the tax deductions were assessed as inefficient. Experts calculated that 68% of all investments that the EI tax credit was used for were end-of-pipe technologies, the remainder being used for financing integrated cleaner technologies. This proportion was much higher than Spanish firms’ environmental investments overall, suggesting that tax credit had an important role in influencing the type of technology, but not necessarily the degree of innovativeness the government desired to tackle and hence seems to supports the effect the theory of the tax deduction suggests above (OECD, 2010).

As a result, the government has announced in 2006 a progressive phase-out of both tax incentives. Officials have argued in Memoria Justificativa of the Law 35/2006 that these investments "in many occasions are no longer optional for companies, but compulsory (...)

Today, it would be a paradox for a State to provide tax incentives for some investments, which are compulsory according to environmental legislation (...)". Regarding the EI tax credit specifically, the phase out had been planned as a yearly depreciation by 2% from 2006 when it was still equal to 10% until 2011 when it was planned to disappear completely (art. 39.1, Royal Legislative Decree, 4/2004) - please see Table X below. The pending EI tax credits were allowed to be used after the phase out was completed (OECD, 2008).

Surprisingly, however, without any previous warning, possibly to mediate the economic downturn related to the Spanish financial crisis and boost environmental investment, Spanish government through the Law 2/2011 has decided to re-introduce the EI tax credit in March.

3Ley 2/2011 de 4 de marzo de Economía Sostenible)
of 2011 at the rate of 8% - 3 months after it was phased out completely. The mentioned
tax incentive has been re-introduced but in the form that was much stricter towards making
sure it finances cleaner production technologies rather than end-of-pipe technologies (which
were usually the ones legally required). The EI tax credit has remained in that form until
the end of the financial crisis that is 2015 when it was eliminated completely and definitively
with the new Law of Corporate Tax 27/2014.

What makes the EI tax credit reintroduction interesting, is that it generated a lot of
confusion until the very last moment and even though re-introduced - was specifically re-
turned to encourage energy efficient rather than abating technologies. With the Sustainable
Economy Law 2/2011, the percentage was increased by 8% for investments made in the tax
period that began after the entry into force of this Law. In accordance with article 92 of
the aforementioned Law, as of January 1, 2011: If the beginning of the tax period is prior
to the entry into force of the Sustainable Economy Law, a deduction of 8% may be applied
to investments made as of January 1, 2012. In this case, the investments put into operation
in 2011 will only be entitled to a 2% deduction. If the beginning of the tax period is after
the entry into force of the Sustainable Economy Law (March 6, 2011), the investments made
in this period will be entitled to a deduction of 8%. With the publication of Law 27/2014,
of November 27, on Corporate Tax, which came into effect on January 1, 2015, investments
with environmental improvement objectives are no longer subject to tax deduction. Taking
into account this modification, the investments put into operation as of January 1, 2015
can not be subject to certification of investment validation by the General Directorate of
Environmental Quality and Climate Change.

4 Data

As in most of the cases of quasi-experimental approaches and especially due to the confiden-
tial nature of the database itself, we must face the constraints of data availability. In this
paper, we use data provided for the first time by Instituto Nacional de Estadística gathered

4Ley 27/2014 de 27 de Noviembre, Impuesto Sobre Sociedades
5Department of Territory and Sustainability of Spain, http://mediambient.gencat.cat/es/details/tramits/Deduccions-
per-inversiones-amb-objectius-de-millora-ambiental, accessed, 24.10.2018
over the span of 7 years between 2008-2014 through the Survey on Industry Expenditure on Environmental Protection (SIEEP). The main purpose of it being the assessment of current expenditures and investments of the Spanish industry to reduce negative environmental effects. SIEEP provides also information on the size (includes all establishments hiring 10 and more remunerated employees) and a number of capital environmental expenditure, investment and research data. The firm level data is available between 2008 and 2014, creating an unbalanced panel data set for 2,562 companies, where each company has at least 4 observations across 7 years. Out of all 26 variables provided we chose the most suited for our investigation, which are briefly described below. INE ensures the quality of the data by employing CCU (centralised collection unit), which is dedicated to obtaining all the information from the questionnaire. Once survey is created errors are detected and corrected. Unclear answers are double checked through a phone interview.

In accordance with the literature review carried out, the survey provides us with diversified data of the fundamental variable investment in green technology: either 'end of pipeline' or "integrated cleaner technology". Additionally, it also provides a very important variable "environmental R&D" constituting a substantial input to eco-innovation, which enriches our results considerably. We do not only can see how particular tax related environmental instrument affects adoption and diffusion of energy but also the invention efforts themselves. Lastly, the survey provides us with a variable on the number of green employees that each company has decided to hire.

While it is true, the study could gain much from merging the given data set and getting additional control variables from a Panel de Innovació\'n Tecnolà\'gica (PITEC), sadly we have not been given a permission to do that. That being said, I still believe lots of fixed effects can be captured thanks to the size of the dataset and the variables available.

4.1 Variables

For a better understanding of the variables available, please see Table 2. for a list of variables and descriptive statistics. The data is divided into 4 main subgroups. The first one
includes typical firm’s characteristics such as location, number of employees, the activity the firm is known for. The second group includes the transaction associated with Public Administration and hence all environmental policy instruments voluntarily or involuntarily applied such as different types of environmental taxes, subsidies, tax deductions and investment grants. Group 3. includes variables of current expenditures, that is payments to other companies of environmental protection services, to public administrations such as certifications, repairs and others. The third group also includes “other current expenses: environmental R&D”. The last group includes our fundamental variables that is the integrated cleaner production technologies such as installations for reducing the emissions of atmospheric pollutants and installations for reducing consumption and energy and end of pipe-line technologies such as air emissions. All of the variables from group 2,3 and 4 have values presented in Euros.

When it comes to environmental protection investment tax credits - unfortunately, firms that decide to benefit from voluntary policies such as this one, might suffer from self-selection, and hence the choice of appropriate methodology becomes much more stringent. By exploiting the fact that the environmental protection tax deduction suffered an unexpected re-introduction at the moment they were supposed to be phased out in Spain, we can assess its impact on different types of eco-innovation using a difference-in-difference model in combination. Unlike Propensity Score Matching alone, difference in difference estimator allows to control for unobserved heterogeneity that may lead to selection bias such as natural willingness of certain type of companies to use environmental protection tax credits and non-random popularity of this policy instrument across different sectors. More specifically, I plan to run regression in combination and without the matching of firms of their pre-treatment characteristics to further control for the existing endogeneity within our treatment variable.

4.2 Descriptive Evidence

We describe the policy reform and the rates of the investment tax credit for the year of our sample in Table 1. We include the anticipated tax credit rates - descending from 6% in 2008
and 2% in 2010 to 0% in 2011, and the actual rates which have increased to 8% in 2011 and remained that way for the next years.

Table 2. presents descriptive statistics. We include number of observations (N), their mean and standard deviation (SD) for the outcome variables (lnCP, lnCPair, lnCPenc, lnEP, lnEPair lnRD), and the control variables. The table also reports descriptive statistics of the overall "treatment dummy" and for different years. We also show how many firms have received an investment tax credit in each year (Figure 1.) and what was its average annual amount for the treatment variable as well as the main dependent variables (Figure 2 and 3.)

Significant differences are also reported when contrasting investment levels before and after policy change. [Need to develop this section further] Of course, those are just preliminary and descriptive findings, which do not account for time and firm heterogeneity and may not be interpreted as conclusive.

5 Methodology

This section briefly discusses the estimation strategies implemented in our empirical assessment of re-introduction of an environmental investment tax incentive in Spain. Exploiting the exogenous re-introduction of the tax credit as well as the fact that the before mentioned tax credit did not have any specific eligibility criteria, we have decided to use difference in difference estimator with propensity score matching. The inclination to reduce biases arising from non-random assignments makes these methods widely unstilted in the field of causal inference in observational studies. To provide some insights into the methodology as well as to discuss its strengths and weaknesses of each method, we discus them separately.

In the previous section we have analysed thoroughly exogenous policy setting and the need to match firms on their characteristics to control (not ideally) for self-selection. In the following section we will assume that once we match firms on their pre-treatment characteristics - such as size, sector, their previous green investment activity and organisational capabilities such as having green employess - the difference between firms’ arises mostly from
receiving a tax incentive. Quite naturally, ideally for investigating the effect of a tax incentive we would have preferred to use some kind of eligibility criteria and the RDD design. However, as it is often the case with observable data, we are faced with its numerous limitations. Given no eligibility criteria, we have decided to combine instead two quasi-experimental approaches.

We will be using Propensity Score Matching (PSM) proposed by (?). More specifically, in the first step we implement simple matching as used by Marino et al. (2016), thanks to which we can compare between treated (receivers of tax credits) and not treated (non-receivers of tax credits). In the second step, we run a difference in difference model, which aids with the conclusion on the sudden reintroduction of such tax credit.

5.1 Propensity Score Matching

The evaluation of technology policy has evolved rapidly over the years. However, the traditional problems of evaluations of such policies, which include endogeneity and sample selection (?) still remain. We believe that self-selection might be a threat to our study, as we assume plants might have some endogenous capabilities that push them to apply for a given tax credit. The second problem, however, endogeneity comes from the fact that the variables used to measure these effects of public interventions can be endogenously determined if we assume that firms making a greater effort in case of existing environmental policy stringency.

Most recent studies use nonparametric matching techniques in order to ensure the maximum degree of similarity between control and treated groups. Matching techniques allow the comparison of two potential results, I for those that have received an investment tax credit, T=1, and T=0 for those firms that did not receive such tax incentive. Matching is based on the conditional independence assumption, which states that, conditional on a vector of covariates, potential outcomes I1 and IO are independent of T. In order to ensure that fulfillment of this assumption it is necessary to observe those variables simultaneously affect the outcome and the reception of the treatment exhaustively.
The data for the period 2008-2014 are treated as pooled data, thus observations for the same firms in different years are considered as independent observations. After describing variables with missing values, PSM is run thus providing a sample of treated and control firms, matched on the set of variables. Define the PSM as the condition probability of being treated, given a vector of covariates X:

\[ p(X) = P(T = 1|X) = E(T|X) \] (1)

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

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

where:

Y(1) represents the expected outcome for the firms with tax credit
Y(0) represents the outcome for the firms without the tax credit

However, such simplistic effect of environmental investment tax credits, would not take into account the unobserved heterogeneity, therefore, in the second step we will combine this with difference-in-difference. To ensure quality of matching we select counterfactuals by utilising the caliper method (0.01) with replacement, and the average for most of our regressions is below 25% as recommended. Please see Figure 4 for the example of kernel densities of treated and non-treated. We also match exactly on sectors and size groups.

5.2 Main Specification

By exploiting the fact that the environmental investment tax credit was unexpectedly re-introduced to the Spanish Corporate Tax in March of 2011, we assess the impact of this sudden change using difference-in-difference (or more generally fixed effects) model in combination with Propensity Score Matching to address self-selection of firms receiving an in-
vestment tax credit. In the first step, by estimating propensity score matching and using exact matching on sectors we match "treated" and "untreated" companies - those companies that have received an investment tax credit with those that did not - to assure that we have a robust control group.

In the second step, we run regressions of firm level investments in end-of-pipe, cleaner production technologies and their private environmental R&D expenditure. We control for time fixed effects to control for the introduction of the policy in 2011 and the effects of a business cycle that could have been important during the financial crisis. Additionally, we control for the firm fixed effects to control for whether the firm has received a tax credit on an environmental investment. Standard errors are clustered at the firm/sector level throughout so that these standard errors are robust to arbitrary forms of error correlation within the firms/sectors. The empirical model, estimated by OLS, takes the following form:

\[
\ln(ECO - INNOV)_{i,t} = \alpha + \beta_1 \text{Treat} + \beta_2 \text{Post2011} + \delta (\text{Treat} \times \text{Post2011})_{i,t} + \beta_3 X_{i,t} + f_i + \epsilon_{i,t}
\]

where \(i\) refers to the firm and \(t\) to the year. Our outcome variable \(\ln(ECO - INNOV)_{i,t}\) is a log transformation of the investment variables at the firm level. Those are: investments in CP, CPair, CPenc, EP and EPair in a given year. But we do not only look at the direct effects on the levels of investment in green technology - investing in abatement and efficient technologies. We also look at the indirect effect the policy has had on the level of private environmental R&D and the level of green employees within the company (this analysis still pending). We add 0.10 to all our dependent variables to include observations that would otherwise be associated with missing values. The \((\text{Treat} \times \text{Post2011})_{i,t}\) is the key variable. It is a dummy variable and it is an interaction between the policy dummy and tax credit dummy. It carries the difference in difference coefficient \(\delta\). Quite naturally, we are also controlling for others firms’ characteristics, which are captured in the matrix \(X_{i,t}\). Firms and time fixed effects are \(f_i\) and \(f_t\), respectively. \(\epsilon_{i,t}\) is assumed to be an idiosyncratic term, unrelated to other independent variables. However, the standard errors are robust and clustered at the
The presence of systematic differences between the treatment and control groups in the sample is not an issue because the difference in difference methodology does not rely on random assignment to treatment (Angrist and Pischke, Cameron and Triverdi). DID is based only on the assumption that the two groups follow the same trend in the absence of treatment. This is likely to happen in our setting because we include firm and year fixed effects, which are not included in the standard DID approach. Please see Figures 5 and 6. for the parallel trends.

In order to correct for both autocorrelation and heteroscedasticity it is suggested to cluster standard errors on the panel unit id (firm level), which we do.

### 5.3 Dynamic Specification

Given the evidence of the significant impact of our policy change on investments levels, it is quite natural to wonder how the effect has changed over time since the first year of implementation. Does the effect get stronger or fade out? Have the firms adjusted their budgets relatively quickly and we could see a decay of the negative effect? Or on the contrary the firms continued to invest less and less through the financing from the investment tax credit?

To provide some sense of the dynamics of the *treatment* effect using the data we have, we perform an exercise similar in spirit to the causality analysis in the paper by Autor (2003). The exercise also lends us insights into any behavioural effect that may be present. We do this by replacing the interaction dummy \((Treat \times Post)_{i,t}\) with a series of lead dummies indicating the time passage relative to the policy implementation.

The specification we consider is the following:
\[ \ln(\text{ECO} - \text{INNOV})_{i,t} = \alpha + \beta_1 \text{Treat} + \gamma_1 \text{INTER}_{2011} \\
+ \gamma_2 \text{INTER}_{2012} + \gamma_3 \text{INTER}_{2013} + \gamma_4 \text{INTER}_{2014} + X_{i,t+1} + f_i + f_t + \epsilon_{i,t}, \]

where instead of a single treatment we now have four lag dummies of the treatment effect and \text{INTER} is the interaction dummy of treatment with each year. Those terms capture the post-policy trend. An ascending trend in the magnitude of the set of coefficients would suggest a slowly decaying effect, while a descending trend would translate into the increasing reluctance/inability of firms to use tax-credits to finance environmental investments. All other variables remain the same as in the baseline specification.

5.4 Extensions: the indirect effects on private environmental R&D and the number of green employees

[WORK IN PROGRESS]

5.5 Extensions: heterogeneity analysis (effects smaller for firms that have innovated before? that have received the tax credit before? of certain number of employees? of certain sectors?)

[WORK IN PROGRESS]
6 Results

The preliminary results are presented in Tables 3, 4 and 5.

- we find evidence for a negative relationship of re-introduction of the investment tax credit with the investment in both types of green technologies - though the coefficients are not statistically significant at the 10 percent level

- for the end-of-pipe technologies, the negative relationship seems to be increasing in magnitude over time however the effect disappears once we introduce matching into the model

- upon analysing the channels and specific technologies that the re-introduction of the investment tax credit did affect the investment, we find that the reintroduction of the tax credit with stricter rules on EPair technologies was successful. There exists a statistically significant negative coefficient on the general interaction term as well as the one for 2014 and the dynamic analysis

- furthermore, it seems that the re-introduction might have positively affected the investment in one specific type of green technology that is lnCPenc (cleaner production technology aimed at energy consumption). this remains platform for further research.
References


### A Appendices

#### Table 1: Tax Deduction Rates - planned versus actual.

<table>
<thead>
<tr>
<th>Year</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax Credit Planned</td>
<td>6%</td>
<td>4%</td>
<td>2%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Tax Credit Actual</td>
<td>6%</td>
<td>4%</td>
<td>2%</td>
<td>8%</td>
<td>8%</td>
<td>8%</td>
<td>8%</td>
</tr>
</tbody>
</table>

#### Table 2: Variables and Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>size</td>
<td>number of employees</td>
<td>274</td>
<td>548</td>
</tr>
<tr>
<td>tax_credits</td>
<td>tax credits received for adoption of eco-innovations (euros)</td>
<td>9,018</td>
<td>261,007</td>
</tr>
<tr>
<td>dtax_credits</td>
<td>= 1 if the firm received tax credits</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>CP</td>
<td>Cleaner Production technologies (euros)</td>
<td>172,579</td>
<td>1,363,846</td>
</tr>
<tr>
<td>lnCP</td>
<td>natural logarithm of CP+0.001</td>
<td>-3.22</td>
<td>9.36</td>
</tr>
<tr>
<td>dCP</td>
<td>= 1 if the firm invested in CP in a given year</td>
<td>0.30</td>
<td></td>
</tr>
<tr>
<td>CPair</td>
<td>air pollution reducing CP technologies (euros)</td>
<td>94,263</td>
<td>1,115,950</td>
</tr>
<tr>
<td>lnCPair</td>
<td>natural logarithm of CPair+0.001</td>
<td>-6.77</td>
<td>6.65</td>
</tr>
<tr>
<td>dCPair</td>
<td>= 1 if the firm invested in CPair</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>CPenc</td>
<td>energy consumption reducing CPenc technologies (euros)</td>
<td>22,927</td>
<td>281,354</td>
</tr>
<tr>
<td>lnCPenc</td>
<td>natural logarithm of CPenc+0.001</td>
<td>-7.13</td>
<td>6.10</td>
</tr>
<tr>
<td>dCPenc</td>
<td>= 1 if the firm invested in CPenc</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>EP</td>
<td>End-of-Pipe technologies (euros)</td>
<td>116,973</td>
<td>1,074,002</td>
</tr>
<tr>
<td>lnEP</td>
<td>natural logarithm of EP+0.001</td>
<td>-4.57</td>
<td>8.51</td>
</tr>
<tr>
<td>dEP</td>
<td>= 1 if the firm invested in EP</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>EPair</td>
<td>air pollution reducing EP technologies (euros)</td>
<td>41,432</td>
<td>741,608</td>
</tr>
<tr>
<td>lnEPair</td>
<td>natural logarithm of EPair+0.011</td>
<td>-7.62</td>
<td>5.46</td>
</tr>
<tr>
<td>dEPair</td>
<td>= 1 if the firm invested in EPair</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>RD</td>
<td>private environmental Research and Development (euros)</td>
<td>4,668</td>
<td>70,434</td>
</tr>
<tr>
<td>lnRD</td>
<td>natural logarithm of RD+0.001</td>
<td>-8.16</td>
<td>4.30</td>
</tr>
<tr>
<td>dRD</td>
<td>= 1 if the firm invested in RD</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>env_cert</td>
<td>implementation of the environmental certifications (euros)</td>
<td>74,025</td>
<td>412,334</td>
</tr>
<tr>
<td>denv_cert</td>
<td>= 1 if the firm paid for environmental certifications</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>green_empl</td>
<td>annual salaries spent on employees dedicated to environmental protection (euros)</td>
<td>72,087</td>
<td>197,800</td>
</tr>
<tr>
<td>dgreen_empl</td>
<td>= 1 if the firm has employees dedicated solely to environmental protection</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td>lagCP</td>
<td>lagged amount of investment in CP (euros)</td>
<td>172,434</td>
<td>1,363,780</td>
</tr>
<tr>
<td>llagCP</td>
<td>natural logarithm of lagCP+0.001</td>
<td>-3.22</td>
<td>9.33</td>
</tr>
<tr>
<td>lagEP</td>
<td>lagged amount of investment in EP (euros)</td>
<td>116,943</td>
<td>1,074,032</td>
</tr>
<tr>
<td>llagEP</td>
<td>natural logarithm of lagEP+0.001</td>
<td>-4.57</td>
<td>8.51</td>
</tr>
</tbody>
</table>

**Note:** The mean of a dummy variable represents the proportion or percentage of cases that have a value of 1 for that variable. All firms have at least 10 renumerated employees. Based on an unbalanced panel of 2563 individual firms across 7 years (half of the firms have data from 6 out of 7 years); 14723 observations in total.
Figure 1: Average annual percentage of companies receiving environmental investment tax credit.

Figure 2: Average annual expenditures on green technologies (CP and EP) as well as average annual tax credits received in euros.
Figure 3: Average annual expenditures in all types of green technologies: CP, CPair (B411), CPenc (B416), EP and EPair (B421).

Figure 4: Example of a kernel density of treated and control groups for lnEP.
Table 3: Main Results: Fixed effects regression estimations for log investment in CP for simple and dynamic difference in difference, with and without matching.

<table>
<thead>
<tr>
<th></th>
<th>Without Matching</th>
<th>With Matching</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lnCP</td>
<td>lnCP</td>
</tr>
<tr>
<td>dtaxcredit</td>
<td>0.56***</td>
<td>1.93***</td>
</tr>
<tr>
<td>post2011</td>
<td>-0.55***</td>
<td>0.31</td>
</tr>
<tr>
<td>inter</td>
<td>-0.21</td>
<td>-0.46</td>
</tr>
<tr>
<td>inter11</td>
<td>-0.01</td>
<td>-0.20</td>
</tr>
<tr>
<td>inter12</td>
<td>-0.41</td>
<td>-1.24*</td>
</tr>
<tr>
<td>inter13</td>
<td>-0.78**</td>
<td>-0.14</td>
</tr>
<tr>
<td>inter14</td>
<td>-0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>controls</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>firm FE</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>time FE</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

Note: All standard errors are clustered at the firm level. *** , ** , * denote significance at the 99% level, 95% level and 90% level, respectively.
Table 4: Main Results: Fixed effects regression estimations for log investment in EP for simple and dynamic difference in difference, with and without matching.

<table>
<thead>
<tr>
<th></th>
<th>Without Matching</th>
<th>With Matching</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnEP</td>
<td>1.25***</td>
<td>1.90***</td>
</tr>
<tr>
<td>dtaxcredit</td>
<td>0.94**</td>
<td>0.93*</td>
</tr>
<tr>
<td>post2011</td>
<td>-0.16**</td>
<td>-0.30</td>
</tr>
<tr>
<td>inter</td>
<td>-0.47*</td>
<td>-0.21</td>
</tr>
<tr>
<td>inter11</td>
<td>-0.39</td>
<td>-0.04</td>
</tr>
<tr>
<td>inter12</td>
<td>-0.64*</td>
<td>-1.27</td>
</tr>
<tr>
<td>inter13</td>
<td>-0.82**</td>
<td>-0.21</td>
</tr>
<tr>
<td>inter14</td>
<td>-1.89***</td>
<td>0.26</td>
</tr>
<tr>
<td>controls</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>firm FE</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>time FE</td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>

Note: All standard errors are clustered at the firm level. ***, **, * denote significance at the 99% level, 95% level and 90% level, respectively.

Table 5: Extensions: Fixed effects regression estimations for log investment in EPair, CPair and CPenc with simple and dynamic difference in difference.

<table>
<thead>
<tr>
<th></th>
<th>lnEPair</th>
<th>lnEPair</th>
<th>lnCPair</th>
<th>lnCPair</th>
<th>lnCPenc</th>
<th>lnCPenc</th>
</tr>
</thead>
<tbody>
<tr>
<td>dtaxcredit</td>
<td>2.16***</td>
<td>5.61***</td>
<td>3.34***</td>
<td>8.00***</td>
<td>0.46</td>
<td>2.95</td>
</tr>
<tr>
<td>post2011</td>
<td>-1.46***</td>
<td>-0.77***</td>
<td>-0.21</td>
<td>0.32</td>
<td>0.11</td>
<td>1.41</td>
</tr>
<tr>
<td>inter</td>
<td>-2.09**</td>
<td>-1.04</td>
<td>0.17</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>inter11</td>
<td>-0.89</td>
<td>1.13</td>
<td>2.27*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>inter12</td>
<td>-1.86</td>
<td>-0.21</td>
<td>0.32</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>inter13</td>
<td>-1.64</td>
<td>-1.95</td>
<td>0.11</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>inter14</td>
<td>-3.14***</td>
<td>-0.11</td>
<td>1.41</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>controls</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>firm FE</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>time FE</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: All standard errors are clustered at the firm level. ***, **, * denote significance at the 99% level, 95% level and 90% level, respectively.